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Computational Modeling of User States and Skills for Optimizing BCI Training Tasks

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TITRE

Modélisation Computationnelle des États et Capacités de l'Utilisateur afin d'Optimiser des Tâches d'Entrainement BCI

Résumé

Les Interfaces Cerveaux-Ordinateur (ICO) sont des systèmes qui permetent de manipuler une machine avec sa seule activité cérébrale. Elles sont utilisées pour accomplir des objectifs variés, par exemple afin qu'un amputé puisse manipuler un bras robotique, pour une réhabilitation neuronale en cas d'accident vasculaire cérébral, dans un cadre ludique pour jouer à des jeux vidéo, etc. Une ICO comprend l'acquisition du signal cérébral (le plus souvent par électroencéphalographie, EEG), le décodage et l'interpretation de ce signal, et enfin la production d'un retour sensoriel à l'utilisateur. Ce retour guidera l'utilisateur pour réguler son activié cérébral et apprendre à manipuler la machine. La morphologie du cerveau difère cependant entre utilisateurs, et les pensées d'un même individu varient au cours du temps. Ces fluctuations rendent les ICO moins performantes, qui sont alors difficiles à utiliser hors des conditions du laboratoire. Nous avons donc besoin d'une machine dynamique, qui puisse s'adapter au cours du temps à son utilisateur. Dans la littérature les approches proposées afin de remédier à ce problèment décrivent des machines qui décodent de manière adaptative les signaux EEG, mais ces systèmes ne sont pas assez robustes et ne permettent toujours pas aux ICO d'être utilssées dans la vie quotidienne.

L'objectif de cette thèse est d'améliorer les performances et l'utilisabilité des ICO basées sur de l'EEG, en les adaptant de façon innovante aux états et compétences des utilisateurs. Pour ce faire, nous avons premièrement mis en évidence tous les facteurs changeants dans une ICO en définissant trois séquences : 1. Les états psychologiques fluctuants de l'utilisateur qui modifient la signature du signal EEG ; 2. Ce signal qui varie et qui amène la machine à ajuster son décodage ; 3. La tâche qui est présentée à l'utilisateur via le retour sensoriel de la machine, et qui influence à son tour les états psychologiques de l'utilisateur. Nous avons ainsi mis en évidence la possibilité d'adopter un nouvel angle de recherche, en utilisant *la tâche adaptative* pour diriger les états psychologiques de l'utilisateur et aider ce dernier à manipuler une ICO. Au lieu de seulement adapter le décodage aux signaux cérébraux, nous avons donc considéré l'adaptation de l'interface (via le retour sensoriel produit par la machine) afin d'influencer les signaux et d'en faciliter le décodage. En utilisant des connaissances issues de la psychologie comportementale et des sciences de l'education, il est en effet possible de créer des taches et des interfaces qui incitent les utilisateurs à réussir et même à prendre plaisir à utiliser une ICO. Ces différents facteurs, liés à la motivation, participent à produire des signaux plus predictibles et plus facilement decodables par la machine, augmentant d'autant la performance du système. Nous avons donc formulé une taxonomie des ICO adaptatives en définissant *la tâche adaptative* comme un nouveau moyen d'améliorer les performances des ICO.

Une fois que la taxonomie des ICO adaptatives a été mis en place, nous avons cherché à identifier chez l'utilisateur quel était l'état psychologique optimal qui puisse servire de critère d'optimisation de la tâche. La litérature en psychologie indique que cet état est l'état de flow, un état d'immersion, de controle et de plaisir optimal qui incite les gens à se surpasser, quel que soit la tâche, le sexe, la culture ou bien encore l'âge. En étudiant plus avant la littérature en psychologie positive et en sciences des l'éducation,

nous avons remarqué que cet état est souvent induit en adaptant la difficulté de la tâche aux capacités de la personne. Nous avons donc choisi d'évaluer l'impact de cet état à l'aide d'une expérience dite d'imagerie motrice, où la machine est manipulée par la seule imagination de mouvements comme ceux des mains. Nos résultats ont montré que l'adaptation de la tâche augmente l'état de flow, qui se trouve lui-même corrélé positivement avec les performances des ICO. Une fois que nous avons eu trouvé puis évalué l'état optimal de l'utilisateur, nous avons investigué l'influence du retour sensoriel fourni à l'utilisateur par la machine. Ces nouvelles recherches nous ont conduit à étudier plus profondéments les profils des utilisateurs, notamment leurs traits de personalité, afin d'adapter au mieux la tâche. Nous avons alors mené une deuxième expérience impliquant de l'imagérie motrice. Les résultats de ces travaux suggèrent que les performances pouraient augmenter si la difficulté de la tache est modulée en fonction des traits de l'utilisateur.

À l'issu de ces expériences nous manquions cependant toujours d'un modèle matémathique générique qui permette à la machine de trouver et d'appliquer ces règles elle-même, en apprenant à partir des réactions de chaque utilisateur et en inférant leurs intentions. Seule l'utilisation d'un tel modèle permettrait enfin le déploiement des ICO hors des environnements contrôlés des laboratoires. Il se trouve que les dernières avancées en neuroscience computationelle ont abouti à l'établissement d'une approche nommée Inférence (Bayesienne) Active, proposée pour modéliser mathématiquement la perception, l'apprentissage et l'action du cerveau. Inspirés par ces recherches, nous avons intégré un modèle computationnel à une ICO, donnant alors au système une représentation de ses propres composants. L'intelligence probabiliste qui en résulte permet alors au système de s'adapter automatiquement à l'activité cérébrale de l'utilisateur, de la même manière que l'activité cérébrale s'adapterait à une ICO. Nous avons démontré la flexibilité, la généricité et l'efficacité de ce modèle grâce à des simulations sur des données réelles. Comparé aux autres algorithmes de la littérature, l'utilisation de l'Inférence Active a permis d'augmenter les performances du système. Grace à ces différentes contributions nous esperons avoir fait un pas qui nous rapprochera de l'utilisation des ICO au quotidien.

Mots clés
Interfaces Cerveaux-Ordinateur; Modèles Adaptatifs; Inférence Active; État de flow

TITLE

Computational Modeling of User States and Skills for Optimizing BCI Training Tasks

Abstract

Brain-Computer Interfaces (BCIs) are systems that enable a person to manipulate an external device with only brain activity, often using ElectroEncephaloGraphgy (EEG). Although there is great medical potential (communication and mobility assistance, as well as neuro-rehabilitation of those who lost motor functions), BCIs are rarely used outside of laboratories. This is mostly due to users' variability from their brain morphologies to their changeable psychological states, making it impossible to create one system that works with high success for all. The success of a BCI depends tremendously on the user's ability to focus to give mental commands, and the machine's ability to decode such mental commands. Most approaches consist in either designing more intuitive and immersive interfaces to assist the users to focus, or enhancing the machine decoding properties. The latest advances in machine decoding are enabling adaptive machines that try to adjust to the changeable EEG during the BCI task.

This thesis is unifying the adaptive machine decoding approaches and the interface design through the creation of adaptive and optimal BCI tasks according to user states and traits. Its purpose is to improve the performance and usability of BCIs and enable their use outside of laboratories. To such end, we first created a taxonomy for adaptive BCIs to account for the various changeable factors of the system. Then, we showed that by adapting the task difficulty we can influence a state of flow, i.e., an optimal state of immersion, control and pleasure. which in turn correlates with BCI performance. Furthermore, we have identified the user traits that can benefit from particular types of task difficulties. This way we have prior knowledge that can guide the task adaptation process, specific to each user trait.

As we wish to create a generic adaptation rule that works for all users, we use a probabilistic Bayesian model, called Active Inference used in neuroscience to computationally model brain behavior. When we provide such probabilistic model to the machine, it becomes adaptive in such a way that it mimics brain behavior. That way, we can achieve an automatic co-adaptive BCI and potentially get a step closer into using BCIs in our daily lives.

Keywords

Brain-Computer Interfaces; Adaptive Models; Active Inference; Flow state

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Abstract

A Brain-Computer Interface (BCI) is a system that enables direct interaction between the brain and an external device, be it (i) for establishing a new form of control (e.g. for movement or communication); (ii) for implicit environment adaptation for safer or more comfortable user experience (e.g. ease the task in case of a high cognitive workload) or (iii) for enabling the regulation of brain activity for therapeutic purposes (e.g. neurofeedback).

The main elements of a BCI are: (1) acquiring brain activity with measuring tools like Electroencephalography (EEG) for instance, (2) decoding of brain activity with signal processing methods and machine learning that translate the brain activity into simple machine commands, and (3) presenting these commands through feedback to the users as guidance for regulating their own brain activity.

For the sake of improving BCI performance, signal processing and machine learning techniques have been studied and developped on one hand, as well as the human learning and psychological relation with the system on the other. The latter involves applying various educational and motivational theories as part of interface and feedback design. When using a BCI one aquires or develops a new form of skill or brain activity regulation, which means its mastery could be learnt and trained. For some BCI paradigms such user training seemed essential to ensure the system usability. This meant designing a suitable, often playful interface for assisting users in accomplishing the BCI training task and thus increasing system performance. Such interface designs applied empirical knowledge from cognitive and behavioral psychlogy. On the other hand, when acknowledging the adaptive, changeable human nature, an adaptive machine (that for example automatically re-calibrates) was proposed as another way to increase the overall BCI performance. Typically, adaptive BCIs are those in which the machine adjusts its decoding methods to the signal changes or variability. Such signal variability is often partially caused by the user fluctuations in attention or mood for instance. In turn, a machine that adapts to particular changeable user states is still lacking. It would recquire a co-adaptive system, involving a machine that adapts in response to the user changes in real time, and predicts user intentions in short and long term. We believe that the community is lacking a new perspective or generic framework conceptually and computationally speaking, to unify these two major courents (inerface design and adaptive decoding), and achieve an automatic human-machine co-adaptation.

In this thesis, we work on EEG-based BCIs, and consider 2 well-known paradigms: (1) Motor Imagery, i.e. imagination of motor movements of one's own limbs to actively control a device, and (2) P300-speller, i.e. brain reactions to stimuli that are elicited and

detected in order to spell letters and enable communication. The purpose of this thesis is to study the ways that increase BCI performance by optimizing the training task and assisting the user to master the "BCI skill". This requires studying user profiles, their relations to the BCI content, the influence of such content on the user, and on the other hand, investigating ways to optimally adapt such content to each user and their reactions in real-time. To enable data-driven adaptation, we operate with computational, probabilistic models of the user, as well as empirical, psychological user data. This way we can provide optimal training tasks to each user states and traits.

As a first step, we propose a taxonomy for adaptive BCIs in which we explicitly regard the *BCI task* as a new category separate from the standard user factors and decoding pipeline. As the user psychological fluctuations in attention or mood are often considered to be one major cause for signal variability and poor performance, we propose influencing the user through an adaptive machine interface so to increase performance and system usability. When considering the *task* as a new category, adaptive BCIs cease to simply adjust the decoding methods to the signal variability but also influence their cause (the user). Such categorization can enable us to provide adaptive short-term tasks that vary in modality or difficulty and are optimal for a particular user state and trait. We consider interface designs within a *BCI task* and apply them in an adaptive manner that is optimal for each user.

We first investigate the kind of optimal user's states that could potentially increase performance. We found that such psychological state could be the so called state of *flow*, i.e., optimal state of control, immersion and pleasure. With such information, we further investigate a way to reach that state through adaptive *BCI task* difficulty. Our Motor Imagery (MI) BCI experiment provides promising results, indicating that through adaptive task difficulty we can indeed increase the state of flow which showed to be in a positive correlation with performance. Additionally, we observed an unexpected effect of sound and background music on MI performance. We learned that within the *BCI task* interface, we should also acknowledge the influence of the "background" sensory information it can have on the user states and thus performance. In a preliminary study, we show the potential benefits of using congruent (task-related) sound as *MI task* feedback.

Such results led us to investigate more thoroughly the relationship between human factors, performance, and learning MI skill. We created predictive models of performance and learning based on human factors (personality traits such as extroversion, and states such as *flow* or workload). Thanks to the models, we unveil which task difficulties are optimal for which personality type. Notably, the optimal level of difficulty would depend on a *criteria of optimization*, i.e., whether we favour maximization of performance, learning or user experience.

Furthermore, using data from MI experiments, and results from MI prediction models, we simulate a simple adaptive method to prove the usefulness of adapting the task difficulty according to each user. This model is fed with priors about the user traits, and a criteria of optimization (here to maximize performance).

We then go further from simple adaptation rules to a generic, probabilistic computational framework, enabling full automatization of adaptive tasks. Such computational framework, called Active Inference, is a well known neuroscience approach that mathematically models brain processes. When such a model (of the brain) is endowed to the machine, Active Inference enables co-adaptation between the brain and the machine which mimics brain behavior. Our simulation of Active Inference on a P300- speller BCI represents a step towards enabling a fully automatic BCI task co-adaptation.

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Contents

Introduction

Brain Computer Interfaces (BCIs) are systems that enable a living being to interact with a machine using only brain activity. Thanks to the technological advancements, the interest in BCIs has grown immensely during the last decades. BCIs are mainly used to facilitate the interaction between people with different disabilities and their environment [Milan and Carmena, 2010], Although there have been outreach in non-clinical domains such as gaming and art [Tan and Nijholt, 2010]. BCIs have many potential and vast application range, however they are not yet robust to be used outside of research labs. The community's priority today is to assure the system robustness and its usability. It is quite a difficult task, considering the abundant inter (e.g. brain morphology) and intra-subject (e.g. attention drops) variability. The major obstacle lies in the large spectrum of sources of variability during BCI usage, ranging from (i) imperfect recording conditions, e.g. environmental noise, humidity, static electricity etc. [Maby, 2016] to (ii) the fluctuations in the user's psycho-physiological states, due to e.g. fatigue, motivation or attention [Jeunet et al., 2015a].

In this thesis, we choose to focus on the user as cause of signal variability, as it has shown to have a strong influence on BCI performance and it contains many facets yet to be explored [Lotte et al., 2013]. By influencing user motivation, immersion and sense of control, we wish to evoke an optimal psychological state so to implicitly increase BCI performance overall. The human changeable (adaptive) behavior is seen as a problem in BCIs, as it causes signal variability which is then difficult to decode, and in turn it decreases the system performance. As a solution, many adaptive machines were designed to recalibrate, and update the classifier, adjusting to user changes [Faller et al., 2012, Woehrle et al., 2015]. However we can use human changeability to our advantage, to influence their states so that they can learn more easily and with high motivation. We can consider that the user changes in different time scales, e.g. attention drops operate within shorter periods, while a skill requires a longer period. Knowing this along with educational and cognitive theories, we can provide optimal tasks with adapted difficulty and represent them in different time scales, such that the user learns and performs to the maximum of their capacity, implicitly improving system performance overall. In that way, we propose to perceive the task as a new category, separately from the user and system decoding pipeline, so that we can not only adjust to the user changeability, but also steer such changeability to maximize learning and performance. The goal of this thesis is to explore and propose adaptive tasks that influence users so to increase their experience, learning and BCI performance.

Thesis Structure

This thesis is comprised of three parts:

Part I Brain & Machine

In Chapter 1, we introduce the concept, Application, and Principles of a BCI. We develop in more detail the EEG-based BCI Paradigms and Decoding Techniques, from Signal Processing, Machine Learning to Metrics used to represent user performance. Finally, we describe the Feedback provided to the user, which guides them to learn self regulation or gain control over their brain activity. We describe various interface designs inspired by educational theories, and highlight their influence on user learning. Furthermore, we unveil the chronological evolution of BCI feedback designs according to educational and cognitive theories.

In Chapter 2, we present a taxonomy for adaptive BCIs, in which we try to account for most of the changing (adaptive) factors coming both from the human and the machine. We provide a novel perspective on the adaptation process. We accomplish this by using a Task model, which adapts according to the changing user factors that are arranged in a User model. The user model contains human factors such as various personality traits, skills and states that have shown in the literature to influence BCI performance. Furthermore, we highlight the fact that every BCI is used for a certain purpose, be it for mobility, communication or other. On account on such purpose, we propose to build a *criteria* of optimization, e.g. maximization of performance or user motivation, that would guide the whole adaptation process. We validate our taxonomy (also referred to as a generic conceptual framework) by providing a comprehensive and extensive literature review from interface designs to adaptive decoding techniques. This framework can serve as a graphical representation of existing (human/machine) adaptation methods, while it can also enable a straightforward visualization of the missing gaps to be filled with new approaches.

Part II Influencing the User with *BCI task*

In Chapter 3, we first investigate the optimal user state for performance, called the *flow* state (optimal control, immersion and pleasure), and detail ways to attain such state. We then present our Motor Imagery (MI) experiment in which we influence the user's state of *flow* by adapting the BCI task difficulty. Furthermore, we show that flow is positively correlated with performance and that we indeed can influence *flow* with adaptive BCI task difficulty. An auxiliary study is performed to explore the influence of auditory sensory information on MI performance.

In Chapter 4, we investigate more thoroughly the relationship between the human factors and performance. We investigate the importance of user personality traits and states on learning the MI skill, i.e., evolution of performance over a session. We conduct another MI experiment in which we influence the user through task difficulty. We acquire data to build a predictive model that could unveil which kind of task is optimal for what kind of user. Moreover, depending on what we set to be predicted, be it a flow state or performance, it can serve as a guide for overall adaptation, i.e., it can serve as an optimization criteria to wager between user experience and system accuracy for instance.

In Chapter 5, we use priors about user traits and states acquired from the prediction models to perform a simple adaptive method which provides optimal task difficulty to each user. To demonstrate the usefulness of the model for maximizing performance, we perform a simulation using real data from the MI experiment from the previous chapter.

In Chapter 6, we propose the use of a generic, computational framework – Active (Bayesian) Inference to automatically lead the adaptation process towards a goal (automatically incorporating an *optimizarion criterion*). Active Inference is a computational neuroscience approach, a Bayesian framework that models learning and decision making of the brain. As such, we endow such computational model of the brain to the BCI machine, so that the machine can then adapt in a similar fashion as the brain would. We demonstrate an implementation of Active Inference on a simulated P300-Speller BCI using real data from 18 subjects.

Part III Thesis Contribution and Perspectives

In Chapter 7, we share perspectives to influence the cause of signal variability (the user states) through optimal task. Moreover, considering perceptual affordance, we describe the importance of acknowledging the effect various task representations (2D, 3D, congruent or not, continuous or discrete task representations for instance) can have on the user. We demonstrate how different sensory input can trigger involuntary motor reactions for instance. We provide a short review of well established Human-Computer Interaction training Task models, and we appeal to the community for a BCI task design standardization. Finally, to close the loop, we present our contribution to the BCI community through a graphical representation of the adaptive BCI taxonomy (framework) introduced in Chapter 2. We highlight all the elements of the framework that we adapted in this thesis along with the gaps to be filled by our future work. We list all the potential improvements of our methods. We regard *the task* as a central element that can bind together adaptive machine and human approaches, and could make their automatic co-adaptation possible.

PART I

Brain & Machine

This part contains a short: "*Everything you need to know about Brain Computer Interfaces*", and a detailed: "*Everything my research is built upon*".

The selected publication for this part is Mladenović, J., Mattout J., Lotte, F., (2017) *A Generic Framework for Adaptive EEG-Based BCI Training and Operation*. Chapter 31 in BCI Handbook: Technological and Theoretical Advances. Taylor & Francis, CRC Press.

Chapter 1

The Brain-Computer Interface

Philosophical Thought The following chapter is about the fundamentals of brain computer interfaces (BCIs), the relation between brain and machine. Our way of reasoning, perceiving and measuring events and relations in the world is modeled on the basis of premises developed during a long path of philosophy. I think that it is useful to understand what it means to measure brain activity, and what drives this kind of research. I wish to share some philosophical thoughts about the origin and evolution of premises that grounded the connection between brain and machine, or human thinking and machine "thinking".

Since Parmenides (ancient Greek philosopher 6.BC) and his ontological statement: "Thinking and Being is the same", the process of thinking became a central subject in western philosophy. Furthermore, as it was presumed that only humans can think, ontology (i.e., question of existence) became a matter of anthropology. Sophists, particularly Protagoras, expressed this statement as "Man is the measure of all things, those that exist that exist, and those that do not that exist not ". Later, to escape relativism of individual reasoning, Aristotle added that one cannot think of such things that do not exist, showing that thoughts dwell in the realm of reality, of the existing. He thus developed *Organon* or Logic to serve as a verification tool for the correctness of reasoning. Almost a millennium later, Parmenides' statement was interpreted by Descartes as "Cogito ergo sum" ("I think thus I exist") placing an individual as the reference or measure of all, of reality. [1] It seemed as though the question of existence and reality is placed in the hands of each and every person, to build it or project it from their own being or by their own measure. To escape this conclusion, Descartes introduced matter and its extension in space and duration in time as the general characteristic of reality, hence of existence. The abstract representation of space-time relation, his invention, is known as Decartes' (Cartesian) product. It became a tool to quantify any relation in realty, primarily in mechanics. Le Roy and La Mettrie, French

[1] So if *man* is the measure of reality, and *man* is a process of thinking, then the measure of reality lies within the measure of the thinking process? Does research in brain activity then provide measures of reality?

medical doctors in the 17th century followed Descartes teaching and concluded, if body as matter carries thoughts: "Thought is a simple modus of body, a form of mechanical movement", and defined "man as machine". The division between body and mind, the issue that brought many debates and created many philosophical currents got similar mechanical expression in the area of psychology. In the 20th century, behaviorists believed that man's mind can not be objectively studied, but his behavior can, i.e., we can know only what we observe, that is, input-output, action and reaction.

While, according to some, the existence of *man* got reduced into a mechanical device (machine), in parallel from Aristotle's *Organon* or tool for thinking - logic evolved through predicate logic to Boole's algebra (0-1, true-false) which is the foundation of every machine today. This means that the machine was given a logical, objective way of human-like "thinking" while human process of thinking came to be regarded as less objective and less reliable than that of the machine. 20th century philosophers who were still trying to explain the mind-body or thought-brain concept, started explaining it through the functionalities of the machine, or hardware-software, and as one entity.

Today, in BCI and Physiological Computing, the measure of human psychological (subjective) states, feelings (that could not have been observed by behaviorists), can be "objectively" quantified through machine. Hence, using brain imaging, and sophisticated measuring tools (machines), Varela, Damasio and other cognitive neuroscientists, found scientific grounding in monism (mind-body as one), i.e., there is no cognition without the body. Hence, research of the self and reality has never ceased, but only tools have changed, from human logic to now machine logic. However, it is still within the boundaries of logic, and categories set by Aristotle.

1.1 Introduction

Research in brain processes has been a growing topic for the past decades. Brain Simulation as part of the Blue Brain project [Markram, 2006], Brainbow project – understanding the neural connectivity by coloring neurons [Livet et al., 2007], Optogenetics – influencing behavior by screening the brain with light, achieved through genetic mutation with photo-sensitive (retinal) cells [Deisseroth, 2011], and finally Brain-Computer Interfaces (BCIs) which can be seen as an evolutionary step of *man* which expands brain control from one's own body onto a machine. As this thesis revolves around the improvement of BCIs, we will provide more details on this topic.

The term Brain-Computer Interface (BCI) was coined by a researcher Jacques Vidal in the 1970s [Vidal, 1973]. However, in 1965, American composer Alvin Lucier, as well as a French composer, Pierre Henry, with his Corticalart, were already using a BCI-like system. With his system, a person was able to perform music only by producing a certain brain wave [Straebel and Thoben, 2014]. Thanks to the neural plasticity, i.e., the ability of the brain to rewire its neural pathways or create new ones, "the brain can appropriate external devices as natural sensor or effector channels" [Levine et al., 2000]. One of the first successful human neuroprosthetic implant was made in the early 2000 [Hochberg et al., 2006], and BCIs potential has been growing ever since [Lotte et al., 2017]. BCIs today are often "directed at researching, mapping, assisting, augmenting, or repairing human cognitive or sensory-motor functions" [Krucoff et al., 2016].

In this chapter we start with section *1.2* in which we describe the various applications of BCIs today; followed by section 1.3, in which we present the essential functions and elements of a BCI. Continuing with section *1.4* in which we provide the underlying neurophysiological phenomena and measuring techniques that enable such brain-machine relation. After introducing electroencephalography (EEG) as our main measuring tool, in section *1.5*, we develop EEG-based BCI paradigms, and in section *1.6* we further develop decoding techniques used to interpret EEG-based brain activity. Furthermore, in section *1.7*, we highlight human learning and training as an important part of a successful BCI task.

1.2 Application

BCIs are systems that enable a direct interaction between the brain and an external device. They have various applications, be it (1) for establishing a new form of control (e.g. for movement or communication); (2) for implicit environment adaptation for safer or more comfortable user experience (e.g. ease the task in case of a high cognitive workload); and (3) for enabling the regulation of brain activity for therapeutic purposes (e.g. neurofeedback). We briefly develop each type of application, as follows.

(1) A new form of control is mostly used in medical purposes for patients with severe motor impairments, e.g. to manipulate wheelchairs or prosthetic limbs by imagining limb movements [Milan and Carmena, 2010], to communicate by reacting to various visual or audio stimuli such as flashing letters on a screen [Farwell and Donchin, 1988], or for neuro-rehabilitation or neural rewiring by mentally training motor movements of the impaired limb [Ang and Guan, 2013, Soekadar et al., 2015] and as such, re-routing the damaged neuronal connections thanks to brain plasticity. Even though the main forms of control are medical, there are also artistic ones in music performances [Miranda, 2014] and plastic art for experimental artists or again, patients [Münßinger et al., 2010].

(2) An implicit adaptation (often not in a form of conscious control as in (1)) called passive BCI, or recently renamed into neuro-adaptive technologies [Zander and Kothe, 2011] represents an adaptation of a non-BCI task in order to increase comfort or safety (in driving or piloting, [Gateau et al., 2018]) or immersion in gaming for instance [van de Laar et al., 2013a]. This is possible because some cognitive states such as workload for instance can be inferred by monitoring brain activity during a task, thus such task can be adapted in real time to the mental workload of the person engaged in it.

(3) A therapeutic technique for restoring cognitive function, or brain activity regulation, called neurofeedback. It is being explored for stroke rehabilitation or to serve as replacement for medications such as Ritalyn which has many side effects for patients with attentional deficits [Sitaram et al., 2017]. If there is a known form of brain activity that is "healthy", then there is a reference point that can be provided (e.g. visually) to a person, so that one can observe it and notice how far they deviate from that "healthy" reference. Even though the idea behind is to consciously regulate the brain activity so to reach such desired level (e.g. of attention) without the need of

medications, the evidence of the efficacy of neurofeedback still remains controversial [Batail et al., 2019, Ghaziri and Thibault, 2019].

Although there is a vast spectrum of applications, a BCI is still mostly tested in controlled conditions, such as in laboratories, because it is prone to error [Wolpaw and Wolpaw, 2012]. One exception is for artistic performances that do not necessarily need exact control. A BCI does not have an easily predictable behavior due to numerous causes that vary from moment to moment, between users, and environment that is difficult to anticipate and influence. In the following section, we describe the principles that make a BCI system, and we mention ways of improving a BCI.

1.3 Principles

A BCI includes a living user and a machine, and as such it incorporates many composite elements such as: (i) the user that produces brain activity that depends on complex psycho-physiological phenomena, (ii) measuring tools that capture user's brain activities, (iii) the machine that decodes such activities and produces some output perceivable to the user, and (iv) various relations between not only the user and machine, that are, the machine interface influencing the user psychological states, and the user states influencing the machine decoding, but also the environment factors that can influence both the machine and user, see figure 1.1. The environment can influence the machine directly because it contains for instance electromagnetic waves that can create interference with the (electromagnetic) measuring tools. As for the environmental or social influences on the user, it is shown that the gender of the experimenter can influence the user, for instance [Roc et al., 2019].

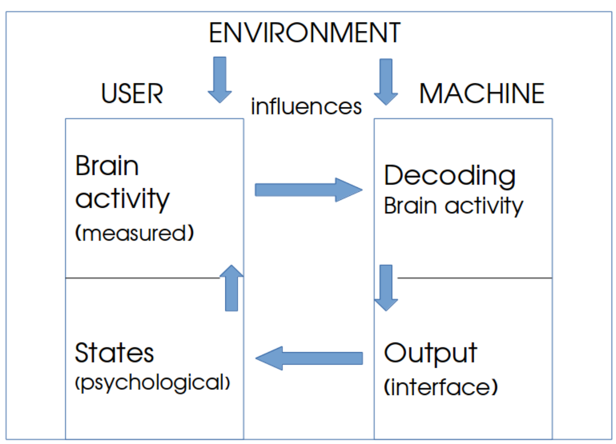


Figure 1.1: Depiction of the user, the machine and their inter-influences, along with the external (environmental) influences.

All of these elements have room to be improved and explored. The BCI community was mostly focused on improving the measuring tools and decoding techniques, but only recently the user's physical and psychological states have shown to be of major importance to the success of a BCI use. Once the user got acknowledged, various environmental and machine elements that influence the user's psychological states were brought into consideration. Notably the content that the user interacts with, presented as a machine output within a graphical or tangible interface for instance.

In principle, a BCI relies on one hand on the user's capacity to create stable and distinct brain activity and on the other hand on the machine's ability to measure and decode such activity. A major obstacle lies in the large spectrum of sources of variability during BCI use, ranging from (i) imperfect recording conditions: environmental noise, humidity, static electricity etc. [Maby, 2016] to (ii) the fluctuations in the user's psycho-physiological states, due to: fatigue, motivation or attention etc. [Jeunet et al., 2015a]; experimenters presence during BCI use [Roc et al., 2019]. For these reasons, only a few BCIs have managed to be reliable enough to be used outside the laboratory [Wolpaw et al., 2018]. Particularly, it is still almost impossible to create one BCI design effective for every user, due to large inter subject variability, such as the differences in brain morphologies [Allison and Neuper, 2010]. That is why, most BCI machines need a calibration period before their use, so that the machine can learn to decode the brain activity particular to every person. The main concerns are to create a more robust system with the same high level of success for everyone, at all times, and to improve the current usability of the system [Wolpaw and Wolpaw, 2012, Lotte et al., 2013].

In the following sections we briefly describe each of the above mentioned BCI elements (measuring, decoding brain activity and feedback on one's brain activity); and we also mention some of their potential improvements.

1.4 Measuring Brain Activity

In this section we describe the underlying processes of the brain, be it in form of electric currents, magnetic fields, light refractions. Moreover, we briefly present the tools that enable their measurements today.

1.4.1 Neurophysiological Phenomena

The human brain is composed of about 80 billion glial cells and 100 billion neuronal cells [von Bartheld et al., 2016]. The former provide energy and protection to the neurons which in turn control all physiological activity in the body through the nervous systems spread throughout the whole organism. When a living organism engages in an activity, be it cognitive or physical, many neurons communicate between each other in a form of electrical currents. Sources of electrical impulses, those that we can measure, are mostly pyramidal neurons because of their size and group orientation [Nunez, 1974]. Depending on their orientation, the electrical signal (i.e., voltage in time) can be measured on the scalp (noninvasively) with more or less precision. ElectroEncephaloGraphy (EEG) uses electrodes that capture this electrical property of neurons, whereas MagnetoEncephaloGraphy (MEG) uses very sensitive magnetometers to measure the magnetic field arising from the electrical currents. Such electric current coming from aligned pyramidal cells (perpendicular to the cortical surface) needs to pass through many layers of tissue and bone before reaching the electrodes – sensor space.

Thus, the sensors record the linear mixture of the source activity – firing neurons, which is spread spontaneously within the head (volume conductor). Volume conduction can be defined as the transmission of electric or magnetic fields from an electric current source through biological tissue towards the sensors Furthermore, when one brain region is active, there is an increase of blood flow and oxygen. Thanks to this phenomenon, we can scan brain activation using various magnetic coils, using magnetic resonance imaging (MRI) that aligns nuclei, or by sending near-infrared (NIR) light. The latter is possible thanks to the fact that human tissue can be transparent, penetrable or absorbent to NIR light, depending on the density of hemoglobin in blood (i.e. transporter of oxygen).

The most developed brain regions are the sensory-motor cortex, producing strong signals coming in most cases from the motor neurons, or sensory neurons (visual, tactile or auditory) that react to various external stimuli. If human form would be linearly dependent to the brain region size, a human would look like the homunculus [Schott, 1993], see figure 1.2.

Figure 1.2: Homunculus, a representation of a linear mapping of the sensory-motor cortex to the human morphology.

1.4.2 Measuring Tools

Tools that measure brain activity can be divided into two main categories: invasive and non-invasive ones, see figure 1.3. The most used non-invasive tools are: (1) ElectroEncephaloGraphy (EEG), a portable measuring tool consisting of a number of electrodes that record electrical current on the scalp; (2) MagnetoEncephaloGraphy (MEG), a non-portable, functional neuroimaging tool consisting of a number of very sensitive magnetometers that record the magnetic field around the scalp; (3) functional Magnetic Resonance Imaging (fMRI), a non-portable, scanning tool consisted of magnetic coils creating a magnetic field that differently alligns blood nuclei depending on its levels of oxygen; (4) functional Near-Infra-Read Spectroscopy (fNIRS), a portable, neuroimaging tool that is consisted of optodes that emit and receive optical waves which then reveal the density of blood flow and oxygenation. The most used invasive tools are: (a) ElectroCorticoGraphy or ECoG, similar to EEG, it captures electrical activity of millions of neurons, but with higher precision as it is directly placed on the cortex, and

(b) Subcortical Arrays are similar to ECoG but as the name suggests, these electrodes are placed inside the cortex and they can capture the activity of one or a few specific neurons.

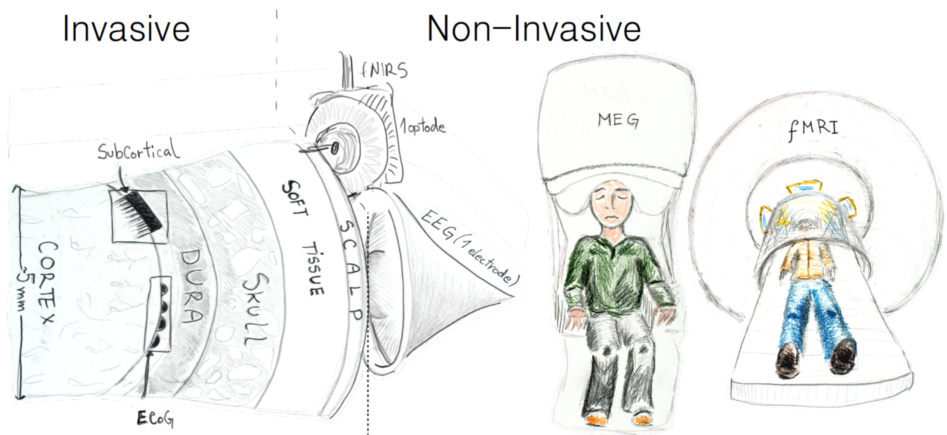


Figure 1.3: Tools measuring brain activity, from invasive (subCortical Arrays, ECoG) to non-invasive (EEG, fNIRS, MEG and fMRI).

Short History EEG – First registered human testing was done by Hans Berger, a German physiologist, in 1924, coining the term EEG [Berger and Gloor, 1969]. His work was inspired by discoveries of electrical current in animal brains [Caton, 1875]. On a personal level, he believed that humans could communicate telepathically at distance because when surviving a deadly accident, his sister "heard" him and urged their father to send a telegraph [Berger, 1940]. Today, there are many EEG devices, that vary from (i) the number of electrodes for commercial (e.g. Muse of 8 electrodes) or medical, scientific use (e.g. Brain Products from 32 to 162 electrodes), (ii) electrodes that use conductive gel or dry electrodes, (iii) electrodes that contain impedance regulation – active electrodes, or without – passive electrodes.
MEG – First such magnetic fields were captured by physicist from Illinois University, David Cohen, in 1968, using copper induction coil. Later on, James E. Zimmerman, a Ford Motors researcher, developed more sensitive SQUID detectors at MIT, which Cohen integrated in the MEG, and also built a highly magnetically shielded room to decrease noise [Zimmerman et al., 1970].
fMRI – The fact that neural activity is closely related to changes in blood flow and oxygenation in the brain, was experimentally discovered by Charles Roy and Charles Sherrington, at Cambridge University, in 1890. In 1936, Linus Pauling and Charles Coryell discovered that oxygen-rich blood with hemoglobine (Hb) was weakly repelled by magnetic fields, while oxygen-depleted blood (dHb) was attracted to a magnetic field. So far, an MRI machine could capture only static brain structure, so Seiji Ogawa would enhance it in 1990 by using the BOLD (Blood Oxygen Level Dependent) contrast that results from changing regional blood concentrations of oxy- and deoxy-hemoglobin as mentioned above [Huettel et al., 2004].

fNIRS – In 1977, Frans Jobsis at Duke University, showed how brain tissue and skull transparency with Near-InfraRed spectroscopy can enable a real-time, non-invasive detection of oxigenated hemoglobin, based on the same technique, BOLD used for fMRI [Jobsis, 1977].

Tools Characteristics EEG is accessible, portable with high temporal resolution (i.e. captures very fast frequency changes), however its spatial resolution is quite low, i.e. lack of precision in determining the source of brain activity (firing neurons). MEG is an expensive and cumbersome machine, needing careful maintenance, a special installation and a highly isolated chamber. However, it has fairly good both temporal and spatial resolution. fMRI is a cumbersome and expensive machine having a low temporal resolution (captures changes within seconds), but a high spatial one. fNIRS is portable, accessible, but it is fairly sensitive to external light and cannot be used to measure cortical activity more than 4 cm deep due to limitations in light emitter power, having a fairly good temporal but lower spatial resolution. The most commonly used tool is EEG, for its high temporal resolution and accessible prices.

1.5 Paradigms of EEG-based BCIs

There are two main paradigms in EEG-based BCIs, depending on the type of neural activity being measured, as follows. The first paradigm is (1) **spontaneous** BCIs, typically measure oscillatory EEG activity, and the event related desynchronisation / synchronization (i.e., decrease / increase of power at a certain frequency band) in for instance Sensorimotor Rhythms (SMR) [Pfurtscheller et al., 2006] or Slow Cortical Potentials [Birbaumer et al., 2000]. Spontaneous BCIs can be instructed, i.e., guided by machine instructions, called synchronous BCIs, or a person can initiate a self-paced cerebral activity, called asynchronous BCI. Spontaneous BCIs are mainly related to Motor Imagery (MI) BCI, for instance imagining left or right hand movements [Pfurtscheller et al., 2006], and to Mental Imagery, such as mental object rotation or calculations [Faradji et al., 2009]. The second paradigm is (2) **evoked** potentials or ERPs (Event-related Potentials) BCIs which are based on the attentional selection of an external stimulus among several others. Be it in the visual (V), the auditory (A) or the somatosensory (S) modality, this approach can give rise to various types of well-known responses such as the P300 component [Farwell and Donchin, 1988] or Steady State Sensory (Visual, Audio, Somatosensory) Evoked Potentials, (SS(V/A/S)EP) [Middendorf et al., 2000]. The most used ERP is the P300 which is a positive deflection of the EEG signal occurring about 300ms after the user perceived a rare and relevant stimulus [Fazel-Rezai et al., 2012]. Note that we mostly focus on spontaneous and synchronized MI and P300 ERP BCI paradigms as they are most common and fair representatives of main BCI systems. In the following section, we describe how the brain activity is being decoded depending on the chosen paradigm.

1.6 Decoding EEG-based Brain Activity

The machine decoding is comprised out of signal processing and machine learning approaches. Signal processing englobes temporal and spatial filtering, extraction and selection of features of interest, while machine learning contains the labeling or classification process of the selected features.

As each and every brain is different (e.g. morphology or neural alignment) and produces different brain signals, typically there is need for machine calibration or training before a BCI can be successfully used. During the calibration phase, one could say that the machine is collecting EEG training data from the user and learning from it, while the user is not seeing any effect of her mental commands on the machine. Later on, during the testing phase, the machine classifies new unknown data based on its training, permitting the user to control the machine and receive a feedback, see figure 1.4

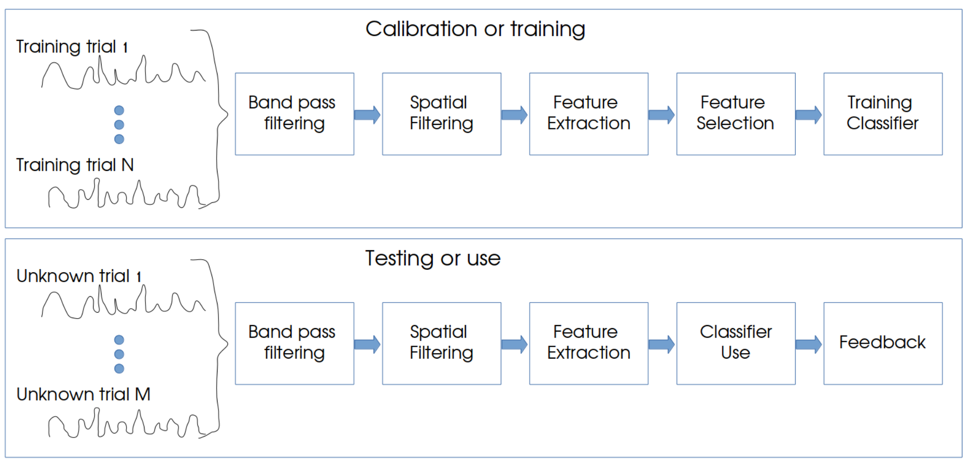


Figure 1.4: Representation of signal processing and machine learning steps during training and testing phases.

1.6.1 Signal Processing

Electrodes capture a linear mixture of neural activity that propagates throughout the head tissue. Temporal filtering enables noise reduction and selection of the most discriminant frequency. Once the frequency is selected, it is provided to the spatial filter, that performs a selection of most significant electrodes and reduces sensor dimensionality. Signal epoching represents slicing the signal in time windows in which the signal is typically averaged, and from which features are extracted. They are extracted by computing the frequency band power (MI BCI) or the amplitude mean of sub-epochs (P300) for example. All these actions take part in Signal Processing which results in a feature vector at each time point of the signal. In other words, these feature vectors are a condensed representation of the raw EEG signal [Lotte, 2014].

1.6.1.1 Temporal Filtering

In the following, we list some neurophysiological priors we know about brain rhythms, and the reasoning behind their appearances [Campisi et al., 2012].

- alpha wave (8-12Hz) appears when a person is relaxed, typically with eyes closed but awake, and can be detected near the occipito-parietal lobe.
- beta wave (16-30Hz) appears when a person is physically engaged or imagining it to be.
- gamma wave (above 25Hz) found mostly during conscious perception and high cognitive involvement.
- delta wave (0.5-4Hz) is characteristic for deep sleep.
- theta wave (4–7 Hz) is characteristic for a meditative or drowsy state.
- mu wave (8-12Hz) same frequency as alpha however it appears near sensory-motor cortex, during physical activities.
- ERD/ERS stand for Event Related Desynchronisation and Synchronisation and appear in such order when one performs or imagines a movement. More precisely, ERD involves a power decrease in mu wave, while ERS includes an increase in the beta wave.

In order to extract frequencies of interest, we can simply apply a band pass filter. As an example, imagination of a hand movement leads to a decrease in power in the mu and beta bands during movement imagination, and to a power increase in the beta band, right after the motor imagination ended, called the beta rebound [Pfurtscheller and Da Silva, 1999]. So, typically for oscillatory activity of sensory-motor rhythms (SMR) one can use a band pass filter between 8-30Hz, which includes mu and beta. Typically then, the frequency of interest is squared, and then these values are averaged within a 1s window or epoch. This process differs for event-related responses, or P300 as the ERPs do not change in power but simply contain amplitude changes in time starting from the stimulus onset. The ERP feature vector is a concatenation of amplitudes of different sub-epochs of all the channels of interest. Both feature vectors can benefit from spatial filters, described in the following.

1.6.1.2 Spatial Filtering

Spatial filtering is a method that virtually reduces the number of channels (electrodes) by first weighting them, then summing them as a linear combination which creates a smaller set of "virtual electrodes". It can be fixed (e.g. Bipolar and Laplacian) or data-driven (e.g. supervised Common Spatial Pattern and its variants, or unsupervised Principal Component Analysis and Independent Component Analysis) [McFarland et al., 1997, Blankertz et al., 2007]. It is also important to note that spatial filtering not only reduces the dimensionality of the signal, but also gathers and recovers the relevant signal that are distributed over several electrodes. It is thus a way to address the EEG volume conduction effect. [Lotte, 2014]

In this thesis we use CSP for oscillatory sensory-motor rhythms used in motor imagery BCI, so we will briefly provide a few more explanations. As it is data-driven and supervised, it means it is configured to each person and in a supervised manner, i.e., classes are defined in advance. CSP is a discriminative spatial filter, i.e., it maximizes the difference between two classes using spatial covariance matrices. Meaning, if the power of a band-pass filtered signal (i.e., variance of such band-pass filtered signal) is very different in an electrode between two classes it will have a large weight, and if the difference is small between two classes it will have a small or negligible weight.

There are many variants of CSP that for instance combine spectral and spatial signal processing, such as the Filter Bank CSP, for more information see [Ang et al., 2008].

For ERPs, a CSP does not work as it does not take into account temporal information needed for classifying ERPs, so there is another commonly used spatial filter called X-Dawn that considers the EEG time course. X-Dawn chooses the weights that maximize the ERP response by powering the time course, while minimizing the entire signal variance being ERP + noise [Rivet et al., 2009]. For more information on spatial filters, see [Lotte, 2014].

1.6.1.3 Extracted Features

As mentioned above, feature vectors that are most commonly used are power band features for spontaneous or time-point features for ERP BCI. There are many other types of features such as as connectivity features [Astolfi et al., 2007], correlation or synchronization between signals from different sensors and/or frequency bands; signal complexity measures or higher order statistics as features of EEG signals and so on [Lotte et al., 2018]. Other than using vectors of features, recent research has also explored how to represent EEG signals by covariance matrices or by tensors (i.e. arrays and multi-way arrays, with two or more dimensions), and how to classify these matrices or tensors directly. Some research has shown that combining time points and band powers, or band powers with connectivity features gives higher classification accuracy as compared to single feature type [Lotte et al., 2018]. Once the features are extracted, they can still contain high dimensional data which can be redundant. There are many feature selection methods that investigate the relationship between the feature and the target class from correlations, mutual information, evolutionary algorithms and other meta-heuristics [Lotte et al., 2018].

1.6.2 Machine Learning

Most BCIs follow the same rationale, they typically consist of (i) a calibration phase, in which the classifier learns to discriminate and translate signal features of each person into machine commands, sometimes (ii) a training phase, in which the user learns to manipulate the system and to regulate his/her EEG patterns, and (iii) the application, in which the user has hopefully full control over the system and uses a BCI in real-life conditions. Often, the user training phase (ii) takes part of the application or testing phase (iii). The system calibration is often mandatory and lasts about 10 minutes for ERP based BCIs [Fazel-Rezai et al., 2012] or rather 20mins for MI BCIs [Lotte, 2015].

The calibration phase is often long and the risk inducing fatigue before starting the BCI application. Therefore, there are many attempts to remove this phase with unsupervised machine learning (i.e., in which the classes are not predefined), Riemannian classifiers (i.e., that use Riemannian geometry to calculate distances between covariance matrices) [Lotte, 2015] and transfer learning (i.e., that transfer the data from other subjects) [Gayraud et al., 2017].

In [Lotte et al., 2018], recent classification algorithms for EEG-based BCIs are divided into four main categories: adaptive classifiers, matrix and tensor classifiers, transfer learning and deep learning. Authors state that (1) adaptive classifiers are generally superior to static ones, even with unsupervised adaptation, (2) Riemannian geometry-based methods reached state-of-the-art performances on multiple BCI problems, along with tensor-based methods, (3) transfer learning can prove useful although the benefits are unpredictable, and (4) deep learning methods have not yet shown convincing improvement over state-of-the-art BCI methods.

Nevertheless, the most commonly used classification algorithms real-time still are the simple Linear Discriminant Analysis (LDA, [Mika et al., 1999]) and Support Vector Machine (SVM, [Suykens and Vandewalle, 1999]) because of their simplicity and robustness to small training data set.

1.6.2.1 Performance Evaluation

There are many evaluation metrics that determine how well the classifier performs the labeling of features. The most known are the classification accuracy (CA). To calculate it we can simply count the number of correctly classed trials and divide it by the total number of trials. However, we can also use a confusion matrix (i.e., true positive and negative, and false positive and negative) to calculate the rate of successfully classified features [Thomas et al., 2013a]. For instance, in a two class problem of left-right hand MI, at each trial there is one class that is true and the other false. Lets take for example that if left hand class is the positive class, then the true positive (TP) will be equal to the number of times the classifier labeled left correctly, and true negative (TN) when it labeled the right class correctly. On the other hand, false positives or negatives (FP and FN) is the case when it labeled the classes incorrectly. Then the classification accuracy is a ratio equal to (TP+TN) / (TP+TN+FP+FN). You can remark that this metric does not produce correct classification if the number of trials per classes are unbalanced. In self-paced BCIs, the user can choose one class more frequently than the other. In such case, the CA would be biased and assign stronger weight to that more frequent class. Hence, CA works only in BCIs that are balanced which is often the case in synchronous BCIs, as we can directly control the number of classes the user would choose. It also works only on unbiased classes, i.e., if the maximal value for one class is equidistant for the other, e.g. from point 0 the distance to -1 and 1 is equal, requiring equal mental effort for each class. Various solutions are proposed for unbalanced datasets, such as the Cohen's Kappa [Schlogl et al., 2007]. To determine which class is biased, one can investigate the confusion matrix with specificity = TN/(TN + FP), that is, the capacity to correctly detect correct trials, and sensitivity = TP/(TP + FN), the capacity to correctly detect errors. Furthermore, receiver operating characteristic (ROC) is a probability curve of Sensitivity and (1-Specificity) over different classification thresholds, see figure 1.5.

The area under the curve (AUC or AUROC) can serve as a separability index of features [Thomas et al., 2013a]. AUROC is the most common metric used in ERP BCIs.

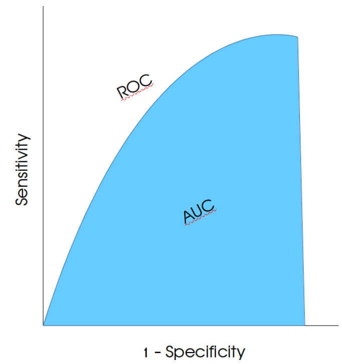


Figure 1.5: Example of ROC and AUC or AUROC

If we wish to determine the classification performance offline, we often use cross-validation [Hjorth, 2017]. Cross-validation separates a set into k-folds, and uses k-1 folds as training set while 1 fold as testing data. Each fold produces a classification accuracy or a performance value. It then performs many permutations, using what was previously a training fold as part of the testing fold. In turn a fold from testing will serve as a new training fold, and so on. The final performance value is a mean of all performances calculated from all folds.

On the other hand, classification can be perceived as a communication or information channel. In that case, Information Transfer Rate (ITR), bit rate or number of bits transfered per second, can be used for both balanced and unbalanced classes. There is also a variety of ITR, for detailed information see [Thomas et al., 2013a],

Lastly, as Riemannian geometry showed high success in classification, new form of metrics have risen, such as the stability of the signal and distinctiveness of classes [Lotte and Jeunet, 2018]. The idea of having distinct or separable classes, was mentioned earlier as the "separability index" in [Perdikis et al., 2016]. However, instead of the Riemannian distance, it used a Kullback–Leibler (KL) divergence between the two multivariate normal class distributions corresponding to the two MI tasks.

1.7 Feedback on EEG-based Brain Activity

With the first BCI system, the importance of feedback for human training was clear [Wolpaw et al., 2002b]. Normally one cannot observe one's own brain activity, nor can one be fully conscious of it. Therefore, the necessity of observing neural activity is crucial for learning and brain regulation [Wolpaw and Wolpaw, 2012]. Such physical manifestation of one's brain activity is comprised within the feedback of the machine output or interface. In other words, the feedback is the classification output that is mapped in real-time onto a perceivable (visual, auditory, tactile) representation. Today, for MI-BCIs, user training is a necessary and often cumbersome process, during which novel functional circuits for action are created, referred to as the "neuroprosthetic skill" [Orsborn et al., 2014]. As for ERP-based BCIs, a general opinion is that there is very little need for user training with [Fazel-Rezai et al., 2012], even though the user can improve his/her P300 marker with training [Baykara et al., 2016].

In this section we will describe the importance of creating a correct feedback for human training. We will also point out the educational theories that can be shown useful for such learning.

1.7.1 Human Factors and Training

The feedback can be erroneous due to classification errors and bad calibration. If the error is too high, the user can be misguided and confused by perceiving “wrong” feedback, leading to even higher error rates [Margaux et al., 2012, Mattout et al., 2015]. What the person perceives is a mismatch between the expected output and the perceived one, losing self-confidence and sense of agency or control. For this reason many design strategies were developed in order to prevent such decreasing performance rates. For instance, it was shown that with positively biased feedback, naive users generally perform better [Barbero and Grosse-Wentrup, 2010]. However, depending on many human psychological states and traits, such design strategies do not apply for everyone. Indeed, it was shown that novel users who are independent and confident and motivated are more likely to reach high performance rates than those who are anxious and tense [Jeunet et al., 2015a]. This brings us to some general principles of educational theory and cognitive psychology. In the following, we describe attempts of the BCI community to create meaningful feedback and interface designs that comply with the said theories.

1.7.1.1 Educational Theories lead to Flow theory

Since the beginning of the 20th century, behavioral reactions to a variety of stimuli were recorded influencing the development of learning strategies and conditioning. Most known were Pavlov’s conditioning [Spence et al., 1956], Law of effect [Thorndike, 1905] and Operant Conditioning and Reinforcement Learning [Skinner, 1938]. Behaviorists perceived a living being as a black box, being only interested in what they can control and observe. For instance, Skinner realized that when rewarding a mouse with food after performing a desired action, the mouse would most likely repeat the same action expecting to get more food. In other words, such activity is positively reinforced, and food increased the mouse’s extrinsic motivation.

– In MI BCI, Wolpaw’s moving ball on the screen, and Pfurtcheller’s Graz protocol was designed with respect to Skinner’s Operant Conditioning [Curran and Stokes, 2003]. Even though feedback such as Graz became a standard in MI BCI, it showed to be suboptimal for training and performance [Jeunet, 2015]

Later on, Cognitive Developmental theories such as the Zone of Proximal Development (ZPD, [Vygotsky, 1978], but written in 1930s), includes a tutor who strives to induce intrinsic motivation by providing learning content adapted to the student’s cognitive capacities. The ZPD is the zone in which the student is guided and encouraged by the tutor.

– In parallel, in BCI, we can find the works of [McFarland et al., 2010], who proposes MI tasks that gradually increase in difficulty in order to assist the user training. Additionally, [Pillette et al., 2017] propose a social agent for providing emotional encouragement for novice MI users.

More recent theories are Motivational ones, that combine intrinsic motivation (i.e., learning is self-rewarding) and extrinsic motivation (e.g. good grades or monetary rewards). Such educational or instructional design theories are the ARCS model [Keller, 1987] stating that the content should be relevant and bring attention, confidence and satisfaction in the student, while the Taxonomy of Intrinsic Motivation [Malone and Lepper, 1987] states that the best way of learning is through play.

– In parallel, in BCI, numerous playful interfaces (machine output) were designed in order to increase intrinsic motivation of users and thus increase performance. For instance, [Van Erp et al., 2012] explore the social and collaborative aspect of learning, [Ron-angevin, 2009] investigate game-like and playful 3D games, [Alimardani et al., 2014] provides immersive content through VR environments, highlighting the importance of body-ownership illusion for reaching sense of agency and high performance rates, while [Kleih et al., 2010] provides monetary rewards to increase extrinsic motivation and performance.

Finally, what we can conclude from the literature is that we aim at inducing desired user states such as sense of agency, attention, immersion and pleasure (experiencing a self-rewarding sensation) in order to reach high performance rates in BCIs. One such holistic state includes all these "sub-states", and it is called the state of flow [Csíkszentmihályi, 1975]. I will provide a few citations from the book "Flow: The Psychology of Happiness" [Csikszentmihalyi, 2013]:

- "...It is when we act freely, for the sake of the action itself rather than for ulterior motives, that we learn to become more than what we were."
  - Such intrinsic motivation can be induced by using game-like training.
- "...the self expands through acts of self forgetfulness."
  - This phenomenon could be reached by assuring immersive content, no matter the modality (be it a book or a 3D video game).
- "Enjoyment appears at the boundary between boredom and anxiety, when the challenges are just balanced with the person's capacity to act."
  - This state can be induced by matching the task difficulty with the user's skills in real-time.
- "It is not the skills we actually have that determine how we feel but the ones we think we have."
  - We must assure that the users believe they are in control of the machine, by positively biasing the feedback and or by providing the body-ownership illusion through a VR environment.

Flow has not been studied in BCI, even though such state seems to be important for a BCI user training and task design. Hence, in Chapter 3, we study the potential benefits of flow state for performance.

1.8 Conclusion

In this chapter we provide an overview in which we describe key elements and principles of BCIs, their application, underlying neuro-physiological phenomena, measuring tools, signal processing and machine learning techniques and so on. Most of all, we focus on the feedback as an important and somewhat novel approach to improve BCI performances through user training. In this thesis we work on MI and P300 BCIs, hence in this chapter we focused mostly on methods and designs that apply to these two well-known paradigms.

BCIs have a lot of room for improvement, from measuring tools, signal processing, machine learning to feedback content and representation of the machine interface. One promising way to improve BCIs is to consider using adaptive systems which is what we detail in the next chapter.

Chapter 2

Adaptive BCI

Philosophical Thought In the following chapter we describe adaptation or change, we create categorizations and models that should capture such change. We also unveil the necessity to dig deeper into the human psychological nature in order to create valid adaptive models. I find it fit to briefly mention what was said about change, about categories, concepts and their meaning.

One of my favourite quotes, "Panta rei" or "All flows", from Heraclitus (ancient Greek philosopher) states that the only constant is the rhythm of change, measurable duration of its cycles. Interestingly, we "recently" discovered that the brain is in constant movement [Enzmann and Pelc, 1992]. Therefore if our brain is constantly evolving, and our reality is a mental construct, would that prove Heraklitus' statement, that our reality is then in a constant rhythm of change? Moreover, we have already detailed that the brain of each person is different in Chapter 1. So each brain can have different rhythm of change and thus states of reality. Is this evidence that every reality is specific to each person?

Aristotle was the first to talk about categories, trying to explain the connection between reality and our concepts, intermediated by language. As we can think only about the existing objects, the main problem was the nature of a linguistic expression of the thought, i.e., of the concept it presents. In his *Organon*, or Logic as we call it, he introduced notions of concepts and their meaning, which we are familiar to as connotation and denotation, or a bit simplified, as form and content of the notion. Notions are in a hierarchical order. Those that display the highest degree of generality are on the top of the hierarchy and are called categories. Namely, their (denotation) form is the richest, they include the largest number of other notions. But, regarding their (connotation) content, they are the poorest, the least informative about the specific features of the objects they refer to.

We could say that the BCI community was for long only interested in the form of the BCI system, i.e., decoding the observable EEG signal. In a sense, concording with the behaviorists' point of view, that *man* is a black box, only accounting for the observable. However, as the brain is in constant movement and is different for each person, its activity cannot be easily observed or anticipated by a non-adaptive machine based on form. For that, we need to dive into the content of the human, such as one's psychological factors, states, and experiences. That way the BCI machine could attempt to anticipate or influence human change.

2.1 Introduction

There are two main approaches engaged in improving BCI systems: (i) improving the machine learning techniques [Makeig et al., 2012], and (ii) improving human learning, by using the knowledge from instructional design and positive psychology [Lotte et al., 2013]. Both agree that the system needs to be adapted to the user but rely on different sources of adaptation: the machine for the former and the brain for the latter. In particular, machine learning algorithms should adapt to non-stationary brain signals, while human learning approaches assist in the production of coherent and stable EEG patterns of the user, or in the adaptability of the brain to the machine. This implies that these approaches should guide the machine adaptation according to the various users' skills and profiles.

To our knowledge, there is no work devoted to classifying the literature on adaptive BCI in a comprehensive and structured way. Hence, we propose a conceptual framework which encompasses most important approaches to fit them in such a way that a reader can clearly visualize which elements can be adapted and for what reason. In the interest of having a clear review of the existing adaptive BCIs, this framework considers adaptation approaches for both the user and the machine, i.e., referring to instructional design observations as well as the usual machine learning techniques. It provides not only a coherent review of the extensive literature but also enables the reader to perceive gaps and flaws in current BCI systems, which would, hopefully, bring novel solutions for an overall improvement. EEG-based BCIs are in the center of our attention throughout this chapter. Nevertheless, the proposed solutions for adaptation can be applied to other techniques such as invasive recordings, functional Near-Infrared Spectroscopy (fNIRS) or Magnetoencephalography (MEG).

This chapter is organised as follows. Section 2.2 contains a reasoning behind creating adaptive BCIs, it will guide the reader through the aspects of human and machine learning that call for adaptive methods. Section 2.3 presents our contribution to the field, a comprehensive framework to design and study adaptive BCI systems. We show that the framework encompasses most techniques of adaptive BCIs, which we briefly review. In Section 2.4. we describe the challenges and future work. Finally Section 2.5. is the concluding section of this chapter.

2.2 Reasons for Adaptation

Currently, adaptation is mainly done by using different signal processing techniques without including the human factors [Allison and Neuper, 2010, Makeig et al., 2012]. However, the user's success in mastering the BCI skill appears to be a key element for BCI robustness. If the user is not able to produce stable and distinct EEG patterns, then no signal processing algorithm would be able to recognize them [Lotte et al., 2013]. Up to a certain extent, machine learning techniques can adapt to the signal variability. However, most of those techniques are blind to the causes of signal variability. Identifying those causes, accounting for them and possibly acting directly on them may assist the decoding of (effected) signals. Such causes may act at different time scales, for instance a person's drop of attention may have a sudden and dramatic impact, while learning rather operates on the long run. The term variability is used to describe the user, environment and equipment "variability" , and more frequently, the signal variability. These two types of variabilities are often treated as the same however we consider them as one being the cause (the environment, the user etc.) and the other the effect (the signal), respectively. Throughout this chapter, we mostly address the user variability as the main cause and denote its various expressions as components.

2.2.1 Causes of Signal Variability

Causes of low BCI performance and usability can be somewhat solved with adaptive techniques. We list and describe these causes and reason about the methods used to improve the system. Methods are separated in two levels, as user or machine adaptation methods. We add a time dimension to both levels in order to give a hint of the regularity the adaptivity could take place.

Variability can be distinguished as: (1) short-term [Schlogl et al., 2010], i.e., signal variabilities within trials or runs caused by, e.g. fluctuations in attention, mood, muscle tension [Jeunet et al., 2015a]; (2) long-term [Schlogl et al., 2010], e.g. regulations of sensorimotor rhythms (SMR) over sessions because of learning [Wolpaw and Mcfarland, 1994].

EEG variability can appear due to many causes, as follows:

- The equipment and experimental context: Equipment sensitivity to electric noise present in the environment [Niedermeyer and da Silva, 2005], [Maby, 2016];
- Quality of the instructions given to the user to follow through the task [Neuper et al., 2005].
- Short term user components: Attention, mood [Nijboer et al., 2008], muscle tension [Schumacher et al., 2015], naturally evolving during, and somewhat driven by, the interaction with a BCI system. In case that there is no specific instruction, user's mental command itself can be a cause of signal variability. For instance, during an MI task, the user may use a mental control in many different ways using e.g. kinesthetic or visual motor imagery [Neuper et al., 2005].
- Long term user components: The user's learning capacity to control the machine depending on e.g. memory span, intrinsic motivation, curiosity, user profiles and skills [Jeunet et al., 2015a]. Negative or positive loop in learning progression could occur (see instructional design - [Keller, 2010]). For instance, a positive loop concerns a motivated user whom being motivated has a higher attention level, which would in turn, ideally, enhance learning and control, and finally, induce higher motivation, and so complete the (virtuous) cycle [Mattout et al., 2015].

2.2.2 Principles of Adaptation

When considering adaptation, here we mean adaptation of the machine to reduce the negative effect of some user's fluctuations onto the measured signals. In practice, (i) reducing the impact of signal variability would require the use of advanced machine learning techniques, such as adaptive spatial filters [Woehrle et al., 2015]; (ii) influencing the user variability would require adapting the machine output (feedback and instructions) in order to keep the user in an optimal psychological state. The latter could follow instructional design theories, e.g. by simplifying the layout or diminishing the task difficulty if the user is in a state of fatigue [Sweller et al., 1998]. Ideally, the BCI system should be (i) configured a priori for each subject, for instance based on their stable characteristics, e.g. skills or profile, and also (ii) dynamically readjusted during the usage, according to, e.g. their evolving cognitive and affective states.

Machine Learning The BCI community has long been aware of the need for adaptive signal processing and classification. Experimental results have confirmed that using adaptive features and classifiers significantly improves BCI performances, both offline and online [McFarland et al., 2011, Mattout et al., 2015]. Signal processing adaptation appears to be particularly useful for spontaneous BCI such as motor imagery [McFarland et al., 2011]. However, it can also be useful to reduce calibration time in ERP-based BCI by starting with generic, subject-independent classifiers, and then adapting them to each user during BCI use [Kindermans et al., 2014a].

Human learning The BCI community has concentrated on designing adaptive machine learning techniques, somewhat because algorithms can be more objectively analysed than the human psychological states. On the other hand, the effect of adapting the BCI output (feedback and instructions) is harder to perceive because it indirectly modifies the signal, involving a spectrum of user's psychological states. If inappropriate feedback is provided, subjects can learn incorrectly or have negative emotional reactions, which could impair performance and discourage further skill development [Barbero and Grosse-Wentrup, 2010]. This means, it would also highly affect the signals and system's accuracy [Wolpaw et al., 2002b]. In order to adapt the machine learning techniques favouring the user needs and learning, we should investigate the instructional design theories[Lotte et al., 2013]. These theories are useful for finding the appropriate task and feedback for each user by adapting it according to their abilities, profiles and performances. This way, the EEG patterns are regulated, which implies that to assist the user's learning also means to assist the machine learning.

2.3 Taxonomy for Adaptive BCI

We introduce a conceptual framework (taxonomy) which can be used as a tool for a clear visualisation of the elements being adapted, as well as of the missing methods which could possibly lead to optimal adaptive BCI design. It emphasizes existing solutions encompassing most information used for creating a fully adaptive BCI system. The taxonomy (see Figure 2.1) has a hierarchical structure, from the lowest level elements which endure rapid changes, to the highest level elements which change at a much slower rate.

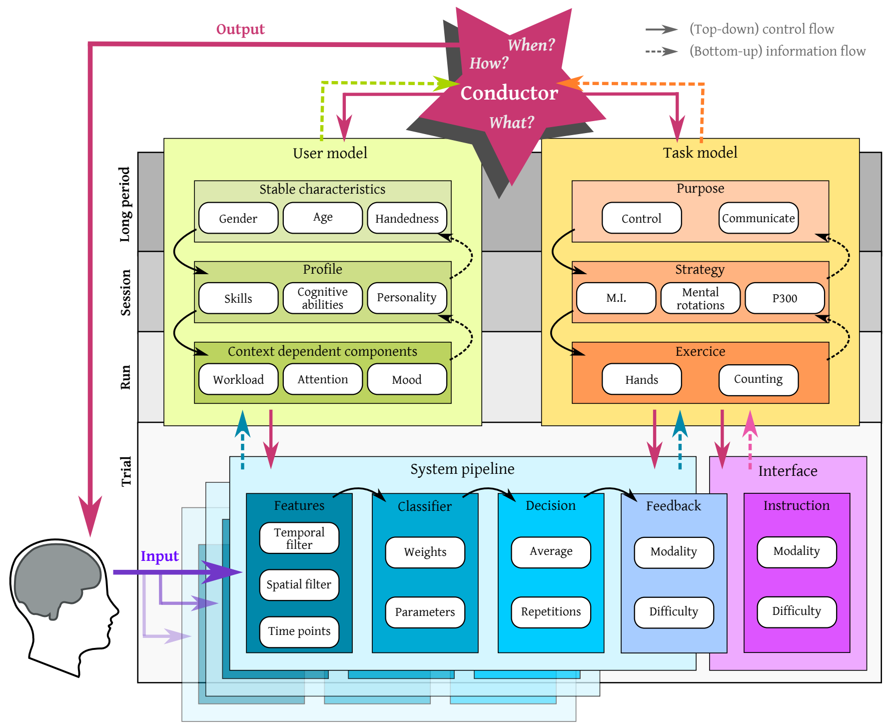


Figure 2.1: Multiple signals (input) maybe observed and processed in parallel in order to infer complementary states or intents, at the trial-wise time scale. All the information extracted from these parallel pipelines may trigger the up-dating of the user or task model, which in turn might yield a decision from the conductor to take action, such as adapting one of the elements of the pipeline, the interface, or within the user and task models. It is comprised of 4 major elements, presented bottom-up: (1) the system pipeline is the path in which the raw EEG signal goes through when manipulated by the computer; (2a) the user model is an abstraction of the user's states, skills and stable characteristics; (2b) the task model is an abstraction of the BCI task, one that is tightly related and fully dependent on the user; (3) the interface is a representation of the BCI task, i.e., what is observed by the user from the machine output; (4) the conductor masters the adaptation process by deciding the moment, the manner and the elements of the whole system (pipeline, task, user, interface) to adapt.

The input of the system pipeline comes from brain activity patterns measured on the user, while the output of the system (interface containing feedback/instruction) is handled by the conductor and employed by the user. As they undergo rapid changes, input and output take place in the bottom level, as summarized in Figure 2.1. To our knowledge, for the first time, we conceptualize a possibility of having an intelligent agent which could eventually replace the experimenter. For the sake of readability, we introduce step by step each element of the taxonomy, starting bottom-up.

2.3.1 The system pipeline

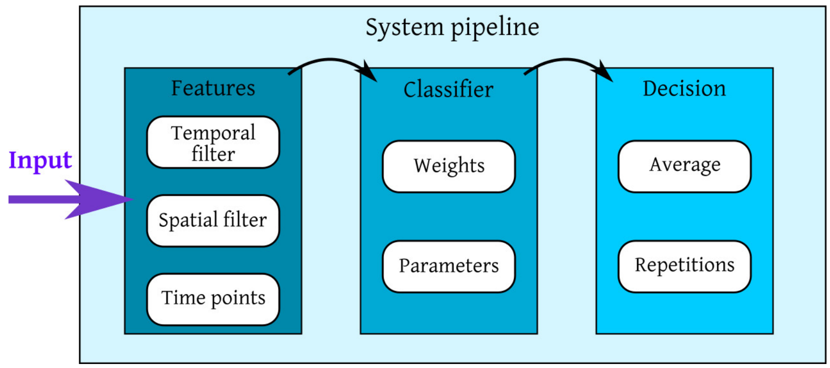


Figure 2.2: The system pipeline, acquiring and processing one of the input signals measured with e.g. EEG. For the sake of readability, we explain the feedback as part of the system's interface, coming from machine output.

The system pipeline includes:

(1) EEG features extracted from the raw signal (the input), possibly passing through: a temporal filter, e.g. to filter noise or to choose an optimal frequency band; a spatial filter, i.e., combining those electrodes which lead to more discriminable signals; e.g. Common Spatial Pattern (CSP) filter and its variants. signal epoching, i.e., selecting a time window to target an event of interest (a motor command or a stimulation);

The extracted EEG features are sent to (2) the classifier which translates signal features into the estimated mental commands, using different machine learning classification methods, e.g. Linear Discriminant Analysis (LDA), whose parameters (e.g. weights) could be adapted.

The accumulation of classification labels over several time samples or epochs give rise to (3) a decision, which often defines a speed-accuracy trade-off. Typically, with ERP-based systems such as a P300-speller, this is done by accumulating evidence over multiple stimulus repetition, to select a given letter when its probability of being the target letter is higher than a given threshold, e.g. [Kindermans et al., 2014a, Mattout et al., 2015].

In order to maintain or improve BCI performances, one requires to accommodate the signal variability, by adapting either one or several elements of the pipeline, e.g.:

- Feature extraction, in order to adapt to fast (e.g. a sudden faulty sensor) or slow (e.g. change in the frequency of the signal of interest) changes;
- Classification, in order to change the number of classes, or to change the mapping between each class label and signal features;
- Decision, in order to optimize performance, e.g. by adjusting the speed-accuracy trade-off.

2.3.1.1 Literature review on adaptive signal processing / machine learning

Adaptive feature extraction In order to extract features that adapt to the signal variability, a number of adaptive filters have been proposed for BCI. To the best of our knowledge, they are all supervised, i.e., they require the actual EEG class label. Most of the proposed adaptive filters were spatial filters, and in particular adaptive CSP for motor imagery-based BCI applications. For instance [Shenoy et al., 2006, Sun and Zhang, 2006] proposed to re-optimize the CSP filters as a new batch of labeled data becomes available. Later, [Zhao et al., 2008, Song et al., 2013] proposed new algorithms to incrementally update the CSP spatial filters without the need to re-optimize everything. [Tomioka et al., 2006] proposed a method to adapt spatial filters to changing EEG data class distribution. Finally, an incrementally adaptive version of the xDAWN spatial filter was proposed [Woehrle et al., 2015], dedicated to ERP based BCI. Adaptive temporal filters were proposed in [Thomas et al., 2013b]. In this work, the optimal frequency bands for discriminating motor imagery tasks were regularly re-estimated, and the temporal filters adapted accordingly. It is worth noting that all these adaptive filters algorithms were evaluated only in offline experiments. So, it is unknown how changing the filters influences the users. Features extracted from EEG signals can be also computed adaptively [Vidaurre and Schlogl, 2008]. In particular, there are a couple of methods used to estimate features adaptively, with each new EEG sample measured, rather than estimating them as the average feature from a full window of samples in a fixed way. For instance, Adaptive AutoRegressive (AAR) features, estimates AR parameters and use them as features for each new EEG sample [Schlogl et al., 2010] which was proven superior to (fixed) AR parameters estimated on a full time window of samples, including for online experiments. Another example of adaptive features is Adaptive Gaussian Representation, which uses as features time-frequency weights that are adaptively estimated for each time window [Costa and Cabral Jr, 2000]. Finally, compensating for the features change is possible through the estimation of this change before being used as the classifier input. As such, the corrected features will follow, more or less, the same distribution over time, and thus a classifier trained on features at t-1, will still be relevant to classify features at time t+1. For instance [Satti et al., 2010] proposed a "Covariate Shift minimization" which first estimates a polynomial function, modeling the moving of the features' distribution center within time. Then, they subtracted this function value at time t from the features at the same t, to correct for the deviation due to time, which led to improvement of the classification accuracy.

Adaptive classifiers The majority of the work on adaptive signal processing for BCI was so far on the design of adaptive classifiers, i.e., classifiers whose parameters were incrementally re-estimated over time. Both supervised and unsupervised (not having the class labels) adaptive classifiers were proposed. In the supervised category, multiple classifiers were explored offline including Gaussian classifiers [Buttfield et al., 2006], LDA or Quadratic Discriminant Analysis (QDA) [Shenoy et al., 2006, Schlogl et al., 2010] for mental imagery-based BCI. For ERP-based BCI, [Woehrle et al., 2015] explored adaptive Support Vector Machine (SVM), adaptive LDA, a stochastic gradient-based adaptive linear classifier, and Online passive-aggressive algorithms. Online, still in a supervised way, only the LDA/QDA [Vidaurre et al., 2007] and an adaptive variational Bayesian classifier [Sykacek et al., 2004] were explored. Unsupervised adaptation of the classifiers is obviously much more difficult since the class labels, hence the class specific variability, is unknown. Thus, unsupervised methods were proposed that try to estimate the class labels of the new incoming samples first, before adapting the classifier based on this estimation. This was explored offline in [Blumberg et al., 2007, Gan, 2006] for an LDA classifier with motor imagery data. Another simple unsupervised adaptation of the LDA classifier for motor imagery data was proposed and evaluated both offline and online in [Vidaurre et al., 2010]. The idea is not to incrementally adapt all the LDA parameters, but only its bias, which can be estimated without knowing the class labels if we know that the data are balanced, i.e., with the same number of samples per class. For ERP-based BCI, semi-supervised learning also proved useful for adaptation. Semi-supervised learning consists in using a supervised classifier to estimate the labels of unlabelled data, so to adapt this classifier, based on these initially unlabelled data. This was explored with SVM and enabled to calibrate P300-spellers with less data than with a fixed, non-adaptive classifier [Li et al., 2008, Lu et al., 2008]. Finally, both offline and online, [Kindermans et al., 2014a] proposed a probabilistic method to adaptively estimate the parameters of a linear classifier in P300-based spellers, which led to drastic reduction in calibration time, essentially removing the need for the initial calibration altogether. This method exploited the specific structure of the P300-speller, and notably the frequency of samples from each class at each time, to probabilistically estimate the most likely class label. In a related work, [Grizou et al., 2014] proposed a generic method to adaptively estimate the parameters of the classifier without knowing the true class labels by exploiting any structure that the application may have.

Fully adaptive signal processing It is possible to use fully adaptive BCI signal processing pipelines. Several groups have explored BCI designs with both adaptive features and classifiers. Offline adaptive xDAWN and several adaptive classifiers for ERP-based BCIs are studied in [Woehrle et al., 2015], showing that each improved performances as compared to a non-adaptive version. Even so, combining them both improved the classification accuracy even further. Online for motor imagery based BCI, [Vidaurre et al., 2007] explored using both Adaptive AR features with an Adaptive LDA. Later, she also explored co-adaptive training, where both the machine and the user are continuously learning, by using adaptive features and an adaptive LDA classifier [Vidaurre et al., 2011]. This enabled some users, who were initially unable to control the BCI, to reach classification performances better than by chance. This work was later refined in [Faller et al., 2012] by using a simpler but fully adaptive setup with auto-calibration, which proved to be efficient including for users with disabilities (Faller 2014). Co-adaptive training, using adaptive CSP Patches proved to be even more efficient [Sannelli et al., 2016]. Altogether, these studies clearly stress the benefits of adaptive signal processing for EEG-based BCI, both at the feature extraction, classifier and decision levels. However, these works often omit the human factors.

Adaptive decision methods The decision can be adaptive as well, by e.g. adapting the speed-accuracy trade-off for wheelchair control [Saeedi et al., 2016], or adapting the number of repetitions in a P300 speller [Mattout et al., 2015]. While monitoring the user's state, it is also possible to inhibit BCI interaction until specific requirements, such as the user attention levels are met [George et al., 2011]. Monitoring the user during the BCI task could be useful for revealing a way to adapt features over time, e.g. an increase in workload which can impact MI features [Gerjets et al., 2014]. Hence, we introduce what the user, and the task have to do, as a guide for adapting the system.

2.3.2 User and Task Model

In order to adapt all the elements of the system pipeline with respect to the user skills and needs, it is useful to consider a user model (Figure 2.3). We assume that the user components have a degree of changeability within certain time intervals and also react to the machine output. Hence, we categorized the user model according to time, within a timeline based on 3 time scales: runs, sessions and a loosely long time period. Note that these time limitations can vary or be adapted as well if necessary. To create a complete automatic adaptation would mean to refine the machine to manage more precisely the user's responses. For that purpose, we created a task model (Figure 2.4), containing the necessary BCI task information, which components follow the same time intervals as the user model. The timeline prescribes how often the system should be adapted/updated and according to which element. Notably, the time intervals are chosen as they are commonly used in the BCI community, but it is not necessary to have them fixed as such.

2.3.2.1 User model

We accustomed the Scherrer's classification of affective states [Martín et al., 2011] for the BCI purposes, and arranged them in the user model. Namely, the user model is an abstraction of the user, where their skills, states, and stable characteristics are arranged according to the time needed for them to change. The more we climb up, the more stable the components are.

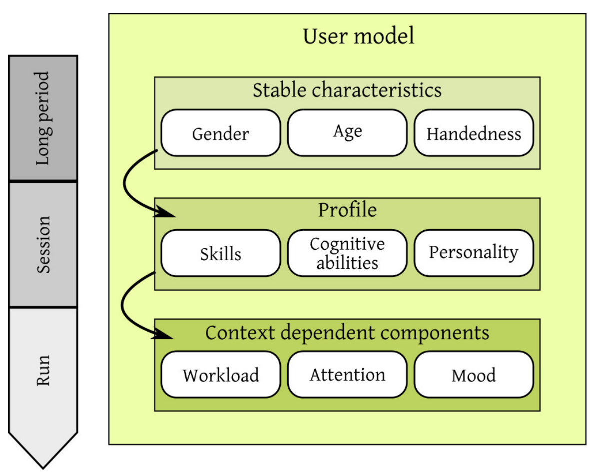


Figure 2.3: User model, containing 3 levels, arranged from the least stable (context dependent), to the most stable components (stable characteristics).

- Stable user characteristics: gender, age, culture, background, genetic predispositions (handedness) etc. These elements can also help accounting for inter subject variability.
- User profile: (i) a given user may have developed particular (non-BCI or BCI) skills which may help in the current BCI context or may be reinforced by the ongoing practice. (ii) same for personality traits (openness, conscientiousness, extroversion, agreeableness, neuroticism, flow proneness etc.); (iii) cognitive abilities (memory span, imagination, attention span etc.);
- Context dependent characteristics, i.e., the user's cognitive and affective state (attention level, fear, stress, etc.) are very much related to the current task set and environmental situation.

Note that context based characteristics can be assessed with questionnaires but also physiological data, using different metrics. In that sense, we somewhat try to implicitly represent these states through performance levels (classification accuracy), e.g. high performance could be an indicator of high attention level, and so on. Hence, we could add another contextual based, quasi state, that is, the performance.

Short review of adaptive methods related to the user model There have been many works done in trying to predict the users' performance (predictors) in order to fully customize the system to their needs [Jeunet et al., 2016]. At the same time, knowing that users will have different performances according to their various components, they can be trained/adapted before using a BCI to improve those skills which have been found to relate to the BCI skills, such as spatial abilities [Teillet et al., 2016].

Table 2.1 gathers several of these predictors along with BCI training methods that can be used to take them into account, for each element of the user model. For a more comprehensive report on existing predictors, see [Jeunet et al., 2016].

Table 2.1: Examples of predictors and user training methods regarding each user model component.

	Stable characteristics	Profile	Context dependent components
Predictors	Age determining performance [Zich et al., 2016]; Paraplegic [Vuckovic, 2014] Gender [Randolph, 2012]	Visual-motor coordination [Hammer et al., 2012]; Acquired skill (gaming, sport - [Randolph, 2012]); Spatial abilities [Jeunet et al., 2015a]; High Θ and low α powers reveal illiteracy [Ahn et al., 2013]	Confidence [Nijboer et al., 2008], Motivation [Kleih et al., 2010, Hammer et al., 2012] Fear of BCIs and sense of control [Witte et al., 2013]; γ oscillations [Grosse-Wentrup and Schölkopf, 2012]
Training adaptation	/	Spatial ability training [Teillet et al., 2016];	Mindfulness training [Tan et al., 2014]; Attenuating γ-power for good BCI-performance (attention) [Grosse-Wentrup, 2011]

2.3.2.2 Task Model

The goal of the task model is to assist the BCI user in accomplishing his/her goal (communication/control, rehabilitation, amusement or artistic expression). Similarly to the user model, the task model can be organized hierarchically according to the three following time scales: runs, sessions and long period.

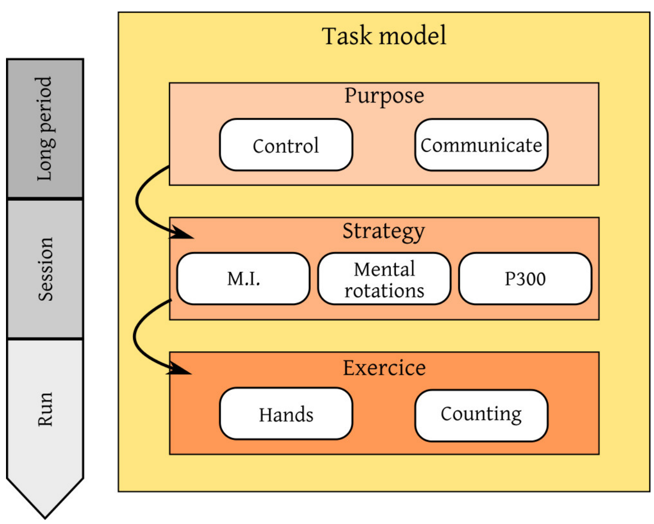


Figure 2.4: Task model, arranged within 3 time scales.

Components of the task model are typically determined beforehand, by the experimenter, and are not changed during the BCI session. Nevertheless, we envision the possibility to adapt each of these elements within the timeline.

The task model is comprised of:

- Purpose of a BCI: e.g. (1) a tool to control: prostheses, wheelchairs and other devices; (2) a communication device: writing words on a screen etc; (3) a tool for rehabilitation; after stroke (Birbaumer 2007), for paraplegic patients [Vuckovic, 2014], for autistic and ADHD children [Friedrich et al., 2014], and others; (4) a tool for artistic expression (creating music or paintings) or entertainment [Lécuyer et al., 2008].
- Strategy: the most used strategies include Mental Imagery, P300 or SSEP. The strategy will influence the choice of the initial signal processing and classification techniques, e.g. using the Motor Imagery BCI strategy, the band-power initially considered could be 8-12 Hz (mu rhythm) and 13-30 Hz (beta rhythm), measured on the electrodes placed over the sensorimotor cortex, while P300 would mean considering band-pass filtered time series (e.g. between 1-20 Hz) on fronto-central, parietal and occipital regions.
- Exercise: It indicates the mental command to be used given a strategy, e.g. for MI strategies, an exercise is chosen between various motor imageries such feet, hands, or tongue movements. This may also includes defining the type of movement (e.g.discrete or continuous).

The purpose or BCI goal is what influences or guides the overall adaptation. The strategy and exercise, initialized by the BCI purpose, can be adapted automatically based on the evolution of the user's need or state, as informed by bottom-up message passing e.g. the user's performance being lower than a certain threshold could indicate the need to change strategy or exercise.

Short review of adaptive methods related to the task model

Purpose – Depending on the purpose of the BCI, the adaptation methods will differ. Rehabilitation will favour methods engaged in learning and self-regulation, Communication will favour methods that improve accuracy and speed, while application for entertainment will favour design and innovation etc. We have not found literature fostering this idea, thus it should be left as a perspective for future adaptive BCIs.

Strategies – A strategy can be switched to another, favouring the one in which the user produces the clearest EEG patterns and has the highest performance. In [Pfurtscheller et al., 2010, Müller-Putz et al., 2015], the use of Hybrid BCIs is suggested, i.e., switching between or using multiple BCI strategies (e.g. P300, MI, SSEP); or combining different measuring techniques (e.g. M/EEG or fNIRS); or using tools apart from those in BCI, such as eye trackers, electrocardiograms, etc. To account for these possible hybrid BCIs is why there are multiple instances of the system pipeline in Figure 2.1.

Exercises – An exercise depends on the chosen strategy. Adapting exercises within runs means e.g. variating between hand or foot imagination, choosing the one that had better performance [Friedrich et al., 2013, Fruitet et al., 2013]. Adaptation is possible in larger time intervals such as within sessions, e.g. switching from 1D, 2D, to 3D MI-BCI tasks [McFarland et al., 2010], changing everything related to it (the instructions and feedback).

Note that bottom elements can partake larger time-scales, however top level elements such as purpose should not be changed within short-time intervals.

2.3.3 Machine Interface and Output

The machine interface is the representation of the BCI task. It is a set of somatosensory information a user receives from the machine output. It is an environment containing feedback and instructions, which is what the user can observe from the machine output. They can be adapted by the conductor based on the information flowing from the various signal processing pipelines, and through the user and task models, see figure 2.5.

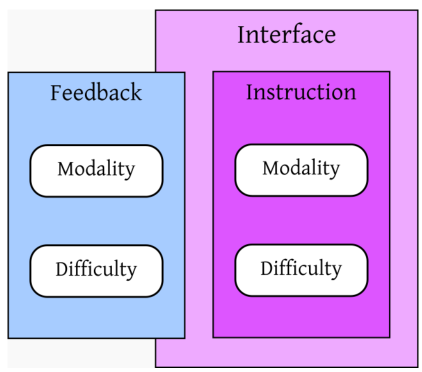


Figure 2.5: Machine output, i.e., what the user can observe being: (i) Feedback that takes part of both the signal processing pipeline as it is a representation of the classifier output, and the Interface as part of the sensory information of the machine output; and (ii) Instruction which is independent from the classifier output and is purely part of the Interface, but can be data-driven.

An interface can be designed to target some stable user characteristics, such as applications for autistic children [Friedrich et al., 2014], or context dependent user components, such as inducing motivation in a social context [Bonnet et al., 2013], or catching the user's attention with video games[Ron-angevin, 2009]. Interfaces or the observable machine output can appear in various modalities: typically visual [Neuper et al., 2005], auditory [Daly et al., 2014], in an immersive virtual environment [Alimardani et al., 2014, Vourvopoulos et al., 2016], tactile [Brouwer and Van Erp, 2010] or in a tangible form such as robotic arms [Meng et al., 2016], or wheelchairs [Waytowich and Krusienski, 2017].

2.3.3.1 Feedback

The feedback is usually a representation of the classifier's output, managed by the decision. It can be seen as the machine's response to the user's performance or states. It is useful for the user's self-regulation process or learning, to be informed on his/her progress when accomplishing the task. There are many different types of feedback, supporting emotional or cognitive states of the user. It does not necessarily need to be in the same modality as the interface, for instance [Jeunet et al., 2015b] wish to decrease the cognitive load from the visual feedback and interface, by presenting vibrotactile feedback. Hence, there can be multiple feedback at the same time and they can be given in: (i) different modalities, typically visual [Neuper et al., 2005], but also e.g. tactile [Brouwer and Van Erp, 2010], or a tangible avatar providing motivational support [Pillette et al., 2017]; and with (ii) degrees of assistance or perceived difficulty (biased feedback - [Barbero and Grosse-Wentrup, 2010]) to increase motivation and sense of control. Adapting feedback could potentially bring benefits which favor ergonomy, minimize fatigue, and optimize learning. This mostly remains to be explored.

2.3.3.2 Instructions and Stimuli

Instructions and stimuli are typically part of synchronous BCIs, which guide the user to a timely or synchronized brain (re)activity. Instructions are for instance arrows indicating the user to perform left or right hand motor imagery in MI BCI. Stimuli are, for instance flashing letters in P300-spellers. Instructions and stimuli could be presented independently from the classifier's output, and not necessarily in the same modality as the interface itself: visual, auditive or tactile for instance. Notably, the instructions and stimuli can be adapted according to user components to vary in difficulty: (i) in speed, e.g. the speed of instruction's appearance might decrease over time, according to the user's attention levels, or (ii) order of appearance, to evoke desirable P300 reactions. Additionally, it would be interesting to investigate whether presenting a block of instructions for one-class motor imagery (arrow for left-hand) and then a block of the other class (arrow for right hand) is easier for some users than presenting them in an alternate manner (left-right). Or we could present haptic instructions that could be especially useful for motor imagery. They could assist users in "remembering" the somatosensory sensation of a specific movement, and more easily create mental commands.

2.3.4 Conducting adaptation with the Conductor

As each of the framework elements can be adapted/updated separately, or in combination, using various algorithms or criteria, we explicitly refer to a controlling agent in our conceptual framework, which would preferably be created for a global adaptive BCI. It gathers all the information available from the user, the task, the interface and the signal processing pipelines, in order to decide the how, when and what to adapt. The conductor would need an objective function or *criteria of optimization*, upon which it would make its decisions. The criteria could favour only user states instead of system's accuracy for instance, which would highly depend on the BCI goal, situated in the Task model.

We draw an analogy with Intelligent Tutoring Systems (ITS), which are methods creating objective metrics and computational models for learning with digital environment. With our adaptive framework, our user is the ITS student, the conductor is the ITS tutor, and the task the ITS expert[Nkambou et al., 2010]. ITSs adapt content and activities for the purpose of challenging and guiding students in an optimal way, i.e., preventing them from being too overwhelmed with difficult material or too bored with easy or repetitive material [Murray and Arroyo, 2002]. There are many methods dealing with adapting the content of the task to keep students' attention and motivation up, and most of them are inspired by the following two approaches: (i) maintaining the zone of proximal development (ZPD) [Vygotsky, 1978]; (ii) being in flow [Nakamura and Csikszentmihalyi, 2002]. The first, based on cognitive load theory for instructional design [Luckin, 2001], may guide an indirect estimation of the person's cognitive resources [Allal and Ducrey, 2000]. Flow, originating from positive psychology, is an autotelic (self-rewarding) state, where one is immersed in a task so that one loses the sense of time, of self, and of the environment. They both concord with theories of intrinsic motivation which suggest that motivation and learning improve if the proposed exercises are at a level that is equal or slightly higher than the current user's skill level. Choosing automatically the optimal task, in real time, while considering the user and task models, could bring promising results for BCI training and operation. For instance, the conductor, as for some ITS, could use Multi-Armed Bandit algorithms to select an optimal sequence of tasks and outputs [Clement et al., 2015].

2.4 Perspectives and Challenges

The perspectives we consider here correspond to some gaps we noticed while confronting the literature we are aware of, to the proposed new taxonomy. First of all, the gaps in the user model: training methods (outside the BCI context), and feedback and instructions (during the BCI task) should adapt considering user's:

(i) stable characteristics, e.g. considering patients with different disorders (paraplegic, after stroke, autistic etc), also considering different preferences between children and adults, women and men etc;

(ii) profile, i.e., for individuals who differ in their skills or personality traits;

(iii) context dependent characteristics, favouring those methods which increase attention level, motivation etc.

Another important matter, instead of adapting the nature of the exercise based on the user's performance only (typically the classifier's output), we could also account for context dependent components e.g. the user's attention or workload level, as monitored through a passive BCI pipeline [Brouwer et al., 2012] or with other physiological sensors (e.g. electro-dermal activity).

The challenges we encounter when considering the full adaptation with the conductor are; (1) identifying metrics and criteria to optimize depending on the task, to ensure relevant adaptation, i.e., favouring those adaptation methods which most concur to user's needs and goals; (2) designing computational models of the user and task models; (3) testing the adaptive BCI online and validating it with real experiments; (4) designing unsupervised adaptive features and classifiers, and validating them online (most of them are supervised and only evaluated offline so far); (5) proposing adaptive feedback and exercises. As for the conductor, beside the algorithm that should decide when and how to perform the adaptations, the *criteria* for adapting the whole system is hidden in the "purpose" of the BCI, i.e., what one wishes to achieve. Hence, will the conductor aim for flow or ZPD as an objective function (by adapting the task difficulty or by presenting a biased feedback for example) or for system's performance and speed (by favouring higher classification accuracy). Finally, we need to ensure that adapting the system will not impede the inevitable user adaptation (human learning), and thus lead to a virtuous co-adaptation.

2.5 Conclusion

Throughout this chapter, we emphasized the need for adaptive methods in order to optimize the design and online performance of BCI. We stressed out the fact that, in order to create an overall adaptive system, it is not sufficient to consider adapting the signal processing and classification techniques, but also the output (interface) and the task parameters, in order to fully accommodate the user's variability in terms of needs and psycho-physiological states. Following that requirement, we created a taxonomy (framework) for adaptive BCIs, comprised of: (i) one or several BCI systems/pipelines; (ii) a user model, whose elements are arranged according to different time scales ; (iii) a task model, enabling the system adaptation with respect to the user model; (iv) the interface, being the task representation or the observable part of the machine output (v) the conductor, an intelligent agent which implements the adaptive control of the whole system.

For the first time, we conceptualize a fully adaptive BCI system, with respect to the user needs and states. We introduce the BCI **task** with its representation (interface) as a separate category from the standard user and system pipeline. We find that acknowledging the role of a BCI task could be the key element to achieve full co-adaptation between the user and machine. It enables a form of adaptation that not only adjusts its system pipeline to the signal variabilities or the effect, but also influences the cause – the user psychological states. That way we can prevent or minimize undesired signal variabilities, and thus increase performance.

The existing adaptation methods are described through an extensive literature review of each element of both types of models (user and task) and of possible low-level pipelines for raw signal processing. The potential benefits of using this taxonomy are numerous, for one it enables clear and methodological visualization of all the BCI system components, their possible interaction and the way and context in which they could be adapted. Moreover, this framework is also convenient for mapping the literature onto each of the components in order to understand current issues in BCI in general, and to visualize the gaps to be filled by future studies in order to further improve BCI usability. We believe this taxonomy will contribute to delve possible future research paths, and give rise to novel challenges and ventures.

PART II

Influencing the User with BCI task

In this part, we adapt the BCI task that is observed by the user within a trial or run-wise timescale (as presented in our taxonomy above 2.3). By adapting the content that is perceived by the users is a way to influence and assist them to achieve optimal behavior. Instead of waiting to deal with hughly noisy signal and its variabilities, we can influence it beforehand by steering user psychological states to their favour, and increase performance and learning.

The questions of how to influence or assist the user with a Motor Imagery task, what is the optimal user state we wish to reach, and if we reach such state does it improve performances? All these questions are considered in the first chapter 3.

If we can influence the user through a feedback and increase performance, then we wish to know who would benefit from such adapted feedback? Furthermore, we investigate whether an adapted feedback can increase learning as well. In the second chapter 4, we use prediction models of user personality traits to tackle these questions.

If we can predict what type of personalities would benefit from what type of feedback to increase their performance and learning, than we can use this knowledge to build a simple adaptation model that would automatically select the optimal feedback for each user. In the fourth chapter 5, the question is: can we find a model that can automatically select and adapt optimal feedback to users depending on their personalities? Can we increase performance with such an adaptive model?

In the third chapter 6, we propose a computational, data-driven and probabilistic model to automatically provide optimal feedback and instructions by responding to user short-term reactions, within a P300-speller BCI task.

The selected publications for this Part are:

J. Mladenovic, J. Frey, M. Bonet-Save, J. Mattout and F. Lotte (2017) *The Impact of Flow in an EEG-based Brain Computer Interface*; Short paper, Graz BCI Conference;

E. Christophe, J. Frey, R. Kronland, J. Micoulaud, J. Mladenovic, G. Mougin, J. Vion, S. Ystad, M. Aramaki (2018) *Evaluation of a Congruent Auditory Feedback for Motor Imagery BCI*, Poster at BCI Meeting, Asilomar, USA;

J. Mladenovic, M. Joffily, J. Frey, F. Lotte, J. Mattout (2017) *Endowing The Machine with Active Inference: A generic Framework to Implement Adaptive BCI*, Oral Presentation, NaT Conference, Berlin;

J. Mladenovic , J. Frey , E. Maby , M. Joffily , F. Lotte , Dr. J. Mattout (2018) *Active Inference for Adaptive BCI : An application to the P300 Speller,* Poster at BCI Meeting, Asilomar, USA.

J. Mladenovic , J. Frey , E. Maby , M. Joffily , F. Lotte , Dr. J. Mattout (2019) Active Inference as a Unifying, Generic and Adaptive Framework for P300-based BCI, Journal of Neural Engineering; DOI: https://dx.doi.org/10.1088/1741-2552/ab5d5c

Chapter 3

Evaluating the Influence of Flow on BCI Performance

Philosophical Thought Csikszentmihalyi, from Flow theory: "It is not the skills we actually have that determine how we feel but the ones we think we have". This is closely related with our first philosophical part 1, in which we mention ontological statements placing *man* as measure of all. In other words, if reality is *man* made, then each person is a measure of one's own reality. Hence, the belief in one-self defines the "reality" or perception of self.

The mismatch between what is observed and expected (thought) can lead to a dissociation of the self, lack of self-esteem, and sense of agency. So, to reduce such a mismatch, we must provide observations that approximately fit expectations of each person. In this chapter, we could say that we try to find what users expect from themselves in general and what they expect from a BCI in that moment, and we provide observations approximate to their expectations until they gain enough confidence, and are truly able to perform what they expect by themselves. In other words, we present the users with what we believe they wish to perceive, and not what is in reality, in order to increase their confidence, sense of agency.

3.1 Introduction

BCI systems showed quite an improvement with adaptive methods, i.e. adapting the machine to the changeable brain signals of the user during a BCI task, as detailed in chapter 2. Typically, adaptation is mainly done by using different signal processing techniques without including human factors [Makeig et al., 2012]. However, if the users do not understand how to manipulate a BCI system, or are not motivated to make necessary effort for such manipulation, then they are not able to produce stable and distinct EEG patterns. In that case, no machine would be able to decode such signals [Lotte et al., 2013]. Thus, for designing an interface, ignoring certain information about the users, e.g. their skills, cognitive abilities and motivations, may represent one of the major drawbacks for the advancement of BCIs. We have provided an extensive review and proposed many solutions to adapt the machine by taking into account the user traits and skills (reffered to as user profile) and states (referred to as context dependent components) in chapter 2.

A potential improvement in BCI is to acknowledge how difficult it can be to learn to produce mental commands (a very atypical skill) without a proper feedback about the progress one has made. In every discipline, a certain feedback on one's performance is necessary to enable learning, as shown in the earliest work about Operant Conditioning and Reinforcement Learning [Skinner, 1938]. Notably, this question was studied by behaviorists for decades on animals, using rewards e.g. food, as extrinsic motivation to promote desired behavior. As humans have more complex cognitive functions, a more effective way to promote learning is in a social context, with a tutor who would prepare and adapt a task according to the student's competences. The tutor's feedback and well organized tasks would lead the disciple to gradually build up knowledge and skills, to feel confident and to be intrinsically motivated, or to be in the Zone of Proximal Development (ZPD)[Vygotsky, 1978]. Derived from cognitive developmental theories [Vygotsky, 1978] and refined through instructional design theories [Keller, 1987, Malone and Lepper, 1987], intrinsic motivation is to be a substantial element for learning. Thus, it is important to carefully design the task, and especially the feedback if we want to encourage learning and optimal performance.

Unfortunately, for long this was not the case in BCI community, as BCI systems were improved mostly with novel machine learning techniques [Makeig et al., 2012]. The result of neglecting the task representation or interface (feedback and instruction design) led to often monotonous and repetitive content, further discouraging the user, and leading to reduced skill and impaired performance [Cho et al., 2004, Kleih et al., 2010], thus highly affecting the system's accuracy. Potentially, instructional design theories could add a missing piece for designing optimal BCI feedback [Lotte et al., 2013].

There have been extensive literature describing higher BCI user performance and experience using game-like interfaces [Ron-angevin, 2009, Scherer et al., 2015]. Immersive and game-like environments attract users' attention, induce intrinsic motivation, thus promote learning and performance with less effort and frustration – for a review see [Lumsden et al., 2016]. Even using extrinsic motivation such as monetary reward can encourage users to perform better [Kleih et al., 2010]. Some studies showed that user's belief on their performance with biased feedback induced motivation and thus higher performance [Barbero and Grosse-Wentrup, 2010]. Hence, sometimes it is worth to trade the system's accuracy to the perceived, subjective user's feeling of control.

Keeping that into account, a way to promote efficiency and motivation while respecting the principles of instructional design leads us to the Theory of Flow introduced by Csikszentmihalyi in [Csíkszentmihályi, 1975]. He was fascinated by the capacity of artists to be in a state of enjoyment while effortlessly focused on a task so immersive that one looses the perception of time, of self and of basic human needs (hunger, sleep etc.). When in the flow state, people are absorbed in an activity, their focused awareness is narrowed, they lose self-consciousness, and they feel in control of their environment. As a consequence, they often perform to the best of their capacity with a sense of automaticity and a high level of confidence. Studies report flow experience in numerous activities including rock climbing, dancing, chess, reading, etc. [Csíkszentmihályi, 1975, Csikszentmihalyi and LeFevre, 1989].

Another pertinent element which encourages intrinsic motivation and is showed to be in relation with flow, is music [Croom, 2015]. Recent studies showed that music has an ergogenic effect on humans, i.e. physical enhancement while performing a physical activity [Anshel and Marisi, 1978]. In [Karageorghis et al., 2010] was reported that Haile Gebrselassie, an athlete who broke 10 000m world record in 1998, paced his running on music he was listening to, i.e. synchronous music. There is evidence that synchronous music, as a strong motivational effect, directly enhances physical performance [Simpson and Karageorghis, 2006] while asynchronous (background) music induces flow when accomplishing a task [Pates et al., 2003, Pain et al., 2011]. Most of all, background music with medium tempo (speed) has showed highest impact on flow [Karageorghis et al., 2008].

Therefore, in order to improve BCI users' performance and experience, it seems promising to try to guide them towards the state of flow. Notably, in this chapter. we want to improve user performance and overall experience during a BCI task. In particular, our research question is: *Does flow improve BCI user performance?*

In section 3.1.1, we introduce the vast usage of Flow theory in task adaptation, then we describe our MI BCI experiment, that includes an adaptation based on Flow theory and is accompanied with asynchronous music in the background. Further in this section we include the experiment details and we present the results of the performance online and offline using standard metrics, but also using various novel metrics. From this experiment we found interesting results concerning music influence on performance, thus we performed an auxiliary experiment. We describe this experiment and provide preliminary results in 3.3. Furthermore, we tackle the literature that explains the benefits of sound on motor functions in general and provide perspectives that could be useful for the BCI community.

3.1.1 Flow Theory for Adaptive Tasks

To be in the state of flow, a task needs to have the following requirements:

- **To be immersive**, with attractive visual/audio stimuli to maintain the user's attention. The principle of preserving flow with aesthetically pleasing and playfull content have been researched largely in the context of human computer interaction [Webster et al., 1993] and Internet navigation, e.g. e-learning [Esteban-millat et al., 2014];

- **To adapt** the task difficulty with the user's skills, i.e. an easy task might be boring as a difficult one might be frustrating, hence finding the golden middle is the way of feeling in control and keeping the motivation. Such difficulty adaptations were found in games, to keep the gamer in flow [Bulitko and Brown, 2012], or during teaching activities [Clement et al., 2015] to improve learning and keep the student in the ZPD [Vygotsky, 1978].

- **To have clear goals and immediate feedback / rewards**; aspired for educational purposes [Heutte et al., 2016], so that learning becomes an enjoying and autotelic (self-rewarding) process [Ninaus et al., 2015].

In [Bulitko and Brown, 2012] they create a computational model of flow, using reinforcement learning [Sutton and Barto, 2018] and Markov Decision Process (MDP), in which the artificial agent at each state (task) has to choose such action that maximizes the cumulative reward. They introduce into the decision making (action selection) *the degree of flow*, being equal to : $F(s) = f/|n_t(s) - t_{max}(s)| + \xi$, where f is a constant, or "flow-awareness coefficient" that is specific to every agent, $n_t(s)$ is the "per-action amount of deliberation of the agent in state *s*" or simply put, the cognitive effort necessary for finding the correct action in that state, while $t_{max}(s)$ represents the "domain specific constant" being simply the task difficulty in state s; and ξ is a very small constant to keep *F(s)* bounded in case $n_t(s) = t_{max}(s)$. They show that a higher flow awareness coefficient increases the reward and decreases the number of steps necessary for correct action selection. This formula is inspired directly from the flow "function", represented in [Nakamura and Csikszentmihalyi, 2002], see figure 3.1.

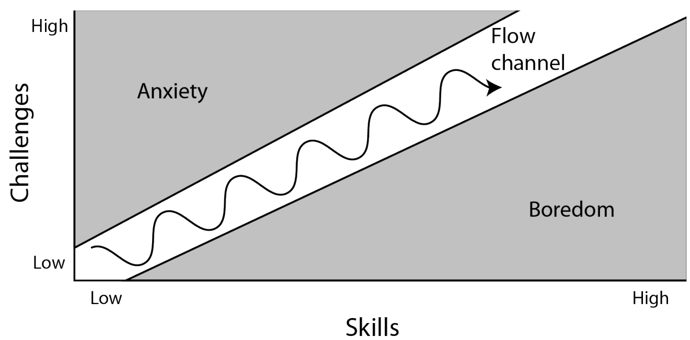


Figure 3.1: Representation of flow state as "function" of skill and challenge (from Csikszentmihalyi).

If we present the same formula as a normal distribution $F(s) = f \cdot e^{-x^2}$, where $x = \sqrt{(n_t(s) - t_{max}(s))^2}$ is a simple Euclidean distance. Then this formulation of flow resembles to the Yerkes-Dodson law about optimal stress and performance, see figure 3.2. The principle is the same, however here we have a direct relation with performance and flow. If the task is too "stressful" or too challenging, it provokes anxiety, on the other hand if it is too easy it provokes low arousal or boredom. This means that the task should be nor too challenging nor too boring in order to provoke optimal user's state (intrinsic motivation) and optimal performance. Furthermore, experimental evidence (recorded ERPs) of such "inverted curvilinear" relation between intrinsic motivation and challenge was confirmed in [Ma et al., 2017]. They examine the near miss comparing to the absolute loss of control of a game, measuring a sustained, negative shift in potential that mirrors the anticipation of a motivational stimulus during the pre-feedback period [Brunia et al., 2012].

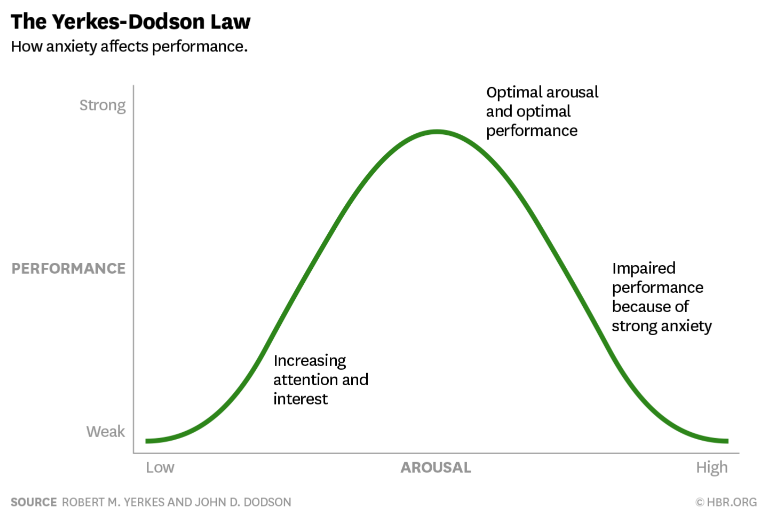


Figure 3.2: The Yerkes-Dodson Law on performance and optimal stress, from (hbr website)

The computational model of flow for task adaptation, proposed in [Bulitko and Brown, 2012] works if the task has different degrees of difficulty that requires different cognitive effort, with a reward that can be intuitively calculated (e.g. achieving a goal with high score in a game). In standard gaming it can work, however in a BCI in real-time it is a lot more difficult, as the performance metrics are not quite accurate (e.g. we cannot know the degree of cognitive workload or stress by simply evaluating the classification accuracy for instance). If we do not know how to evaluate the effort, then we do not know for certain in which direction to steer the task difficulty or the reward. Nevertheless, if we have one clear goal, one task that is known beforehand, we can assume that the user wishes to reach it. In that case, we can try to adapt the difficulty by assisting the user in reaching that one goal, without knowing exactly how it might reflect the real performance. We can first try with a simple computational model or rather with simple rules that include the degree of flow (matching an approximation of user skill and difficulty) and observe whether it made an impact on overall user experience and performance.

3.2 Adapting Motor Imagery task with Flow

We want to improve user performance and overall experience during a BCI task. In particular, our research question is: *Does flow improve BCI user performance?* We chose to manipulate flow in a game-like environment with 2 factors: 1) Feedback adaptation to match perceived task difficulty to user skills, and 2) Asynchronous music to encourage the user. Thus, our following hypotheses are:

H1. Adapting the feedback improves flow, thus improves performance.

H2. Asynchronous music improves flow, thus improves performance.

In consonance with the Flow theory, a motor imagery (MI) BCI task was presented in an open-source 3D video game (TuxRacer [1]). We investigated the effects of these two flow factors on user's flow state as well as on user performance, i.e. classification accuracy.

Manipulating Flow: In order to fulfill Flow theory requirements, we considered the following:

- **An immersive and ludic environment**, here the **TuxRacer** video game was adjusted for a 2-class Motor Imagery (MI) BCI. The game depicts a ski course, in which a virtual penguin, Tux – controlled by the player – slides through various slopes and has to catch as much fish as possible. With the BCI adjustments, Tux was maneuvered with kinesthetic imagination of either left or right hand, see Figure 3.3.

- **The adaptation** of the feedback bias, i.e. users were made to believe they performed differently from what they really did, in order to be in the flow state. If they had poor performances they were positively biased to a higher degree than if they had fairly good performances, meaning they observed better performances than real. However, when the performances were too good, then the users were slightly negatively biased, so that the task would not seem too easy. This was achieved by adaptively increasing or decreasing the classifier output, i.e. the decoding of MI commands would seem different from what it was in reality.

- **Asynchronous music** consisted of 3 songs with medium tempo (120-160 beats per min), played in the background during the BCI task. 15 persons (not related to the experiment) voted on social media for songs which would motivate them while playing TuxRacer. The selected songs are "Epic" by Alexey Anisimov (113s), "Confident & Successful" by MFYM (168s) and "Acoustic Corporation" by OAP (132s), all available on Jamendo[2].

- **Clear goals with immediate audio and visual feedback**, i.e. to collect maximum points by manipulating Tux to move either left or right to catch fish. The feedback is clear – once caught, the fish disappears with a brief audio stimulus stressing that the fish was reached.

[1] https://extremetuxracer.sourceforge.io/
[2] https://www.jamendo.com/

Figure 3.3: Participant using MI commands to play TuxRacer, e.g. imagining right hand movement to catch fish on the right.

3.2.1 Experiment Details

We created a 2 (*adapt vs no-adapt*) by 2 (*music vs no-music*) mixed factorial design, i.e. a between-subject adaptation factor, and a within-subject background music factor.

Protocol: 28 healthy subjects, naive to BCI, participated in the ~2 hour-long experiment (5 women, mean age: 25.23 years, SD: 2.98). The first 30 minutes consisted of (i) signing a consent form, (ii) installing of a 32 channels Brain Product LiveAmp EEG, (iii) instructions given to the user and preparation, (iv) ~10 minutes system calibration (40 trials of 7s) with the standard 2-class MI BCI (left/right hand) Graz protocol [Pfurtscheller and Neuper, 2001]. In the Graz protocol, the user was presented with arrows indicating the left or right side, to instruct the participant to imagine a left or right hand movement. Afterwards, each participant took part in 2 counterbalanced conditions of 20mins each with TuxRacer, (a) with and (b) without background music. 3 songs were repeated to accompany the music condition of 6 runs (1 song per 2 runs). Each condition comprised of 6×3min-runs, with 22 trials per run (11 for left and 11 for right hand, in random order), see Figure 3.4. Each trial consisted in performing left/right hand MI to move Tux in order to catch fish on the left/right of the ski course, respectively. There were 8 closely arranged fish per trial, to be caught within 3 seconds. During 5-second long breaks between trials, the BCI controls were disabled so that Tux would return in a neutral position (center on the ski course) and participants could rest. The study was approved by the Inria ethics committee, COERLE (Comité opérationnel d'évaluation des risques légaux et éthiques).

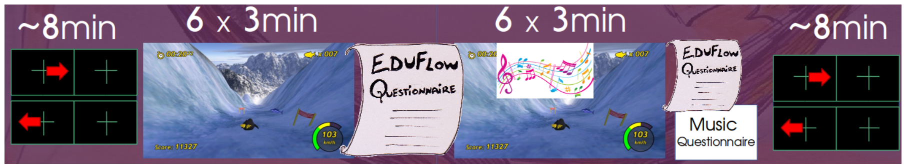


Figure 3.4: The session started with 8min calibration of Graz protocol[Pfurtscheller and Neuper, 2001], followed by 2 conditions, counterbalanced between subject. Each condition was either with or without music comprised of 6 runs of 3 minutes each. The session ended with another Graz protocol for MI. The adapt group received an adapted (biased) feedback for the whole session, contrary to the no-adapt group. Both groups were asked to fill EduFlow [Heutte et al., 2016] questionnaires for the flow state assessment and BMRI [Karageorghis et al., 1999] questionnaire for investigating the quality and motivation effect of music.

Questionnaires:

- Prior to the experiment, a Swedish Flow Proneness Questionnaire (SFPQ) [Ullén et al., 2012] was sent to subjects to fill in at home. This 5 points Likert scale questionnaire measures flow proneness – flow as a person's trait.
- To estimate to which extent users were in the state of flow, they were asked to fill in the EduFlow questionnaire [Heutte et al., 2016] after each condition (*music* or *no-music*), i.e., 2 times during the session. This 7 points Likert scale measures flow state through 4 dimensions: 1^{st}D is cognitive control, 2^{nd}D is immersion, 3^{rd}D is selflessness and 4^{th}D is autotelism – a self rewarding experience.
- To have a measure of the quality and motivation of the selected music, the participants also filled a dedicated questionnaire, the Brunel Music Rating Inventory (BMRI) [Karageorghis et al., 1999].

Signal processing: The real-time signal processing was performed using OpenVibe. Acquired EEG was band-bass filtered with a Butterworth temporal filter between 8 and 30Hz. We computed the band power using a 1s time window sliding every $1/16^{th}$s. We used a set of Common Spatial Patterns (CSP) spatial filters to reduce the 32 original channels down to 6 "virtual" channels that maximize the differences between the two class motor imagery [Ramoser et al., 2000]. A probabilistic SVM (Support Vector Machine) with a linear kernel was used to classify the data between left and right classes (regularization parameter *C = 1*). That way, the output of the SVM between 0 and 1, indicated a class recognized with a certain degree of confidence. We scaled the output to be between -1 and 1, to ease the computation and mapping to the game; e.g. -1 means that the left-hand class was recognized with high confidence. We used a simple formula for such scaling, $y_i = 2x_i - 1$, where $y_i \epsilon [-1, 1]$ and $x_i \epsilon [0, 1]$. We could easily scale from one space to another, back and forth. The CSP and SVM were trained on data acquired during the calibration phase (around 8mins of Graz protocol). The classifier output was recorded in order to be analyzed later on and to compute the "online" performance.

Performances: The online performance corresponds to the peak and average performance of the classifier that controlled the video game, i.e. the highest and the mean classification accuracy over all trials' time windows, respectively (see figure 3.5). To see to which point the classifier output is stable, we calculated std_output. It is the mean value of the standard deviation of the classifier output for each trial, i.e., it gives an std_output per class which is then averaged. Another metric of online performance we used is the absolute distance between the classifier output and the extreme output values (-1 for left class, and 1 for right class), for each trial.

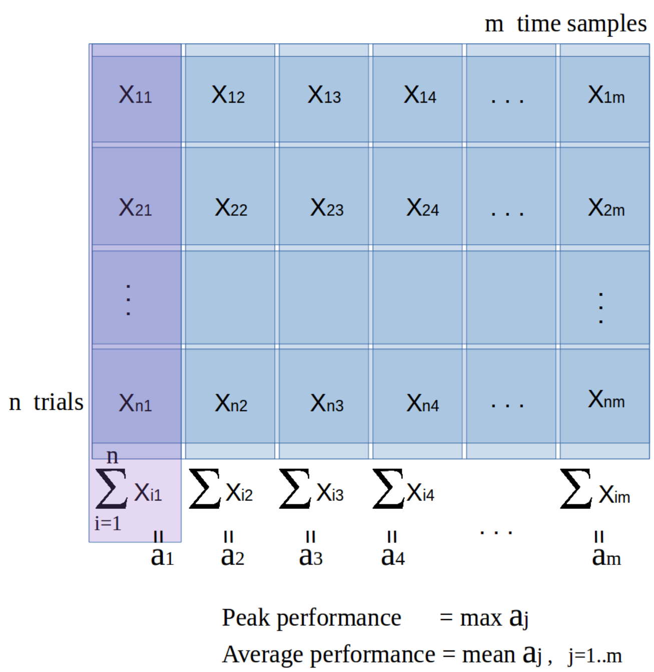


Figure 3.5: Visual representation of peak performance and average performance, where $x_{i,j}$ is the classification accuracy (i.e., number of in/correctly labeled class) for every trial i=1..n (for all runs together), and sample j=1..m; while a_j is the sum of all trials i=1..n, per sample j.

The offline performance was computed with a 4-folds cross validation per run, regarding only the data recorded during the video game. In other words, data recorded during the Graz protocol was not used to compute offline performances. We used a LDA (Linear Discriminant Analysis) for the offline classification, since it is less computationally demanding and it is based on same principles as SVM which would produce same results. Both for online and offline analyses, one accuracy score was computed over the music / no_music condition (i.e. one value per 6 runs of 22 trials).

Game controls: The TuxRacer game was controlled *via* a virtual joystick, using Lab Streaming Layer (LSL) communication protocol. When a right hand movement was recognized with the highest confidence (SVM output of 1), it was sent *via* LSL to the virtual joystick which was tilted toward the right at its maximum angle, 45 degrees. Inversely, when a left hand movement was recognized with high confidence (SVM output of -1), the virtual joystick was tilted 45 degrees to the left. Between -1 and 1, the values of the virtual joystick were mapped linearly (from minus 45 to plus 45 degrees). Thanks to this simple virtual joystick, we did not need to modify the usual input commands to the complex BCI ones in the game. Basically, the virtual joystick can act as or replace the usual computer controls, such as keys on the keyboard. Our freely available source code[3] could be used to control any (linux) joystick-based game with a BCI.

Game modifications: We designed the BCI TuxRacer game so that its trial-timing and structure mirror that of the Graz motor imagery BCI protocol [Pfurtscheller and Neuper, 2001], but in an immersive and motivating environment, as follows. We modified the shape of the terrain, curving it alike a bobsleigh course. Consequently, by the force of gravity, Tux would slide back to the middle of the course between trials, when the commands were deactivated. Between trials, Tux is continuously skiing towards the following trial with constant speed, enabling the users to see the next fish (the upcoming class). By perceiving the side (left or right) of the fish, the users intuitively knew which hand to imagine in order to push Tux towards the right direction and catch fish. We added little flags before and after the fish to indicate the beginning and end of the trial, and assist user with the timing of the mental command. We fixed the position of the fish on the ski course edges, so that the targets were equidistant from the center of the ski course, i.e., same distance from Tux at the beginning of each trial. The reason for the equal distance from the center is to enable the user to make the same mental effort for both MI classes (left/right hand). By assuring a constant speed for Tux, a race (run) always lasted 3 minutes. The course was generated for each run to randomly change order of fish.

Game adaptation: The *no_adapt* (control) group was the first to participate in the experiment. From the data acquired from the no_adapt group we wished to empirically calculate a flow function with which we could adaptively bias the feedback in the adapt group. This meant calculating an attractor point that represents the position of Tux in the ski course in which users felt most in flow.

As a performance metric, we chose the Euclidean distance between classifier output and its maximum values (-1 and 1), because in that way we could easily map it to the classifier output. To reduce the potential confounding factor from the flow trait, we subtracted the EduFlow scores (mean of all 4 dimensions) with the SFPQ (flow proneness) score normalized with z-score. As consequence, it adjusted the overall flow score around its average, i.e., high scores (above mean) decreased while low scores (below mean) increased.

We mapped the performance (Euclidean distance) onto the classifier output and performed a correlation with the flow score (Eduflow score - normalized SFPQ score). We found a significant and positive correlation (Pearson's coefficient: 0.42, $p < 0.05$), see figure 3.6. We prolonged the linear regression line to the point in which the users would have a maximum flow score (7 out of 7 points) and traced the according classifier output value. That classifier output value represents a position of Tux in which the users felt most in flow, and we call it the **attractor *a*.** We chose the attractor to be symmetrical between classes, i.e., for right class it is ***a*** and for left class it is -***a***.

[3] https://github.com/conphyture/LSL2joy

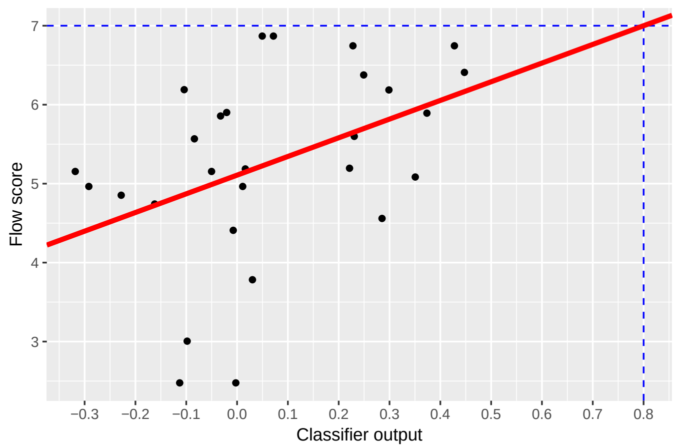


Figure 3.6: Positive correlation between Flow score (EduFlow subtracted with normalized SFPQ) and classification output. The regression line (red) is prolonged to the maximum flow score point allowing us to trace the "optimal value" of the classification output.

Thanks to the correlation, we empirically calculated the attractor to be $a = 0.8$ for the right class or ($a = -0.8$ for the left class).

We used the **attractor** to adaptively lure Tux in. At each instant ($1/16^{th}$sec sliding window) we would retrieve the classifier output and add to it a value which would push Tux a **half-way** towards our **attractor**. We chose to add half distance based on Flow theory, to keep the difficulty in the "golden middle". Consequently, when user performances were very poor, Tux was boosted to a higher extent towards the attractor, i.e. in this case users were helped (positively biased) more than when their performances were fairly good. However, when the performances were too good, over the attractor value, Tux was pushed half distance towards it, i.e., the perceived performances were deteriorated (feedback was negatively biased). The "flow" function is: $f(s_i) = s_i + \frac{(a-s_i)}{2}$, $s_i \in [-1, 1]$, where s_i stands for user skill (i.e., classifier output scaled to -1 for left, 1 for right, to ease the computation); *a* being the attractor and constant value for all users, while $(a - s_i)/2$ being the half distance between the attractor and skill, for all instants i within 22 trials of 3seconds, $i = 1, ..(16Hz \times 66s)$. For better understanding of what the users observed, see figure 3.7.

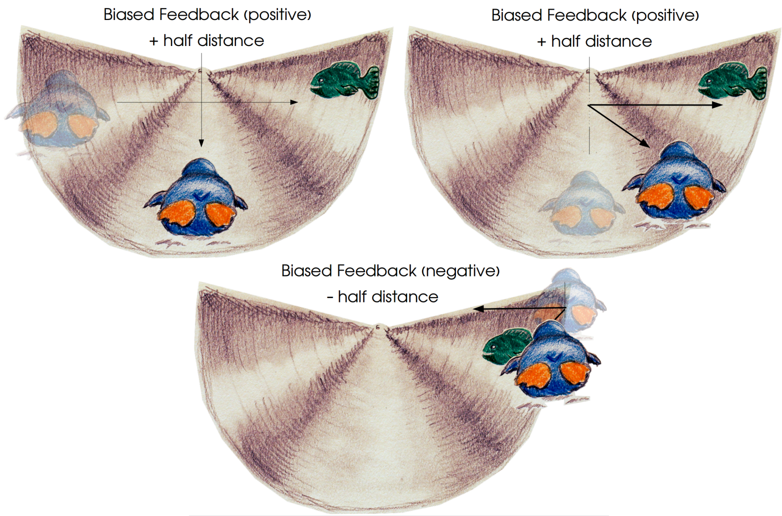


Figure 3.7: Examples of perceived position of Tux with biased feedback. Transparent Tux is a representation of the real classifier output, while the biased Tux is represented in opaque. First case (left) is when real classifier output is completely on the wrong side, thus Tux is more biased, than in second case (right), when real output is near the center of the course. In the third case (below), the classifier output is above the attractor value, thus Tux is negatively biased.

3.2.2 Results

The normal distribution of all the data was verified using a Shapiro-Wilk normality test. Also, there was no significant difference between groups regarding their flow trait, measured with SFPQ (1-way ANOVA, $p = 0.25$). ANCOVA tests showed that the flow proneness or trait (measured by SFPQ) was not a confounding factor for neither the mean of all 4 dimensions of EduFlow nor performances. There was no difference between groups regarding music motivation BMRI (1-way ANOVA, $p = 0.53$). Mean score: 15.80, SD: 4.14 – maximum score with the questionnaire we distributed: 25.3. This means that music motivation or flow proneness could not influence the results.

3.2.2.1 Flow-factor's influence on EduFlow

Difference between groups adapt and no_adapt: We tested the effects of our mixed factorial design on each of the 4 dimensions measured by the EduFlow questionnaires using a Markov Chain Monte Carlo (MCMC) method [Hadfield, 2010]. The MCMC showed a significant difference between *adapt* and *no-adapt* along the 1^{st} dimension ($p < 0.01$). Participants in the adapt group reported higher cognitive control (mean: 5.38, SD: 0.84) compared to the no_adapt group (mean: 4.49, SD: 0.83), see Figure 3.8.

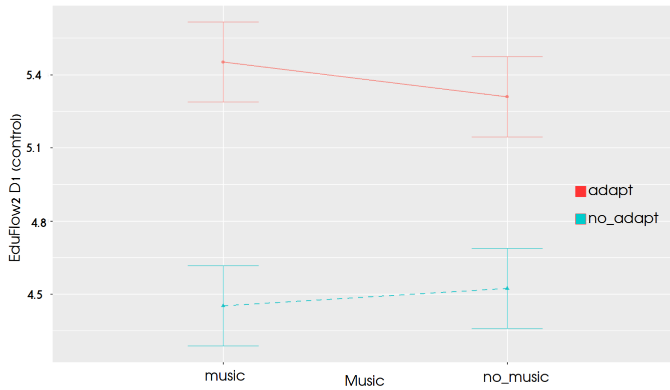


Figure 3.8: EduFlow score (7 Likert scale) for D1 (cognitive control) depends on the between-subject factor *adapt* and on the within-subject factor *music*. Users were in higher cognitive control in the adapt group (red) than in no_adapt group (blue).

Music & EduFlow score: There was no correlation between the level of motivating music, BMRI scores, and flow (p = 0.54).

We investigate the music order and separate users who had music as first condition, called musicFirst and those who had music as second condition, called musicSecond, the conditions were counterbalanced between subjects. A 2-way ANOVA, showed there was a significant interaction between music presence and music order on the flow state (EduFlow mean, $p < 0.05$) and especially on immersion (D2, $p < 0.01$). As in figure 3.9, it looks like the users felt more in flow (immersed) with the type of condition they were presented with first, i.e., if they started without music they felt more in flow without the music (in the no_music condition) than with music in the background. On the other hand those who started with music felt less in flow when the music was turned off in the second condition.

On the side note however, this phenomenon could be explained not only by the presence of music but simply that users felt more in flow during the first condition as it was a new experience, and lost interest during the second one as it was roughly the same setting.

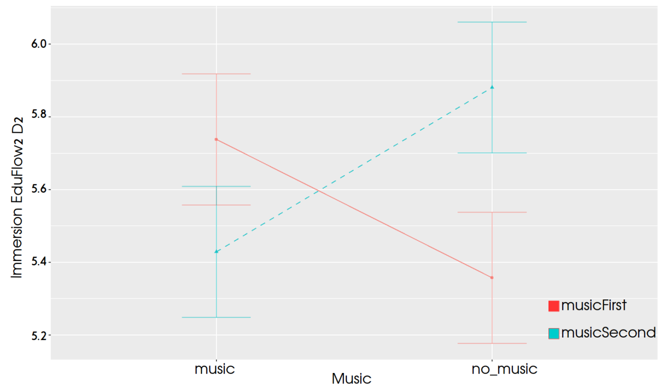


Figure 3.9: 2-way ANOVA between music order (musicFirst vs musicSecond) or simply between conditions, shows difference in immersion (2nd dimension of EduFlow score).

If we separate the adapt and no_adapt groups, we can see the same phenomena with both groups, see3.10.

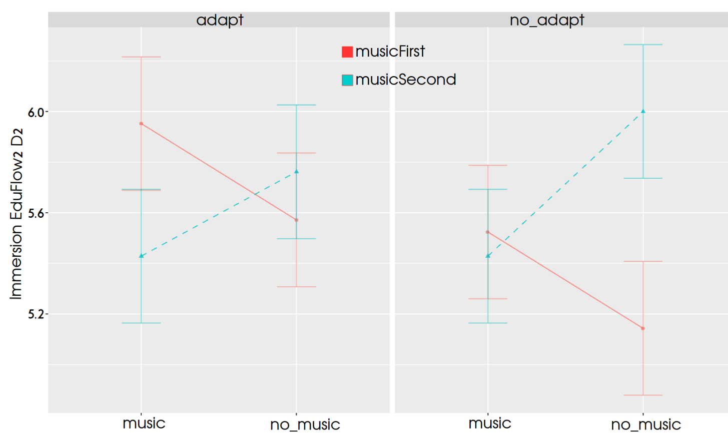


Figure 3.10: 3-way ANOVA showing immersion (D2 EduFlow) to be influenced by the music order (between subject factor) and on music presence (within subject factor).

3.2.2.2 Flow-factor's influence on Performance

Difference between groups adapt and no_adapt: The question whether our conditions could directly improve the online performances was tested with a 2-way ANOVA. There was a significant interaction between music and adaptation (with peak performance $p<0.05$, see Figure 3.11, as well as with average performance $p<0.01$).

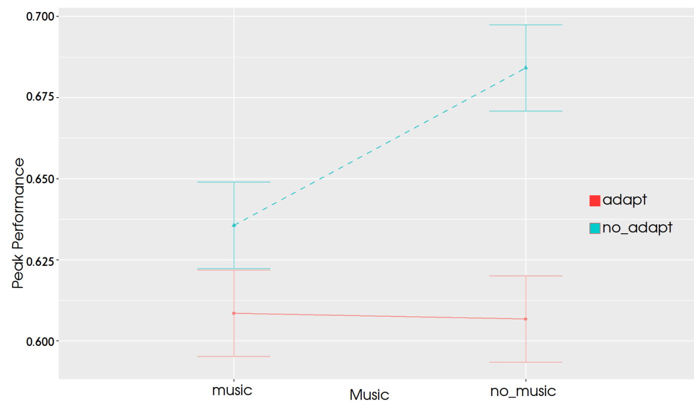


Figure 3.11: The peak performance during the video game depending on the between-subject factor *adapt* and on the within-subject factor *music*. In the no_adapt condition (right), users had higher online performances without music.

We have also found such significant interaction between music and adaptation when considering the distance between classifier output and the maximum values, -1 and 1, (*p<0.001*) see figure 3.12.

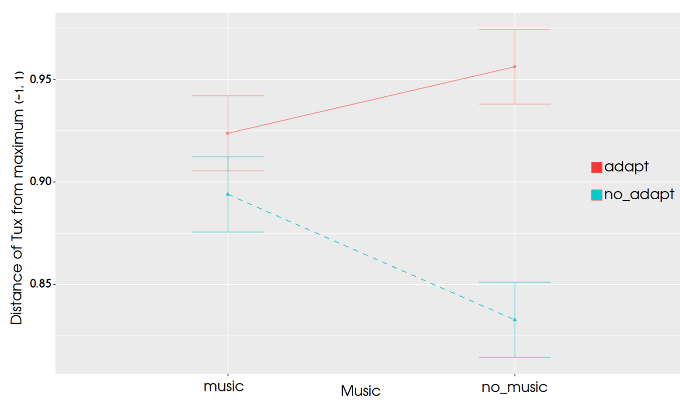


Figure 3.12: Significant interaction between adapt and music when considering the distance between classification output and maximum output values (-1, 1). Note that the smaller the distance, the better the performance.

Music had a significant effect on the mentioned online performances (e.g. peak performance mean with music: 0.62, SD: 0.09, and mean with no_music: 0.65, SD: 0.11, *p<0.05*) but adaptation had not (*p=0.08*) nor did the music order (p=0.24). A post-hoc Tukey analysis reveals that the one significant interaction occurs in the no_adapt condition, between music (mean: 0.64, SD: 0.11) and no_music (mean: 0.68, SD: 0.13) (*p<0.001*).

There was no significant difference between groups for other performance metrics (online – std_output and offline – cross-validation).

Performance (online and offline) & EduFlow score: In the following we present various correlations between flow score (accounting for its dimensions separately and in average) and performance (offline, and online peak and average performance). The correlations used is with repeated measures from [Bakdash and Marusich, 2017] as we had 2 different conditions (music and nomusic) per subject. In other words, our grouping factor are these 2 conditions. The repeated measures correlation is implemented using an rmcorr package in R which uses Bootstraping to asses the parameters' accuracies [Efron and Tibshirani, 1994].

- *Correlation Offline and EduFlow score*

There was a positive correlation between the mean of all 4 dimensions of EduFlow and offline performance (r = 0.36, *p<0.01*), see Figure 3.13. More precisely, offline performances are significantly correlated with two dimensions of flow: the 2nd – immersion ($p<0.01$, coefficient: 0.38) and the 4th – autotelism, ($p<0.05$, coefficient: 0.34). We corrected the p-values for multiple comparisons with false discovery rate (FDR) [Noble, 2009].

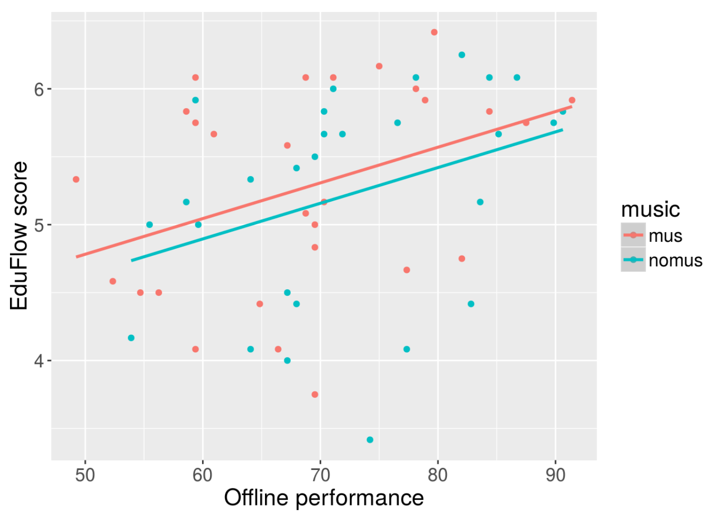


Figure 3.13: Positive correlation between EduFlow score (mean of all 4D) and offline performance.~

When separately analyzing the 2 groups adapt and no_adapt, we find that there is no signifiacnt correlation between any dimension of eduflow and offline performance in the adapt group, while the no_adapt group has significant correlations as follows. Eduflow D1 with *r= 0.57* and *p<0.01,* and eduflow D2 with *r= 0.72* and *p < 0.001.* P-values were corrected with FDR.

- *Correlation Online (peak and average performance) and EduFlow score*

There was no correlation between flow (mean of all the EduFlow dimensions) and online (peak and average) performance, even when separating into adapt and non-adapt groups and flow dimensions.

- *Correlation of Standard deviation of classification & EduFlow score:*

We were interested to see the relationship between flow and the standard deviation of the classifier output (std_output), i.e., the perceived frequency of movements of Tux that is a non-linear mapping of the stability of mental commands. We found a positive correlation between the mean of all dimensions of Eduflow, D1, D2, and std_out of both groups together (*eduflow: r=0.31, p<0.05*, D1: *r= 0.34, p<0.05*, D2: *r= 0.35, p<0.05*).

This makes sense because when the classifier is very erroneous it will be perceived as "pushing" Tux directly to the opposite direction and "blocking it" there. Same for the very high performances, it will directly "push" Tux towards the maximum value and "stay" there. As we know from flow literature that people are most in flow when there is small uncertainty to win, the "near-miss" effect [Ma et al., 2017]. Meaning, when the classifier does manage to classify data to some degree, the movement of Tux makes more micro variations, giving the feeling that Tux can still be pushed towards or away to/from the target, which could indeed increase immersion.

When separating groups and dimensions, we found a positive correlation only between std_output and immersion or D2 of EduFlow score in the non-adapt group only (*r= 0.62, p<0.01*), see figure 3.14. P-values are corrcted with FDR.

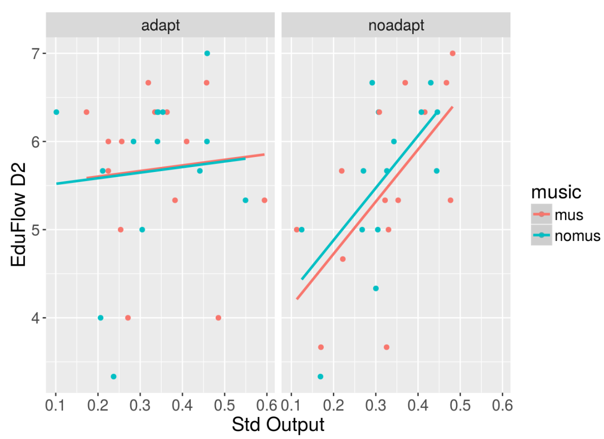


Figure 3.14: Positive correlation between standard deviation of classifier output or the frequency of perceived movement of Tux and immersion score of EduFlow (significant for non-adapt group).

This can be explained because the adapt group would perceive a generally lesser degree of movement of Tux, a biased std_output. It was biased in a way that Tux had no access to the wrong side of the course, that is opposite from the one in which the target was. We can see especially in figure 3.14 that there is a stronger correlation within the non-adapt group, probably because Tux had more degrees of freedom to move as compared to the adapt group.

This result is unexpected if we think of the std_output as a variability or stability of mental command, but as the Tux movement is a non-linear mapping of the mental commands, we cannot assume this result applies to mental stability. However, it could be explained if the person is being very much engaged, as opposed to when one abandons the task. As the classifier we use is discriminant, it can choose either left or right-hand class, than the resting state of the participant or the abandon of the task could be far from the hyperplane and closer to one of the classes, thus the classifier will simply choose that one class more often.

- *Correlation of Distance of classification and maximum values & EduFlow score:*

We also investigate the relationship between the perceived distance of Tux from the extreme points (-1, and 1), and the EduFlow score. There is a negative correlation between the perceived distance and D2 of EduFlow – immersion (Pearson coefficient: -0.33, $p<0.05$). This can be interpreted that the further Tux is from the fish (higher distance) the less participants were immersed in the game, or that the less they were immersed the further Tux was from the target. Both are possible as we cannot conclude the causality with a correlation. Again, when we separate the groups, we find no correlation for the adapt group. However, after applying the FDR (as we are separating into 4 flow dimensions), the p-value ceases to be significant, and becomes a tendency ($p=0.07$).

- *Combining Distance and Standard Deviation of classification:*

As immersion increases with std_output, while it decreases with distance, we can assume that the immersion is highest when Tux is not far from the target and when it is not "blocked" on one side but it makes frequent micro movements. This concords with the literature about flow and the near-target, near-miss effect [Ma et al., 2017]. It seems that due to the non-statoinarities in the signal, the online performance (peak and average) might not be the best metric to measure user mental effort, but the std_out and distance might be a better measure.

Performance (online and offline) & Music score: As tihs correlation includes only one condition (in which the music was played), we use regular Pearsons correlation. There was no correlation between BMRI scores and user performance, online ($p = 0.78$) or offline ($p = 0.20$). However, when we separate the groups, we find that BMRI correlates negatively with performances online (average performance with Pearson coefficient: -0.45, $p<0.05$; and peak performance with Pearson coefficient: -0.41, $p<0.05$) in the adapt group, while there is no correlation with the no_adapt group, see figure 3.15.

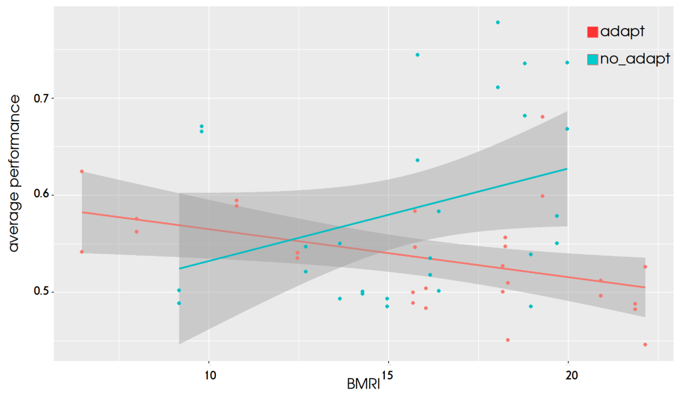


Figure 3.15: Significant negative correlation in the adapt group between BMRI scores (level of motivating music) and average performance, in red (Pearson coefficient: -0.45, *p<0.05*). The blue is the the non_adapt group and BMRI has no significant correlation with performance. Although non-significant, performance has a positive relation with motivating music in the non-adapt group.

From such result, we can assume that high performance subjects are not as perturbed by motivating music as compared to the poor performance subjects (although we cannot assume causation from a correlation). Note that there is no interaction between adap and non-adapt groups, as one does not contain a significant correlation.

- *Not balanced groups?*

The Graz protocol (around 7mins) was conducted before and after the Tux Racer gamer, as reminder see 3.4. Graz protocol performance was calculated using 4-fold cross-validation. ANOVA shows no significant difference in pre-Graz performance (p=0.16) between groups, however there was a significant difference between the post-Graz performance between groups (p=0.02). Although the groups were balanced statistically, the no_adapt group achieved a higher mean in Graz protocol score than the adapt group (no_adapt group with a pre-score mean: 61.3, post-score mean: 72.9, and adapt group with pre-score mean: 56.1, post score mean: 61.1), see 3.16. Hence, overall results of flow and performance could have been slightly biased as the no_adapt group achieved higher performances from start.

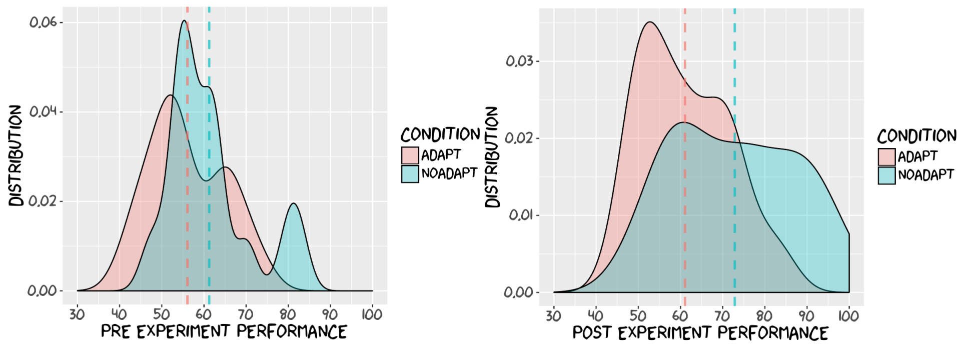


Figure 3.16: Density plot of participants' performance between adapt and non-adapt groups during Graz (pre and post)

Furthermore, the groups could have been not balanced considering music education or the user relation with music in everyday life, but unfortunately we have not acquired such information. However, we have noted that some subjects imagined playing their instrument for the Motor Imagery of hands in which case music perturbed their concentration. This shows how music can give controversial effects on performance, depending on the personal preferences. Note that we have only verified whether there is difference in flow proneness between groups.

- *High non-stationarity due to different training/testing environments?*

We noticed that there was a negative correlation (Pearson's coefficient: -0.88, $p<0.001$) between the distinctivenesses (Riemannian distance between the covariance matrix of each class) of the left and right classes of the classification accuracy (CA), see figure 3.17. This can be related to the work from [Vidaurre et al., 2010] who showed that to account for such data-shifts (due to non-stationarities), the hyperplane of the classifier should be re-centered over time. Hence, here we can see that the differences in training and testing environments (Graz training versus Tux game) could have an impact on performance.

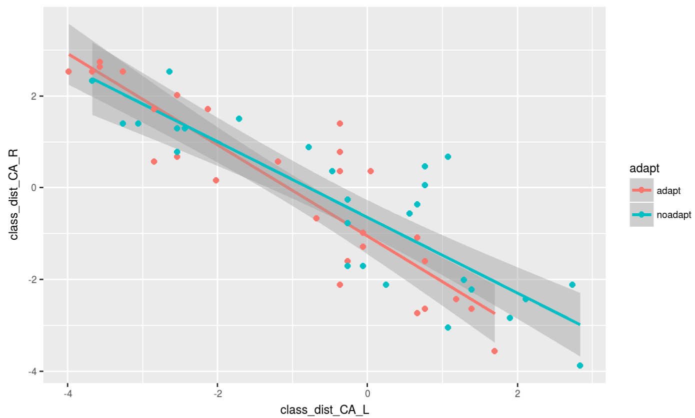


Figure 3.17: Negative correlation between the distinctiveness of left and right classes in Classification Accuracy (CA_L for left and CA_R for right-hand class).

3.2.3 Discussion

We suppose that flow would increase performance, and we posed 2 major hypothesis:

H1. (a) Adapting feedback improves flow, (b) thus improves performance.

H2. (a) Asynchronous music improves flow, (b) thus improves performance.

H1. partially validated: (a) Adapting the task difficulty to users skill improved one dimension of flow state, cognitive control. People who faced a challenge better suited to their skill felt more in control. Thus, taking into account user's states and skills when designing a BCI task could lead to a greater user experience.

(b) Also, we showed that offline performances increase along with the flow score. Notably, performances (offline) correlate mostly to the degree of user's immersion and control (when we analyze EduFlow score dimensions separately).

H2. in contradiction: (a) The presence of a background music had no effect on flow. However the music order showed to have a significant effect on flow. If users started with music they felt more in flow during music, and less in flow when the music turned off, and vice versa. However, this could also be simply due to the loss of interest during the second condition, unrelated to music order, i.e. level of flow decreased in the second condition no matter the music.

(b) Music deteriorated the online performance (we could see that especially in no_adapt group, see figure 3.11). Also, possibly, users who had poor performance could have either been more easily distracted by motivating music or the music seemed more motivating as their performances got lower, see figure 3.15. Therefore, this result contradicts our second hypothesis.

As opposed to what we expected, we could not directly improve performance by manipulating the flow factors we chose (adaptation and music). This could be because the adapt group had lower performance on average than no_adapt group during Graz protocol (although not significant), see figure 3.16. Furthermore, they could also have been non-balanced on account on music education.

Song Choice. The negative music influence could be also explained by the songs we chose, since the motivational qualities of the music (measured with the BMRI questionnaire) were not very high and were not correlated to any dimension of flow. Instead of picking those songs from the public domain, users may have been more motivated should they have chosen their own music.

Pace mismatch. The decrease of performance in the music condition might come from the mismatch between the rhythm of the music and the pace of the game, i.e. with the pace of the imagined hands movements. Indeed, some users shared informally that they were imagining playing their musical instrument as MI commands and that the songs further disturbed their own imagined song and MI pace.

Different training environment. There was no correlation between flow state and online performances. That could be due to the differences between the calibration environment (Graz protocol) and the game, e.g. the first being minimalistic (without sound) and the latter a 3D video-game. Moreover, as the calibration was done without music, maybe the performances online were better without it because the EEG signals might have changed, therefore the classifier could not recognize them anymore. When analyzing the overall classifier output (the average output per run and per class), we noticed that around 78% of the time the classifier chooses the same class. This could be related to the work from [Vidaurre et al., 2010] who showed that the data move in time due to non-stationarities, and to achieve better performance is to move the hyperplane of the classifier across time.

Online performance is not the best metric. Due to the difference in training versus testing environments, the data shifted away from the hyperplane and caused the online performance (peak and average) to shift as well. In that case, it might be better to use the standard deviation of the classifier output (std_out) and the distance of the penguin from the extreme classifier output points (-1, 1). To support this claim, we found that the flow score, esspecially immersion and control correlate positively with std_out, and negatively with distance, as opposed to average and peak perf which showed non significant correlations.

Different experiment settings between 2 groups. Unfortunately during the first half of the experiment (the non-adapt group) there were three experimenters present, however due to medical issues, there was only one or two experimenters during the second half (accompanying the adapt group). This is certainly one major drawback of our experiment and possibly ther reason why the non-adapt group performed better, as they had more encouragement and explanations provided by the experimenters .

Flow increases with performances. There was a positive correlation between flow scores and offline performances (cross-vaidation of only the game data, without Graz protocol). The state of flow was then positively correlated with users' performance: the feeling of immersion and the autotelic experience (i.e. the completion of the task was self-rewarding) increased with the offline performance. Hence, not only encouraging a state of flow would produce BCIs more pleasing to the users, but it might also benefit the accuracy of the system. We still have to identify the direction of the correlation though: does flow state increases performances or do good performances increase flow state?

3.2.4 Conclusion

By investigating means to improve BCI user performance and usability through instructional design theories, we came across the Flow Theory. This theory, which describes an optimal user state, showed to improve performances in many fields. We hypothesized that the state of flow could benefit BCIs. In a MI BCI task, we manipulated flow by adapting the perceived difficulty and by adding a background music. We used an immersive environment, a 3D video game, TuxRacer (the modification can be found online [4]).

Our main findings show that the adaptation increases one of the dimensions of flow – cognitive control, and that user's performances are positively correlated with flow. In the future we could attempt to better suit the adaptation of the task to the users: it could be biased adaptively over time, across several sessions, following the progress of the user. We could re-calculate the attractor value over time as well (for reminder on the attractor, see paragraph 3.2.1). We could also try to account for the amount of effort that the user puts into the completion of the task in order to better comprehend such complex phenomena. For example, measuring workload [Frey et al., 2016] could facilitate the assessment of the challenge that users are facing and computationally predict the state of flow [Bulitko and Brown, 2012].

According to the literature, asynchronous music with medium tempo would be the best choice to follow the BCI task. Unexpectedly, the background music impeded the performances of the user. This result stresses the importance of the choice of music to accompany a task, and music education. One explanation could lie in the very BCI paradigm we chose. Indeed, a motor imagery task might share similarities with actual physical activity, where it had been shown that *synchronous* music could effectively stimulate the sensory-motor cortex[Hardy and Lagasse, 2013]. Hence, a future work would consist in synchronizing music to game's cues (e.g. trials sequences) or to user's motor imagery pace. Such music, generated in real time, might enhance the flow state and intrinsic motivation. Concurrently, we should verify if the user is musically educated, as in some cases users imagined playing instruments as MI commands, and because musicians elicit different brain activity in motor areas [Luo et al., 2012].

As a more technical improvement, in the future we should not change the environments between training and testing, especially not when involving sound. To reduce the effect of the classification of one class more often, we can recenter the hyperplane over time, as suggested in [Vidaurre et al., 2010].

Overall, the discrepancy in our results could stress that flow is a complex phenomenon, and however beneficial to obtaining better BCI, the emerging interaction between its components should be more thoroughly investigated. In addition, the influence of sound should be more investigated as well, as detailed in the following section.

[4] https://github.com/jelenaLis/tux-modifs)

3.3 Influence of Sound on MI performance

3.3.1 Introduction

Rhythmicity During the above-mentioned experiment, we found it interesting that subjects reported to have been perturbed by the rhythm of the music which did not follow their imagined motor movement. Indeed, rhythm not only activates motor areas of the brain, there is evidence of rapid motor synchronization to an external rhythmic cue in persons with and without neurological disability [LaGasse and Hardy, 2013]. Rhythmicity plays a critical part in learning, development, and performance, as timing of movement is essential in many motor control and cognitive functions [Thaut et al., 2009]. Specific findings indicate that auditory rhythmic cues add stability in motor control immediately (within two or three stimuli) rather than through a gradual learning process [Kenyon and Thaut, 2000]. The auditory external cue acts as a "forcing function" that optimizes the efficiency of kinematic movement parameters [Thaut et al., 1999]. As we can see, rhythmicity is closely related to motor control, thus having a mismatch between motor imagery and music pace could greatly deteriorate performance in our experiment, mentioned above.

Task-Related feedback Various congruent (task-related) visual feedback have been examined and showed promising results, e.g. using body ownership illusions in VR [Alimardani et al., 2014]. Even though in [Neuper et al., 2009] when closely examining performance between congruent and abstract visual feedback of a hand grasp, it showed no differences in performance. However, we believe that the reason might be because the calibration was done in an abstract (Graz protocol) environment for both congruent and abstract conditions. Meaning that the fact that the environment stayed the same for the abstract condition while it changed for the congruent one could have biased their results. Furthermore, the use of congruent sound versus non-congruent and out-of-pace one, in combination with the visual modality demonstrated to increase performances in MI of feet [Tidoni et al., 2014].

Auditory feedback We can see in several studies that performance in auditory feedback tends to take more time to increase than in visual feedback [Nijboer et al., 2008, McCreadie et al., 2013]. Thus, in short term the visual feedback tends to give higher performance but the auditory feedback has shown potential and should be more investigated. Moreover, it seems that the conditions (visual vs audio) were not comparable as the short prerecorded sound samples of harp and bongo used in [Nijboer et al., 2008] could have led to over-familiarization [Daly et al., 2014], while the visual feedback does not have such negative effect. Also, the ERD/S were mapped on the sound volume, which depending on age, can give impression of different note duration, time and arousal [Kellaris et al., 1996]. For this reason, in [Daly et al., 2014] they have explored variations of music tempo of a piano sound generated in real-time. They showed a strong correlation between music tempo variations and ERD/ERS power. They explain it might be due to the surprise effect, "the greater the variation of the tempo, the greater the level of surprise that may be induced". When comparing such auditory feedback with visual one (manipulating a ball on the screen), they have realized their mistake in the design, as follows. With the visual feedback, users had a reference point, a central line that indicated how far they have gone with the ball, comparing to the audio feedback in which they did not have any baseline to compare their newly created tempo with. Therefore, the user had to rely on their memory of the baseline tempo to judge whether the current tempo of the music was greater or less than this. Thus, the additional short-term memory requirements of this feedback modality may place additional restrictions on the users' ability to control it effectively. It seems that creating fairly comparable conditions between visual and audio is a difficult task, so we will first explore the benefits of congruent versus non-congruent sound in one modality before comparing it to the visual one.

Sense of Presence There are many works that try to increase the sense of presence using realistic, spatial sound in VR [Nichols et al., 2000, Västfjäll, 2003, Larsson et al., 2004] or games [de Gortari and Griffiths, 2014] or audio dramas, dialogues [Fryer et al., 2013]. It is shown that realistic sound effects may contribute to the sense of presence by triggering vivid mental images [Fryer et al., 2013], or the auditory illusion of the sense of presence (similar to the VR effect). Some also report that there is involuntary movement during immersive sound cues [de Gortari and Griffiths, 2014]. This means, if we use only realistic sound effects to describe an action or movement, we could create rich visual, mental interpretations of such event and enhance motor functions.

All this research inspired us to explore the benefits of a realistic, task-related (congruent) and "synchronised" audio feedback which would comply with the user's imagined movements. We investigate the potential of realistic and natural sounds as audio feedback using a synthesizer from [Verron et al., 2009]. We made sure the sound is **not** comprised of pre-recorded sound samples which repetition can become annoying [Nijboer et al., 2008], and that the classification output is **not** mapped on volume [Nijboer et al., 2008] to avoid different impressions of note duration and time, or tempo [Daly et al., 2014] to avoid different levels of engagement of working memory.

Differently from previous works, we map the classification output on the synthetic sound transformation between two realistic environmental sounds (the sound of footsteps on gravel and the sound of water) within the congruent condition; and a transformation from one abstract sound to another in the non-congruent condition. The effect of such transformation is a sharper sound, or less noisy when classification output is closer to its maximum values. The novelty of our work is that we use realistic sound effects of the movement imagined, that we hope would provoke a high sense of presence, or a sensory illusion (as the body-ownership illusion in congruent VR, but an audio one) and increase performance in Motor Imagery BCI.

3.3.2 Experimental Design

Users task was either to imagine moving their feet or to rest during a 45min session. The instructions consisted of 4-taps of sticks for MI of feet, and a relaxing sound of glass harp for the resting state (figure 3.18).

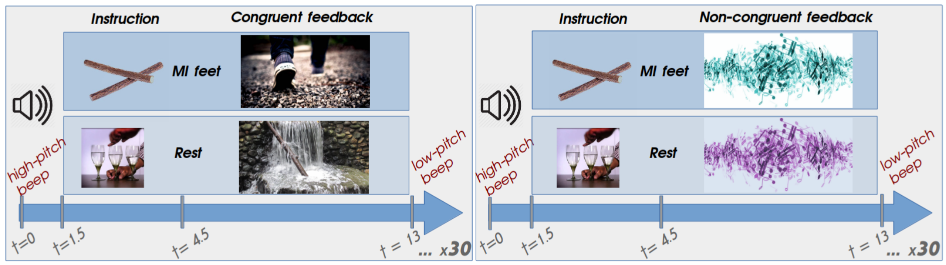


Figure 3.18: 2 conditions per session, congruent and non-congruent. A condition contained 2 runs of 30 trials each. A trial lasted 13s and started with a high-pitch beep that announced the beginning of the condition at t=0s, the instruction followed at t=1.5s for 3seconds and it was the same for both congruent and non-congruent conditions. The feedback that followed at t=4.5 was either: (1.) congruent feedback which, depending on the classifier output, could be a transformation a from sound of footsteps on gravel (for MI) to sound of water (for rest); or (2.) non-congruent feedback transformed from one (MI) to another abstract sound (rest).

There were two conditions: (1.) "non-congruent", during which the feedback provided was abstract (harmonic sounds with a different pitch, similar to glass harp) and not related to any task (abstract sound for MI, and another abstract sound for rest) and (2.) "congruent", during which the MI feedback reflected the sound of one's footsteps on gravel while the *rest* feedback was a relaxing sound of water. The choice of such sound for the congruent MI task was motivated by the fact that rhythmical sounds relate to motor cortex [Bengtsson et al., 2009]. We also wanted to provide an illusion of presence for the congruent condition, provoking a kind of somatosensory effect through realistic sound (gravel for MI and water for rest). For the same reason, both tasks in the non-congruent condition were as non-rhythmic and as abstract as possible. The influence of feedback was evaluated within-subjects, i.e., each subject had both congruent and non-congruent feedback. The conditions were counterbalanced between subjects. Non-congruent and congruent feedback were generated in real-time, the former with Max-MSP and the latter with a dedicated synthesizer of environmental sounds [Verron et al., 2009].

Ten participants were recruited (2 women, mean age: 24.8, SD: 4.98, all BCI naives). They were seated in front of a single speaker. 7 passive gold cup electrodes were placed over Cz, C1, C2, FCz, CPz, CP1 and CP2 in the 10-20 system and connected to an OpenBCI Cyton amplifier. Before the experiment, participants heard an example of each sound to get accustomed to the task. This was chosen after a few pilot tests who imagined walking on grass or other surfaces during the calibration phase which impaired their MI during testing. Meaning, during the testing they were surprised when they heard gravel (something else then what they expected and imagined beforehand, during calibration). In order to keep the purpose of the experiment uncompromised and subjects unbiased, the word congruent was not mentioned, but the feedback was simply described as "environmental sounds" or "musical sounds". Calibration was purely audio, it consisted of the same instruction as during testing, but without any feedback. A run of calibration (30 trials of 13 seconds) was followed by two runs of congruent or two runs of non-congruent feedback. Meaning that there were 4 runs in total during the testing phase. A run contained 30 trials of 13 seconds, 15 for each class (rest or MI) in random order.

Signal Processing Data was calibrated on the training data during the calibration phase (around 7mins). Using OpenViBE, the signal was band-bass filtered with a Butterworth temporal filter in the mu (8-13 Hz) and beta (13-30 Hz) bands, passed to a Filter Bank Common Spatial Pattern filter (FB-CSP), reducing 7 channels into 4 virtual ones that maximize the differences between the two classes rest vs MI of feet [Ramoser et al., 2000]. We computed the band power using a *1s* time window sliding every $1/16^{th}$ second. Each feature was classified real-time using linear discriminant analysis (LDA). Typically, the LDA classifier returns distances from a hyperplane that are "not bounded" or can be between $\pm\infty$. However, in OpenVibe the LDA is bounded between 0 and 1, returning a "fake" probability value. The classifier output was recorded in order to be analyzed later on and to compute the "online" performance.

In offline analysis, we used the same band-pass filter and FB-CSP. There was no use of a sliding window, in order to ease the computation and avoid overlapping samples between training and testing datasets. For offline processing we used a regularized LDA [Ledoit and Wolf, 2004] and 10-fold cross-validation (not including calibration data),

In EEG-Lab, we filter raw EEG between *1Hz* and *40Hz* and analyze the differences in power spectral density.

Statistical analysis For the statistical analyses of performance (online and offline), we tested for significance using Wilcoxon signed-rank tests, considering the population was small, and it did not follow a normal distribution.

When considering the power density analysis between (*1Hz* and *40Hz*), EEG-Lab function integrates an ANOVA, in which we selected $p<0.05$, for observing any significant differences.

3.3.3 Preliminary Results

There was no significant difference in online (peak) performance between the two feedback (Figure 3.19). An offline analysis revealed a significant difference ($p < 0.05$) in classification accuracy when a classifier was trained separately on the "congruent" and "non-congruent" runs (respectively 66.1%, SD: 7.45 and 63.9% SD: 7.8, 10-fold cross-validation, Figure 3.19).

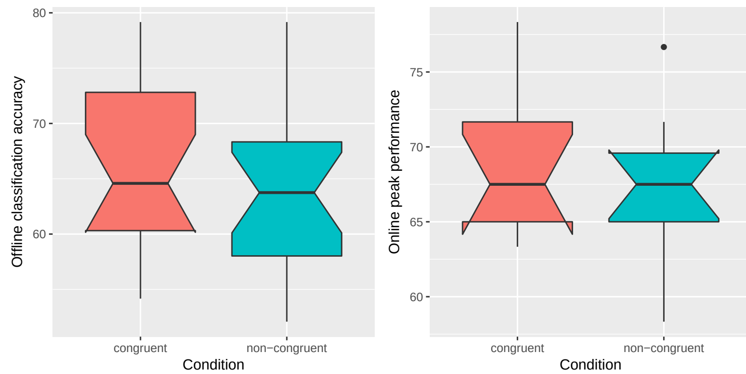


Figure 3.19: Differences between the congruent and non-congruent conditions, in offline (left) and online (right) performances,

As online performance, we also investigated the absolute distance of the (LDA of OpenVibe) classifier output from the maximal values (scaled from 0 and 1 to -1 for rest class, and 1 for feet class). The distance in congruent condition (mean; 0.96, SD: 0.03) is significantly smaller than in non-congruent condition (mean: 0.98, SD: 0.03), see figure 3.20.

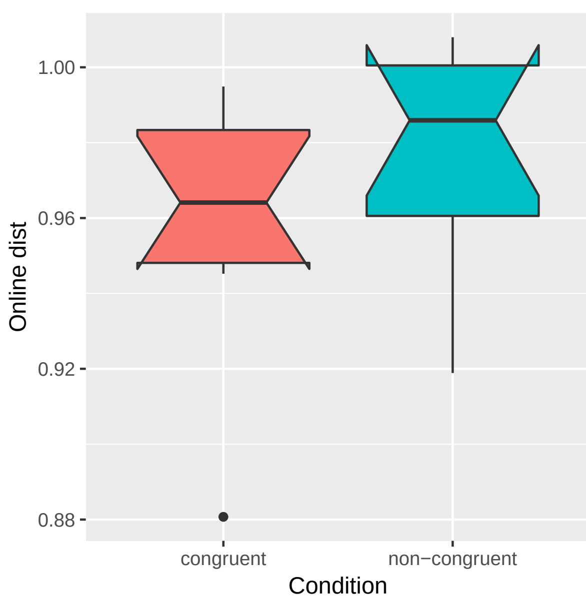


Figure 3.20: Difference in distance between congruent and non-congruent conditions.

In EEG-Lab, we can observed changes in EEG spectral power, with more activation in the "congruent" condition than in non-congruent one, within the beta band during rest (Figure 3.21) and within both mu and beta bands during MI (Figure 3.22).

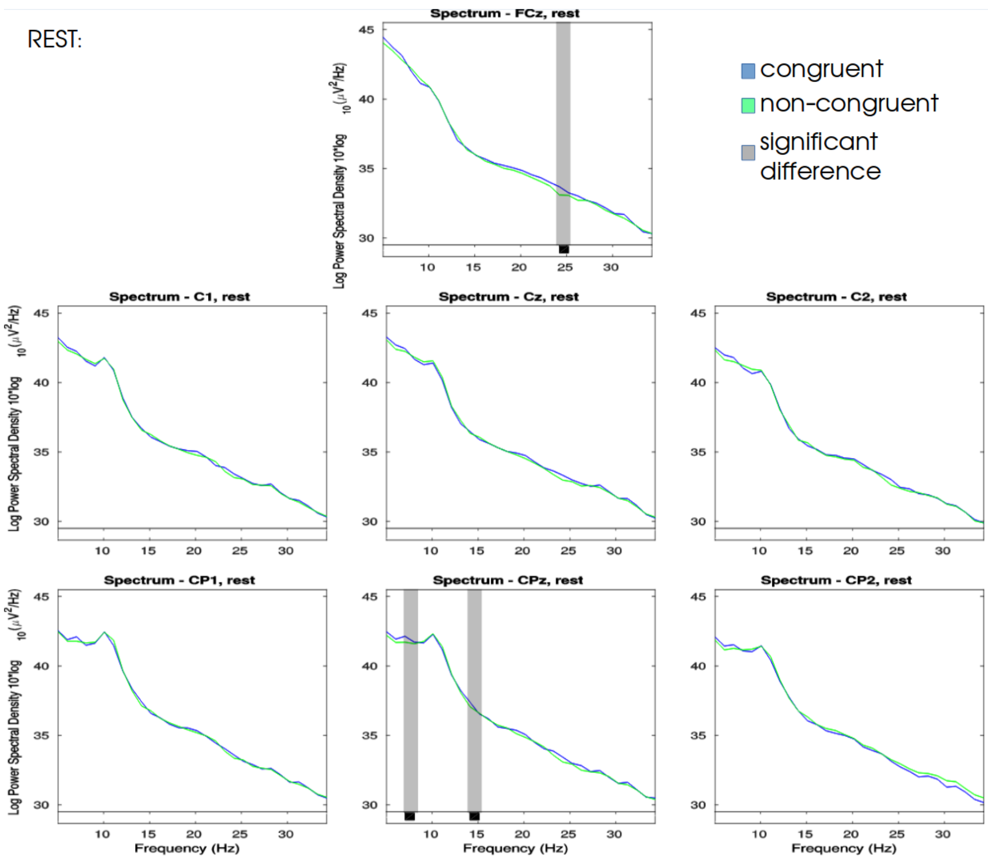


Figure 3.21: EEG spectral power during **rest** for each electrode (7 in total). The gray area indicates a significantly higher power (log-power spectral density) around beta (25Hz) in FCz, and around mu (8Hz and 15Hz) in CPz, for congruent (blue) than for non-congruent (green).

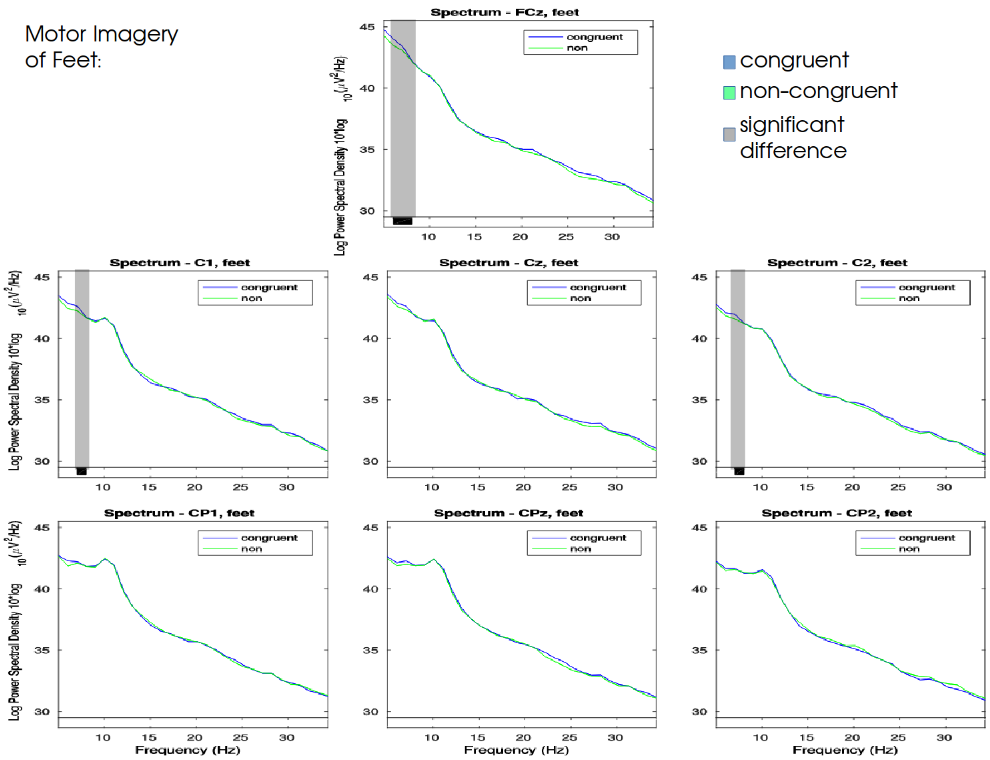


Figure 3.22: EEG spectral power during **MI of feet** for each electrode (7 in total). The gray area indicates a significantly higher power (log-power spectral density) around 8Hz in FCz, in C1, and in C2, for congruent (blue) than for non-congruent (green).

When comparing the spectral analysis between congruent and non-congruent, we observe significant differences as follows.

1. During rest:

- Stronger power around 25Hz could be an indication of a stronger beta rebound, providing a stronger ERS.
- Stronger power around 8Hz and 15Hz indicating a stronger mu, could indicate a stronger relaxing effect, producing stronger alpha waves (CPz could capture signals from occipito-parietal lobe).

2. During motor imagery of feet:

- Stronger power between 1-8Hz could be an indication of a stronger mu, providing a stronger ERS which is unusual as during the motor imagination we observe rather a stronger ERD. Hence, here we actually observe a weaker ERD.

3.3.3.1 Brief Discussion:

While peak performance remained unchanged with a congruent feedback, we could observe an increase in offline performance (and decrease in distance) in the congruent feedback between rest and MI signals. As for the spectral analysis, we observe that there is stronger power in both beta and mu bands during both rest and MI of feet of the congruent as compared to non-congruent feedback. It could be that the rhythmicity and realistic sound influenced a more vivid imagination, thus stronger power. These analyses should be more thoroughly investigated before reaching any conclusion.

Informal post-hoc interviews revealed that participants felt assisted by the congruent feedback. However, when their intentions were wrongly classified in congruent feedback, e.g. the classifier would produce the sound of footsteps instead of relaxing water, this perturbed the participants more than in non-congruent case, in which the wrong feedback would just be another abstract sound.

In a pilot study, we demonstrate how a congruent auditory feedback could improve classification in a MI BCI, a promising result (considering the equipment and number of data) for creating alternate feedback modality. This prompts for further investigations on a larger sample and with more channels to better assess the underlying change in brain activity. In the future, the experiment could benefit from a surround sound system (multiple speakers) that could enable full immersion in such realistic environmental sound [Hendrix and Barfield, 1996]. This study encourages further research on congruent BCI tasks, which can assist users to achieve better performances.

3.3.4 Conclusion

The environment, the content, and task difficulty have great impact on the user performance in general. Indeed, what seems to be additional "side" sensory information such as sound effects or background music, it has showed to be of significant importance for BCI performance as well (see experiment on flow 3). Therefore, it is to be used with caution. Considering that a BCI user is not only a standard *user* of a computer device, but is a part of the system (one's brain activity is an essential part of BCI), such sensory information can greatly influence the machine performance. Thus we should acknowledge their potential impact and explore more thoroughly the influences on neurophysiological processes as well as on the system performance.

Moreover, we should investigate more thoroughly the user factors such as traits, to understand better the effects of the BCI task representation on performance. In the next chapter, we perform such investigation using prediction models.

Chapter 4

Predicting Optimal Feedback Bias for Performance and Learning

"*All models are wrong, but some are useful*," George Box.

4.1 Introduction

As detailed in chapter 2, user traits such as independence, self-reliance and abstractedness positively relate to performance, while tension negatively relates to performance [Jeunet et al., 2015a]. Hence, among other traits, we focus mostly on user personalities such as **independence**, i.e., a composite personality trait containing dominance, social boldness and so on; **anxiety**, i.e., a composite trait containing tension, worry and so on. We believe that competitiveness should be investigated as well. Notably, in sports there is evidence of a strong relationship between competitiveness, anxiety, self confidence and performance [Martin and Gill, 1991]. When exercising on a stationary bicycle in a VR game environment, those who were competitive showed to give more effort when compared to non-competitive players [Snyder et al., 2012]. Furthermore, the use of games and competitions to promote intrinsic motivation and performance has shown useful for learning various programming skills [Burguillo, 2010]. Following such rationale, it was shown that influencing human factors with positively biased, congruent, game-like and proprioceptive feedback, from VR to robotic hands, can increase performance [Barbero and Grosse-Wentrup, 2010, Ramos-Murguialday et al., 2012][Alimardani et al., 2014, Braun et al., 2016].

In our first MI BCI experiment, detailed in Chapter 3, we wished to explore the influence of an adaptive biased feedback on one's performance and psychological state of flow, a state of immersion, control and pleasure. Thanks to this experiment, we have confirmed that by adaptively biasing the feedback we can increase the state of flow (especially the sense of control). However, we have not explored exactly what kind of bias would be useful for what type of user personality. Moreover, we performed only one session experiment, hence we could not investigate the effects on learning rate, i.e., the evolution of performance over time. Note that, to our knowledge, none have included the user traits when investigating the effect of a bias on learning but have indeed mentioned it to be a usefull information[Alimardani et al., 2014, Barbero and Grosse-Wentrup, 2010].

That is why in this experiment, we perform two sessions and investigate the relationships between personality traits, performance and learning the motor imagery skill, that is, to achieve a fluent control of the BCI machine. For our new MI experiment, we use the same game-like environment (Tux Racer) and task settings (motor imagery of hands) as in our previous experiment, in order to favor a robust experiment design. As the MI BCI task is in a game-like setting (accumulating points with every fish caught), we consider the competitiveness trait as a new potential predictor for BCI performance and learning.

We believe that adaptation should dynamically vary for each user in order to increase both performance and learning. In other words, we want to acquire enough data to be able to predict what bias would assist what type of personality in order to increase performance and learning. To acquire enough data, we limit ourselves into using 3 different biases: positive, negative or none throughout both sessions; differently from our previous experiment where each person could receive a positive and negative feedback within one run.

In this chapter, we wish to answer the question "What is the best feedback bias (positively biased, negatively biased, zero bias) for what personality type, initial user state (cognitive load and flow) and performance during calibration, in order to increase learning and performance?"

Considering the results and suggestions from [Barbero and Grosse-Wentrup, 2010] and [Jeunet et al., 2015a]. We thus make the following hypotheses:

H1. We expect that positive bias will motivate those achieving low performance (as hypothesized in [Barbero and Grosse-Wentrup, 2010]), who are at the same time typically anxious, non-independent and non-competitive. We believe that such motivation will increase performance and learning.

H2. We expect that negative bias will demotivate users achieving low performance [Barbero and Grosse-Wentrup, 2010], who are at the same time typically anxious, non-competitive, and non-independent. We believe that such demotivation will deteriorate performance and learning.

H3. We expect that positive bias will demotivate those achieving high performance [Barbero and Grosse-Wentrup, 2010], who are at the same time non-anxious (in flow), competitive, and independent. We believe that such demotivation will deteriorate performance and learning.

H4. We expect that negative bias will motivate those achieving high performance [Barbero and Grosse-Wentrup, 2010], who are at the same time non-anxious (in flow), competitive, and independent. We believe that such motivation will increase performance and learning.

From these collected data and results, we wish to find a general model that could predict the optimal feedback bias for each user, depending on one's *profile* (user traits) and *context dependent components*, that are, states (cognitive load and flow) and calibration performances. We assume that the best choice of feedback bias would change whether it is learning, performance or the state of flow we wish to increase/predict. In other words, we can propose different models depending on the *criteria* we choose.

In this chapter, in section 4.2 we describe what we have learned from our previous MI experiment which enabled us to improve many design parameters in our new MI experiment. In section 4.3, we describe the experimental design, our bias function, signal processing and performance metrics used, as well as our prediction models. In section 4.4 we present our preliminary results including short comments; in 4.5 we interpret more thoroughly our results, and finally in section 4.6 we provide our concluding words, and describe future works and challenges for creating an adaptive model for MI-BCI based on this research.

4.2 Lessons learned from our first MI experiment:

We have performed a MI experiment in which we investigated the influence of an adaptively biased feedback on performance and flow state. In that experiment, we tried-out many novel methods which permitted us to learn many lessons, as follows.

The unmatching rhythmicity. We learned the importance of rhythmicity between background music and imagination of one's motor movements. Also, it is possible that the more such "asynchronous" music is motivating, the more distracting it can be for performing motor imagery for users having poor performance (see reminder of negative correlation between motivating effect of music and performance 3.2.4).

Current Improvement. This gave us the insight of the strong and controversial impact music can have on MI performance, so we removed background music during both calibration and testing. We kept only the sound of special effects, such as the sliding sound of Tux through snow, and a "bloop" sound when the fish is caught.

Changing environments. We learned the impeding effect a changing environment (in visual and auditory modalities) between calibration and testing can have on performances (see 3.2.3).

Current Improvement. Thanks to this discovery, we kept the same environment between calibration and testing phases, that is, the Tux Racer game with special sound effects in both phases.

Data non-stationarity. We learned that due to non-stationarities in EEG especially due to different environments between calibration and testing, the discriminative classifier output is often inclined towards one class, i.e., it chooses one class more often, even if the classes are balanced in number of trials, as reminder see 3.2.3.

Current Improvement. To account for the data non-stationarity, (i.e., data moves in time, which puts the classifier out of center), we implement the method from [Vidaurre et al., 2010]. They recenter the hyperplane over time to avoid any inclination towards one class, and assure the validity of our positive/negative bias strategies. We provide more details in 4.3 later on.

Linear bias function. As mentioned, due to signal non-stationarity, Tux would often result in going towards one side, which brings frustration, and lack of feeling in control which relates to performances. To increase sense of control and flow, in our previous experiment, we reduced the possibility of Tux going to the opposite (wrong) direction from the target. Even though we succeeded by using a simple linear function for the adaptive bias, it might not be optimal for increasing learning as it reduces the space of Tux movement into almost half, see figure 4.1.

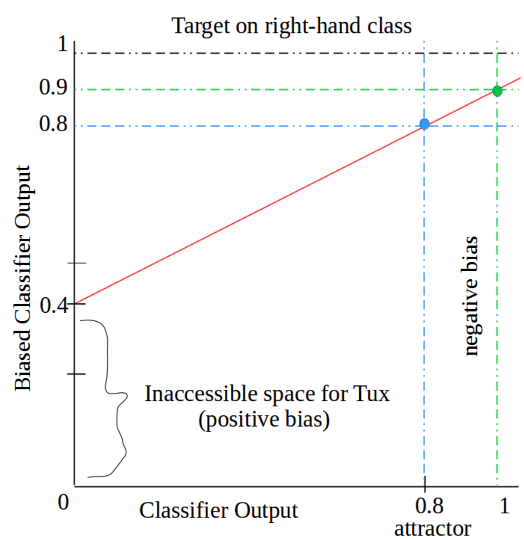


Figure 4.1: Representation of classifier output (*x-axis*) with biased output (*y-axis*) for the right-hand class, using the linear function from previous experiment. At classification output of 0 (complete left, opposite from target) the penguin is pushed for a half distance to the attractor (*0.8*), i.e., the biased output has a value around *0.4*. This means that Tux will never get to the complete opposite of the target. If the values from classification output are above the attractor, the user receives a minor negative feedback, again half distance to the attractor. As you see in the figure, when the classification output is *1*, it is reduced to around *0.9* in the biased output. Being that the bias is smoothed, it induces Tux to make micro movements between these biased values, e.g. it can shortly reach the maximum value *1* when classification output is above the attractor, or around *0.3* when it is below.

Current Improvement. To enable users a full progress in learning by allowing Tux to access all the spaces of the ski-course, we use a non-linear function for our bias. As the classifier (SVM) output are probabilities [0 ,1], we used a beta cumulative distribution function (beta CDF) to bias the feedback. This enabled Tux to access every point of the course while being biased. We provide more details in 4.3 later on.

Motor Imagery task. The imagined movements of motor imagery can be very different between participants. Novices often do not understand what a MI task implies as its sensation is difficult to explain, i.e., the community still lacks dedicated terms for such phenomena. Typically in standard motor imagery experiments, we do not control for such variabilities unless it is the subject of research as in [Neuper et al., 2005].

Current Improvement. To assure less variability between the movements imagined by the participants and reduce ambiguity in motor imagery task, we offered a set of objects suggesting movements to train on before the BCI task. The possible movements included: 1. moving and clicking on the mouse, 2. tapping on the computer keyboard, 3. tapping on the drums of the piano keyboard (without sound), 4. playing the piano keyboard (without sound), 5. turning the switches for volume on the piano keyboard (without sound), 6. pinching with a pinch or a nail-cutter, 7. writing with a pen on the paper, 8. cutting with scissors, 9. squeezing a shower gel bottle or a heating pad (without heat), see figure 4.2. The participants were suggested these objects if they needed a somatosensory reminder of a movement. Otherwise, they could choose whatever movement they wanted, preferably those which they perform the most in their daily lives, and those that include finger movements.

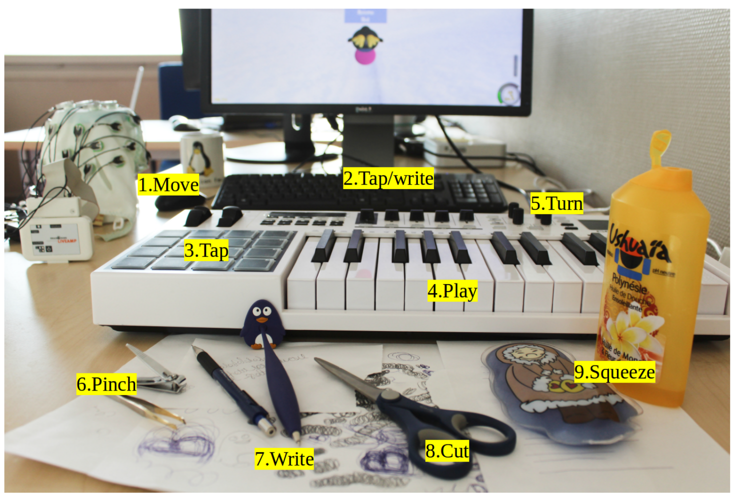


Figure 4.2: We suggested physical training on objects during the placement of electrodes and experience preparations. By showing what kind of movements they could imagine, novice users could have a better idea of how an imagined movement can look or feel like. Of course, the participants were not obliged to choose any object if they did not want to.

4.3 Experimental Design

We created a 3-conditions between subject design: (1.) the no_bias (control) group in which the classifier output was not biased, (2.) the positive_bias group in which the classifier output was positively biased in real-time, and (3.) negative_bias group in which the classifier output was negatively biased real-time. The bias function was the same per group throughout the two sessions. The study was approved (validation number *2019-05*) by the Inria ethics committee, COERLE (Comité opérationnel d'évaluation des risques légaux et éthiques).

Protocol: 30 healthy participants were recruited (6 not BCI naive, 12 women, mean age: 28.56 years, SD: 6.96). We created 3 groups, hence 10 participants were randomly assigned to each group. Each participant was engaged in 2 sessions (2 different days of a 1-to-5 days interval). A run contained 40 trials (20 trials per class) making each course or run last 5 minutes and 25 seconds. Each 4 second trial was enclosed by two flags, within which a set of 8 closely arranged fish in a row were to be caught within $\sim$3 seconds. It was followed by a $\sim$4 second pause, during which Tux controls were deactivated, and participants could rest or adjust their position if needed. Each session lasted $\sim$2 hours and consisted of 3 main parts, see figure 4.3.

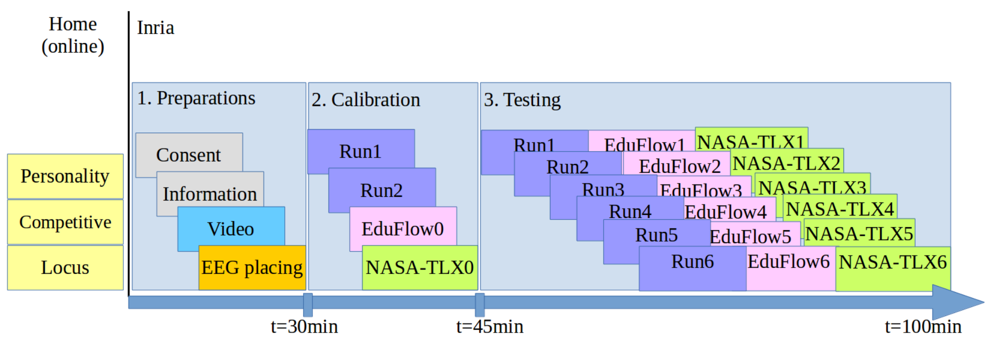


Figure 4.3: Experimental Protocol in which participants filled 3 questionnaires at home; and during the experiment there were 3 parts: preparations, machine calibration during which users did not control the machine and testing phase during which the users controlled the machine.

1. Part I is the experiment preparation (around 30mins), during which the participants:

- signed the consent form which contained all the details about the experiment and their ethical rights;
- filled in an information form about their demographics, previous encounters with BCIs, and music/sport/gaming/meditation experiences or education:
- watched the explanatory 3-minutes animated movie about what we can measure with EEG, advices on how to produce motor imagery and control the machine, and the principles of the TuxRacer game;
- asked remaining questions about the experiment and tried-out objects for motor training (see figure 4.2); while the experimenter was placing the EEG cap. Participants were not obliged to try-out any of the presented object unless they needed a somatosensory reminder of a movement, so that they could more easily reproduce such movement mentally.

- watched their own raw EEG signals in real-time to see for themselves the negative effects of facial movements and blinks.

2. Part II is the machine training or calibration (2 runs of 40 trials each, around 15mins), during which participants:

- repeatedly performed their imagined movement for left or right hand at a time according to the position of the fish;
- received "fake" feedback in which Tux was controlled by a script that generated quasi-random behavior (it was coded to go more often towards the fish). Users were told that they were not the ones controlling the game.
- perceived Tux sliding on a pink snowboard, instead of its own belly, which was the visual indication of the calibration phase.
- filled out a questionnaire on perceived difficulty (NASA-TLX) [Hart and Staveland, 1988] and flow (EduFlow) [Heutte et al., 2016], once after the 2 runs were finished.

From the data acquired during calibration, the machine:

- trained the CSP spatial filter;
- selected optimal frequency bands [Blankertz et al., 2007];
- trained an SVM discriminative classifier for left and right hand-class.

3. Part III is the testing phase (6 runs, around 45mins) during which the participants:

- controlled Tux with their motor imagery.
- filled in NASA-TLX and EduFlow questionnaires after each run.
- played a bonus run (non obligatory), choosing an existing ski course from the original Tux game to manipulate it as self-paced MI BCI.

Note that for the second session we did not use the data from the first one, i.e., calibration phase was performed again from zero giving the subjects the opportunity to choose another movement if they wanted.

Questionnaires. The questionnaires to be filled at home are:

- Personality tests 16PF5 [Cattell and P. Cattell, 1995], providing 16 primary scores of personality traits such as warmth, reasoning, emotional stability, dominance, liveliness, rule consciousness, social boldness, sensitivity, vigilance, abstractness, privateness, apprehension, openness to change, self-reliance, perfectionism and tension; and 5 global scores of personality being extroversion, anxiety, tough-mindedness, independence and self-control that are computed as linear combinations of the primary ones. For a better understanding of the global personality traits, we detail their composition:

  - **Extroversion** contains liveliness, warmth, social boldness, a negative self-reliance and negative privateness;
  - **Anxiety** contains tension, apprehension, vigilance, and emotional **in**stability;
  - **Tough-mindedness** is the opposite of all following factors: warmth, sensitivity, abstractedness (creative, focused on internal self), and openness to change.
  - **Self-Control** contains rule consciousness, perfectionism, and opposite of liveliness and abstractedness.
  - **Independence** contains dominance, social boldness, vigilance, and openness to change.

- Revised Competitiveness Index [Houston et al., 2002], providing 2 scores such as competition enjoyment and social contentiousness, i.e., querulous behavior.

With this information we can find on account to which factor, users could benefit from a biased feedback, and increase performance and learning. This information can be used for a model that could predict the optimal feedback bias for each user.

Signal Processing. The same equipment and software as in the first experiment was used: (i) 32 channel Brain Products LiveAmp (a wireless amplifier), (ii) OpenVibe for the real-time signal processing which uses Butterworth temporal filter, CSP spatial filter and classification (SVM, scaled between -1 and 1). As reminder, see paragraph 3.2.1. Specifically in this study, not only SVM and CSP were trained on calibration data, but also the selection of optimal frequency bands was performed for each subject, as in [Blankertz et al., 2007].

Game controls. We used again the Lab Streaming Layer (LSL) to control a virtual joystick that in turn controls the penguin. Meaning that the classifier output from OpenVibe was streamed via LSL real-time and mapped onto the angle Tux would take, see reminder 3.2.1.

Game modifications. We kept the same ski-course, a bobsleigh through which Tux slides in constant speed. One row of fish at the extreme left or right could be difficult to reach and thus insufficient to motivate participants with lower performances. Hence, we added another row of reward (in form of squid). In other words, there is one row of fish that is closer to the center (giving 1 point each as it is easier to reach) and a row of squid that is placed at the extremities (giving 5 points each), see figure 4.4.

Figure 4.4: Screen-shot of the Tux Racer game, customized for synchronous MI BCI. Here, the penguin already passed the flag denoting the beginning of the trial. An additional row of reward (squid) was added to reduce frustration, and increase motivation.

Mean re-centering. As mentioned earlier we want to account for the problems of EEG non-stationarity by re-centering the classifier hyperplane from [Vidaurre et al., 2010]. We apply this method by calculating the mean or center *c* of the classifier output for both classes in each run. If $c \neq 0$ we then move the hyperplane for the amount that overpassed the 0 value or the old center, i.e., this value becomes the new center. For instance, let's say our classifier output is bounded between $x \in [-1, 1]$. When we move the center for the mean c, we consequently move the maximum values (-1 and 1) as well. In order to fit the mean without changing the limits, we perform a scaling depending on two cases as follows. (i) if $x < c$ then it is mapped with $f(x) = (x - c)/(1 + c)$, or (ii) if $x > c$ then it is mapped with $f(x) = (x - c)/(1 - c)$, see simplified figure 4.5.

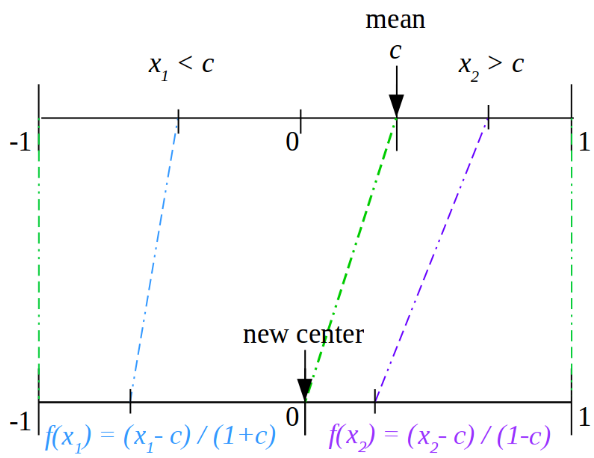


Figure 4.5: Simplified example of re-centering when $c > 0$, and two cases of classifier output $x_1 < c, x_2 > c$. Such re-centering includes a scaling factor in order to fit the classifier output within the same limits [-1, 1].

We perform re-centering of the hyperplane after each run during testing (without the calibration), and calculate the mean from only the previous run. There are many issues that could arrive during a run, for instance, a faulty electrode would impact the classifier to choose one class throughout the whole run and would cause the hyperplane to undergo a drastic movement for the wrong reason. Hence, we bounded the mean $c \in [-0.5, 0.5]$, i.e., if $c > 0.5$ then *c = 0.5* or *c < -0.5* then *c = -0.5*. This method is implemented in every group, including the no_bias group. Note that this method increases performance only if there are equal number of classes per run. After the re-centering of the classifier output, we re-scale the maximum values between 0 and 1, and feed it to the bias function. The scaling is used in the first place to ease the computation and mapping to the game, same as in chapter 3. Note that we perform such scaling back and fourth, as the output of SVM are probabilities between 0 and 1, see 3.2.1.

Bias function. As for the positive and negative_bias groups, we used a beta cumulative distribution function (beta CDF) that maps the classier output (which are probabilities) to a biased classifier output. Beta probability density function (PDF) is a power function of a variable *x* and its shape parameters *a*, *b > 0*:

$$f(x; a, b) = const \cdot x^{a-1}(1-x)^{b-1}$$

The beta cumulative distribution function (CDF) is then:

$$I_x = \frac{\int_0^x t^{a-1}(1-t)^{b-t}dt}{const}$$

where const is a normalization constant to assure the total probability is 1.
We list a few of Beta CDF properties:

- $I_0(a, b) = 0$;

- $I_1(a, b) = 1$;
- $I_x(a, 1) = x^a$;
- $I_0(1, b) = 1 - (1 - x)^b$;
- $I_x(a, b) = 1 - I_{1-x}(b, a)$.

In practice, we chose this function because it permits us to control the slope with many degrees of freedom using its two parameters, *a* and *b*. For instance, *a* influences the slope near 0, while *b* influences the slope near 1, see figure 4.6. This way, these two parameters enable us to assist users more when the classifier output has low performance (near 0), and less when it has high performance (near 1).

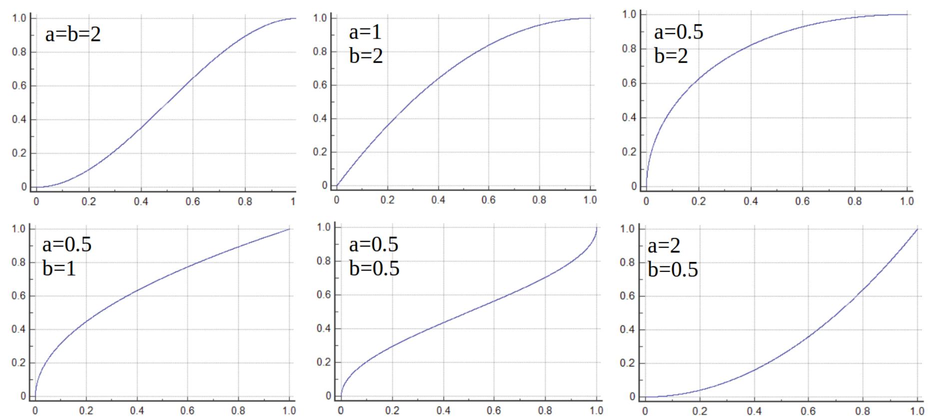


Figure 4.6: Examples of beta CDF, with random variable *x* in the *x-axis* and the function $I_x(a,b)$ in the *y-axis,* when changing the shape parameters *a* and *b*.

As all beta CDF, the function starts in *0* and ends in *1*, so we used $a = b = 1$ as a linear (identity) function for the no_bias group. Hence, from the identity function we started adding and subtracting values for our bias function, Meaning, *a=(1 - k),* and *b=(1 + k)* represent the parameter values for positive bias group, while *a=(1 + k)* and *b=(1 - k)* for the negative bias group, where *k-values* we call shifts. We tried out multiple shifts, and empirically chose *k = 0.33* as a best fit for our bias. see figure 4.7.

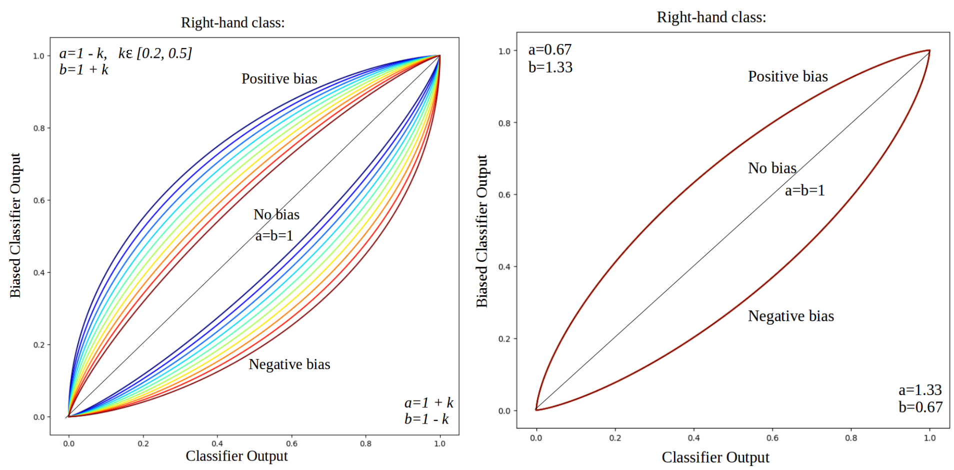


Figure 4.7: Example for the right-hand class bias function: negative, positive and no_bias. We map the classifier output (*x-axis*) to the biased output (*y-axis*), using different shift values (*k*). Left – the different colours represent the various bias functions based on shifts $k\epsilon[0.2, 0.5]$ for both positive and negative bias function; Right – bias function for both negative and positive bias function with only one average shift value that we chose, *k=0.33*.

Note that beta CDF is symmetric for positive and negative bias, however it is not symmetric below and above the middle value (0.5). For instance, in the case of positive bias (again for right-hand class) when the classifier output is closer to 0, we wanted to assist users more than when the output is closer to 1. For the left-hand class we simply inverted the function to get the same effect.

Performance. To measure performance, we keep the same regular metrics online (peak and average performance, standard deviation of classifier output, and distance from maximal output values) and offline (classification accuracy of cross-validation, using only testing data), as in our previous experiment. If a reminder for their definitions is needed, see 3.2.1.

The best representative of performance is the online performance after the re-centering method was applied. Thus for analysis, e.g. prediction models and correlations, we use only centered performance.

Additionally, we are interested in the learning rate which is the slope of the linear regression of online performance (centered) of runs within a session. We also measure learning as a simple difference in performances between sessions, that measure we call progress.

Prediction models. As we mentioned in our conceptual framework of adaptive BCI (chapter 2), the adaptation should depend on the *criteria* we wish to optimize, i.e., would we prefer rather the user to be in a state of flow or the system to achieve highest performance accuracy. In that sense, we can create a model that predicts performances, learning rate, flow state and so on, on account on user personalities, calibration performances, and initial states (flow and workload). Meaning, if for instance we favour flow, we can predict the factors necessary to evoke such state, or if we wish to increase performance, we can build a prediction model that highlights factors necessary to reach high performance, and so on.

Lets say our *criteria* is to maximize performance, so we wish to predict performances Y^n for *n* number of subjects, using $X^{n \times p}$ covariates for *p* prediction factors (user traits, states, bias and so on).

We implement an Elastic-Net regression, which combines both Ridge (Tikhonov regularization) and Lasso (Least Absolute Shrinkage and Selection Operator) regression, as follows.

$$\beta_{net} = \underset{\beta \epsilon R^p}{argmin}(\|Y - X\beta\|_2^2 + \lambda_2\|\beta\|_2^2 + \lambda_1\|\beta\|_1)$$

If $\lambda_1 = 0$, then it is a Least Squares method with the $\|\beta\|_2^2$ penalty, called Ridge regression, otherwise if $\lambda_2 = 0$ it is a Least Squares method with the $\|\beta\|_1$ penalty called the Lasso regression. In other words, $\|Y - X\beta\|_2^2$ is a l_2 norm (i.e., Euclidean distance), being $\sqrt{\Sigma_{i=1}^n (Y - X\beta)_i^2}$; and $\|\beta\|_2^2$ is an l_2 norm, accounting for the number of prediction factors *p*: $\sqrt{\Sigma_{j=1}^p \beta_j^2}$; while the penalty for Lasso, $\|\beta\|_1$ is an l_1 norm: $\Sigma_{j=1}^p \mid \beta_j \mid$. With β_{net} calculated, it is used as a coefficient for the regression model.

Lasso is better suited for model complexity reduction, while Ridge is better suited for correlated data. Elastic-net combines the strength of both. We use a parameter α to wager between the two penalties or regressions, if $\alpha = 0$ then it is Ridge, and if $\alpha = 1$ it is a Lasso regression. One use of α is for numerical stability; for example, the elastic net with $\alpha = 1 - \xi$, for some small $\xi > 0$ performs much like Lasso, but removes any degeneracies and wild behavior caused by extreme correlations. The equation 4.3 then takes the following form:

$$\beta_{net} = \underset{\beta \epsilon R^p}{argmin}(\|Y - X\beta\|_2^2 + \lambda[(1\text{-}\alpha)||\beta||_2^2/2 + \alpha||\beta||_1])$$

Now the tuning parameter λ controls the overall strength of the penalty. Hence, to optimize the prediction model, we need to find both the λ and α parameters. In order to do so, we perform a Leave One Subject Out (LOSO) cross-validation using the R package cva.glmnet, from glmnetutils[1], which by default selects between 100 values of λ and 10 values of $\alpha \epsilon [0, 1]$ with an exponential step.

We performed a nested 2 cross-validation (LOSO) in order to have different sets for training and testing during parameters search and avoid over-fitting. As we have n=30 subjects, we performed a n-fold cross validation in the outer loop and a (n-1)-fold cross validation in the inner one. To explore the α parameter, in the inner loop we tested 10 default α values from R function cva.glmnet. This means that within the inner loop we performed 10 α iterations x 29 LOSO. In each α iteration, we test a100 default λ values, and we choose such λ leading to minimal prediction error. Once the minimal α and λ are selected within the inner loop, in the outer loop we obtain 30 values of α and 30 values of λ. We retrieve the corresponding error, being the mean error of all folds of the outer loop (mean of 30 errors).

[1] https://cran.r-project.org/web/packages/glmnetUtils/vignettes/intro.html

In order to asses the validity of this model, and verify if it has better prediction power than chance, we compare it with randomized data which is run on the same parameters 1000 times. We compare the mean error of our model to the error of random data. If the error of our model is lower than the 5^{th} percentile of the random one, we can say it is better than chance, with a *p<0.05*. Finally, in order to get the final coefficients of the regression, we run the model using the selected parameters α and λ on the whole dataset.

4.4 Preliminary Results

4.4.1 Differences between groups according to performance and learning.

Differences during calibration. There is no significant difference between groups for both session 1 and 2 (using 1-way ANOVA, independent variable: session, dependent: calibration performance), see figure 4.8. .

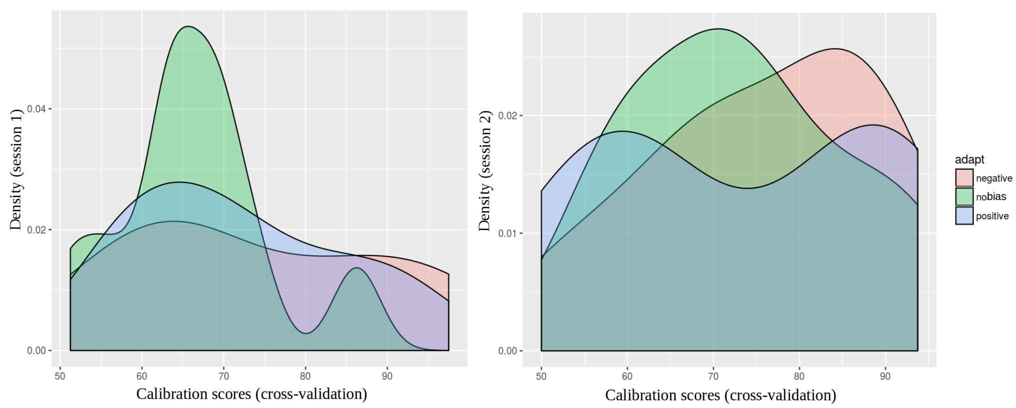


Figure 4.8: Density of participants' scores of calibration between groups for session 1 (left), and session 2 (right). Green denotes no_bias group, purple positive and red negative_bias group.

Good/poor performers. Our hypothesis treats differently those who achieve low versus high performance rates, or "good" and "poor" performers. We expect to see that positive bias will assist while negative decrease performance and learning for "poor" performers, and the inverse for the "good" ones. For that reason, we investigate the groups by their performance (cross-validation) during calibration. We use the median value of performance within a group for only the first session (without the second session, to avoid including a learning effect) and thus separate the "good" from "poor" performers. Note that a good performer is placed in such category according to its group, but not according to all groups.

Differences in performance between sessions. When performing a 3-way ANOVA (independent variables: group, session and performers, dependent variable: peak, average centered or regular performance). We did not find any significant difference between groups (for all users together) when considering performance (online and offline). We only observe a difference between performers (*p<0.01*) which is trivial, i.e., good performers during calibration are still good during testing when compared to poor ones in their group. Although the difference in peak performance for 2 sessions is not significant between groups, we can observe that the negative bias is somewhat decreasing the performance between sessions, positive one is increasing for poor and decreasing for good subject performances, while no_bias is somewhat stable for both, see figure 4.9. We observe similar phenomena in average performance, as well. Note as performance metric, we use the centered peak performance.

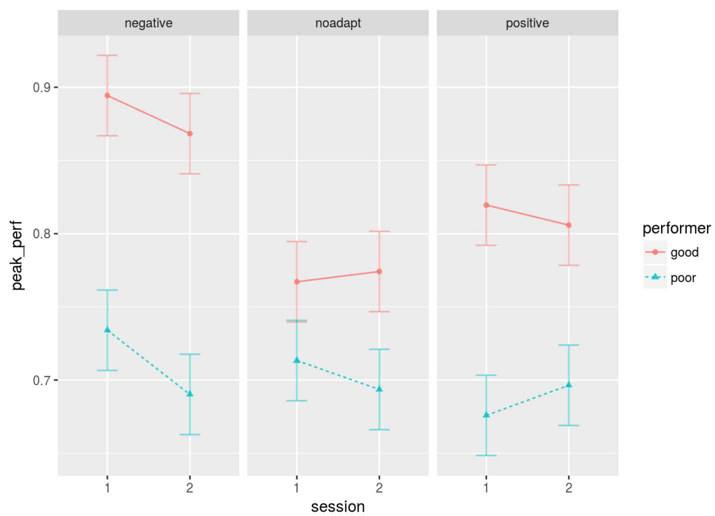


Figure 4.9: Peak performance, no significant difference between groups (only between performers). Red denotes subjects with good performance, while blue subjects with poor performance.

Differences in learning rate between sessions. With 2-way ANOVA (independent variable: session, dependent variable: learning rate); we found a significant difference in learning rate (calculated with peak and average performance, for both regular and centered), between groups and sessions (interaction: group and session, *p<0.01*, as well as interaction: group, performer and session, *p<0.01*).

The learning rate decreased in the negative group, increased in positive group and stayed the same in the no_bias group between sessions, see figure for learning rate of peak performance centered 4.10. Similar results were observed with all other performance metrics.

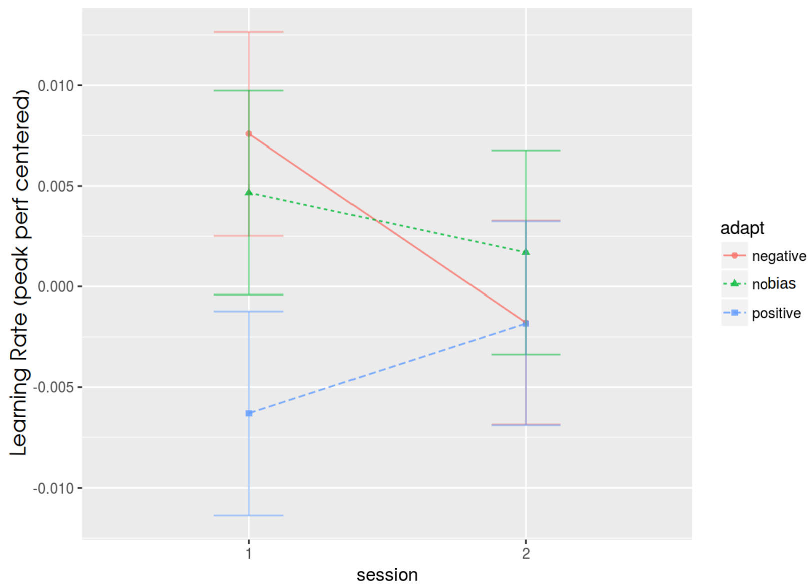


Figure 4.10: Learning rate of centered peak performance (denoted as *peak_perf_LR*) changes between sessions for each group.

This is not what we expected, we can observe that in the positive_bias group, the learning curve is negative during both sessions, however it has a positive evolution between session 1 and 2. On the other hand, within the negative_bias group, participants have a positive learning curve during the first session, but it severely deteriorates during the second session, and becomes negative. It seems the negative bias increased learning in short-term, but decreased in long-term, while positive bias decreased in short-term and increased in the long-term. As for the no_bias group, they slightly decreased but remained within the positive learning curve between sessions.

Including performers. When we look closer at the significant interaction in learning rate between performers, groups and sessions, we get a better explanation for the above phenomena, see figure 4.11.

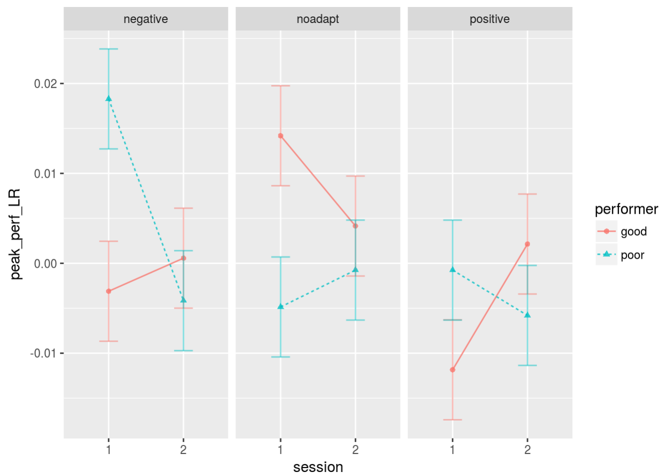


Figure 4.11: Significant interaction of group, performer and session, for learning rate of peak centered performance (denoted as *peak_perf_LR*).

Negative Bias. We can observe clearly that the negative bias influenced negatively the poor performers between sessions (from a positive learning curve to a negative one), while the good performers increased in their learning between sessions (from negative learning to slightly positive). This can be explained that good performers do not have much "space" for progress as they are already achieving high performances, while the poor performers "try hard" locally (during first session) to make it work and progress. However on the long run, in session 2, the poor performers might observe that their performances do not improve (visually, as they are negatively biased) so they possibly start to slowly abandon the task.

Positive Bias. It seems that with positive bias, good performers increased their learning between session (from a negative learning curve to positive one), while the poor performers did not benefit much from the positive bias. The good performers have the most negative learning curve during the first session (when compared to all groups), it can be explained that they give no effort as the task is too easy. Interestingly they might expect the task to be even easier for the second session, but as it requires the same amount of effort they have a positive learning curve. It seems as if subjects with low calibration performance can not benefit from a positive bias.

No Bias. It seems that good performers had a positive learning curve during both sessions, although it decreased from session one to session two. On the other hand the poor performers had a negative learning curve in both sessions, although it increased from session one to session two.

These results are not entirely consistent with our hypothesis nor between themselves. This only shows that we should take a look not only at the performances, but also at the users' psychological traits in order to better understand their learning rate.

4.4.2 Differences between groups according to psychological states and traits.

Differences during calibration. There were no differences in EduFlow score during calibration (1-way ANOVAs), which could indicate that the groups were balanced considering their flow states at the beginning of both sessions, see figure 4.12.

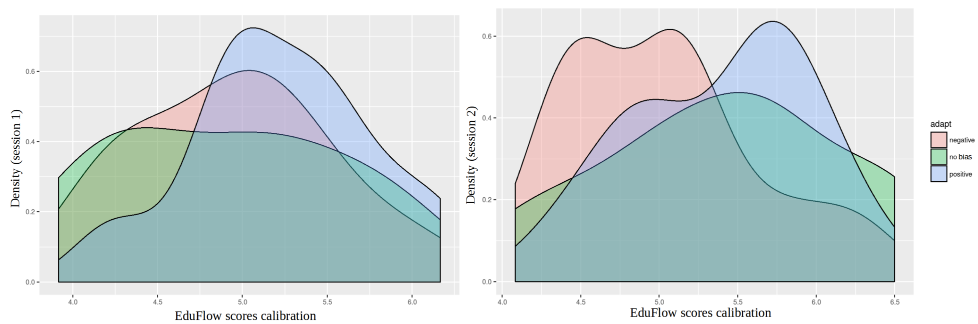


Figure 4.12: Density of EduFlow scores during calibration for session 1 (left) and session 2 (right).

There were no differences in NASA-TLX score during calibration (1-way ANOVAs), which could indicate that the groups were balanced considering their workload at the beginning of both sessions. Also, when comparing personality traits between groups, we do not find any significant difference between groups.

Differences between sessions. As reminder, EduFlow questionnaire provides 4 dimensions, that are, cognitive control, immersion, autotelism, and loss of self, and one score that is the mean of all 4 dimensions, dented here as *eduflow.* On the other hand, NASA-TLX has only one score of workload (denoted as *nasa_score*).

We acquired EduFlow questionnaires scores from testing phase (6 runs), or 1 value per run per subject. When performing a 2-way ANOVA (independent variables: session and group, dependent: one of EduFlow dimensions or the mean of all dimensions); we find a significant difference between groups only in cognitive control, the first dimension D1 of EduFlow score ($p<0.05$), see figure 4.13.

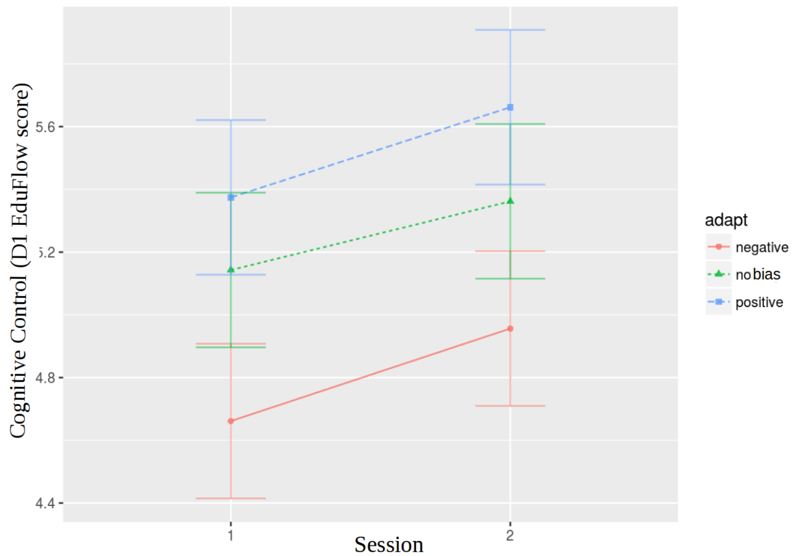


Figure 4.13: Significant difference between groups concerning the D1 of EduFlow score (cognitive control).

As for other dimensions and the mean of EduFlow score there is no significant difference. We have seen the same result in out first Tux experiment, the only significant difference between groups is in cognitive control, as reminder see subsection 3.2.2.1.

We have not found any significant difference between groups in their workload, when performing 2-way ANOVA (independent variables: session and group, dependent variable: NASA-TLX score).

4.4.3 Correlations between psychological states, traits and online performance.

For all correlations, the p-value was corrected for multiple comparisons with false discovery rate (FDR) [Noble, 2009], and the threshold set for p-value is $p<0.05$. The online performances we analyze are centered peak and average ones, denoted as peak_perf_centered and avg_perf_centered.

Psychological States. Thanks to the amount of data acquired during runs, we were able to find a precise relationship between flow, workload and performances, and confirm some results from our previous experiment.

We found positive correlations between flow state, workload and performances , see figure 4.14.

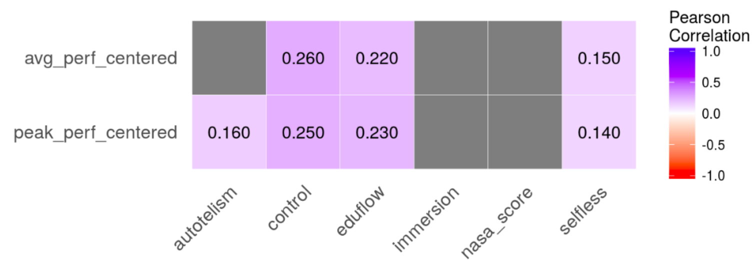


Figure 4.14: Significant correlations of *p<0.05* (corrected with FDR), with values referring to Pearson's coefficients. Blue represent positive, red negative correlations while gray are non-significant correlations.

There is a positive correlation between control, selfless, the mean of 4 dimensions (*eduflow*) and online performances. However immersion was positively correlated with flow in our previous experiment, here surprisingly it is not. It can be explained by the fact the the bias was not adaptive for each user, i.e., each user had only one bias type which did not particularly influence immersion, as in the previous experiment (reminder see **??**). On the other hand, there is no correlation between workload and performances.

Personality traits. The traits we explore are 5 global personality factors (from 16FP5 questionnaire), and 1 factor for competitiveness.

We have found significant correlations between 2 global traits (extroversion and anxiety) and performance, see figure 4.15.

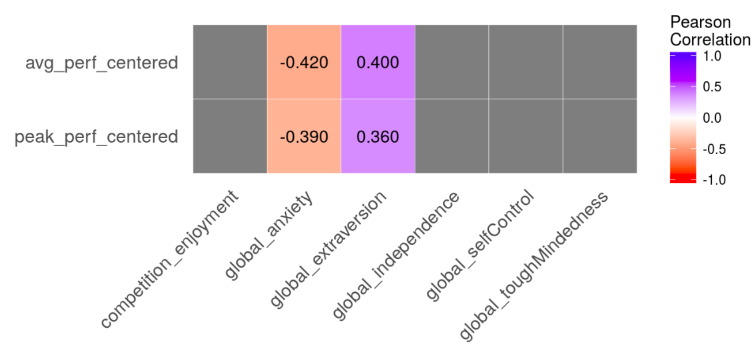


Figure 4.15: 2 (extroversion and anxiety) out of 5 global, correlate with online performance (peak, average performance). Non-significant correlations are gray, while significant ones (*p<0.05*) are presented with the Pearson's coefficient. Blue represent positive, and red negative correlations.

We can observe that extroversion is positively correlated with online performance (Pearson coefficient with average: 0.40, and with peak performance: 0.36); while anxiety is negatively correlated with online performance (Pearson coefficient with average: -0.42, and with peak performance: -0.39).

4.4.4 Correlations between psychological states, traits and learning rate.

For all correlations, the p-value was corrected for multiple comparisons with false discovery rate (FDR) [Noble, 2009], and the threshold set for p-value is $p<0.05$. For the learning curve (evolution of performance over 6 runs or one session)we use peak or average (centered) performance, which are denoted as *peak_perf_centered_LR, avg_perf_centered_LR*.

Psychological States. We found interesting correlations between flow states, workload and the learning curve, see figure 4.16.

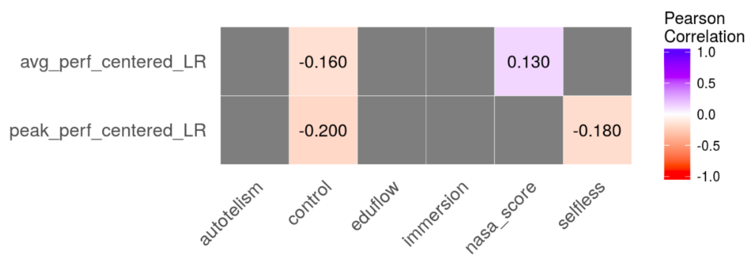


Figure 4.16: Correlations between states (flow and workload) and learning rates. Non-significant correlations are in gray, while significant ones ($p<0.05$) are presented with the Pearson's coefficient. Blue represent positive, and red negative correlations.

EduFlow dimensions (control and loss of self) correlate negatively with learning, especially the sense of cognitive control (coefficient with average: -0.20, and with peak: -0.16). In contrast, workload correlates positively with learning (coefficient: 0.13).

Personality Traits. The traits we explore are 5 global personality factors (from 16FP5 questionnaire), and 1 factor for competitiveness (competition enjoyment).

We evaluated correlations with only centered (average and peak) performances, and found no significant correlations between traits and learning rate.

4.4.5 Prediction Models

Prediction models can provide us with information about what type of personalities can benefit from which biased feedback (positive, negative or none) to increase performance and learning.

As we do not have a large enough population to validate all possible factors for the prediction model, thus we choose to consider only:

- 5 global personality traits (each global score contains a linear combination of a few out of 16 principal traits);
- 1 competitiveness index, that is, *competition enjoyment*, which is the principal factor of competition (the second one relates to social conscientiousness);

- calibration baseline, those are scores corresponding to the cross-validation of classification accuracy during calibration for each session (2 values per person).
- Eduflow baseline, those are EduFlow scores from the calibration of each session (2 values per person).
- Nasa baseline, those are scores from NASA-TLX scores from the calibration sessions (2 values per person).
- eduflow, nasa, and calibration reference are only the scores from the first session used for predicting learning (to avoid the learning effect of the second calibration scores).

4.4.5.1 Prediction of Online Performance.

To find the optimal bias for online (average and re-centered) performance per run, depending on calibration performance, initial states and personality traits, we investigate their interactions with bias within the prediction model. We could not select biased performance as then any bias would produce an influence on biased performance, so we keep only centered performance. The reason why we choose average over peak performance per run as it seems more stable or robust metric for predictions.

To select significant factors for the prediction model, we use Elastic-net (see reminder 4.3). Practically, the notation used in R package *glmnet* is, let *bias* and *traits* be factors used to predict performance, *bias* can be positive, negative or none, and *traits* are for instance 5 global traits, calibration scores etc. We use a notation such that *(bias*traits)* answers how *bias* and *traits* separately predict performance, plus how their interaction *(bias : traits)* predicts performance. The notation in R of *bias*traits = bias + traits + bias : traits.*

We perform 3 models, 1^{st} is *bias*traits*; it selects each factor that significantly predicts performance, along with their interaction (*bias : traits*); the 2^{nd} is only *bias : traits*; it selects only significant interactions with the bias, while the 3^{rd} is also only *a:b;* i.e., only interactions with the bias that significantly predict performance, but the *traits* are divided in high-low groups, e.g. high-low anxiety.

We start by presenting the 1^{st} model (*bias*traits*), see figure 4.17.

Factors and their interaction to bias:
average_perf_centered ~ bias * (calib_baseline + competition_enjoyment + extroversion + anxiety + toughMindedness + independence + selfControl + eduflow_baseline + nasa_baseline)

Factors:	Coefficients:
(Intercept)	0.2887258315
calib_baseline	0.0032051476
competition_enjoyment	0.0013646467
extroversion	0.0087888650
anxiety	-0.0116006207
self-Control	-0.0001929394
tough-Mindedness	-0.0005510454
eduflow_baseline	0.0054907214
nasa_baseline	0.0175709439
negative:calib_baseline	0.0002910754
negative:extroversion	0.0022014430

Figure 4.17: First prediction model with selected factors for prediction and their interaction with bias factor. The names of factors is on the left, and the coefficient of the regression is on the right.

Factors that predict performance. *First* model, contains separate factors *a* that predict performance, from figure 4.17.

- calibration score positively relates to performance, e.g. an increased score predicts increased performance.
- subjects who **enjoy competition** might be predictors of increased performance, and vice versa.
- subjects who are **extroverted** might be predictors of increased performance, and vice versa.
- subjects who are **anxious** might be predictors of low performances, and vice versa.
- subjects who are in flow state during calibration might be predictors of high performances, and vice versa.
- subjects who have high workload during calibration might be predictors of high performances, and vice versa.
- subjects who have high **self-Control** might be predictors of low performances, and vice versa.

Optimal bias for performance. The *Second* model, includes only interactions with bias, see figure 4.18.

Only Interaction:

average_perf_centered ~ bias **:** (calib_baseline + competition_enjoyment + extroversion + anxiety + toughMindedness + independence + selfControl + eduflow_basline + nasa_baseline)

Factors:	**Coefficients:**
(Intercept)	0.477400072
negative:calib_baseline	0.003295131
positive:calib_baseline	0.002170128
noBias:competition_enjoyment	0.003364943
negative:extroversion	0.006701674
negative:anxiety	-0.018009754
positive:anxiety	-0.006372881
noBiast:independence	0.002334867
positive:independence	-0.004962635
noBias:selfControl	-0.012260238
positive:selfControl	0.009057039
noBias:nasa_baseline	0.023045435

Figure 4.18: Second prediction model with only interaction between factors (traits, initial flow and workload states, and calibration scores) with bias factor. The names of interactions is on the left, and the coefficient of the regression is on the right.

We present the same results, but within a table to summarize the significant interactions between bias and user traits, initial states and calibration performance score, see table 4.1.

bias	positive	negative	none
calibration scores	+	+	
competitiveness			+
extroversion		+	
anxiety	-	-	
self-control	+		-
independence	-		+
workload			+

Table 4.1: Positive (+) and negative (-) interactions between bias and factors selected by Elastic-net that predict performance.

Separating groups. When we separate users into groups of high-low global personality traits, initial flow and workload states (*g_eduflow_baseline* and *g_nasa_baseline*), and calibration performance (*g_calib_baseline*) using the median values (e.g. *g_anxiety* contains *anxiety_high* scores above the median, and *anxiety_low* are scores below the median), we produce a *Third* model, and we consider only interactions with bias, see figure 4.19.

Only Interaction:

average_perf_centered ~ bias **:** (g_calib_baseline + g_competition_enjoyment + g_extroversion + g_anxiety + g_toughMindedness + g_independence + g_selfControl + g_eduflow_basline + g_nasa_baseline)

Factors:	**Coefficients:**
(Intercept)	0.580393375
negative:calib_baseline_high	0.032275213
positive:calib_baseline_high	0.057928522
noBias:calib_baseline_low	-0.022920887
positive:calib_baseline_low	-0.021322727
noBias:eduflow_baseline_low	-0.057887471
negative:competition_enjoyment_low	0.064748866
negative:anxiety_low	0.087088453
noBias:toughMindedness_low	0.035659301
positive:toughMindedness_low	0.009003250
negative:independence_low	-0.005684646
positive:independence_low	0.002933082
noBias:selfControl_low	0.091013729

Figure 4.19: Prediction model for performance with interactions between factors separated in groups of high-low and bias (on the left) and regression coefficients (on the right).

We represent the results within a table, for better visibility and understanding, see table 4.2.

bias	positive	negative	none
high calibration scores	+	+	
low calibration scores	-		-
low flow state			-
low competitiveness	+		
low anxiety		+	
low self-control			+
low independence	+	-	
low tough mindedness	+		+

Table 4.2: Positive (+) and negative (-) interactions between bias and factors selected by Elastic-net that predict performance.

4.4.5.2 Prediction of Learning.

As we do not have enough data for predicting learning rate, we simply calculate a progress rate, that is, the difference in online performance (average and re-centered) between 2 sessions. As we are predicting learning, we use only the calibration score from first session (denoted as *calib_reference*) as the calibration score can change between sessions due to learning effect.

The Elastic-net prediction model (*bias*traits*) selects 9 factors and 9 of their interactions with bias to predict progress, see figure 4.20. Note that this model does not contain eduflow_reference nor nasa_reference scores, because in that case the mean error of the model is not better than chance.

Factors and their interaction to bias:

progress ~ bias * (calib_reference + competition_enjoyment + extroversion + anxiety + toughMindedness + independence + selfControl)

Factors:	**Coefficients:**
(Intercept)	-0.3500351985
negative	0.3483481570
positive	-0.0126424816
calib_reference	0.0007000034
competition_enjoyment	0.0069020811
extroversion	0.0022261507
anxiety	0.0001757505
toughMindedness	-0.0001014706
independence	0.0093523160
selfControl	0.0168137628
positive:calib_reference	-0.0012288728
negative:competition_enjoyment	0.0002378596
positive:competition_enjoyment	-0.0024987514
positive:extroversion	0.0226584685
negative:toughMindedness	-0.0141569794
positive:toughMindedness	-0.0045899179
negative:independence	-0.0155302650
positive:independence	0.0208871987
negative:selfControl	-0.0653647149

Figure 4.20: Selected factors and their interaction with bias for prediction of progress (i.e., difference in average centered performance between sessions). The names of factors is on the left, and the coefficient of the regression is on the right.

Factors that predict learning (progress). From figure 4.20.

- negative bias positively relates to progress, e.g. negative bias might increase learning.
- positive bias negatively relates to progress, e.g. positive bias might decrease learning.

- calibration reference positively relates to progress, e.g. an increased score predicts increased progress.
- subjects who **enjoy competition** might be predictors of good progress, and vice versa.
- subjects who are **extroverted** might be predictors of good progress, and vice versa.
- subjects who are **anxious** might be predictors of good progress, and vice versa.
- subject who are **though-minded** (not open, not warm etc.), might be predictors of low progress, and vice versa.
- subjects who are **independent** might be predictors of good progress, and vice versa.
- subjects who have high **self-Control** might be predictors of good progress, and vice versa.

Optimal bias for learning. We present only the interactions with bias for predicting progress, in a table 4.3.

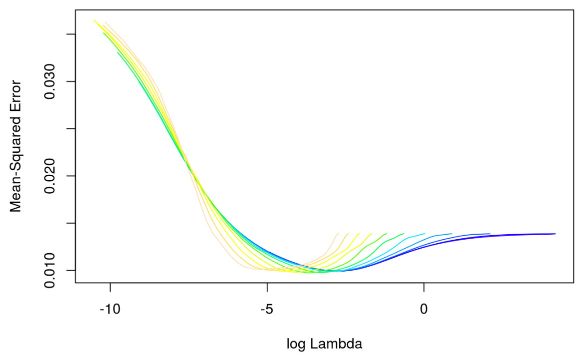
bias	positive	negative	none
calibration reference	-		
competitiveness	-	+	
extroversion	+		
tough mindedness	-	-	
self-control		-	
independence	+	-	

Table 4.3: Positive (+) and negative (-) interactions between bias and factors selected by Elastic-net that predict progress.

When separating groups into high-low, we get zero predictors for progress. Possibly not enough data, and too many factors.

4.4.5.3 Model parameters and validity.

Prediction models of performance. For the First model, the selected value of $\alpha = 0.9819333$ (i.e., Elastic-net chose an almost Lasso regression), and selected the penalty $\lambda = 0.007027121$, giving a *mean_error= 0.01015779*. We perform a nested cross-validation, i.e., select the alpha and lambda values for each person, see figure 4.21.



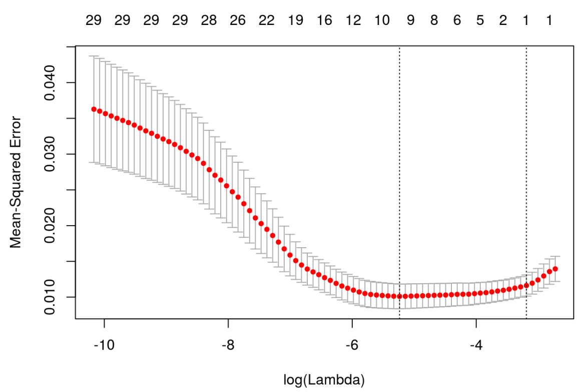


Figure 4.21: For each subject we perform parameter selection, as follows. Upper figure: Mean-Squared Error of *10* α values (10 colours). Bottom figure: Such α is selected for which λ has minimum error; there are 2 proposed λ values (gray vertical lines) left gives minimum error, and the other one is more regularized (selects less factors). Values presented above the bottom figure are the numbers of selected factors for each λ. 10 factors provide minimal error λ.

The mean error of both models are significantly lower than chance, see figure for the first model 4.22.

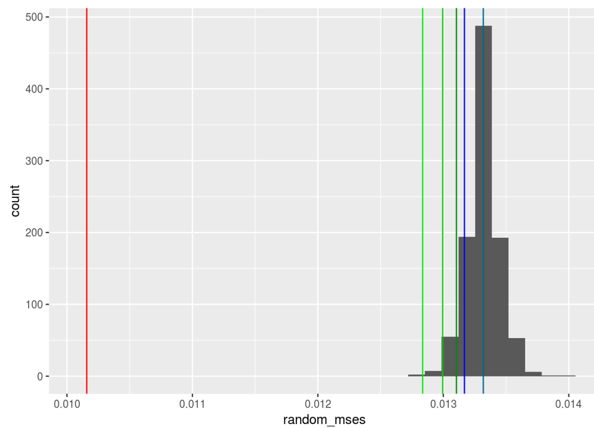


Figure 4.22: Histogram of mean errors. Mean squared error values (denoted as *random_mses*) are in *x-axis*. Our model mean error (30 iterations, in red), and random mean error (1000 iterations) of which blue and green colours represent different percentile values. The most left green is 0.1 percentile, and we can clearly observe our model is significantly better than chance (*p<0.001*).

For the sake of readability, details and figures for the *Second* and *Third* model (only interactions with bias), can be seen in the appendix 7.5 and 7.5, respectively.

Prediction Model of Learning. The model selected $\alpha = 1$, being a Lasso regression with penalty $\lambda = 0.000509262$, giving a *mean error: 0.003405696,* see figures in appendix 7.5. The validation of this model is performed by comparing the mean error with the error of random data shuffled 1000 times. If our error is less than the 5^{th} *percentile (p<0.05),* of the random mean error, than we assume the model is better than chance, see figure in appendix 7.5.

4.5 Discussion

In this chapter, we show that **biased feedback** directly influences the user's:

- flow state, especially cognitive control: with positive bias, users feel significantly more in control than with no bias, and the least in control with negative bias.
- learning; positive bias seems to decrease learning during the first session, but increases in the second, however still remaining a (slightly) negative effect on learning; in contrast, negative bias increases learning in the first session, but severely decreases in the second (passing from positive to negative effect on learning). Finally, no-bias seems to provide stable (positive) learning during both sessions. However, there are still lacking evidence that concern the personality traits that influenced learning. That is further discussed below.

Although there is no evidence (from ANOVA tests) of direct significant influence, biased feedback seems to influence performance indirectly through flow. Moreover, flow state also reveals an indirect influence of biased feedback on learning as well, as follows.

- performance is related:
  - positively with flow; positive correlations (with mean of all dimensions of flow) indicate that the more one feels in control, immersed, without feeling judged, self-critical or tense, and is in a pleasurable state, the higher the performance levels. Considering that positive feedback increases flow, it indirectly increases performance.
- learning is related:
  - negatively with flow; negative correlations (with control and loss of self, 2 dimensions of flow) indicate that the more one feels in control, without feeling judged or self-critical, the less one progresses. This could also explain why positive biased feedback negatively influences learning, as it significantly increases sense of control; the same as negative feedback decreases control, which in turn increases learning.

This is indeed quite interesting but unexpected. Flow state represents a state of pleasure, to be immersed in the present moment, thus performances in short term can benefit from such a state. In contrast, on the long run, it is possible that in the flow state, there is a lack of "minimal cognitive stress" necessary for learning, for progress. Ironically, the flow state means that the person is too relaxed which is not beneficial for learning a MI skill.

When we consider prediction models, the user profiles (e.g. personality traits and calibration scores) directly predict or relate to:

- performance:
  - positively; especially competition enjoyment, extroversion (i.e., being warm, lively, socially bold etc.), and calibration scores from performance, flow and workload; This means that an increase in calibration scores, and traits (competition enjoyment and extroversion) predicts an increase in performance;
  - negatively; especially anxiety, self-control, and tough-mindedness; This means that the more one is anxious, self-controlling and tough-minded, the lower the performance.
- learning:
  - positively; especially calibration (performance) score, competition enjoyment, extroversion, anxiety, independence, self-control; this means that those who tend to be more extroverted, anxious, independent, self controlling and enjoy competition benefit from learning MI BCI.
  - negatively; tough-mindedness.

Interestingly, personality traits such as anxiety (being tense, vigilant, worried and emotionally unstable) and self-control (being perfectionist, rule conscious, non-lively and abstracted – withdrawn with internal ideas) are not useful for performance, but show useful for learning. The only trait that is equally inefficient for performance and learning together is tough-mindedness (being not warm, insensitive, not open to change and not abstracted).

Increasing performance. In order to increase performance, we can answer – who can benefit from a:

- **positive bias**:
  - those who are self-controlling; who are dependent, i.e., lack social boldness, dominance, vigilance and openness to change; and who have high calibration performance scores; they can benefit from a positive bias to increase their performance.
- **negative bias**:
  - those who do **not** enjoy competition, who are extroverted (in general), who are **not** anxious and those who have high calibration performance scores can benefit from a negative bias to increase performance;
- **zero bias**:
  - those who are competitive, who are independent, who have low self-control, who are not tough-minded i.e., rather warm, sensitive, abstracted and open to change, and those who have high scores in workload during calibration, can benefit from no bias in order to increase their performance.

– In contrast, performance can **decrease** when using a bias that is not suited for some personalities. So, we answer, who does not benefit from a:

- **positive bias**:
  - those who are anxious, who are independent and those who have low performance during calibration, they do **not** benefit from a positive bias;
- **negative bias**:
  - those who are dependent, anxious do not benefit from a negative bias;
- **zero bias**:
  - those who have low calibration performance scores, who are not in flow, and those who are quite self-controlling do not benefit from no bias.

Increasing learning. In the case we want to increase learning, we answer – who can benefit from a:

- **positive bias**:
  - those who are extroverted and independent;
- **negative bias**:
  - those who enjoy competition;
- **zero bias**:
  - none, or simply not enough evidence.

Those for which the learning decreases, or who do not benefit from a:

- **positive bias**:
  - those who have increased calibration performance; who enjoy competition; and those who are though-minded do not benefit from a positive bias;
- **negative bias**:
  - those who are tough-minded, who are independent, and those who are self-controlling do not benefit from a negative bias;
- **zero bias**:
  - none, or simply not enough evidence.

For a clearer visualization of all predictors who benefit or not, what bias and for what criteria (increase performance or learning), see figure 4.23.

PERFORMANCE	POSITIVE BIAS	NEGATIVE BIAS	ZERO BIAS
Good for:	Self-controlling Dependent High calibration scores (performance)	Low competition enjoyment Extroverted (in general) Not anxious High calibration scores (performance)	Enjoy competition Independent Low self-control Not tough Minded High calibration scores (workload)
Bad for:	Anxious Independent Low calibration scores (performance)	Anxious Dependent	High self-controlling Low calibration scores (performance and flow)

LEARNING	POSITIVE BIAS	NEGATIVE BIAS	ZERO BIAS
Good for:	Extroverted Independent	Enjoy competition	none
Bad for:	Enjoy competition Though-minded High calibration (performance)	Tough-minded, Independent Self-controlling	none

Figure 4.23: Clear table of optimal bias depending on criteria (performance or learning) and personality traits, and calibration scores (performance, workload and flow).

Hypotheses validated? **H1.** and **H2.** concern users with low performance during calibration, and who are at the same time typically anxious, non-competitive and dependent. Positive (H1.) would increase, while negative bias (H2.) would decrease both performance and learning.

H3. and **H4.** concern users with high performance during calibration, and who are at the same time typically extroverted, competitive and independent. Positive (H3.) would decrease, while negative bias (H4.) would increase both performance and learning.

Results show that:

A. Different rules apply whether it is for increasing performance or learning.

B. Different rules apply depending on the personality trait such as anxiety, extroversion, competitiveness, and independence.

Hence, we must analyze the hypotheses one by one, for each of these factors and predictors separately.

H1. Partially validated: – Positive bias does increase performance for persons who are dependent. However it does not increase for those who are non-competitive nor anxious. On the contrary, positive bias decreases performance for those who are anxious. Moreover it does not increase learning for neither dependent, anxious nor non-competitive persons. On the contrary, learning increases for independent personalities.

H2. Partially validated: – Negative bias does decrease performance for anxious and dependent persons, However, it does not decrease for non-competitive nor those who achieve low calibration performance scores. On the contrary, it increases performance for those who do not enjoy competition. Moreover it does not decrease learning for dependent, non-competitive subjects. On the contrary, it decreases for those who are Independent.

H3. Partially validated: – Positive bias does decrease performance who are independent. However it does not decrease for those who are competitive, extroverted nor for those who have high calibration scores. On the contrary, it increases performance for those with high calibration performance scores. Moreover, learning does decrease with positive bias for those who have high performances during calibration, and who enjoy competition. However it does not decrease for independent. On the contrary, opposite from what we expected, learning increases with positive bias for independent personality traits.

H4. Partially validated: – Negative bias does increase performance for those with high performances during calibration, and those who are **not** anxious. However it does not increase for independent users. Learning does increase for users who enjoy competition, however it does not increase for those who are independent. On the contrary, it decreases for those who are independent.

Summing interesting results. It seems as if those who are anxious, their performance does not benefit from either positive nor negative biased feedback. Simply, a biased feedback does not influence anxious persons. However, although seemingly a negative trait (and negative for performance), some level of anxiousness seems to be necessary for learning a MI skill.

It seems that low performance during calibration cannot be compensated with any type of bias, their learning curve remains in the negative (see result 4.11). However, clearly negative bias decreases even more their learning between sessions, while positive and no-bias have a tendency of increasing their learning. But it is as if because of the low calibration performance, they cannot surpass a limiting "threshold" and reach higher performances during testing. Possibly for them, there needs to be another assistive strategy as they might not lack control, confidence or useful personality traits to enable learning but might be missing something else. It is possible they could benefit from a training that provides better understanding of "how-to" produce or "what is" MI BCI.

4.6 Conclusion

In this chapter we show that with a biased feedback we can directly influence one's sense of control as well as learning. The sense of control increases significantly with the degree of positive bias. Such state along with other *flow* state dimensions (immersion, loss of self and pleasure) positively relate to performance. Interestingly however, learning does not benefit from a positive bias nor the *flow state*. Positive bias could effect a person to feel highly in control, thus induce no effort or minimal anxiety necessary for progress. On the contrary learning benefits from a negative feedback, but only during the first session, as in the long run it can clearly demotivate users and severely decrease learning.

Furthermore, in this chapter we reveal who would benefit from which type of biased feedback if any. We only partially validate our hypotheses. Partially because we did not account that opposite solutions might apply depending on the *optimization criteria,* i.e., whether it is for increasing learning, performance or pleasurable states.

In sum, we show that depending on the personality trait different bias can be useful be it for learning or for performance. Most interestingly, although still negative for performance, anxiousness seems to be somewhat necessary for learning a MI skill. On the other hand, those who have low calibration rates do not benefit from any provided biased feedback. It could mean that they need other assistive training methods.

On a side note, these results are quite preliminary so they are not to be taken lightly as *de facto*.

In the future, these predictors for optimal bias can provide prior information for an adaptive framework that would adapt the bias automatically for each user (depending on the *criteria* or goal). In the following chapter 5, we describe a simple adaptive method that uses knowledge from the user profile and calibration scores so to select the optimal bias for each user.

Chapter 5

Adapting MI Task with Priors from User Profiles

5.1 Introduction

We presented a taxonomy for adaptive BCIs (in chapter 2) in which we promote the benefits of adaptive tasks as a way to maximize a predefined criteria (performance, learning, *flow* state and so on). So far, we have investigated the influence of different task difficulties (feedback bias) on performance and learning. We have learned what personality types could benefit from which type of influence (positive, negative or zero feedback bias), see 4. In order to demonstrate that a BCI can indeed benefit from an adaptive task, we created a simple data-driven adaptation model that can consider user traits as priors.

In this short chapter, we provide a proof of concept of an adaptive model that selects optimal bias to increase performance in MI BCI. We perform simulations on data from 30 subjects acquired from our previous MI experience, from chapter 4. Personality traits and calibration performances are used as priors in the adaptive model.

In section 5.2, we provide a detailed explanation of our simple data-driven model that selects optimal action (bias) based on online performance at each run. In section 5.3 we describe the dataset, the simulations we performed, and different model variants that enable the validation of our simple model. In section 4.4 we provide our results and in 5.6 we present challenges and future work.

5.2 Adaptive Model

In this section we describe in detail our simple adaptive model that can take into account user priors if any, and adapt the bias (action) accordingly within runs. Let us assume that our optimization criteria is fixed and it is set to maximize performance. It governs the adaptation process of our model that has 5 elements:

- Actions a_i, e.g. one of the feedback biases (positive, negative or none) the machine can perform;
- Observations o_j, e.g. the computed performance per run;
- Priors k_i, that correspond to the relation of user traits and a given action (bias). For instance, for an extroverted user, a negative bias is favourable to increase performance;
- weight *w(t)* assigning preferences to observations that serves as an exploration-exploitation parameter which increases in time *t;*
- α being the confidence about priors k_i.

For each action $a_i(t)$, $i = 1, ..m$, there is a corresponding observation $o_i(t)$, at time *t=1,..,*τ. Let us denote the mean of all observations till time *t*, $\mu_i(t) = \frac{1}{t}\sum_{j=1}^{t} o_i(j)$, for each action $a_i(t)$. Such mean $\mu_i(t)$ is then weighted:

$$\mu_i'(t) = w(t)\mu_i(t) + \alpha k_i$$

where $w(t) = t \cdot \gamma$ and γ is a constant weight that assigns preferences to a certain observation and is multiplied by time, i.e., the weight *w(t)* increases at each time step *t*; while α is the degree of confidence for every prior k_i known for each action; Note that α is same for all priors k_i. Then the probability for the next action $a_i(t+1)$ to be selected is equal to:

$$p(\boldsymbol{a}(t+1)) = \sigma(\boldsymbol{\mu}'(t))$$

where $\sigma(\cdot)$ is a *softmax* function that transforms the weighted mean vector of observations $\boldsymbol{\mu}'(t) = [\mu_1'(t), .., \mu_m'(t)]^T$ into a vector of probabilities $\boldsymbol{a}(t+1) = p([\mu_1'(t), .., \mu_m'(t)]^T)$ which elements are all between (0,1) and sum up to 1. Note that we denote vectors with bold letters.

The probabilities are not stored nor updated, only the mean is updated with each new observation. As consequence, with each new observation, the probability of finding the optimal action increases. If we ought to store the probabilities and update them with newly observed and transformed data (also probabilities), than we would be using a log likelihood matrix $L^{m \times \tau}$, $L_i(t) = l(p(\mu_i'(t)\,; a_i(t))$, i.e., the probability to choose an action given the probability of observations. Nevertheless, we choose to keep this algorithm as simple and least computationally demanding as possible, hence we only store the observations and update their means.

To select the first action before any observation has been made, i.e., the first weighted mean value of observations is equal to the prior values $\mu_i'(t) = 0 + \alpha k_i$, and the first selected action directly depends on its given prior and its confidence, $p(a_i(t)) = \sigma(\alpha k_i)$, for *t=1.* Note that the action will not have equal probabilities to be selected for *t=1*, as the prior is different for each action.

As this model is supposed to be simple and easy to understand, we also provide a less mathematical explanation of the steps the model takes within the figure 5.1.

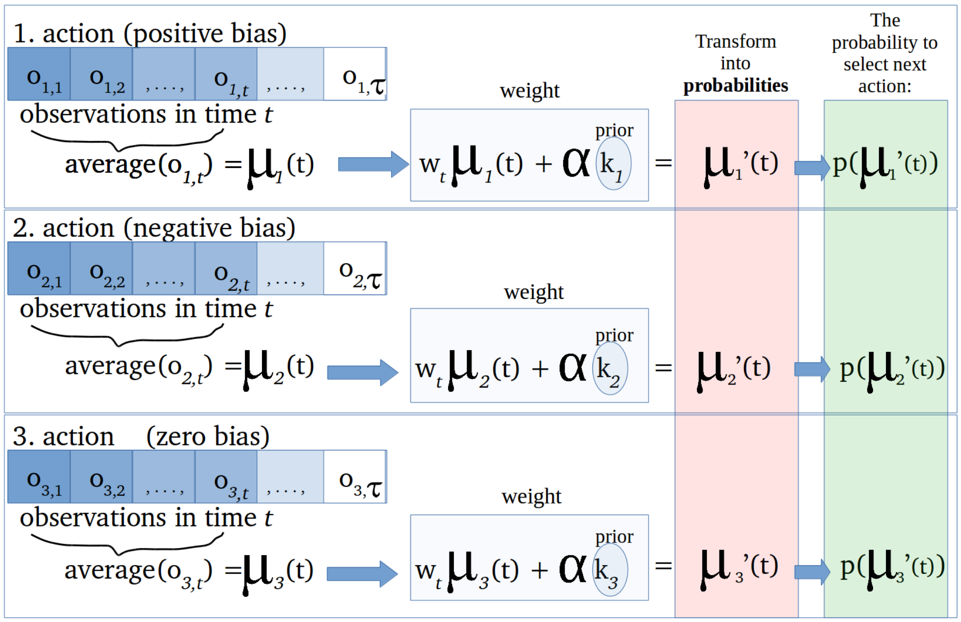


Figure 5.1: Each action $a_i(t)$ causes an observation $o_i(t)$ at time *t*, here *i*=1,2,3 possible actions (3 different feedback biases). After some time has passed *t*=*1..,*τ, each action creates a vector of *t* observations (the number of observations increases with time). At each new observation we re-calculate the mean of observations caused by one of these 3 actions. We then take into account the weights and priors that relate to each action, and "assign" them to the new observation mean $\mu_i'(t)$. The next optimal action *a(t+1)* is simply chosen by transforming $\mu_i'(t)$ into probabilities. This means that the next selected action would be the one that has the highest probability $p(\mu_i'(t))$.

5.3 Experimental Design

5.3.1 Dataset

We use data from 30 subjects, from which each performed 40 trials per run, 6 runs per session, and 2 sessions, giving a total of 480 trials per subject. Half of the trials is for left, and other half for right hand class motor imagery. 30 subjects were divided in 3 groups, each contained one type of feedback bias. Hence, 10 subjects reacted to either positive, negative or no bias. For more details on the protocol, see 4. We retrieve the average online (re-centered) performance of each run, that represent reactions to one of the 3 bias types, for a reminder of centered online performance see 4.3.

5.3.2 Simulations

Virtual Users. We only have data that correspond to one bias type per user, i.e., one person reacted to either positive, negative or no bias throughout 2 sessions. Hence, if we want to prove the usefulness of a bias that adapts within runs we need to create virtual users that contain data or reactions to 3 different biases. This was done by grouping real users into categories, for instance high-low calibration performance by high-low traits (4 combinations for 1 couple). The high-low groups were created by calculating the median value of trait for all subjects. We assured that in each category there was a user that perceived each of the possible biases, so that we can exploit such data reactions. We assume that users belonging to such group have similar reactions to a bias type, according to results from chapter 4. Hence, we created virtual users that contain multiple real users who reacted to all bias types in assumingly similar ways.

All the following combinations for 4-combination virtual users were possible:

- High-low calibration performance (first session) with high-low: tough-mindedness, extroversion, and self-Control
- High-low extroversion and high-low: anxiety, and independence;
- High-low anxiety and high-low: tough-mindedness, independence, and self-Control;
- High-low tough-mindedness and high-low: independence, and self-Control;
- High-low independence and high-low self-Control;
- High-low self-Control and high-low competition_enjoyment.

This means that one virtual user contains for example all the users who showed to be highly extroverted and highly independent. Giving a total of 12 couples x 4 high-low combinations, 48 possible virtual users who reacted to all bias types.

Model Input and Output. The model is fed with observations which are the average centered performance computed on all trials of each run. For more details on centering the classifier output, see 4.3 or [Vidaurre et al., 2010]. For each action, one observation (performance) is randomly fetched from the virtual user dataset. Note, depending on the virtual user dataset, for each action the number of observations can vary, i.e., the number of observations created by an action can belong to at least one user, but there can be more than one user.

The model produces an observation-driven action at every run, selecting one of the 3 possible biased feedback. The action selection depends directly on the observations and the preferences about future observations *w(t)*.

Model Priors. From our previous experiment, we have found what type of bias can increase performance depending on the personality type and calibration performance (see 4.5). We do not have new data to directly test these priors on, as they are predicted using both sessions from experiment 4. To learn the priors and avoid over-fitting, we train the priors on the first session and test them on the second session.

In order to facilitate the computation, note that we used a very simplistic approach for calculating priors. Lets select one virtual user, for instance a low anxiety and high independence user profile. For each action, we calculate the mean of performances for the low anxiety trait, and then separately for high independence trait. This creates 2 mean values for each action (3x2 values). The average value of the 2 means is then used as a prior value for that virtual user, and for each action. Hence there are 3 priors, each corresponding to one action. As consequence, the highest prior value will favour a particular action at time *t=1*. Note that the prior values are fixed, and do not change over time.

In the case in which the model does not contain any prior, the first observation *o(t=1)* is calculated as a mean of all 1^{st} session observations for all subjects (within all trait groups). In this case, each action will have the same probability to be chosen at *t=1* (no priors).

For validation purposes, to test the influences of priors on model adaptation, we created a model that we call the adaptive anti-prior model. For example, let say priors k_i favour actions a_i such that: $k_i \times a_i = [0.5a_1, 0.8a_2, 0.6a_3]$, this means that the anti-prior $\hat{k}_i$ would create such prior-action couples: $\hat{k}_i \times a_i = [0.8a_1, 0.5a_2, 0.6a_3]$. That is, the prior that favoured one action most, will now favour the one it favoured least, and vice versa.

Overall, we created 3 adaptive models: one with correct priors, wrong (anti) priors and one without any priors.

Model Parameters. The model contains two parameters: *w(t)*=γt and α. The first increases at each time step *t*, while the latter is constant for all priors and in time. *w(t)* provides more and more confidence in time about the desired observation, and consequently influences the choice of action related to such observation. Note that all the following simulations were performed on 48 virtual users, for 100 number of runs, and it was repeated 20 times.

In order to assess the effect of the parameters on the performance of the adaptive model, we chose the anti-prior model. Indeed it demonstrates more easily the influence they have on adaptation. If we chose an adaptive model with correct priors, it's progress would have been less obvious as it would have reached rather high performances from the start.

To demonstrate the impact of *w(t)* on adaptation, we present an example of the following values of $\gamma = [0.25, 0.5, 1, 2, 4, 8]$ in an adaptive anti-prior model, see figure 5.2.

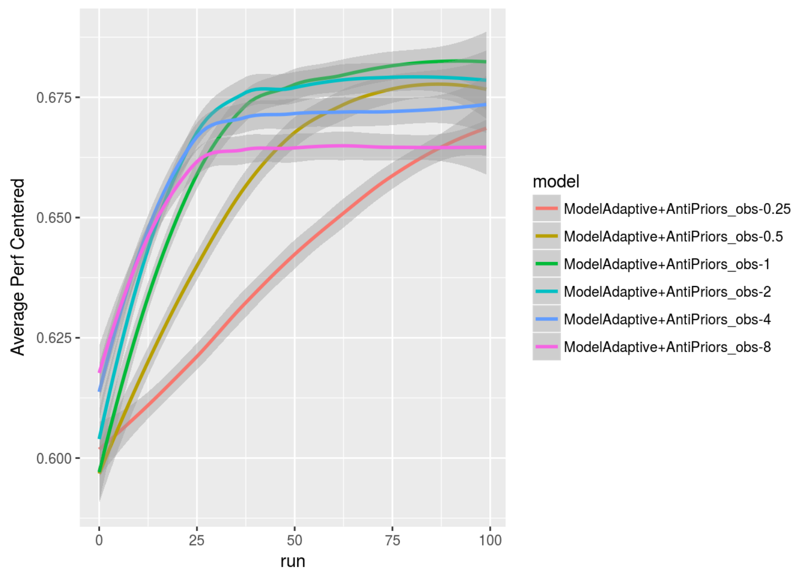


Figure 5.2: Different values of *w(t)*, with $\gamma = [0.25, 0.5, 1, 2, 4, 8]$ are represented in different colours and show their influence on performance across runs. The prior confidence $\alpha = 10$ is fixed.

The stronger the confidence about an observation, the faster the convergence. However if set as too strong (e.g. $\gamma = 8$, from figure 5.2) it might reach a plateau (local maxima) because it would stop exploring possible actions. While the other weights have higher exploration/lower exploitation levels (e.g. $\gamma = 1$) and take more time in the beginning to reach high performances, but manage to surpass the high exploitation weights.

To demonstrate the impact of confidence about priors on adaptation, we present different values of α, see figure 5.3.

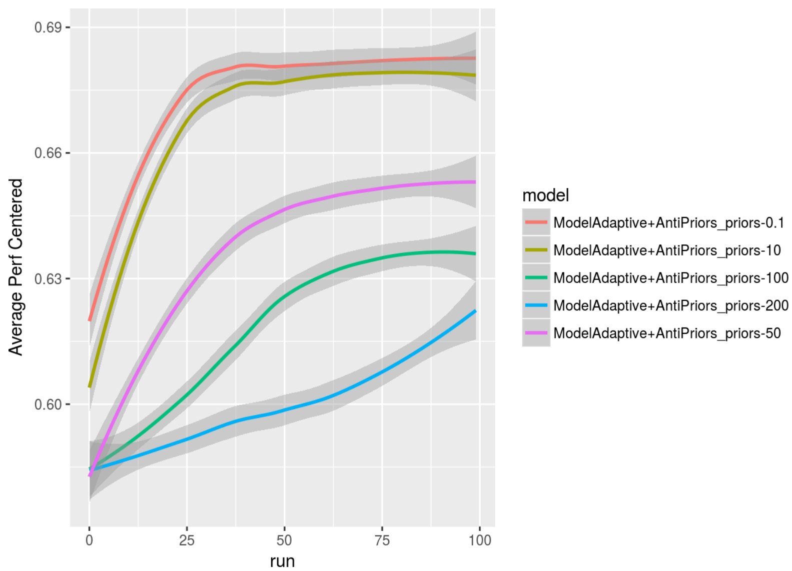


Figure 5.3: Different values of α, presented in different colours, influence the degree of confidence about the priors of the adaptive model. The observation weight $\gamma = 2$ is fixed.

Typically, the more the prior is correct, the model would benefit from a higher confidence parameter. As it is an anti-prior adaptive model, i.e., wrong priors are given, it means that the less confident the model is about the priors the faster it converges ($\alpha = 0.1$ in red from figure 5.3). Note that if the confidence about priors is set too high, (limit use case e.g. 1000), then the model would practically not adapt over time, and alway pick the action believed to be the best.

5.3.3 Evaluation Models

We wish to investigate the usefulness of our model that automatically provides an adaptive bias selection within runs based on user traits. To do so, we compare the following adaptive models:

1. Adaptive model basic (data-driven); it is the model we presented, but without priors;
2. Adaptive model basic with priors about user traits and actions;
3. Adaptive model basic with wrong priors about user traits and actions;

To show the benefits of an adaptive (data-driven) model versus non-adaptive models, we create and compare non-adaptive (not data-driven) models:

1. Fixed negative bias model; this model will always choose a negative bias, for each user;

2. Fixed positive bias model; this model will always choose a positive bias, for each user;
3. Fixed no_bias model; this model will always choose a zero bias, for each user;
4. Fixed bias; user-centered (with prior) model, this model is not data driven (i.e., it does not take into account user reactions to the bias) but uses priors from each user, i.e., it selects such bias that has shown to increase performance for that particular user;
5. Fixed bias with wrong (anti) prior model; this model selects such bias that has shown to influence negatively that user; it uses the wrong priors intentionally.

As a "control" model, we also created a:

1. Random model; this model does not use any prior and it picks observations randomly at every run.

Evaluation Performance. To evaluate the models, we simply compare the performances between each model after 20 repetitions for all 48 virtual users and a fixed number of runs. We then perform a 1-way ANOVA (independent variable: model, dependent variable: performance). with Tukey post-hoc and false discovery rate correction for multiple comparisons [Noble, 2009]. We set the significance threshold at $(p < 0.05)$.

Furthermore, we also depict the convergence over time of the various models. Note that from the dataset we selected average centered online performances which are quite pessimistic but less variable, when compared to peak performances for instance.

5.4 Results

We compare all the presented models with each-other, and show their significant differences. Note that the observations are drawn with repetition from the 2^{nd} session dataset (testing dataset), because the 1^{st} session served as training for the priors. Each box-plot represents 20 repetitions for 48 virtual users and 6 runs. As with the original dataset, we consider that 6 runs compose 1 session and we assess the performance of the model on the first virtual session (1-6 runs), see figure 5.4, for the 3^{rd}virtual session (13-18 runs), see figure 5.5, and 6^{th} session (31-36 runs), see figure 5.6. Regarding the simulations from 5.3.2, we empirically chose the parameter values of $\gamma = 2$, and $\alpha = 10$ for our simulations.

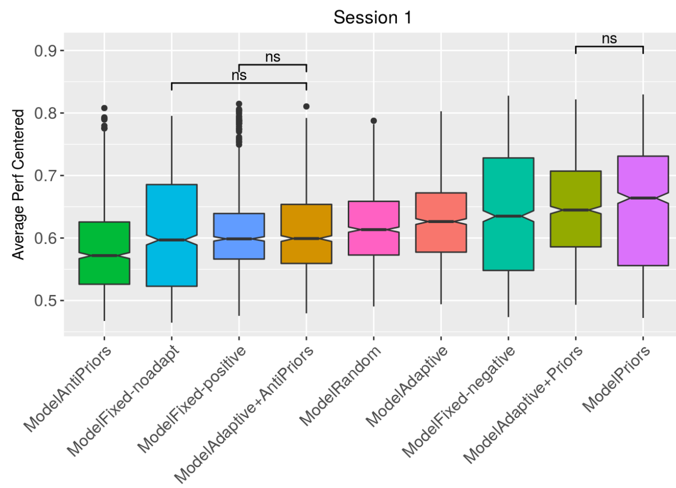


Figure 5.4: Comparison of all models after the 1^{st} (testing) session, i.e., runs 1-to-6, the differences between the pairs of models are significant unless indicated otherwise with "ns". The models are arranged by their median performance, in an ascending order from left to right.

After one session, the worst model shows to be the fixed model with anti-priors, while interestingly the negative fixed model performs the second best after models with priors (adaptive or fixed). The basic adaptive model is in the 4^{th} place.

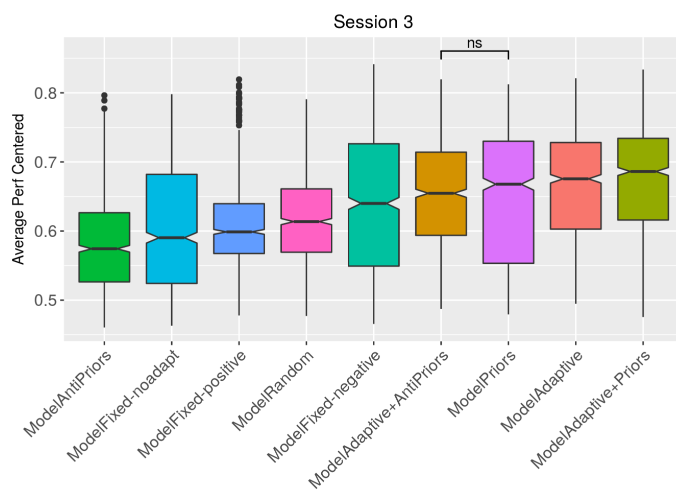


Figure 5.5: Comparison of all models after 3 (testing) sessions, i.e., runs 13-to-18, the differences between the pairs of models are significant unless indicated otherwise with "ns". The models are arranged by their median performance, in an ascending order from left to right.

In the 3^{rd} session, the worst model shows to be the fixed model with anti-priors, while the adaptive models overcome the fixed ones, the basic adaptive model reached the second best place after the adaptive model with priors. The fixed model with priors falls down to the 3^{rd}, while the fixed negative model down to the 5^{th} place.

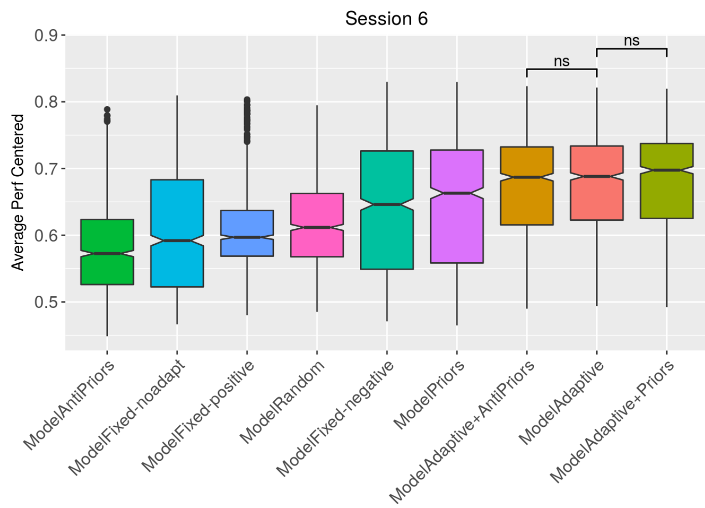


Figure 5.6: Comparison of all models after 6 (testing) sessions, i.e., runs 31-to-36, the differences between the pairs of models are significant unless indicated otherwise with "ns". The models are arranged by their median performance, in an ascending order from left to right.

In the 6^{th} session, the adaptive models (with, without and anti priors) perform best, surpassing fixed model with priors and fixed negative models.

For a better visualization of the evolution of each model (for all virtual users, and 20 repetitions for each run), see figure 5.7.

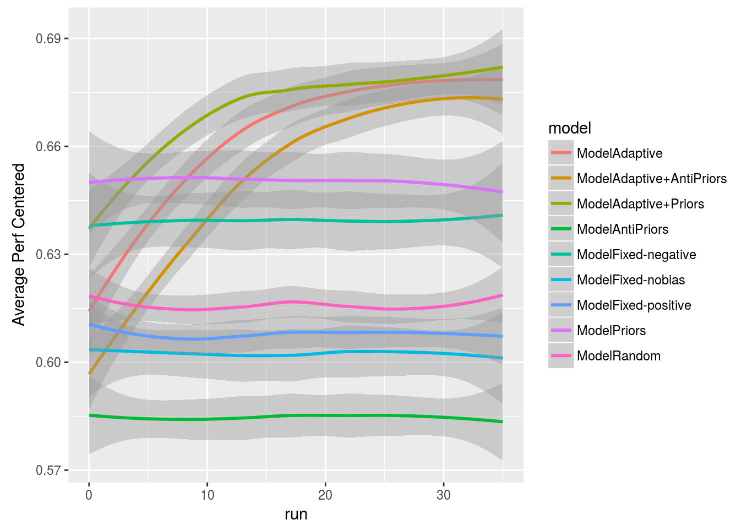


Figure 5.7: Evolution of performance for each model within 40 runs. Each colour represents a different model.

We can see that after about 10 (± 3) runs, the adaptive models reach higher performances than the fixed ones. The model reaching highest performances is the adaptive model with priors. It also has a high start, given the right priors, in contrast the anti-prior model which starts with lowest performances because of the wrong priors.

We summarize the performances between models for sessions: 1, 3, and 6, in table 5.1.

Table 5.1: Mean (SD) of the average performance centered between models for different simulated sessions. N=960 (48 virtual subjects, 20 repetitions).

	Session 1	Session 3	Session 6
ModelAntiPriors	0.58 (0.07)	0.58 (0.07)	0.58 (0.07)
ModelFixed-noadapt	0.60 (0.09)	0.60 (0.08)	0.60 (0.09)
ModelFixed-positive	0.61 (0.06)	0.61 (0.06)	0.61 (0.06)
ModelRandom	0.62 (0.06)	0.62 (0.06)	0.62 (0.06)
ModelFixed-negative	0.64 (0.09)	0.64 (0.10)	0.64 (0.10)
ModelPriors	**0.65** (0.09)	0.65 (0.09)	0.65 (0.09)
ModelAdaptive+AntiPriors	0.61 (0.06)	0.65 (0.07)	0.67 (0.07)
ModelAdaptive	0.63 (0.06)	0.67 (0.07)	**0.68** (0.07)
ModelAdaptive+Priors	**0.65** (0.07)	**0.67** (0.08)	**0.68** (0.07)

It is also interesting to observe the evolution of performance for each virtual user, see examples of a user with high independence and high extroversion in figure 5.8, with high independence and low extroversion in figure 5.9, and with low independence and high anxiety in figure 5.10. In a way these representations can also serve as a validation approach for our predictions about optimal bias for each user from chapter 4.

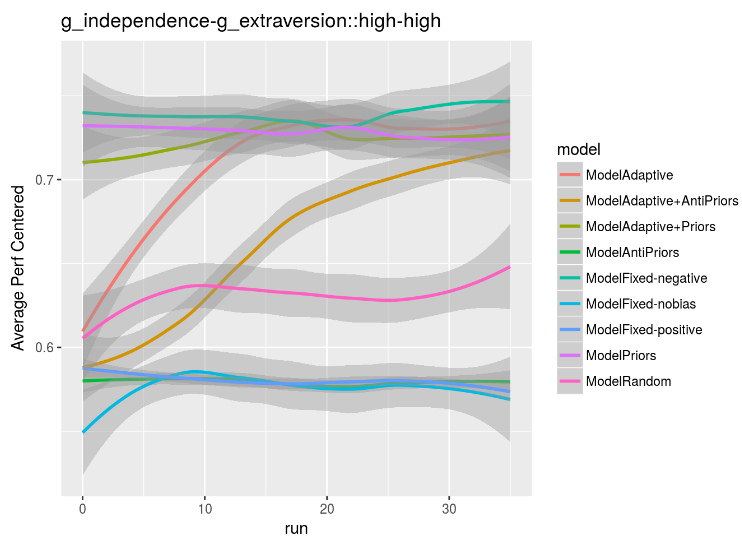


Figure 5.8: Evolution of performance within runs for a virtual user that is highly independent and highly extroverted, denoted as *g_independence-g_extraversion::high-high* (*g_* stands for group). For this user, negative fixed model performs best.

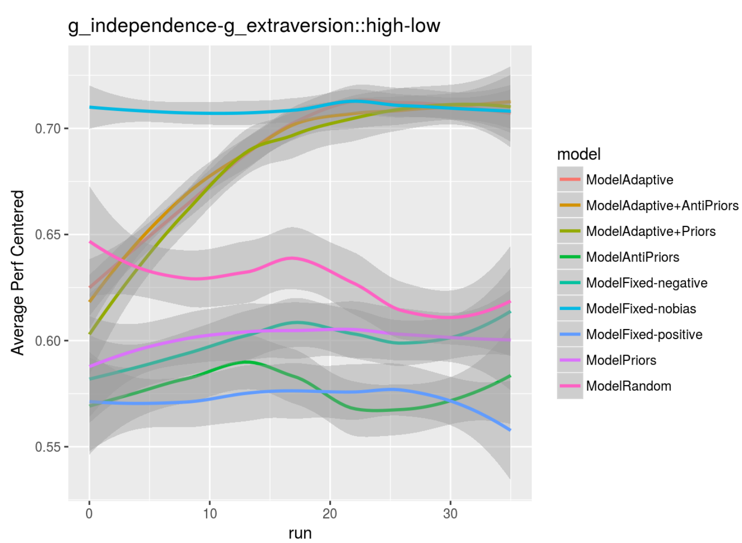


Figure 5.9: Evolution of performance within runs for a virtual user that is highly independent and not-extroverted, denoted as *g_independence-g_extraversion::high-low*. For this user, no_bias fixed model performs best.

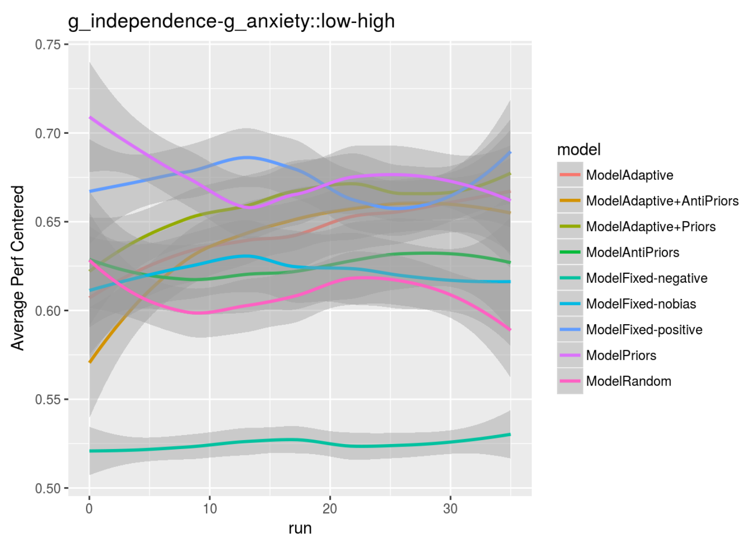


Figure 5.10: Evolution of performance within runs for a virtual user that is highly independent and not-extroverted, denoted as *g_independence-g_anxiety::low*-high. For this user, positive fixed model along with the fixed model with priors perform best.

5.5 Discussion

From table 5.1, the adaptive model with priors performs the best on average. Also, locally, if the model has priors about the user traits, even if it is not adaptive, it can be very useful for increasing performance. That means that thanks to our prediction models from chapter 4, we can use the knowledge about the user traits to locally increase performance with significant rates.

Model convergence on average. Regarding the evolution of performances within runs, of all virtual users on average (figure 5.7), the fixed models do not converge, and after about 10 runs the adaptive models show evident superiority. If the model is adaptive (data-driven) and has correct priors, already after about 3 runs it outperforms all other models on average.

Virtual user models. Regarding the evolution of performances within runs per virtual user, we can observe and somewhat confirm the usefulness of having priors, i.e., knowledge about what type of feedback bias is useful for what type of personality trait. On part with results from chapter 4.5, we confirmed that those who are highly independent and **extroverted** benefit from a **negative** bias, those who are **independent** but not extroverted benefit from a **no_bias** feedback, and those who are **dependent** and highly anxious benefit from **positive** bias. Interestingly when there are opposed groups within one virtual user (high and low), the adaptive model anti-prior has similar success as the adaptive (basic) model, i.e., it reaches quite high performances. When a virtual user is a combination of two very different traits, i.e., traits for which opposite biases would be preferable, the fixed model with priors does not perform best. We could say that is the case for high-independence and low-extroversion traits combination, see figure 5.9. In such situations, i.e., when it is difficult to predict the user performance, adaptive models would be even more useful because they would be able to automatically find the best action for any user profile.

5.6 Conclusion

In this short chapter, we introduce a simple adaptive (data-driven) model that can incorporate user profile as priors to guide its adaptation in a MI (binary class) task. It is computationally very easy to re-create and understand.

Notably, this model produces an action (negative, positive or no bias) that directly depends on its observations and the preferences over future observations. Such preferences govern the exploration-exploitation ratio. When equipped with priors, even with wrong priors, it manages to automatically increase performance after a few runs.

We have presented the benefits of data-driven models when compared to non-adaptive (fixed) models that cannot change actions within runs. Indeed, especially for more than one session, the necessity of an adaptive task is evident for performance maximization (to reach global maxima). The fixed models tend to stay in local maxima, and their success depends purely on the correctness of their priors.

We have also confirmed the usefulness of having priors about user traits. For instance, within one session (6 runs of about 200 seconds trials per run) for a particular user trait, a fixed model with correct bias can be the optimal solution even in the long run. However, if the certainty about the priors is low, then it is much safer to use an adaptive model that can maximize performance even with wrong priors.

At this point, the major drawback of this model is the assumption that, if in the same trait category, multiple users behave the same way when presented with a bias. We randomly fetch data from each virtual user, that can in fact be multiple users. But considering that we did not have any data available, i.e., only one bias type was presented for one user, this was the only possible solution we could think of to simulate user reactions to all 3 biases. The major limitation is that we do not actually have real user reactions, their evolution in time to a changeable bias. Hence, to truly validate the adaptive model, we should to test it online. We could also compare it with state-of-the art adaptive models. Moreover, we could try to configure this model to adapt other types of machine actions, and possibly in other BCI paradigms. Additionally we could also envision combining priors over various optimization *criteria* i.e., performance and state of flow.

Our model might be suboptimal if the user states change over time, e.g. decrease in attention level. Indeed due to the constant increase of observation weight $w(t)$ over time, the model will eventually stop exploring any new possible action. In other words, it does not account for a potential decrease in user performance over time. In that case, we would need a more generic and flexible model. In the next chapter, we introduce a Bayesian (Active) Inference approach that could account for such changeability over time.

Chapter 6

Adapting P300-Speller task with Active Inference

Philosophical Thought Active Inference relies on the fact that we can never know the true nature of the world but have only approximate knowledge based on our sensory evidence. One only has a mental representation of the world that is being updated thanks to new experiences and sensory observations. In other words, the reality is a mental construct represented through only existing means, which are, somatosensory events.

This is directly linked to Kant [Kant, 1998], and a philosophical current called transcendental idealism. Kant stated that we can know only the phenomena of the objects (world), i.e., what appears to our senses and *pure* reason[1]. Such phenomena we than transform according to the predefined structures called categories (from which space and time characterize the senses, while the others, such as quality, quantity, relation, modality, and their subcategories belong to *pure* reason). These universal (i.e., applied to everyone) categories allow processing of data, which we conceive as our experience of the world. What that world is really about, we can never know; in its essence, it is *noumenon* (unknowable).

"...all objects of a possible experience are nothing but phenomena, that are, mere representations ... and have no self-subsistent existence apart from human thought." (page 307 from [Kant, 1998]).

6.1 Introduction

We investigated various influences the task could have on the users, such as sound and the feedback bias. We show that depending on the goal, whether it is a MI training, or

[1] there is also *practical* reason that is linked to morality

P300- speller, different optimization *criteria* may apply from maximizing flow state, performance to learning rate (chapter 2). We proposed prediction models to anticipate which action (biased feedback) is best for certain user profiles, depending on the criteria (chapter 4). Therefore, we created a simple adaptive model that can account for the various user profiles, and adapt its action (bias) within runs (chapter 5). It does so by observing user reactions to its actions, and by following a predefined criteria, i.e., to maximize performance. This model is not realistic as it presumes the performances are stable in time.

What if we can endow the machine with such a model that can account for the changeable user states during a BCI task. A model that is generic enough, but with only a few key parameters, such as: the goal, user states, and machine influence (actions); can it enable the machine to perform adaptation automatically to each user? In this chapter we explore one such generic computational model.

Going adaptive is a major challenge for the field of Brain-Computer Interface (BCI) that struggles to produce efficient and robust applications. This entails a machine that optimally articulates inference about the user's hidden states from measured brain signals by means of controlling the stimulus presentation at each trial. Adaptation can operate over several dimensions which calls for a generic and flexible framework to implement such a dynamic behavior. Therefore, we appeal to what is arguably the most recent and comprehensive computational approach to brain functions: the Active Inference (AI) framework. It entails an explicit (probabilistic) model of the world the AI agent is interacting with, here the user involved in a P300-spelling task. In our context, this corresponds to a discrete input-output state-space model establishing the link between the machine's (i) observations – a P300 or Error Potential for instance, (ii) representations – of the user intentions to spell or pause, and (iii) actions – to flash, spell or switch-off the application. We show how this one model endowed with Active (Bayesian) Inference enables to implement optimal (dynamic) stopping but also optimal flashing (i.e. active sampling), automated error correction, and switching off when the user does not look at the screen anymore. Importantly, this framework enables the machine to automatically decide between all its possible actions. For instance, in the case of correction spelling, the machine evaluates the optimal action whether to spell the next probable letter or to continue flashing to accumulate further evidence. We demonstrate Active Inference for BCI through simulations of a P300-speller task using real data from 18 subjects. Results demonstrate the ability of AI to yield a significant increase in bit rate over state-of-the-art approaches. This approach represents a promising solution for creating a unifying framework for BCI applications while enabling co-adaptation.

6.1.1 P300 Speller

One of the most commonly used non-invasive BCI for communication is the visual P300-speller [Farwell and Donchin, 1988]. It relies on event-related potentials (ERPs) notably including the P300 – an EEG positive deflection occurring around 300ms after a rare and relevant event. This event can be the display or highlighting of an expected item (e.g. a letter, a number or a picture). With a P300-speller, the subjects are typically presented with a 6x6 grid of characters, where a set of items within a row or a column are flashed in a pseudo-random order (the Row-Column – RC paradigm). To select a letter, during the flashing, the users need to focus their visual attention on the item they wish to spell. Once the target item is flashed, the brain reacts with a P300, enabling the machine to detect the particular ERP and spell the desired character. Online, the machine aims at inferring which stimulus corresponds to the targeted item. In order to gain confidence about the target letter, the machine flashes the items in repetition. Intuitively, one would believe that the longer the machine flashes, the higher the confidence. However, this is not necessarily the case, as the user's vigilance may drop over time which affects the EEG signals and hence classification accuracy. For more details see [Sellers et al., 2006].

6.1.1.1 Related Work

Although the P300-speller has a relatively high Information Transfer Rate (ITR) compared to other BCIs, it remains a fairly slow and cumbersome mean of communication due to the necessity of trial repetition for a fairly correct P300 classification [Blankertz et al., 2004]. In our context, it is interesting to consider such improvements as belonging to either one or the other of the two following categories:

(1) Static methods, that implement static design enhancements to increase the signal-to-noise ratio (SNR), e.g. by (i) preventing perceptual errors such as the "repetition blindness" – when flashing the same item consecutively [Schendan et al., 1997, Jin et al., 2012], or the "near-target effect" – when flashing within a close range both temporally and spatially from the target letter [Cinel et al., 2004], varying the inter-stimulus intervals or flashing patterns [Sellers et al., 2006]; or (ii) motivating users with more engaging playful environments [Qu et al., 2018], captivating stimuli (smileys [Jin et al., 2012] or real faces [Jin et al., 2012, Kaufmann et al., 2011]), intelligent (but not data-dependent) order of stimuli apparition [Verhoeven et al., 2015, Mainsah et al., 2017]; inter-symbol distance, symbol size, contrasted foreground and background colours [Salvaris and Sepulveda, 2009] or monetary rewards [Kleih et al., 2010].

(2) Dynamic methods, that endow the machine with flexibility or adaptive behavior such that it will adjust some of its design parameters based on the online acquired signals and the states of the ongoing interaction. These usually include probabilistic or Bayesian approaches to update the machine's belief in real time and optimize the resulting decisions. For instance, optimal (or dynamic) stopping both reduces the number of flashes and increases accuracy by using the brain response to each flash to update both its belief about the target letter and its confidence about this belief [Verschore et al., 2012, Thomas et al., 2014, Mattout et al., 2015].

In [Mattout et al., 2015], the outcome of a probabilistic classifier is updated online, permitting the machine to stop and spell a letter once it attains a predefined confidence level. Here the decision speed (number of flashes) depends on the consistency and reliability of accumulated evidence. Another example is the effort to get rid of individual calibration, by implementing unsupervised classification [Woehrle et al., 2015], or by adopting a transfer learning strategy based on data from previous subjects [Kindermans et al., 2012, Gayraud et al., 2017]. To go further in assisting the user to spell words, some authors implement language models together with the optimal stopping to reach higher ITR [Kindermans et al., 2014b]. Automatic spelling corrections using Error Potentials (ErrPs) have also been used [Margaux et al., 2012, Cruz et al., 2018]. It should be noted that the subject directly influences the level of improvement that can be achieved. Indeed, when users reach higher accuracy thanks to adaptive machines, they become more motivated, which in turn yield higher SNRs hence an even higher accuracy. A virtuous cycle that has been evidenced online when implementing optimal stopping [Mattout et al., 2015]. And most recent advances in adaptive P300 spellers go beyond optimal stopping by also incorporating optimal flashing, a form of active sampling that consists in flashing the group of letters that should provide most information to reveal the target [Kalika et al., 2017].

Considering (1), some "static methods" could apply to every subject (such as prevention of near target or repetition blindness effects), but other solutions, such as different colours, letter size, inter-stimulus intervals, or 3D environments seem to be non-transferable across all subjects. Typically, those are specific to a particular BCI scenario, person or even time period. Furthermore, these methods are not sensitive to changes in user states (they do not adapt), for instance they could not account for user fatigue. We believe that these static solutions can increase the initial usability, but not a long-lasting one. We find it is of essential importance to merge the knowledge used for static design methods and apply it in a dynamic way.

Considering (2), the "dynamic methods" – the few existing adaptive developments have been designed independently of each other, namely, adaptive flashing and adaptive spelling. It appears difficult to combine such adaptive actions in one computational framework, as one needs to find a way for the machine to optimally arbitrate, online, between alternative actions. For instance, in adaptive stimulus presentation as proposed by [Kalika et al., 2017], the authors used a probabilistic model to implement optimal stopping with a fixed decision threshold, and relative entropy with a greedy search algorithm to select the next sequence of flashes. However, such a solution is not generic in the sense that the action space remains limited and specific to the particular phase of the ongoing interaction (e.g. flashing, spelling or correcting). As a consequence, right after spelling an item for instance, the machine cannot choose between validating this item or flashing again to acquire more evidence, or immediately spelling another item instead. Furthermore, as such a decision relies on the ability to detect an Error Potential (ErrP), one has to be able to evaluate the confidence of ErrP detection within a single trial, which is a very noisy step. As a matter of fact, ErrP classifiers have to be used online with precaution. This is because in case of low specificity (i.e. high risk of labeling a correct letter as an error), the correct letters can be replaced with another (wrong) one. This phenomenon has shown to be quite frustrating for users [Margaux et al., 2012]. Some authors even recommend not to use such corrections, stating that word auto-completions using contextual and language models suffice [Mainsah et al., 2015]. Indeed, for such an automated correction to be effective, an adaptive framework is needed to optimally weight all possible alternative decisions, based on their relative predictions and confidence. In particular, this requires a unifying framework in which the various relevant quantities can be negotiated in a common currency. For instance, additional information need to be traded with the time needed to get that information and, as well, with the expected reward associated with error-free communication.

6.2 A Unifying Framework

The required unifying framework puts an emphasis on the various decisions and actions the machine may take. In that sense, it extends the adaptive approaches that implement learning abilities only (e.g. adaptation of feature extraction or classification parameters over time using machine learning techniques) with active sampling which provides actions in a way that also influences the user and optimizes the interaction. We have previously advocated for these two complementary aspects of co-adaptation in BCI and proposed a unifying conceptual framework in Chapter 2 [Mladenović et al., 2017b].

In this chapter, we propose and illustrate an instantiation of the conceptual framework (taxonomy of adaptive BCIs), based on a recent computational model developed in theoretical neuroscience and called Active Inference [Friston, 2010]. It resides on the mentioned perception-action cycles that couple the agent to its environment. Note that in our context, the environment of interest for the machine or (artificial) Active Inference agent is the BCI user. Active Inference rests on a generic Bayesian approach that we show could incorporate various instances of adaptive BCI techniques into one flexible framework. It involves a formal generative model, in which the dependencies between observations, user states (intentions) and actions are specified given a particular context (here a P300-speller BCI). Based on this probabilistic model and an optimization criterion referred to as the Free Energy Principle (FEP), the machine infers the user's intentions (what letter to spell, if none then pause) from EEG observations and computes optimal actions (to flash or spell). Applying Active Inference in a P300 speller context thus naturally endows the interaction with *optimal flashing and spelling*. Importantly, Active Inference turns an optimization problem (action selection) into a Bayesian inference one where preferences or goals are specified in the form of prior expectations. Desired outcomes are encoded in terms of quantitative priors.

We apply Active Inference on a simulated P300-speller, using real data from 18 subjects. Moreover, to demonstrate the flexibility of this framework, we implement various adaptive features such as automated error correction or the detection of a state where the user is looking away from the screen. As these features correspond to alternative (hidden) states that the machine's model of the user considers plausible, and since the Active Inference framework rests on a single optimization criterion (the FEP), the machine will automatically arbitrate between all possible actions based on both in-build priors and incoming observations. Note that in this first demonstration of Active Inference for BCI, we consider a simplified situation where observations are not raw EEG data but appropriately pre-processed, extracted and classified features. In other words, the Active Inference framework is here plugged-in on top of a classical feature extraction and (probabilistic) classifier for P300-based BCI.

In the following sections, we first summarize the general principle of Active Inference in 6.3, emphasizing its genericity and flexibility. We then describe in 6.4 how Active Inference can be applied in the context of P300-speller BCI. We then introduce in 6.5 the real data and features we used to evaluate this new approach by simulating online spelling. The following section 6.6 presents the obtained results, comparing Active Inference with state-of-the art algorithms. Finally, sections 6.7 and 6.8 comprise our final words about this method and future work.

6.3 Active Inference: A Unifying Computational Framework

The Active Inference framework has been proposed as a biologically plausible computational model of the brain [Friston, 2010]. Here we build on the analogy between the brain and any adaptive system. We endow the machine with Active Inference in order to enable it to flexibly interact with the user in a P300-based BCI. In 6.3.1, we introduce Active Inference as proposed in computational neuroscience, and draw the brain-machine analogy.

6.3.1 Active Inference: Model of the Brain

By the end of the last century, neuroscientists ceased to perceive the brain as a passive organ which simply processes stimuli, but as an active organ that constantly updates a (probabilistic) model of its environment and predicts future sensory inputs [Rao and Ballard, 1999]. This view has given rise to the so-called Bayesian brain hypothesis whereby the brain is thought to implement (approximate) Bayesian inference. A compelling computational framework that incorporates the Bayesian brain hypothesis aiming at explaining perception, learning and decision making in biologically plausible terms. In this scope, the most advanced General Framework both computationally and theoretically is Active Inference [Friston, 2010]. It extends approximate Bayesian Inference by tightly coupling perception with action (unifying cause and effect).

In other words, as living beings cannot directly perceive the true states of the world (the cause), they need to infer them from noisy observations (the effect). Such inference is achieved by repeatedly performing perception-action cycles. They constantly anticipate the true states and represent them within a generative model of sensory inputs. This way they are implicit *Bayesian modelers of their environment* [Friston, 2010]. In order to exchange with an ever-changing environment and maintain homeostasis, biological (adaptive) systems restrict themselves to a limited number of states. In other words they are resisting the natural tendency of dispersion (resisting the $2\hat{}nd$ law of thermodynamics) [Friston, 2010]. This mechanism can be seen as minimizing the entropy (disorder or unpredictability) of the distribution over the outcomes they experience (observations) relative to a desired outcome (e.g. homeostasis).

6.3.1.1 A Brain - Machine Analogy

In BCI, the observations (EEG) are often very noisy and contain high variability for which we often do not know the cause, and thus cannot control its outcomes to our favor. We wish to endow the machine with Active Inference, in order to model the causes of observations, to better anticipate and favor certain outcomes. This is indeed what we are looking for in BCI systems. As such, let us draw a parallel between (i) **the brain** as an adaptive system, described by Active Inference, which:

- accumulates observations to update its internal model of the environment,
- optimizes its interactions through making inference about the environment,
- optimizes its interactions through acting upon the environment;

and (ii) **the machine** which should incorporate the same behavior to achieve a co-adaptive BCI (knowing that the brain constantly adapts, changes), namely:

- accumulate observations – EEG data – to update its internal model of the user, e.g. the model containing probabilities of user's intentions, states, reactions to machine's actions etc.
- optimize its interactions through making inference about the user, i.e., with the updated user model, updated prediction for a certain user state e.g. fatigue or intention to spell or pause
- optimize its interactions through acting on the user, i.e., with the updated user model, reinforce predictions or reduce prediction error with optimal action (feedback or stimuli).

Both the brain and the machine behave in order to best anticipate future outcomes by minimizing entropy (minimizing chaos, or maximizing information) relative to a desired outcome. In the following, we expose (a) the generic discrete state space model used by the Active Inference framework to model sequential learning and decision making by the brain, and (b) the objective function (relative entropy) it minimizes – free energy.

6.3.1.2 Generative Bayesian model and Free Energy

Sensory evidence (observation) is evaluated and updated given a generative model m under Markovian assumptions in order to reach optimal predictions. The model contains priors over future outcomes that encode one's goals or preferences. Such priors influence action selection, as depicted in Figure 6.1. Note that m embeds the generative model assumptions specific to each agent.

The generative model m is a joint probability over hidden states $\mathbb{S}$, control states $\mathbb{U}$, observations $\mathbb{O}$ and model parameters:

$\mathbb{S}$ – **finite set of hidden states:** Hidden states are internal representations a living being (or a machine in our case) can have about the hidden causes of their sensations (observations). For instance, they can be the letter on the user's mind that cause a P300 EEG deflection (machine's observation) after the presentation of flashing letters (machine's action).

$$\mathbb{S} = s^{(1)}, s^{(2)}, .., s^{(n)}, \text{ with } |\mathbb{S}| = n;$$

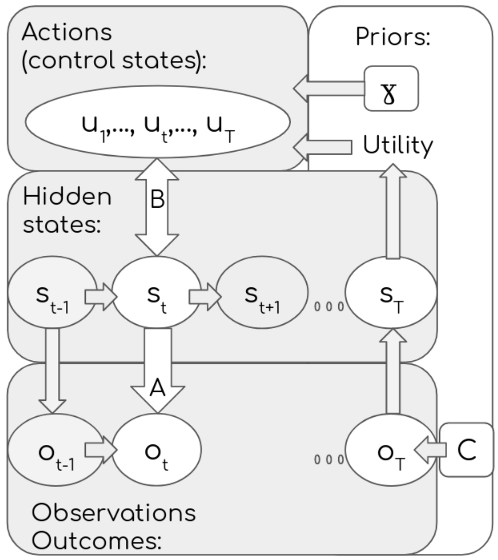


Figure 6.1: Illustrates Markov model of hidden states S, control states U and observations O. Actions are sampled from the posterior probability distribution over control states, which is parametrized by the precision parameter γ and preferences over future outcomes C. The latter assigns high values to desired final outcomes or states and penalizes undesired ones.

Let s map each trial t onto one element from finite set $\mathbb{S}$;

$$s(t) = s_t \in \mathbb{S}, \quad \forall t = 1, ..., T$$

where n represents the number of possible states, or cardinality of $\mathbb{S}$ at every trial t; T is the final trial, and t the current one. This means that only one state out of n possible ones can take place at a time or trial t.

$\mathbb{U}$ – **finite set of control states or actions:** In active inference, actions are sampled from beliefs about control and, thus need to be inferred from observations. However for simplicity, in most implementations of active inference, realized actions are assumed to be known by the agent. The agent entertains posterior beliefs about the control of (hidden) state transitions. In the previous example, a possible action would be the flashing of a specific letter.

$$\mathbb{U} = u^{(1)}, u^{(2)}, .., u^{(r)}, \quad \text{with } |\mathbb{U}| = r;$$

Let u map each trial t onto one element from finite set U;

$$u(t) = u_t \in \mathbb{U}, \quad \forall t = 1, ..., T$$

where r represents the number of possible states, or cardinality of $\mathbb{U}$ at every trial t. Only one action out of r possible ones can take place at a time or trial t.

$\mathbb{O}$ – **finite set of observations or outcomes:** Observations are anything an agent can directly sense. In our example, taking the machine's perspective, they are the (discrete) EEG signal.

$$\mathbb{O} = o^{(1)}, o^{(2)}, .., o^{(z)}, , \text{ with } |\mathbb{O}| = z;$$

Let o map each trial t onto one element from finite set $\mathbb{O}$;

$$o(t) = o_t \in \mathbb{O}, \quad \forall t = 1, ..., T$$

where z represents the number of possible observations, or cardinality of $\mathbb{O}$ at every trial t. Only one observation out of z possible ones can take place at a time or trial t.

The generative (Bayesian) model as defined in [FitzGerald et al., 2015] writes:

$$P(\tilde{o}, \tilde{u}, \tilde{s}, \gamma \,|\, m) = \underbrace{P(\tilde{o}\,|\tilde{s}, m)}_{likelihood} \underbrace{P(\tilde{s}, \tilde{u}\,|\gamma, m)}_{transitions} \underbrace{P(\gamma\,|m)}_{precision} \tag{6.1}$$

where $\tilde{o} = o_1, .., o_T \in \mathbb{O}$, $\tilde{s} = s_1, .., s_T \in \mathbb{S}$, $\tilde{u} = u_1, .., u_T \in \mathbb{U}$. Note that we denote matrices with bold capital letters and vectors with only capital letters. The model is defined by three major elements, as given in equation (6.1):

(i) from (6.1)**, Likelihood matrix A**: represents the likelihood of observations given the hidden states:

$$P(\tilde{o}\,|\tilde{s}, m) = \prod_{i=1}^{T} \underbrace{P(o_i\,|s_i, m)}_{likelihood}, \quad P(o_i = k\,|s_i = h) = \mathbf{A}_{k,h}$$

where $\mathbf{A} \in \mathbb{R}^{z \times n}$. In other words, given each $h = 1, ..n$ states there is a probability to get a $k = 1, ..z$ observation. Thanks to the likelihood, our Bayesian model contains probabilities from the past experience, and enables us to predict the probability to perceive a new observation o_{t+1} given a state s_{t+1}.
(ii) from (6.1), **Probabilistic transition matrix between states B(**u_t**)**, given an action:

$$P(\tilde{s}, \tilde{u}\,|\,\gamma, m) = P(u_t|\gamma, m) \prod_{i=1}^{t} \underbrace{P(s_{i+1}|s_i, u_i, m)}_{transitions}; P(s_{t+1} = w \,\mid\, s_t = q, u_t) = \mathbf{B}(u_t)_{w,q}$$

where $w, q = 1, ..n$, hence $\mathbf{B}(u_t) \in \mathbb{R}^{n \times n}$, and n refer to the number of hidden states. This means that transitions between hidden states depend upon the current *putative* action u_t under policy $\pi \in 1, \cdots, K$. A policy indexes a specific sequence of control states $(\tilde{u}|\pi) = (u_t, \cdots, u_\tau|\pi)$:

$$\begin{aligned} \ln P(\tilde{u}|\gamma, m) &= \underbrace{\gamma}_{precision} \cdot \mathbf{Q}(\pi) = \gamma \cdot (\underbrace{\mathbf{Q}(u_{t+1}|\pi) + \cdots + \mathbf{Q}(u_\tau|\pi)}_{expected(negative)\ free\ energy}) \\ \mathbf{Q}(u_\tau|\pi) &= \underbrace{E_{Q(o_\tau|\pi)}[\ln P(o_\tau|m)]}_{extrinsic\ value} + \underbrace{E_{Q(o_\tau|\pi)}[D_{KL}[Q(s_\tau|o_\tau, \pi)|Q(s_\tau|\pi)]]}_{epistemic\ value} \end{aligned} \tag{6.2}$$

weighted by the precision parameter γ (detailed below in 6.3.1.2), such control states or *putative* actions are chosen to minimize Expected free energy, where D_{KL} is the Kullback-Leibler (KL) divergence or relative entropy (for more on KL divergence, see Appendix 7.5); and $E_{Q(o_\tau|\pi)}$ is the expectation of a future outcome o_τ given policy π. For the sake of readability we develop each element from equation (6.2), as follows.

An action u_t is chosen from a list of putative actions u_τ under a given policy π that minimizes Expected free energy which is comprised of 2 elements:

1. Extrinsic value or the preferred final outcome (the goal we wish to achieve) which we maximize, that is its expectation $E_{Q(o_\tau|\pi)}$.

2. Epistemic value or information which we wish to maximize, that is, its expectation $E_{Q(o_\tau|\pi)}$. That is equivalent to minimizing the prediction error, or the discrepancy between the prior (predicted hidden state or prior $Q(s_\tau|\pi)$) and posterior (actual hidden state given the observation $Q(s_\tau|o_\tau,\pi)$). We achieve this by minimizing the relative entropy (i.e., minimizing the KL divergence relative to the predicted outcome).

You can notice that $E_{Q(o_\tau|\pi)}$ of a probability distribution Q (called the variational) is used twice, and serves as a bound and link between different probability distributions P and Q, that describe the *extrinsic value* and *epistemic value,* respectively (for more details, see Appendix 7.5).
So, we are wagering between the epistemic and extrinsic value at each iteration, i.e., trying to get closer to the prior goal (future outcome) by acquiring maximum information.

The extrinsic value contains $P(o_\tau|m)$, which is the prior distribution over future outcomes, referred to as $\mathbf{C}_\tau$. So, let $\mathbf{C}_\tau$ be the preference of future outcomes $o_\tau \in \mathbb{O}$. As part of *extrinsic value*, it influences the choice of action to reach such desired outcomes. If we consider all available observations from set $\mathbb{O}$ as future outcomes then $o_\tau = o^{(z)}$:

$$\mathbf{C}_\tau = \sigma([C(o^{(1)}), C(o^{(2)}), .., C(o^{(z)})])^T$$

where σ is a *softmax* (normalized exponential function) of final outcomes, such that:

$$\sigma : \mathbb{R}^z \mapsto \mathbb{R}^z,$$
$$\sigma(o_\tau)_j = \frac{e^{(o_\tau)_j}}{\sum_{i=1}^{z} e^{(o_\tau)_i}} \in (0,1), \quad \forall j = 1, ., z \tag{6.3}$$

The *softmax* function here compresses a z-dimensional vector $[C(o^{(1)}), C(o^{(2)}), .., C(o^{(z)})]$ of real values into another $\mathbf{C}_\tau$ vector of the same dimension that contains real values that add up to *1* and reside within the range of *(0,1)*. In other words, we transform all observations from set $\mathbb{O}$ into prior probabilities of future outcomes, some of which we favor, other which we penalize.

(iii) from (6.1), **Precision parameter** γ

$$P(\gamma\,|m) = \Gamma(\alpha, \beta)$$

where Γ is a gamma distribution of scale parameter α and rate parameter β. If a random variable *X* follows a Gamma distribution then:

$$f(x; \alpha, \beta) = \frac{\beta^{\alpha} x^{\alpha-1} e^{-\beta x}}{\Gamma(\alpha)}, \text{ for } x > 0 \text{ and } \alpha, \beta > 0$$

where $\Gamma(\alpha)$ is the gamma function (i.e. an extension of the factorial function):

$$\Gamma(\alpha) = (\alpha - 1)!$$

The precision parameter (also called temperature) determines the degree of confidence of the control states or beliefs over actions. For example, if $\gamma \mapsto \infty$ the beliefs over policies merge into a single policy, being over optimistic and prone to errors, with immediate or fast action (increased exploitation), inversely if $\gamma \mapsto 0+$ the beliefs over policies spread uniformly resulting as a very high exploration or waiting time. In short, the higher the confidence about having a good policy (i.e. belief of high precision), the smaller the exploration and vice versa.

We have detailed the components of the internal, Bayesian, generative model, a distribution $P(o_t, s_t, u_t, \gamma|m)$ that connects observations o_t to hidden states s_t through control states u_t.

"*The agent and the environment interact in cycles. In each cycle, the agent first figures out which hidden states are most likely by optimizing its expectations with respect to the free energy of observations. After optimizing its posterior beliefs, an action is sampled from the posterior marginal over control states. The environment then picks up this action, generates a new observation and a new cycle begins*". [Friston et al., 2014]

6.4 Active Inference for the P300-speller

We aim at designing a fully adaptive P300 speller that learns and acts optimally in real time. The above generic and flexible probabilistic framework, Active Inference enables the machine to automatically and optimally update an internal model of the environment (here the user given a BCI task) and select appropriate actions. Specifically for the P300-speller, the actions to be considered are – flashing or spelling letters or switching off the screen. This allows us to implement within the same framework: (1) optimal stopping & flashing but also when (2) the user is looking away from the screen – "lookAway" case, in which the machine can pause the application; together with above mentioned, we can also implement (3) an ErrP classifier, where after receiving an ErrP, the machine can automatically choose to spell the next probable letter or continue flashing to increase evidence for the target letter.

When endowing the machine with Active Inference, in a P300 speller application (see Figure 6.2), the machine:

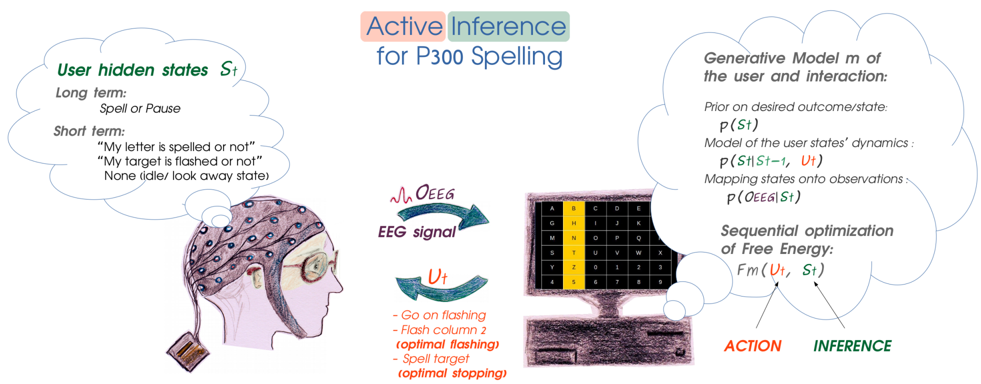


Figure 6.2: A depiction of Active Inference for a P300 speller: (1) the user hidden states on the left represented as long term intentions and short term reactions to stimuli, (2) the observations are the (preprocessed) EEG signal, (3) the actions the machine based on its internal (generative) model of the user. The generative model *m* is simplified in this figure, representing Free Energy as a function of hidden states (updated with observations) and actions $F_m(u_t, s_t)$.

- accumulates the information about the target/non target letters (P300 or not) and incorrectly spelled letters or not (ErrP or not), to update its belief about the user's intention or command,
- optimizes its interactions through inference, i.e., minimizes discrepancy between observed data and predictions about user intentions to spell a letter, or pause;
- optimizes its interactions with the user by spelling and flashing items or switching-off in a flexible and adaptive manner, in order to maximize speed and accuracy.

In the next two sections, we explicitly describe the key model parts when instantiating the P300 speller BCI within the Active Inference framework. We start first with the machine's generative, internal model of the user in section 6.4.1, and then describe its possible actions towards the user in section 6.4.2.

6.4.1 Generative model of the user.

Prior to any observation and in the absence of prior knowledge, the probability of the intention to spell a given letter is the same for all the letters (high entropy). Then, after each flash and electrophysiological observation, these beliefs are updated based on the generative model *m* which embodies the machine's internal representation of the user and task.
The model m rests on transitions among hidden states that are coupled with actions, it contains:

$\mathbb{S}$ – **finite set of user hidden states:**
There are 37 *intentions* x 4 *reactions* = 148 possible user hidden states the machine must

infer. The first are the user's *intentions to spell* one out of 36 letters or digits at a time, within the 6x6 grid, or the 37th intent to pause by looking away from the screen. Such state we refer to a lookAway state and it enables asynchronous BCI behavior. The second represent 4 user's *reactions* to the machine's actions or stimulations. Namely, user intentions are inferred by the machine through an accumulation of short term user's reactions to stimuli being – *"My target letter was just flashed"* – giving a P300 (target) observation, or inversely – *"My target was not flashed"* – yielding a non-P300 (non-target) observation. Another type of user reaction is *"My target letter was spelled"* – or – *"What is spelled is not correct"* – giving rise to an Error Potential (ErrP) as observation. Active Inference enables us to infer the cause of sensory observations, here the user intentions, which in turn are influenced by the machine's actions.

$\mathbb{U}$ – **finite set of machine control states or actions:**

There are 36 *spelling* + 12 *flashing* + 1 *switch-off* = 49 possible machine's actions that can help the machine learn about the user hidden states and accomplish the user's goal. There can be 12 possible *flashing* (6 columns and 6 rows) without repetition, or *spelling* one out of 36 letters; or *switching-off* the screen in the case of a "lookAway" state.

$\mathbb{O}$ – **finite set of observations or outcomes**: Active Inference instantiated in [FitzGerald et al., 2015] deals with discrete observations, namely in our case : (1) high or low confidence discrete values associated with the observation of a target or non target signal, and similarly (2) high or low confidence values associated with the observation of a correct or incorrect feedback. This means that after each flash, the machine observes either target (P300) or non target values with a certain of confidence. Similarly after each spelling the machine observes either an correct or incorrect (ErrP) feedback with more or less confidence. These confidence levels are given by the class probabilities estimated by the classifier. We denote them as follows: for a correctly spelled letter, we refer to as a Feedback Correct FC (FC0, FC1 for not confident and for confident correct feedback, respectively); and Feedback Incorrect as FI (FI0, FI1 not confident and confident incorrect feedback, respectively). If the machine is completely unsure whether the feedback is correct or not, it is classified as undefined feedback, or FXX. Same applies to flash target and non target ($T0$, $T1$ and NT0, NT1 for not confident and confident target, and non target, respectively) and TXX for an undefined response to a flash, as depicted in Figure 6.3. Note that *lookAway* is not specified as an additional observation but can only be recognized after having observed a sufficiently large number of non-target or undefined observations. Note that the latter is not a preset rule but derives automatically from our Active Inference approach.

A **– prior over outcomes given a state (likelihood)**

The likelihood is the probability to observe an outcome o_t, given a state s_t, and ***A*** is a matrix of *z* possible observations, given *n* possible hidden states:

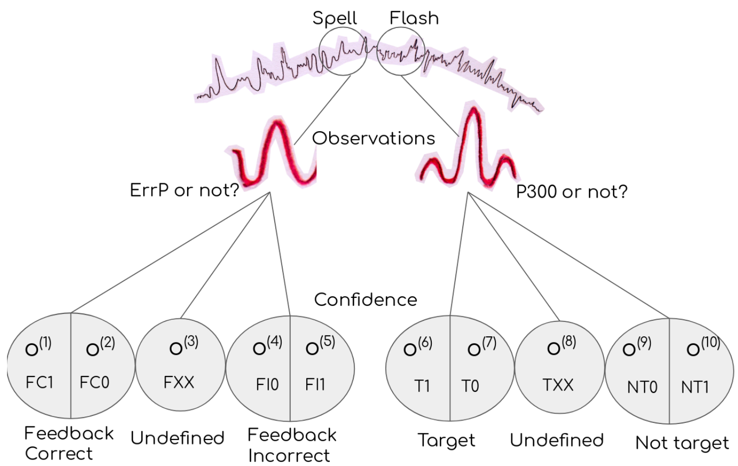


Figure 6.3: After each flash or spell, an observation – target/non-target or feedback correct/incorrect signal – is being mapped to a discrete high-to-low degree of confidence or undefined observation $O^{(i)}$, i=1..10. Those discretized observations are the ones that enter the Active Inference model.

$$A = \begin{bmatrix} o^{(1,1)}, & o^{(1,2)}, & \dots & o^{(1,n)} \\ \vdots & & \dots & \dots \\ o^{(z,1)}, & \dots & \dots & o^{(z,n)} \end{bmatrix}$$

For instance, ***A*** contains the probability to observe a high confidence target – T1 or low confidence incorrect feedback – FI0, given a user hidden state – a *column* flashed or a *letter* spelled, respectively. Thanks to ***A***, the machine knows how reliable is the classification. In BCI, ***A*** may typically be defined based on calibration or training data. This means that ***A*** should ideally be defined for each user specifically. This is indeed important to define the levels of confidence that will drive th BCI interpretations and actions. Namely, Active Inference will rely on those levels to decide whether it should go on flashing in order to make a reliable decision, or spell with no further due. The way we define the matrix for each individual is further described in subsection 6.5.1.3 pertaining to the realistic simulations we performed.

B(u_t) – transitions between states given an action
To transition from one state s_t to another s_{t+1} is possible through action (control states). The choice of action u_t given a state s_t depends on the priors C over the desired final outcome o_τ but also on the precision over action or the exploration/exploitation ratio γ while conforming to the free energy minimization, as mentioned in (6.2). Concretely, transition matrix ***B*** contains all the possible combinations of states or user intentions $n \times n$, with $|S| = n$, which we define prior to the experiment. These are the same for every subject, as follows.

Filing transition matrix B:

$$B = \begin{bmatrix} s^{(1,1)}, & s^{(1,2)}, & \ldots & s^{(1,n)} \\ \vdots & & \ldots & \ldots \\ s^{(n,1)}, & \ldots & \ldots & s^{(n,n)} \end{bmatrix}$$

where $n = 148$, containing 37 × 4: user intentions to spell 36 letters or pause (37^{th} *lookAway*), along with short-term user reactions to stimuli (1. correct/ 2. incorrect spelling, or 3. target/ 4. non-target flashing). For all subjects, the transition matrix B is the same, and its values are either 0 or 1. Values 0 and 1 refer to implausible and plausible state transitions, respectively. For instance, when a set of items has just been flashed, the current state might be the recognition of the target, or not, and a subsequent user's state could be the recognition of a future flash or the recognition of a displayed feedback, depending on the action taken by the machine.

C – **priors over final outcomes**

Vector C influences the choice of action. It expresses a goal or preference in the form of a prior probability over final outcomes, with the highest probability being given to the most desired outcome. Hence, the prior beliefs encode a utility function which, in our case will favor the high confidence *Feedback Correct* 'FC1' as final observation o_τ. This amounts to aiming at the state – *My target letter was spelled* –. In our case, we assign equal values (preferences) to the appearance of target/non target observations, while penalizing incorrect spelling, and favouring correct spelling, as in Figure 6.4. As we tested various values for C, we provide more details in the subsection 6.5.1.3 Simulations.

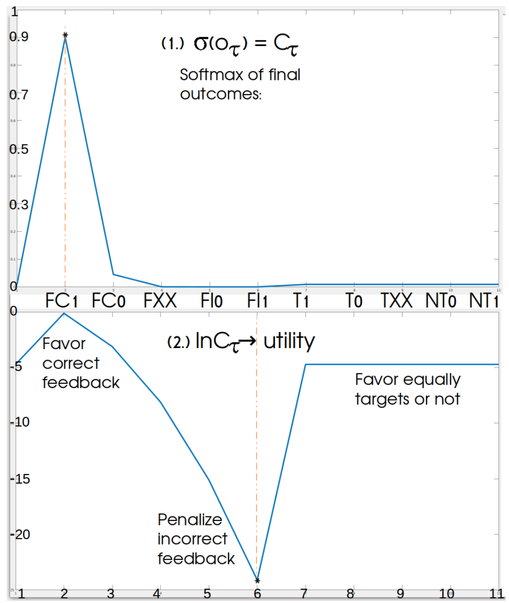


Figure 6.4: *Softmax* function (above), yielding output values between 0 and 1 (y axis) for each observation within the set $\mathbb{O}$; from FC1, FC0, FXX, FI0, FI1 which refer to feedback observations ($o^{(2)}, o^{(3)}, .., o^{(6)}$) and T1, T0, TXX, NT0 and NT1 denoting target/non-target observations $o^{(7)}, o^{(8)}, .., o^{(11)}$ (x-axis). Logarithm of the *softmax* (below) encodes a utility function, in which we favour the *correctly spelled letter* – FC1, and penalize *feedback incorrect* FI1 and FI0, and *undefined* FXX feedback; and equally favour the apparition of target T, non target NT or undefined TXX observations.

γ - precision over priors
In a P300 speller we wish to spell correct letters in a minimum amount of time. However there is always a trade-off between speed and accuracy. This trade off is governed by parameter γ which sets the balance between exploration and exploitation. In practice, this is arbitrarily set by defining the prior distribution over parameter γ (a gamma distribution with parameters α and β). See 6.5.1.3 Simulations, for more details.

6.4.2 Optimal Interaction

6.4.2.1 Optimal flashing & stopping

Vector C, precision γ, and transition matrix B are defined prior to the experiment, given the task and goals. Matrix ***A*** is learned from training data, for each user. Then, here is the course of actions that unfold during the online interaction:

- List all potential actions u_t at time t.
- Compute for each action its posterior expectation or epistemic value $E_{Q(o_\tau|\pi)}$ and compute *KL* divergence (also called relative entropy) between prior $Q(s_\tau|\pi)$ and posterior $Q(s_\tau|o_\tau, \pi)$ over the hidden states (using transition matrix ***B***, likelihood

A, preferences C and precision γ); Note that we use the full transition matrix **B** (meaning that we consider all possible hidden states during a *choice* or time *t*).

- The higher the information (epistemic value), the most likely this action will be chosen. When we consider not only a single putative action, but a series of actions to reach a predefined desired outcome, we then talk about policies π. Hence, we get a list of actions $(\tilde{u}|\pi) = (u_t, \cdots, u_\tau|\pi)$, active inference picks up the optimal policy, that is the one that maximizes the information gain as well as maximizes the reward (outcome).

- Update internal state s_t based on observation o_t.

- Repeat the selection of the next action u_t until the spelling of a letter (the case without an ErrP classifier); or in the case in which we use an ErrP classifier: repeat action selection (to flash or spell) until the machine spells the *correct* letter and detects a feedback FC1 (which will be obtained depending on the error rate of the feedback classifier, set in ***A***).

Active Inference permits a holistic and automatic control over the machine's actions, thanks to the free energy principle that unites action and perception (cause and effect) into a single Bayesian framework, see figure 6.5. As reminder, the machine chooses such action that provides most information (min entropy relative to the predefined goal or *Feedback Correct*). Hence, flashing letters automatically provides more information about the target than spelling one by one letter.

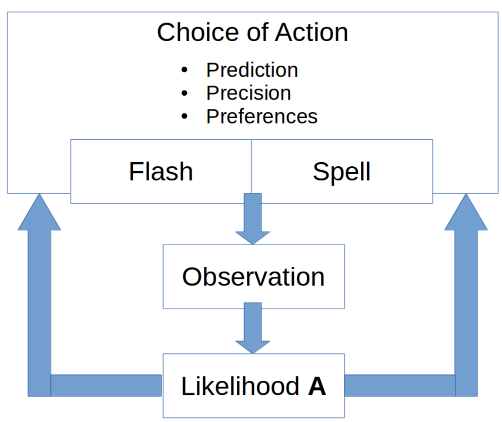


Figure 6.5: Simplified schematics of Active Inference choice of action. It starts by predicting the future observation or hidden state. Using priors and preferences it will choose an action to reinforce its prediction, for instance to flash a certain column; this will produce an observation (within degrees of confidence) and depending on the likelihood it will choose to continue flashing or to spell a letter. In case of an ErrP, the spelling can be followed by more flashing to reinforce its certainty about the spelled letter or immediately spell another letter.

Thanks to Active Inference, the machine is able to execute optimal flashing (with stopping), that is, flashing those letters which give most information about the target letter. Furthermore, Active Inference offers a generic and flexible framework that can also incorporate other adaptive behavioural features as described below.

6.4.2.2 Detecting a LookAway state

We here refer to the situation where the user is not looking at the screen anymore. By simply adding another 37^{th} hidden state to the existing set $\mathbb{S}$, we provide the subject with the possibility to pause the machine. Note that there is no clearly defined single observation associated with that state which instead, can only be inferred through the absence of target like responses. In other words, if the machine observes many consecutive non target signals, it should eventually conclude that the user is not actively looking at the screen. Note that the model thus has to be able to distinguish between a poor performing subject, producing ambiguous signals and a subject which intends to pause the P300 speller. A natural consequence is that the *LookAway* state often requires more flashes than any other user intention to be inferred. That is because Active Inference observes the 37^{th} state, but as it in fact does not exist, it does not elicit a real observation (there is no 37^{th} letter), it will keep receiving non-target responses when flashing. Note that in our case we did not model a "switch on" button action, which could for instance rely on a SSVEP response with a dedicated stimulus always active at a corner of the screen. So far, we only simulate independent trials with different intentions, some of which can be a *LookAway* state to stop the machine.

6.4.2.3 Automated error correction

We added correct and incorrect feedback to the existing set of observations $\mathbb{O}$, see Figure 6.3. We simulated a *perfect* classifier, with either a high confidence correct or incorrect feedback classifier, i.e., assigning zero probability to the appearance of *not confident* correct and incorrect feedback as well as undefined feedback, p(FC0, FI0, FXX) = 0. As this is not a very realistic case, we also simulated a more *realistic* feedback classifier, a 95% specificity (a 0.95 probability to be right about a correctly spelled letter); and 75% sensitivity (a 0.75 probability to be right about an incorrectly spelled letter). This way the confidence for specificity (Feedback Correct) is p(FC1 = 0.95; FC0 = 0; FXX = 0; FI0 = 0; FI1 = 0.05), and for sensitivity (Feedback Incorrect) it is p(FC1 = 0.75; FC0 = 0; FXX = 0; FI0 = 0; FI1 = 0.25).

If Active Inference realizes it spelled an incorrect letter, it will choose by itself to continue flashing gain additional information about the target, or to immediately spell the second most probable letter. In the case of a *perfect* feedback classifier, it will be 100% sure about the letter whether it is incorrect or correct. In the case of the *realistic* feedback classifier, it would not be so sure (5% and 25% error for correct and incorrect letter, respectively).

In the next subsection, we describe the evaluation approach we pursued in order to validate Active Inference for implementing a flexible and efficient P300 speller BCI. This includes a description of the Dataset and Data Features, of the Model, of the Simulation procedure and of the Evaluation Metrics we used.

6.5 Experimental Design

6.5.1 Dataset

We use real training data from on of our previous studies [Mattout et al., 2015] to which 18 healthy subjects (11 males and 7 females) aged from 22 to 30 took part voluntarily to evaluate the P300 speller brain-computer interface (BCI) paradigm. Thirty- two EEG sensors were used and their placement followed the extended 10–20 systems. The P300-speller BCI experiment is made of two recording stages:

- the initial training phase enables to optimize spatial filters [Rivet et al., 2009] and a probabilistic classifier [Mattout et al., 2008] that can then be used to differentiate response-to-target data from response-to-non-target data. In this training phase, subjects were given a sequence of 25 characters to focus on. For one character, matrix rows and columns were flashed alternatively during three complete cycles of 12 stimuli (two of which were including the target item). The training dataset is thus composed of 750 trials for the non-target class and 150 trials for the target class.

- following the training phase, each participant completed 3 copy-spelling sessions as a test phase. Each session was made of twenty-four 5-letter French words, hence 360 letters in total. The process of flashing each row and column was repeated three times (3×12) per character spelled.

6.5.1.1 Features

From the data recorded during the test phase, the features are extracted for our simulation, as follows. A first preprocessing step consisted in applying of a 2^{nd} order bandpass Butterworth filter with cut-off frequencies of 0.5 and 20Hz.

We use Riemannian geometry, the state of the art data classification approach developed by [Barachant et al., 2013]. It uses covariance matrices which are Symmetric Positive Definite (SPD) matrices and lie in a manifold. We define such covariance matrices as follows. Let $X_i \in \mathbb{R}^{S \times N}$ the EEG epoch corresponding to N consecutive samples in response to the i^{th} stimulus recorded on S sensors, we construct the *super-trial* $\widetilde{X}_i$ with the concatenation of X_i and the temporal prototype P which is the average of all target epochs recorded during the calibration phase:

$$\tilde{X}_i = \begin{pmatrix} X_i \\ P \end{pmatrix}$$

Let us compute the corresponding covariance matrix for the i^{th} stimulus:

$$\widetilde{\Sigma_i} = \frac{1}{N-1} \widetilde{X_i} \widetilde{X_i}^T = \begin{bmatrix} \Sigma_P & C_{P,X_i}^T \\ C_{P,X_i} & \Sigma_i \end{bmatrix}$$

where Σ_i and Σ_P are respectively the covariance matrices of the X_i EEG epoch and the temporal prototype P, and $K_{X_i,P}$ the cross-covariance between the X_i EEG epoch and the temporal prototype P.

In the same way, we can compute this covariance matrix for each trial of the calibration phase for the target and non-target classes.

To determine to which class (target or non target) a covariance matrix $\widetilde{X_i}$ belongs, the Riemannian distance is computed between it and the Riemannian means for target and non-target classes respectively denoted $\tilde{\Sigma}_T$ and $\tilde{\Sigma}_{NT}$, as follows. Let us consider two SPD covariance matrices K_1 and K_2, where $\|\cdot\|_F$ is the Frobenius norm, then the Riemannian distance between them is:

$$\delta_R(K_1, K_2) = \left\|(log\ K_1^{-1} K_2)\right\|_F \tag{6.4}$$

Knowing that the diagonal elements of such $n \times n$ covariance matrices are real positive eigenvalues λ_i, we can write the Riemannian distance as:

$$\delta_R(K_1, K_2) = \sqrt{\sum_{i=1}^{n} log^2\, \lambda_i}$$

Then, for each trial X_i we can extract the following measure:

$$rTNT = \frac{\delta_R(\tilde{\Sigma}_i, \tilde{\Sigma}_T)}{\delta_R(\tilde{\Sigma}_i, \tilde{\Sigma}_{NT})}$$

For classification, we used a simple probabilistic generative model of the data, based on a two univariate-Gaussian mixture (one Gaussian distribution per class). Then, following Bayes Rule, the likelihood when seen as a conditional density can be multiplied by the prior probability density of the parameter and then normalized, to give a posterior probability density :

$$p(C_j|Y) \propto p(Y|C_j)p(C_j)$$

where Y is the feature on which the classification C_j was done, $j = 0$ referring to the target and $j = 1$ to the non-target class and with

$$p(Y|C_j) = \frac{1}{\sigma_j \sqrt{2\pi}} e^{-\frac{(Y-\mu_j)^2}{2\sigma_j^2}}$$

where μ_j and σ_j^2 are respectively the mean and the variance of the Gaussian distribution for the class j.

Finally, for our simulation, we calculate the log likelihood lf_j, in case the feature is the $rTNT_i$ measure for each flash, as follows :

$$lf_j = log(p(rTNT_i|C_j)) = -log(2\pi.\sigma_{rTNT_j}) - \frac{(rTNT_i - \mu_{rTNT_j})^2}{2\sigma_{rTNT_j}}$$

where μ_{rTNT_j} and $\sigma^2_{rTNT_j}$ are the means and variances of the two Gaussian distributions estimated from $rTNT$ measures computed on data recorded during the calibration phase.

6.5.1.2 Mapping data features onto model observations.

After each flash, the machine receives 2 values at a time (log likelihood of Riemannian distance to target and non target). To transform such data into a discrete input that is fed to Active Inference, i.e., the set of observations $\mathbb{O}$ with high and low confidence, we do the following. On training data, we first calculate the log-likelihood ratio or a difference $(lf_0 - lf_1)_i$ per class (target, non-target) at each trial or flash i, and from it we calculate a threshold ρ_T for target and ρ_{NT} for non-target. To compute thresholds (using the same training data as for calculating Riemannian distance), we use the Median Absolute Deviation (MAD). MAD is a more robust estimator of scale than the sample variance or standard deviation, and it works better with non normal distributions. Let us denote Md the median of the distribution and L_i a random event or $(lf_0 - lf_1)_i$ drawn at each trial i, then MAD is referred to as $\rho(L) = Md(|L_i - Md(L)|)$. For pairs $(lf_0, lf_1)_i$ that correspond to target, we denote $\rho(L)_T = \rho_T$ and separately, we calculate MAD for non-target observations, and denote it $\rho(L)_{NT} = \rho_{NT}$. However, if the training set does not possess a sufficient number of samples, outliers will have a strong impact on these estimations. This means that the distribution of the classifier output might differ significantly from the test set, and it could be hard to generalize the resulting observations. Therefore, in order to get a more robust MAD estimate, we approximate the distributions of $(lf_0 - lf_1)_T$ and $(lf_0 - lf_1)_{NT}$ with beta distributions, using a maximum likelihood estimate. This yields the mean and variance parameters for both distributions. Thanks to this approach we obtain a more robust calibration and less variability between participants. Note that for each subject, we calculate these individual thresholds from their training dataset.

From the testing data, at each trial $j = 1..M$ we draw with repetition a random likelihood pair $(lf_0 - lf_1)_j$ or L_j. Then depending on how it compared with the pre-determined thresholds (ρ_T and ρ_{NT}), we assign an observation category $\phi(L_j) \in \mathbb{O}$, as follows:

$$\phi(L_j) = \phi(lf_0 - lf_1)_j =$$

$$\mapsto \begin{cases} o^{(6)}, \textit{target} \text{ 'T1', if } L_j \geq \rho_T \\ o^{(10)}, \textit{non-target} \text{ 'NT1', if } L_j \leq \rho_{NT} \\ o^{(9)}, \text{ 'NT0', if } L_j \in (\rho_{NT}, \;\; \rho_{NT} + \frac{1}{4}\Delta\rho] \\ o^{(7)}, \text{ 'T0', if } L_j \in [\rho_T - \frac{1}{4}\Delta\rho, \;\; \rho_T) \\ o^{(8)}, \text{ TXX, if } L_j \in (\rho_{NT} + \frac{1}{4}\Delta\rho, \;\; \rho_T - \frac{1}{4}\Delta\rho) \end{cases} \tag{6.5}$$

where $\Delta\rho = \rho_T - \rho_{NT}$.

If $L_j \geq \rho_T$ then L_j represents a target with high confidence 'T1', also if $L_j \leq \rho_{NT}$, then L_j represents a non-target with high confidence 'NT1'. The undefined 'TXX' are placed half way between the two thresholds ρ_{NT} and ρ_T, while we equally divided this distance for less confident observations. 'NT0' and 'T0' are respectively half-way between ρ_{NT} and ρ_T, see Fig. 6.6. Note that such observations (with degrees of confidence) are fed to Active Inference framework.

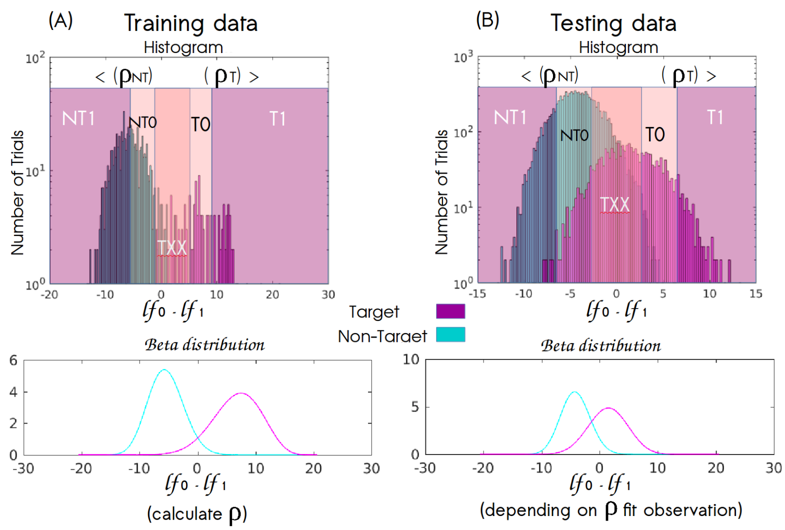


Figure 6.6: Data from subject 13, likelihood distributions for each trial or flash $(lf_0 - lf_1)\_i$. On training data, we calculate a Median Absolute Deviation (MAD) per class – target and non target (left); MAD we denote ρ, which we use for attributing confidence values of testing data (right).

6.5.1.3 Simulations

We simulate the spelling of 1200 random letters per subject. For each target, Active Inference runs until it decides to spell a letter (without ErrP classifier) or runs until it finds a correctly spelled letter (with Errp classifier). If it flashes the row or column which contains the target, we randomly fetch a target pair $(lf_0 - lf_1)_T$ from our testing dataset. Similarly, if one flashes a column or row that does not contain the target, we will fetch a random non target observation from our test dataset. We then map it with ϕ onto one of our *z=6..10* (target/non-target) observations from set $\mathbb{O}$. After this mapping, the pair may turn out to fall in the wrong category depending on the quality of the observation. As we are picking data randomly, after a consecutive flash, we cannot choose to pick a refractored P300 from our data, and provide more realistic scenario. Hence, we are obliged to set a limit to Active Inference choice of flashing by preventing it from flashing a row/column consecutively.

Note that for simulating an ErrP classifier, the possibilities of describing feedback (ErrP) data with a beta distribution are very large including many possible combinations. Hence, we simply create probabilities to choose a correct or incorrect letter truly or falsely with different specificity and sensitivity levels, as reminder see 6.4.2.3.
Prior to the testing phase, we assigned the following values to the model parameters:
———————————

(i) Calculating likelihood matrix A :
Matrix **A** expresses the probability of each observation category, given each possible state value. It is computed individually, from the training data of each subject. In our simulations, we draw N_T*=2000* samples of target data, N_{NT}*=2000* samples of non target data.

We then computed the proportion of samples who fell into each observation category in order to set the above probabilities.

——————————————

(ii) Setting values for C

Values chosen for C are same for all subjects. We assign a high value to a correctly spelled letter, 'FC1', and penalize the wrongly spelled 'FI1', (for a reminder, see Fig. 6.4 above). Here we discuss the empirical evaluation of the distance between the extreme values assigned to observations, i.e., penalty and preferences. For instance, how strong should be the penalty for incorrect feedback 'FI1', 'FI0' and 'FXX'. Observations (target or not) are valued equally (zero vector) $o_T(i) = 0$, where *i=6,..10* (as reminder of observations, see figure 6.3). In contrast, we vary values for feedback observations (correct or not), as follows. A quadratic function $g(d) = d^2$, $d \in [1, 2, ..5]$ maps the penalty to the observations, and a parameter κ, regulates such penalty: $o_T(j) = \kappa + g(d)$ for *j=1,..5*. For instance, the strongest penalty is when $g(d) = 5^2$ is set for an incorrect feedback with high confidence (FI1); κ is a parameter influencing the penalty that we vary for 3 distinct subjects, see Figure 6.7.

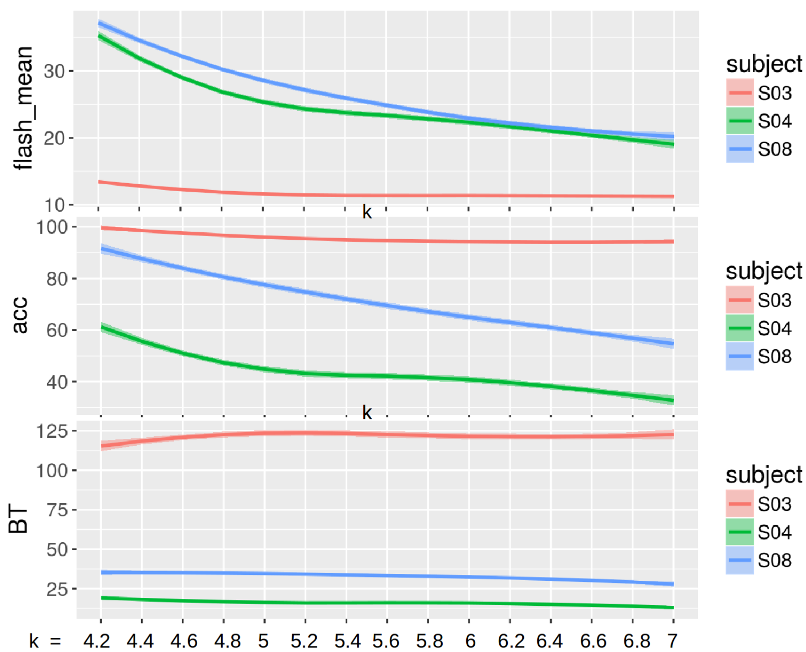


Figure 6.7: Varying κ in C vector to demonstrate difference in speed (flash mean), in accuracy, and Bit Rate for 3 subjects, from good, below average to poor classification performance respectively (S03, S08, S04).

By augmenting κ we can decrease the distance between the feedback correct(max) and incorrect(min). Note that the smaller the penalty (higher κ), the faster the spelling with less accuracy which in total does not significantly affect the bit rate (BT). For all subjects, we empirically fixed $\kappa = 5.6$ i.e. between $\kappa \in [4, 7]$, a range of values that we determined empirically and for which Active Inference is stable and exhibits the expected type of behaviour.

———————————————

(iii) Selecting values for precision, γ

For our thorough evaluation, we considered a unique prior distribution over the precisions parameter γ, for all subjects, with $\alpha = 1$ and $\beta = 128$. To illustrate the effect of this parameter though, we performed a few simulations with three different subjects (S03, S04, S08), varying its prior distribution. For $\alpha \in (1, .., 128)$ and $\beta \in (1, .., 128)$, we performed all the combinations and did not observe any significant change in accuracy, flash mean nor bit-rate, see figure 6.8. This is because of our choice of transition values being either 0 or 1 (high confidence) in the **B** matrix, i.e., the γ parameter in that case has very little influence on the choice of future action and hidden state.

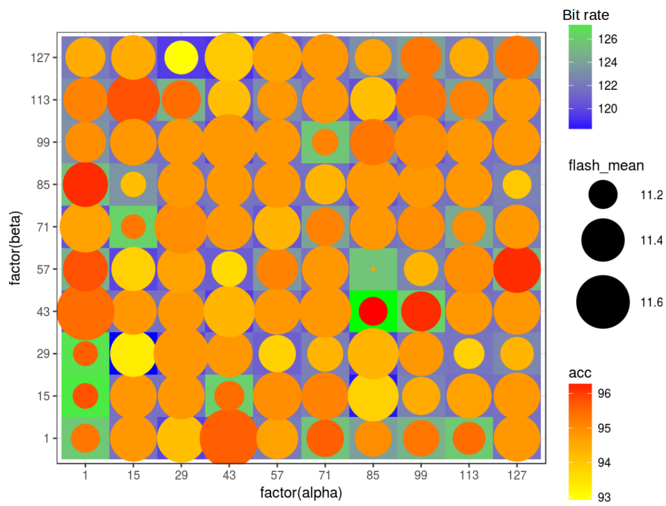


Figure 6.8: Varying α and β parameters of the precision γ. The rectangle colour denotes bit-rate, the size of circles denotes flash mean, and the circle colours denote the accuracy. The values do not significantly vary depending on the changing parameters.

6.5.1.4 Evaluation Metrics

We test the following Active Inference (AI) models:

- basic AI (optimal stopping and flashing);
- basic AI + *lookAway*.

To examine the performance rates of basic AI + *lookAway*, in our simulation (same for 12000 "letters"), instead of selecting random letters as target, we set *lookAway* as the only target "letter" (12000 "*lookAways*").

- basic AI + realistic ErrP classifier;
- basic AI + perfect ErrP classifier.

The ErrP classifier output contains purely simulated data (both perfect and more realistic).
We compare these AI models to two classical approaches:

1. P300-spelling with a fixed number of flash repetitions (12) and pseudo-random flashing, denoted as *fixed-flash*;

2. P300-spelling with pseudo-random flashing but optimal stopping, using Naive Bayes classifier [Margaux et al., 2012]. As mentioned in the related works, optimal stopping spells a letter once the accumulated evidence about a letter reaches a predefined confidence threshold or certainty. We implemented optimal stopping with different threshold values (between *0.8, 0.9, 0.95* and *0.99*). We chose 0.9 as it yielded highest bit rate on average in our dataset.

Note that all approaches apply on the same features – Riemannian distance of covariance matrices, as described above in the subsection *6.5.1.1 Features*.

For each subject, we compared the performance of the various algorithms by measuring the bit rate. The amount of bits (*b*) transferred is given by:

$$b = log_2(K) + P \cdot log_2(p) + (1-p) \cdot log_2(\frac{1-P}{N-1})$$

with K: number of possible choices (classes) and p: P300 classifier accuracy. Considering that each flash lasts 0.2s, the time T it takes to spell a letter is hence $0.2 \times Nb_{flash}$, thus the bit rate br indicates the BCI information transfer rate in bit/min with: $br = b \times \frac{60}{T}$ – see [Yuan et al., 2013].

We tested to which extent the performance (as measured by bit rate) of optimal flashing outperforms classical P300 algorithms. We performed a one-way analysis of variance (ANOVA) with repeated measures and post-hoc Tukey with false discovery rate correction [Noble, 2009] enabling a clear differentiation between algorithms. Independent variable: algorithm (6 groups: 4 Active Inference + 2 standard), dependent variable: bit rate. The threshold of significance is set at $p < 0.01$. Data collected from the simulated spelling of 12000 letters with 18 subjects who were recorded in [Mattout et al., 2015] experiment.

6.6 Results

We present the comparison of AI instances with standard P300-speller algorithms using their average bit rate values, see table 6.1, and see figure 6.9.

Methods	Fixed-flash	Optimal Stop	AI basic	AI ErrP perfect	AI ErrP real	AI *lookAway*
Bit rates	10.49 b/m	45.86 b/m	54.32 b/m	73 b/m	64.94 b/m	51.85 b/m

Table 6.1: Table with bit-rate means for comparing all methods.

Active inference has lower accuracy rates on average than Optimal Stop (71.97% vs 76.62%, Figure 6.10.B.), however it is a lot faster (18.51 vs 24.88 flashes, Figure 6.10.C.).

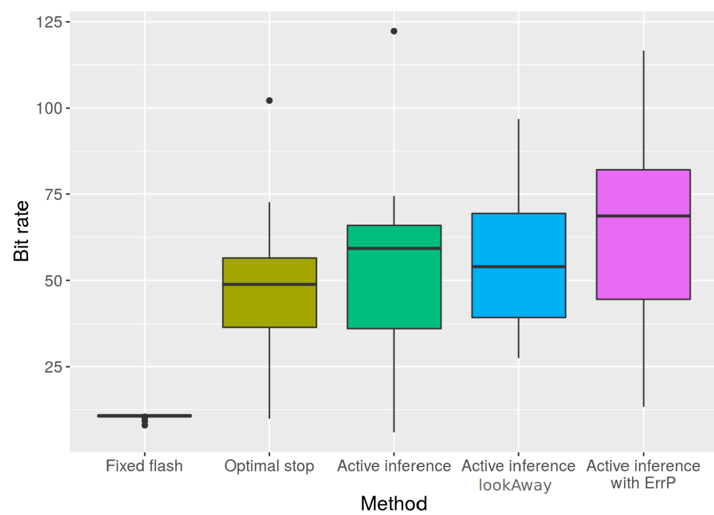


Figure 6.9: Comparison in bit rate (bit/min) between fixed flash, optimal stopping 0.9, AI basic, AI of lookAway, and AI + realistic ErrP. All methods significantly differ from one another ($p < 0.01$).

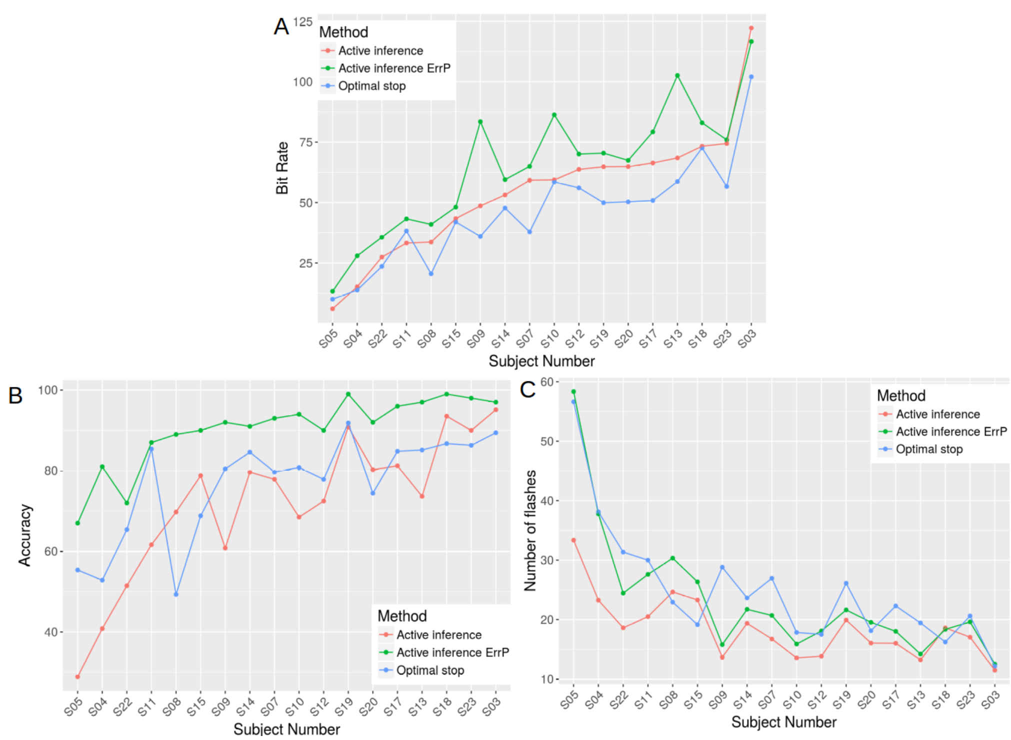


Figure 6.10: Comparison of (A.) Bit Rate, (B.) Accuracy and (C.) Mean number flashes, of Active inference basic (in red), AI with realistic ErrP classifier (in green) and Optimal stopping (in blue) across subjects (sorted by bit rate from left to right).

It is interesting to see how Active Inference adapts its flashing pattern depending on the certainty of the observations. In Figure 6.11 we compared side by side subjects with poor (S04) and good (S03) classification performance.

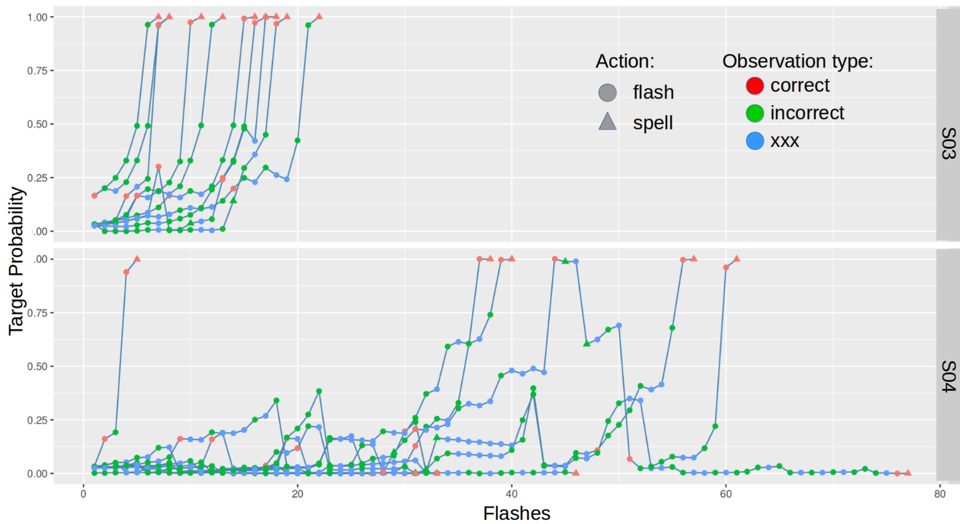


Figure 6.11: Progression of probabilities of letters during flashing of AI with realistic ErrP. Above is a subject with good performance, S03, and below a poor one, S04. Each curve corresponds to one letter and ends with a red triangle that represents a "correctly" spelled letter (what it believes to be correct, but it can be wrong). If the curve ended with a triangle while in low probability, it represents exactly that, a wrong assumption. To avoid saturation of information in this figure, the red refers to correct denoting both correct feedback (red triangle) and target (red circle), while green (incorrect) refers to incorrect feedback (green triangle) and non-target observations (green circle). The undefined target/non-target is in blue. The frequency of error is evident in the lower plot (subject S04) while there is no error (all are correctly spelled letters) in S03.

When studying Active inference with ErrP, we noticed that at least a 75% accurate ErrP classifier (with specificity = sensitivity) is necessary for Active Inference to outperform other algorithms (see Figure 6.12).

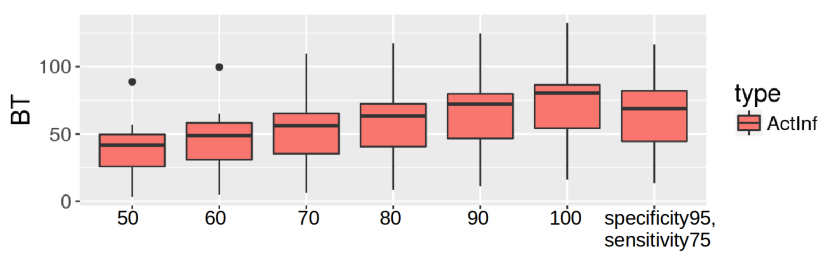


Figure 6.12: Bit Rate increase with feedback classifier's accuracy – from 50 to 100 %

6.7 Discussion

The naive algorithm (Fixed flash) achieves only $(10.49b/m)$. Active Inference showed a significantly higher bit rate $(54.32bit/min)$ than optimal stopping $(45.86b/m)$, giving an increase of about 17%. Active Inference performance increased even further when comparing to optimal stopping by 58% when a perfect ErrP classifier with 100% accuracy is used $(73b/m)$. However, this perfect classifier being over optimistic, we considered a more realistic one with specificity 0.95 and sensitivity 0.75 $(64.94b/m)$; resulting with an increase of about 41% when comparing to optimal stopping. When only idle user or "lookAway" states are simulated, it accurately "switches off" the speller about 90% of the time, after about 24 flashes $(51.85bit/min)$. Results show that Active Inference not only is able to successfully incorporate various instances of a P300 speller within one single framework, but also showed significantly higher bit rate when comparing AI basic to Optimal Stopping algorithm.

When looking at the performance of Active Inference subject per subject it behaves worse than Optimal Stopping for 2 out of 18 of them (i.e. S05 and S11). Interestingly, those are among the subjects with lowest bit rate, Figure 6.10.A.). It can be explained by the fact that Active Inference has a short observation time (flashing, Figure 6.10.C.) if it receives a consecutive number of observations with low probability (e.g. undefined observation TXX). However, the speed-accuracy trade-off can be regulated within the vector C by setting a stronger penalty to wrongly spelled letters.

Overall, Active Inference shows promising results in terms of flexibility, genericity and performance.

6.8 Conclusion

In this chapter, we propose the use of Active Inference, a generic Bayesian framework that provides a computational model of brain processes. If endowed to the machine, Active Inference has the potential to be applied on various BCI tasks, to adapt the machine to the user not only by adjusting to signal variability but by modeling and acting upon its causes (here a simplified example of user states, that are, user intentions in a P300 context). We show that it is very flexible and generic, and demonstrate it *via* a P300 speller simulation on real-data. Furthermore, we demonstrate superiority of Active Inference when compared with well known P300-speller approaches.

To make use of Active Inference one must specify: what the machine observes, here, a P300 or Error Potential for instance; what the machine infers, here, the user intentions to spell or pause; and what the machine performs as action, here, to flash, spell or switch-off the application for example. With such information provided to Active Inference, it builds confidence through observations, predicts user intentions, and chooses the optimal action to minimize prediction error and reach a desired outcome or goal. As consequence of applying Active Inference in a P300-speller context, it performs optimal flashing and stopping, that is, automatic flashing of such letters that maximize information (minimize entropy) about the target letter, and stopping once the goal (correctly spelled letter) is reached. We support our choice for adding yet another method for adapting a BCI as it offers a vast range of adaptation possibilities and flexibility, while minimizing only one objective function, the free energy.

Due to the lack of ground truth, at the moment we implemented only two observations for the ErrP classifier: correct or incorrect feedback (in/correctly spelled letter) high confidence, "FC**1**" and "FI**1**" with a degree of specificity and sensitivity (75% and 95%), but not low confidence "FC**0**" or "FI**0**". In a more realistic scenario, Active Inference would benefit from an increased variety of observations, i.e. correct / incorrect feedback with low confidence and "undefined". In this case its distribution would be calibrated during P300 training, as with target and non-target observations.

Clearly, the fact that this is a simulation is a drawback, as we have no way of controlling the refractory effect for instance. We account for this phenomenon in our simulations by forbidding two consecutive stimulations (which effects in a slight reduction in performance of Active Inference). In the future, we would account for an additional observation representing the decrease in the P300 amplitude with repetition or frequency.

Another constraint with Active Inference is that we must tune all the mentioned parameters as priors beforehand. We presented an application where only the likelihood is learned for each subject while other variables were empirically selected and kept the same for all subjects. In order to learn a sensible range for those parameters and validate our model, we first tested Active Inference on purely simulated data, in [Mladenović et al., 2017a].

In the future we could use an additional "layer" of active inference to implement a language model for word auto-completion. In such case the set of hidden states could be increased with another set referring to correctly spelled word, along with letter. And, desired outcome would correspond to a "correctly spelled word" instead of or along with the correctly spelled letter. Also, we could imagine applying Active Inference to model both the machine and user's actions. Namely, here we provide a model to the machine in order to optimally exchange with its environment, by feeding it with a simplistic model of the user (user intentions and reactions). However, we could first use Active Inference to model the user's learning and decision making with respect to the machine in this specific context, and then feed such Active Inference model to the other, the machine's Active Inference model.

Future developments would consist in testing Active Inference online, also testing, designing as well as applying Active Inference to other BCI context. We plan to demonstrate it on a Motor Imagery BCI paradigm.

Overall, this approach lays ground for future co-adaptive systems. The overarching goal is to "influence" the user through optimal machine action in order to fulfill efficiently user's intent. We envision that Active Inference could unify most approaches in one adaptive BCI framework.

PART III

Contribution and Perspectives

Chapter 7

Task Designs and Adaptive Models

7.1 Introduction

Influencing the User through BCI Interface. Throughout this thesis we show that we can influence users through the Interface (Task representation), or said in Active Inference terms – machine action, to assist them in achieving higher performances, learning, and having a better experience overall. We demonstrate such influence through feedback bias (and briefly, through congruent sound) in a Motor Imagery task, and through data-driven instructions and feedback in a P300-speller task.

Many factors can influence the user, from sensory events (within different modality) of the task, to task difficulty. However when designing a BCI task, the choice of the task representation can vary immensely (3D, 2D, continuous, congruent etc.), and does not seem to follow some standard or guidelines. This means, it is quite uncertain which kind of effect a task design could produce on the user and system performance.

We recently discovered a vast range of Task models in Human-Computer Interaction (HCI). Hence, in this chapter we wish to share such knowledge, as it might come useful for the BCI community when creating user training tasks. When considering task representations and their implication on forming specific neurophysiological reactions, we provide insight in perceptual affordance [Gibson, 1958], i.e. perceptual information of an object implicitly suggesting a set of possible actions to be performed on that object. We invite the BCI community to acknowledge various effects the task representation can have on triggering specific actions (e.g. motor reactions) of the user. Considering training task models and perceptual affordance from HCI, we invite readers to imagine a BCI task standardization, so that we can better anticipate task outcomes, and be able to compare the various BCI methods between them.

Adapting the BCI Task. Throughout this thesis we have proposed several ways to increase performance, learning and overall experience of the user. We focused on adapting the task difficulty to influence the user, with: 1) psychological cognitive theories to increase performance and state of *flow* (a state of immersion, control and pleasure), see 3; 2) prediction models about the user personality traits to increase performance and learning, see 4; 3) simple adaptive model that uses predictions about user traits, to increase performance, see 5; and finally 3) a generic framework that automatically adapts to user reactions, to increase both accuracy and speed, see 6.

Taking into consideration all the presented task models, our proposed taxonomy for adaptive BCIs, and adaptive task models, we provide a new conceptual Task model. It incorporates factors that, from our experiments showed to most influence the users during a BCI task. Additionally, we suggest ways such factors should be adapted by, in real-time, and using new metrics. We hope this new model would inspire the community to create real-time adaptive models based on proposed factors. However, as the new Task model is very hypothetical, it is presented in the Appendix 7.5, available for any curious and imaginative reader.

Perspectives. As part of short-term perspectives, we detail all the gaps to be filled when considering optimal influences on the user. From active inference, task congruency, to adaptive bias model to be tested real-time, and so on.

We believe what is missing the most in this thesis is yet to show that by influencing the user we can indeed modify the signal variability and thus increase performance. The link between the change of signal variability and increase of performance is missing. To evaluate this, we would need to investigate the neurophysiological data, and analyze the EEG signal more thoroughly. This is one of the main future work investigations.

Structure. In section 7.2, we provide some guidelines for designing a BCI task. Consequently, we hope it would inspire the BCI community to acknowledge the need for a task standardization. In the following section 7.3, we highlight our contributions which mainly revolve around BCI task and user models to increase performance, learning and user experience. Finally in section 7.4, we list the immediate perspectives this thesis opened and give our concluding words.

7.2 Standardization of BCI Task Design

The following section is about general perspectives deduced from all chapters' perspectives together. As a leit motive that repeats itself within every BCI task that we designed and performed. We propose a BCI task standardization, by acknowledging: 1. existing task designs from HCI, and 2. the perceptual affordance [Gibson, 1958]of a BCI user.

In order for the BCI system to work, the user generally needs to understand how to manipulate the machine [Lotte et al., 2013]. Hence, user training started to be seriously considered so that the user can learn to control the machine with ease and increase performance. Human learning is often performed through the creation of mental models of the system one interacts with. Mental models[1], a concept used by cognitive psychologists [Johnson-Laird, 1983] and HCI researchers [Norman, 2014] among others, are internal representations of the world that humans create in order to make meaning,

[1] believed to originate from the book *The Nature of Explanation [Craik, 1952]*

anticipate events and act to minimize anticipation error (as in Active Inference, chapter 6)[2]. In [Johnson-Laird and Byrne, 1991], a theory was developed assuming that the reasoning depends, not on logical form, but on mental models.

To assure a correct formation of one's mental model of a computer system, HCI community proposes various task designs for user training that we describe in the following.

7.2.1 HCI Task Designs and User Training

As computer systems have been vastly used for quite a few decades now, already by the 90's, a large number of user training were proposed. From our understanding of the vast literature on task design and user training, there are three main types of user training, which use: conceptual models [Mayer, 1989], procedural models [Card, 2018] and interacting with the system [Carroll and Mack, 1984]. These models are not to be confounded with user mental models. Note that these models can assist in forming mental models which enable users to perform mental actions before actually performing them. Such kind of prediction and reasoning can increase learning, thus represent an essential part of training.

Conceptual models represent manuals (tutorials) that provide an understanding of the underlying processes of the system. It can contain (i) word analogies to describe a new concept by comparing with another familiar one; or (ii) abstract descriptions, such as charts, diagrams, e.g. an inverted tree with a root as a directory and branches for files hierarchy, etc. [Sein et al., 1987]

Using analogies for conceptual models can form wrong mental models in novices, as different persons might project their own experience to the metaphor, and have a wrong action in mind when confronted with the task procedure [Borgman, 1986]. On the other hand, abstract metaphors can be difficult to comprehend to some users, for instance for low-visual and low-abstract persons [Sein and Bostrom, 1989].

Procedural models represent a "how-to" tutorial or task design, describing step by step procedures to follow, in order to achieve a goal. They do not contain any information about the system structure and its components. The most known procedural models are GOMS (Goals, Operators, Methods, Selection rules) [Card, 2018]. To accomplish a goal, one should choose a set of operators leading to various system states. For instance, to copy paste a text, one needs perform a left-mouse click to select the text, then press Ctrl-C on keyboard to copy,.. press Ctrl-V to paste, and so on. It is useful when the system is simple to operate. Specific task instructions have shown to be better than general instructions, as such they create less confusion. However, when it comes to transferring knowledge to a slightly different task or confronting with errors, these models are suboptimal [Santhanam and Sein, 1994].

Training through Interaction is to learn through trial-and-error while interacting with the system directly. Such training models often form incomplete mental models in novices leading to error and frustration [Carroll and Mack, 1984]. However it is an

[2] Note that in that chapter, we endow a "mental" model to the machine, which is a representation it can have of the user, in order to learn and make optimal decisions. However, that computational framework is originally made to model human decision making and learning.

important part for enhancing existing mental models that were for instance already created using conceptual models [Santhanam and Sein, 1994].

In [Santhanam and Sein, 1994] they explain the importance of training models for correct mental model formation, which can assists users to reason and understand better the behavior of the system. They show that mental models formed from conceptual models require deduction to form specific procedures, while procedural require a high level of abstraction to form mental models. The latter is typically much more difficult to achieve. Also, they explain how most manuals that can be found are procedural ones, and seem to be preferred by users as they produce rapid solutions to attain short-term goals.

BCI user training. The ability of users to understand computer systems affects the acceptance and utilization of computers [Nelson and Cheney, 1987, Thompson et al., 1991]. It was shown that fear of technology negatively influences BCI performance [Jeunet et al., 2016]. It is possibly because users lack understanding of the underlying processes of a BCI. In that sense, BCI users could benefit from conceptual models when engaged in training.

BCI user training is mostly Interactive, i.e., the user is supposed to learn through trial-and-error. However, differently from a computer system where users perceive a direct effect of their conscious, physical actions, BCI users have little control over their actions and rarely create a direct link between their mental action and perceptual observation. This often creates a mismatch in what users expect to observe and what they actually observe, leading to a lack of sense of agency or control. Meaning that, standard user training through interaction might not be the optimal solution for BCI users. As mentioned above, even in HCI, such training is shown suboptimal for novice users [Carroll and Mack, 1984]. Again, BCI training might benefit from the use of conceptual and procedural models to first create a mental representation of a BCI system and then enhance such representation with Interaction. In any case, the interaction can always benefit from the use of an adaptive feedback bias that would reduce the mismatch between what is expected and observed, and increase sense of control (as shown in our experiments).

Potential Solutions. Conceptual models for BCI user training could contain of a **short explanatory video** briefly describing the concepts and underlying mechanisms of BCI, so that the users understand that the system directly depends on their attentional focus, effort and motivation. Also, importantly, to reduce fear from technology, the video must specify that a BCI is not a "mind reader", i.e., it cannot infer one's intelligence, emotional stability, general health, cannot insert thoughts into one's mind, and so on. Furthermore, the conceptual model could contain abstract representation of ones EEG signals in real-time, such as the usual representation within a time frequency domain, or users could benefit from visualizing real-time neuronal connectivity on a virtual scalp for instance [Astolfi et al., 2007].

As for procedural models, we lack clear steps to guide the user to achieve a BCI task, that is, to achieve a successful mental command such as motor imagery for instance. For now, we can:

- Advise users to be in certain states (cognitive, emotional and physical) that have shown favourable for BCI performance. For instance, cognitive and emotional states could be the state of flow (immersion, control, motivation), high attention and workload, while physical could be a reduced level of muscle tension and so on. One could use simple breathing exercises that have shown to induce calm and focus, for instance using a biofeedback support (see Appendix 7.5).

- Provide physical training on objects of choice for healthy subjects, in order to assist in the creation and consistency of the motor command, through revoking the memory of such somatosensory information.
- Suggest strategies that have shown to work for most users (mentally close-open hand-palm, a kinesthetic strategy or a mental visualization of an action etc.) for MI BCI or counting the number of flashing stimuli for P300 for instance.
- Gather informal user experience about their "feeling" of how to create mental commands (which are often in form of analogies), and mention those experiences (analogies) to other users. We could experiment with different types of analogies and observe what type of users found it useful and what type did not, and whether it increased performance.

We do not know the exact strategies that work best for each user, hence we can only suggest all the strategies available and let the user choose the one she is most comfortable with. Maybe we could use prediction models to find which strategy could work best according to user skills, and suggest the strategy optimal for each user.

Notice that what is typically used for conceptual models (analogies) in HCI, we must use within the procedural models as well. That is because phenomena such as mental-machine commands are still rare and lack human experience, and thus a dedicated universal category. One day these phenomena might even gain a dedicated name, a term which once evoked would immediately produce an experience that relate to it, as it is the case for clicking a mouse button.

7.2.2 Perceptual Affordance

Perceptual affordance [Gibson, 1958] is a theory that assumes that the mere perception of an object leads to the "mental activation" of possible actions one could perform on this object. For instance, an object such as a eyebrow pinch provides perceptual information of the possible actions that can be performed on it, as picking it up and pinching it (of course given the observer's experience). Such perceptual information actuates in the observer a finite set of possible actions that can be performed. In this theory perception and action are intrinsically linked, in a continuous feedback loop. As Gibson argued, "We must perceive in order to move, but we must also move in order to perceive". Every action provides feedback about the just-performed movement and generates information that can be used for guiding the next movement [Franchak et al., 2010].

Behavioral experiments have shown that depending on the size, orientation and location of the object, one can have different degrees of response time, and precision when performing an action [Symes et al., 2007]. For instance, if the pinch is too small for the size of user's hand, or if it is closer to the non-dominant hand or oriented opposite from the grasp, the response time is lower than if the spatial characteristics were better suited for that user. Furthermore, when there is fluency and ease in performing an action, users usually attribute a pleasurable feeling opposite from a non-fluent action which brings minor frustration [Regenberg et al., 2012].

Neuroimaging experimental studies show when passively observing manipulable objects versus non-manipulable ones, there is stronger activation in motor cortex as shown in fMRI [Chao and Martin, 2000], also stronger mu desynchronisation over centro-parietal region [Proverbio, 2012]; and especially within the range of the dominant hand versus non-dominant one [Gallivan et al., 2011, Rowe et al., 2017]. Furthermore, higher motor evoked potentials were found during the observation of graspable objects falling within peripersonal space (i.e., reachable within a hand grasp) compared to the observation of either non-graspable or graspable objects falling within the extrapersonal space (i.e., out of reach or grasp) [Cardellicchio et al., 2011]. More importantly, when the task is to judge the distance of the object, mu desynchronization is strongest when the objects are within the peripersonal space, and diminishes with distance boundaries of peripersonal space, and extrapersonal space [Wamain et al., 2016]. In the same experiment, when the observers were to focus on object identification, while the object location was changed, interestingly, the mu desynchronization was not modulated. This means that the object location can influence motor activation if the observer is not focused on another task. This suggests that "the involvement of the motor network in the processing of visual objects in peripersonal space is not automatic but rather depends on the goal of the perceptual task" [Wamain et al., 2016].

On the other hand, observing action performed on objects produces the well-known mirror neuron effect that activates motor neurons. Additionally, mu suppression is showed to be significantly stronger when the observation is task-related versus when it is not [Schuch et al., 2010]. In this experiment, subjects were presented a video of repeated mug grasping and in one case they were to count the number of times the mug was grasped (observation is task-related) or the number of colour changes (not task related).

These results could explain the success of using virtual environments for motor imagery BCI [Alimardani et al., 2014, Vourvopoulos et al., 2016] as the objects presented were within the peripersonal space, manipulable and congruent with the MI task, i.e., the movement imagination was related to the visual representation. Also, the objects were easily graspable, i.e., their orientation and size were configured to suit the virtual hands.

The objects represented in a BCI task can differ in size, location (near-far space), orientation, and congruency, without any particular verification or control of potential effects on motor activation. This vast literature indicates that we should design BCI tasks with caution, and that we cannot compare results between such different designs.

Experiments that study the effect of objects presented in 2D or 3D, or in continuous movement versus as discrete apparition, are yet to be investigated. Also, the difference in timing of apparition or speed of movement might as well have an impact, but it is to be further researched in the literature. Typically, the feedback is continuous for MI BCI tasks, while instructions are short and discrete. However, objects in MI tasks could appear discretely and stay within the peripersonal space on the left or right of the observer.

In conclusion, we must acknowledge the fact that different BCI task representations influence users as observers and activate different neurophysiological pathways that in turn modify system performance.

7.2.3 Proposal of a Training and Task Design

We presented the vast literature from both HCI, and cognitive neuroscience and psychology that support the need of a BCI task standardization (notably for MI), from user training to task design:

1. User training should follow some structure or guidelines, using conceptual, procedural and interaction models.
2. When designing BCI task, one should consider that the object characteristics (spatial and temporal) and functions (e.g. congruency) can influence different neural activation (due to perceptual affordance), and in turn produce unexpected results.

We propose that experimenters should account for the categories in which their BCI task designs and training protocols belong to, see figure 7.1.

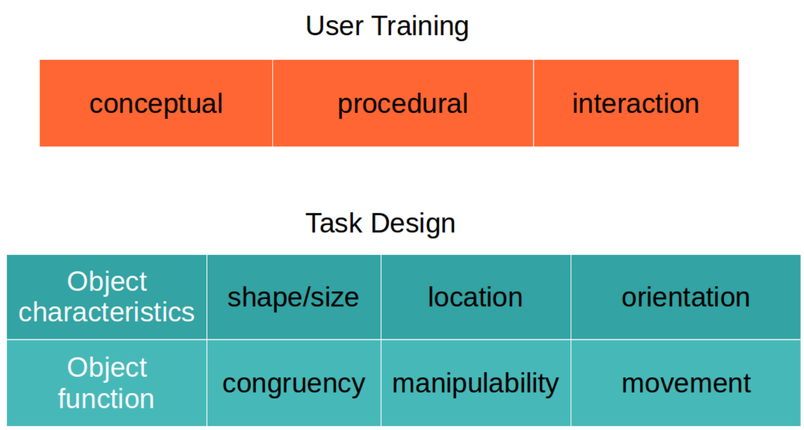


Figure 7.1: A first (preliminary) proposition for task design and user training standardization. Experimenter can choose to provide either one or a combination of the proposed trainings using conceptual (short explanatory video or EEG signal representation real-time), procedural (how-to procedures or experiences/strategies of others) or interaction (directly train through trial and error) models. As for task design, one should note the object characteristics such as shape, size, orientation and location according to the subject, along with the object function: whether it is congruent to the task, a manipulable object and if it is moving in 2 or 3 dimensional space, in a continuous or discrete manner. Note that the object can represent both feedback and instructions.

Although, we have only provided supporting ground for the visual perceptual affordance, this proposed standardization could apply to other modalities. For instance, sound or haptic modality can be presented as an "object" as well, one that we can hear or touch. The orientation and location of the sound coming from different speakers, it can move from one speaker to another or be static; it can present a congruent or non-congruent sound of an action using a manipulable or non-manipulable physical object. The sound "size" can be thought of as intensity (measured in decibels), while the shape can be interpreted as different frequencies used, "wave shapes".

This way, if experimenters acknowledge these categories either for user training or task design, or both, we could more easily compare the results between such task designs that and have for instance the same object characteristics. Moreover, such categorization could provide a clearer expectation of the task outcomes, or less variability in the results.

7.3 Thesis Contribution

In chapter 2, we propose a taxonomy for adaptive BCIs as a conceptual framework, in which we:

1. introduce a novel categorization of User factors (that showed important for BCI performance in the literature) arranged by the degree of changeability in time.

2. introduce for the first time a BCI Task model necessary for achieving an adaptation that is not only based on adjusting the system pipeline to signal variabilities, but that enables influencing the cause of signal variabilities (the user) to increase performance (potentially reduce if not prevent unwanted signal variabilities).

3. introduce the Interface as a representation of the Task model through which we can adaptively influence the user, i.e., through feedback and instructions.

4. propose an intelligent agent that would choose a *criterion of adaptation*, be it to favour user states or machine accuracy, and which the overall adaptation would be based upon.

Guided by the proposed taxonomy, we first explore ways to optimally influence the user basing our task adaptation on cognitive educational psychology. Hence, in chapter 3 we experimentally show that we can influence the user through an adaptive biased feedback to increase a state of flow, i.e., an optimal state of immersion, control and pleasure, which in turn positively correlates with performance.

Promising results from chapter 3 led us to explore further the relations between user traits, states and performance, and even learning rate in chapter 4. Again, guided by the proposed taxonomy for adaptive BCIs, this time we wished to create a predictive model of users that could serve as an *optimization criteri*a that guides adaptation processes overall. In other words, we learned what factors (what kind of feedback bias) to provide in case we want to increase performance or learning, specific to each user profile.

Furthermore, such predictive models serve as priors fed into a simple adaptive model for optimal bias selection, proposed in chapter 5.

Finally, in search for a computational generic framework that can incorporate all the dynamic components of the BCI triplet (the user, the task and system pipeline), we found that best suited for such adaptation is Active (Bayesian) Inference. In chapter 6 we describe such generic and flexible computational framework that enables automatic adaptation based on user reactions, and accounts for a predefined goal. Its adaptation consists of both perceiving the user reactions and acting upon them so to minimize prediction error and maximize information about the user states. It is based upon the fact that perception and action are intrinsically linked, and that to optimize perception or inference of the user it is to optimize its action on the user. Furthermore, its adaptation is led by a predefined goal. In our P300-speller example, we set a simple goal being a correctly spelled letter, i.e., the *criteria* is to increase bit-rate. However, we can consider any optimization criteria such as reaching a *flow* state for instance, by configuring a few key parameters of Active Inference.

7.4 Perspectives

Our work started with the creation of a taxonomy for adaptive BCI, an adaptive framework that includes most possible factors that can change or adapt in a BCI system (from the user, task and machine decoding pipeline). In chapter 2 we highlighted the gaps yet to be investigated in BCI that became visible with such framework. We investigated a few of those gaps, for 2 paradigms, Motor Imagery and P300-speller. To close the cycle, we re-present methods that we evaluated, and the gaps yet to be filled with the same framework, see figure 7.2.

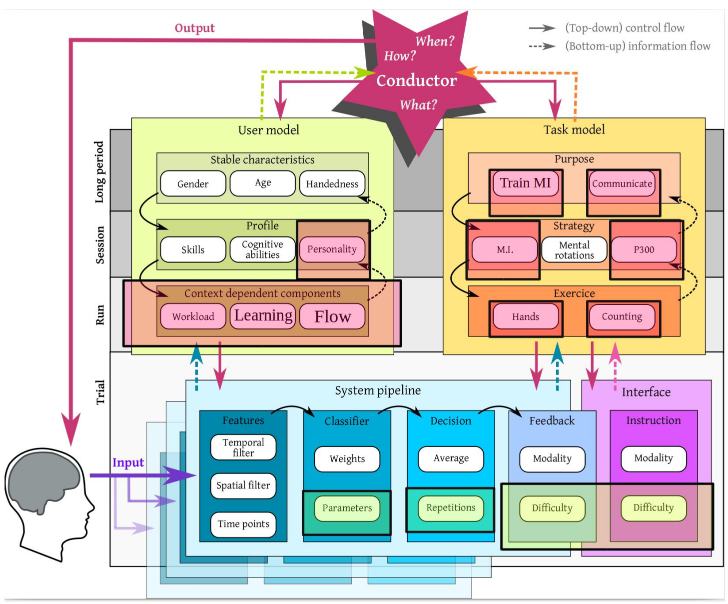


Figure 7.2: Adaptive methods that we investigated in this thesis, using the BCI adaptive framework, proposed in 2. Highlighted in yellow are elements that were adapted, while in red are the factors that guided the adaptation, or simply represent the context in which the adaptation took place (e.g. MI and P300-speller BCIs).

Note that the adaptation from bottom, short-time scale can take place in higher time scales, while the higher ones are not so common to be adapted within the shorter time scales. For instance, we have adapted the classifier parameters (mean re-centering from

[Vidaurre et al., 2010]) within runs for instance. On the other hand, personality traits (scores from questionnaires) will not be recalculated within runs or trials (within lower time-scales) but rather at least within sessions. As well as, for instance the task purpose would not change within trials or runs of a BCI session.

This framework will a new, serve for visualizing what was done (this time by us), as well as the missing gaps yet to be filled. We denote in **bold** the elements that are part of the BCI taxonomy.

First of all, we adapted the MI task **difficulty** through **feedback** bias within trials to influence the **contextual based flow state** (see chapter 3). The users' **exercise** comprised of imagined **hand movements** to control the machine and the **purpose** of the experiment was for enhancing **MI user training**. This purpose integrates an optimization *criteria,* that is to increase system performance and user experience overall.

Second, in a simulation, we adapted the feedback task difficulty within runs to increase performance, while taking into account **user traits** (see chapter 5). In order to do so, we needed to acquire user reactions to different task difficulties (bias types) depending on user trait, which we did in another MI experiment, in chapter 4. In this same MI experiment, we also **adapted the classifier within runs** that would reduce the EEG non-stationarity [Vidaurre et al., 2010].

Third, we adapted a **P300-speller** BCI task to increase both speed and accuracy (i.e., the *criteria* integrated within the **communication purpose**) using data-driven adaptive generic framework – Active Inference. It adapts the number of flashing **repetitions** needed for the **decision** to be made for spelling a letter, for each user. In this way, both **feedback** (spelling) and **instructions** (flashing) were automatically adapted according to short-term user reactions. In this case, the instruction "**difficulty**" is adapted in a sense that the order of flashing items implicitly provided a degree of *difficulty* for the user to elicit a P300 ERP. The adaptive model provided intelligent flashing to elicit such ERP that best reveal the target letter (see 6).

7.4.1 Gaps in Adaptation

Interface.

1. We used only the visual or audio modality separately, however we could have switched between different modalities instead of or along with the task difficulty adaptation.

2. In MI BCI we adapted the difficulty through the feedback bias, however we could have adapted the difficulty of instructions or interface as well, e.g. by modifying the speed or order of instructions' appearance, or changing the interval (pause) between trials.

User Model.

1. We believe that the optimal user context based component (state) is the flow state, state of immersion, control and pleasure. Hence we investigated a way to increase it and along with it, to increase performance. We investigated as well the user

learning and workload. However we could have focused on other states, such as motivation, mood (valence, arousal), and attentional focus for instance.

2. We investigated user traits and their relation to performance and learning. However, we could have investigated skills such as spatial rotation that has shown as a strong predictor of performance [Jeunet et al., 2016], or other cognitive abilities such as memory and attentional capacities and so on.

3. We have not investigated the user stable characteristics such as gender or age, their relation to the change in task difficulty and task representation, or interface.

Task Model.

1. We have mostly focused on adapting the task difficulty within trials or runs. However we could have adapted some higher time-scale elements. For instance, we could adapt between a BCI MI and P300. If we predicted that some users would perform better in a P300 task than in a MI one, than we would provide the same task but within a different task strategy. Or switch between motor imagery and mental calculations or rotations for instance.

2. Within a Motor Imagery task, we could switch between task exercises that involve imagination of hand movement, or tongue or feet for instance.

Note that what we call the task strategy is different from the user strategy which a user performs during the task exercise. For instance, a user can have a kinesthetic or visual strategy to perform the exercise of imagining hand movements.

Signal Processing Pipeline.

1. We could have performed many temporal, spatial or epoching adaptations. However in the end if we would perform such changes along with the task difficulty it would have created too many variables, and we would not have known the exact reason for the potential performance or learning improvements.

2. We also could have used other physiological measurements along with EEG. On the side note, we have investigated some interesting physiological processes (within the enteric nervous system) that could enable an easy assessment of user emotional states (see Appendix 7.5)

7.4.2 Positioning our Task Designs within the Task Standardization

In this chapter (in section 7.2) we present some facts about the perceptual affordance [Gibson, 1958], that is, how the task representation can directly influence user performance, especially motor reactions. Before knowing this, we used as task design, a game called Tux racer that complies with the Instructional Design Theories [Keller, 1987].

We here describe it in the terms of our proposed standardization of task design (see 7.2), and denote in bold the factors of the standardization model. Tux Racer game provides a **3D perspective**, it is **continuous**, i.e., the feedback is mapped to a penguin that continuously slides through a ski course. It is **not congruent** with the MI task, i.e., the users imagine left-right hand movements in order to control a penguin to slide to the left or right, on its belly. It does not have **manipulable objects**, i.e., there are fish located on both left and right side, compensating for the negative effect of non-dominant hand object location. We also added background music as it showed to influence positively the state of flow and motivation (see chapter 3). The music however, was **not synchronized** with the pace of the motor imagery. We additionally had sound effects such as the sound of sliding through snow and a "bloop" when a fish was caught. This sound was **congruent** to the game task but not specifically to a motor imagery or a sound of a hand performing a realistic action; and it was **synchronised** with the imagined movement as it was directly produced by the penguin actions (mapped from the classifier output).

Thanks to this MI experiment, we noticed the importance of perceptual influence on the user performance and conducted a preliminary experiment to investigate the impact of a congruent sound on MI performance (see section 3.3). Unfortunately, we did not have enough resources to perform this experiment as we hoped (it was conducted in a lab that specializes in sound and not BCI, thus lacking the necessary equipment and experience). Although preliminary, the results were quite encouraging (see 3.3.3). We could indeed continue to investigate the importance of a congruent versus non congruent sound. Especially with the newly acquired knowledge from the perceptual affordance, we could design the task more rigorously, and anticipate better the outcomes of such experiment. We could also test the visual modality in VR of a congruent feedback and or instructions and compare it with the auditory one.

7.4.3 Improving Existing Methods

Flow. Our first simplistic task representation and difficulty adaptation method was based on the Flow theory. We should investigate the neurophysiological correlates of flow, and create a computational model of flow that could automatically adapt to each user in order to increase such psychological state. In general, what is missing in our methods is the link or relation between the task influence on the neurophysiology to the psychological states and then system performance. Thus, we ought to perform many physiological analyses.

Prediction Models. We have used too many factors for predicting performance and learning, as opposed to the scarce population of subjects. We should acquire more data that could enable us to find more interesting results, and validate our predictions on the influence of adaptive bias, depending on user traits and states.

As a more technical matter, prediction models are not the only possible solution. We can investigate another approach, called the Structural Equation Modeling or the SEM. It is often used in psychology to analyze various influences between factors that cannot be easily measured, but can be described implicitly through the use of latent variables [Kaplan, 2008]. Its potential advantage, when compared to prediction models, is that it can incorporate more relations and factors within one model representation.

Adaptive Models. We have made a step further into adapting a BCI as proposed in our taxonomy for adaptive BCIs; from simple bias adaptation from flow theory to a data-driven adaptation that takes into account the User model components. That is, we use the information within the user profile (traits) and their relation with feedback bias as priors, in order to enable an accurate task adaptation within runs and increase performance automatically. Within the model, we can choose the *criteria* of adaptation, be it to increase performance, learning or flow state for instance. However, the problem is that we use a simulation and create virtual user reactions from a changing bias between runs. Thus, we could test our adaptive feedback bias model on new real data online.

Active Inference. Active Inference represents a generic and flexible adaptive framework that could incorporate the whole BCI adaptive taxonomy. It could be the intelligent agent, the ***Conductor***, that decides how, when and which element of the BCI should be adapted.

However, we test it only in a simulated P300 context, setting a simplistic goal such as a correctly spelled letter, with short-term user intentions as states, ERP with ErrP reactions as observations, and actions such as flashing, spelling and switching-off. As it is a very flexible framework it could incorporate more complex goals, states, observations and machine actions. However, for such complex cases, the way it is implemented (in matlab) it seems to be not optimal to be used in real-time. Nonetheless, for now it could be easily tested online for the "simple" goals, in the presented P300 (optimal flashing and stopping) and for a MI (optimal bias) BCI task.

Furthermore, we could test whether for simple (short-term) goals, there is a necessity for such a powerful framework such as Active Inference, or a simple adaptive model we proposed in 5 could suffice. To answer this question, we could compare the computational complexity and benefits between the two proposed adaptive models on our existing simulations. For now the benefit of the simple adaptive model is in its simplicity not only concerning data reproducibility but also for theoretical understanding.

7.5 Conclusion

I believe that this thesis brought many novel ideas and useful perspectives on ways to enhance BCIs. We bring a completely new point of view of how an adaptive BCI should be improved; that is, not only through adaptive decoding methods but particularly through adaptive influences on the user.

We have opened many potential research directions, and I personally hope that someone will be interested in joining me in the investigation of optimal, data-driven machine actions to improve performance, learning and user experience for each BCI user.

On a side note, I believe that in order to fully understand the user and complete the user model, we should not only regard the brain activity, but engage in a holistic approach that includes other physiological processes, such as breathing, heart rate, perspiration, and especially gut contractions (see electrogastrography EGG, in appendix 7.5).

Appendix

New Task Model

This model is hypothetical, and although it has foundations in the literature, we give the liberty to the reader to find grounding from this thesis' findings and other scientific links, and form their own interpretations and ideas.

Let us assume that this is a perfect recording where the noise, and variability is minimally caused by the EEG equipment and environment, but only the user. Also, let's say that we know the negative, or unwanted characteristics of EEG signal on the BCI performance and user experience. Those are, (1.) instability, i.e., a signal that varies a lot in time; (2.) un-clearness (low Signal to Noise Ratio, SNR), i.e., if we assume the feature of interest has a dedicated form, or wavelet, a not-clear signal would contain a lot of "other" signal that does not match such form; and (3.) uncertainty or in-distinctiveness, i.e., low confidence to belong to one class, low separability between classes. If we pay attention to the terminology or language we use for describing such phenomena, we could draw a link to the psychological phenomena that have similar effects.

- Instability, low stability of mental commands, i.e., the person alternates her thoughts between several or two "central topics" due to low attention span, fatigue or proneness for boredom or anxiety, for instance.
- Not a clear signal, low matching between the intended command and observed one, i.e., the person lacks a clear intention when performing the mental command due to low understanding, fatigue or lack of confidence (control) for instance.
- Non-separable, Indistinct signals (when including more than one command), i.e., the person lacks a clear differentiation (separation) between the two commands, one be confused with the other due to lack of attentional focus, understanding "how-to" separate one from the other, or lack of confidence again.

All these phenomena can be inter-dependent, especially the last one that can be seen as a combination of the first two, as it includes a *clear* separation between two commands, and necessitates *stability* or "staying" in one state (i.e., to keep performing one command at a time). Note that we have proposed potential causes of such phenomena, such as understanding, attention, confidence and so on. Those causes that relate to more stable user components, they can generally, *a priori* influence all phenomena in the same direction, as they will not change during the BCI task. For instance, anxiety, proneness to boredom, fatigue and so on, they will negatively influence all three mentioned phenomena in the same "negative direction" and keep it that way throughout the session. They provide a certain basis for user contextual based states, as reminder see 2. As we assume they can not be influenced during a BCI task, we focus only on contextual dependent states such as attentional focus and confidence (sense of control), shown to most influence performance [Jeunet et al., 2016]. We add another contextual user component such as task understanding, as we have shown (in 4.5) some users with low performance calibration might benefit only from a better understanding of the task. However, indeed if we have prior knowledge about the user traits as well, it can be always useful for having a better starting point of user's reactions and their evolution (as shown in 5).

This linguistic link between psychological and physiological terms used could provide solutions for adaptive task designs (machine actions) that influence mentioned context dependent user states. We derive potential machine actions that could automatically switch from one to another in order to influence the user and minimize said unwanted signal variability, see figure 7.3.

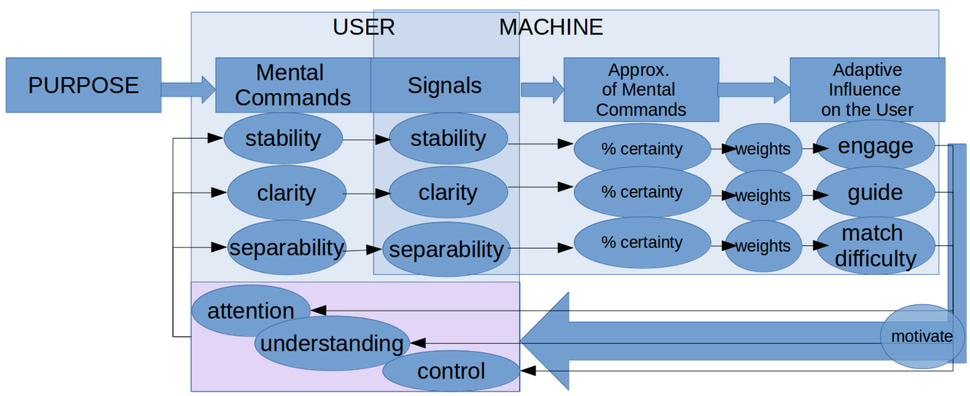


Figure 7.3: Depending on the purpose, using new metrics based on stability, clarity and separability of mental commands, the machine would provide adaptive action (influence) to engage, guide and match task difficulty (bias feedback for instance) following motivational instructional designs to increase attention, understanding and sense of control or confidence.

As proposed in Active Inference (chapter 6), depending on the goal or purpose, this model could adapt according to user reactions that are measured through the stability, clarity and separability of mental commands. These phenomena can be attributed with the following metrics: (1.) stability can be measured with the form of Riemannian standard deviation between each trial covariance matrix and the average covariance matrix for this task [Lotte and Jeunet, 2017], or as KL divergence between 2 probabilities of the same class through 2 consecutive time windows (as in [Perdikis et al., 2016]) (2.) clarity can be measured using convolutions to match the signal with the wavelet that corresponds to the mental command (wavelet learned using dictionary learning [Hitziger et al., 2013]), or it can be measured using distinctiveness – Riemannian distance between the average covariance matrices for each task for one mental command, and (3.) separability between classes can be measured using the same distinctiveness metric [Lotte and Jeunet, 2017] or as the separability index or KL divergence between 2 class probabilities (as in [Perdikis et al., 2016]) for instance.

Once these are measured, the machine would calculate the difference (change) between the previous and new levels of all three metrics. Based on the machine's certainty of acquired information it would attribute weights (or probabilities) on the action to be performed to influence the user (or to keep the same settings as before). We propose 3 types of action, all performed in accordance with the motivational instructional design theories, e.g. [Keller, 2010]:

1. Engage, by modifying (adding or reducing) immersive content (e.g. sound effects, relaxing or exciting background music) or pauses.

2. Guide, by providing supporting cognitive material (e.g. EEG signal represented temporally and spatially, or as network connections), or instructions/stimuli in different modalities (e.g. tactile) to reinforce the somatosensory memory of the mental command.

3. Match difficulty, increase or decrease difficulty either by using biased feedback or by adding/reducing obstacles, speed, target location, orientation or congruency etc. within the Interface.

As the context based user states are inter-dependent, e.g. lack of attention is related to the lack of understanding or control, and vice versa, thus when providing adaptive influence (machine action), it is possible to observe unexpected reactions. For this reason, the inter-relations between there 3 selected user states must be additionally investigated through non-BCI experiments. First of all, what we would need is to design rigorous experiments in which we would acquire and measure physiological correlates to such states and their relations. For instance, we could provide unclear task goals, and investigate whether we observe low clarity in the signal and subjective lack of understanding; we can use distractors to make users think of another topic (thus having 2 topics in total), and then investigate if we observe low stability or an alternation mainly between 2 centroids of data points; and we could provide 2 tasks that are very similar to each-other, and bring confusion, and investigate whether we observe low separability of classes.

Appendix: Validation of Prediction Models

2^{nd} Performance prediction model:

The *Second* prediction model, that contains only interaction between selected factors and bias, that is, *average_perf_centered ~ bias : (calib_baseline + competition_enjoyment + extroversion + anxiety + toughMindedness + independence + selfControl + eduflow_basline + nasa_baseline*). Details about the fitting values, $\alpha = 1$, that is a Lasso regression, with selected $\lambda = 0.002840229$, giving a *mean_error= 0.01097834,* see figure 7.4.

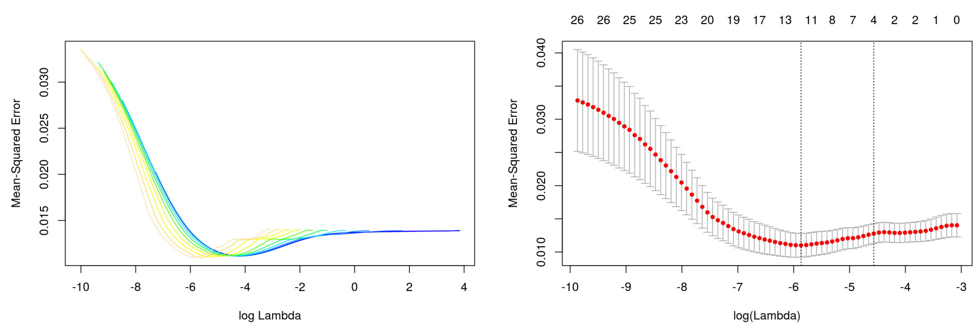


Figure 7.4: Upper figure: Mean-Squared Error of *10* α values (10 colours). Bottom figure: Such $\alpha = 1$ is selected for which λ has minimum error; there are 2 proposed λ values (gray vertical lines) the left one giving minimum error, and the other one is more regularized (selects less factors). Values presented above the bottom figure are the numbers of selected factors for each λ. The model selected 11 factors.

To show the model validity, we compared to a mean error of random data, shuffled 1000 times. It is significantly better than chance, see figure 7.5.

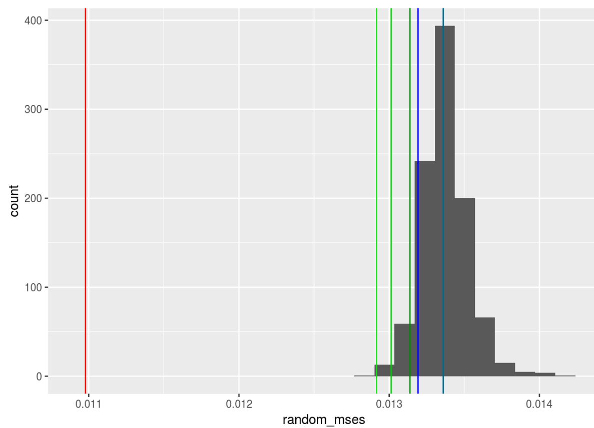


Figure 7.5: Histogram of mean errors. Mean squared error values (denoted as *random_mses*) are in *x-axis*. Our model mean error (30 iterations, in red), and random mean error (1000 iterations) of which blue and green colours represent different percentile values. The most left (lightest) green is 0.1 percentile, and we can clearly observe our model is significantly better than chance (*p<0.0001*).

3rd Performance prediction model:

The *Third* prediction model, that contains only interaction between bias and factors divided in *high-low groups*, that is, *average_perf_centered ~ bias : (calib_baseline + g_competition_enjoyment + g_extroversion + g_anxiety + g_toughMindedness + g_independence + g_selfControl)*. Details about the fitting values: $\alpha = 1$, that is a Lasso regression, with selected $\lambda = 0.007805173$, giving a *mean error: 0.01037466,* see figure 7.6.

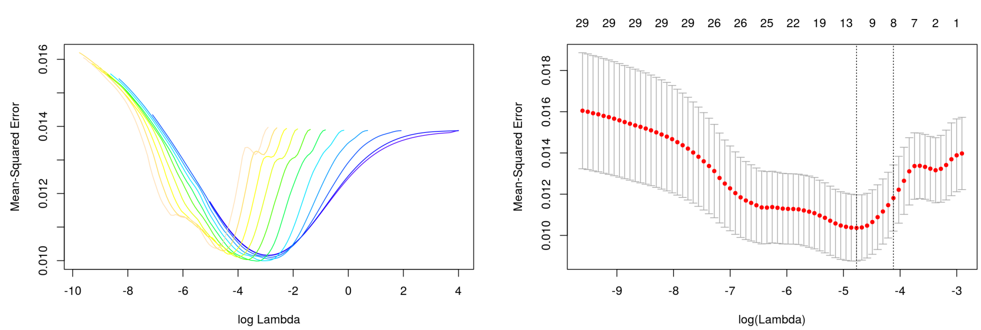


Figure 7.6: Upper figure: Mean-Squared Error of *10* α values (10 colours). Bottom figure: Such $\alpha = 1$ is selected for which λ has minimum error; there are 2 proposed λ values (gray vertical lines) the left one giving minimum error, and the other one is more regularized (selects less factors). Values presented above the bottom figure are the numbers of selected factors for each λ. The model selected 12 factors.

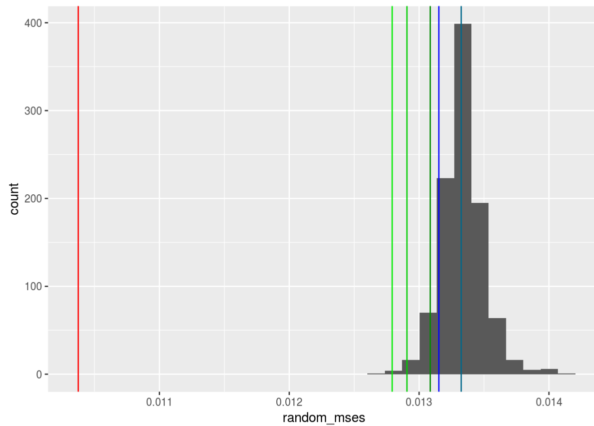


Figure 7.7: Histogram of mean errors. Mean squared error values (denoted as *random_mses*) are in *x-axis*. Our model mean error (30 iterations, in red), and random mean error (1000 iterations) of which blue and green colours represent different percentile values. The most left (lightest) green is 0.1 percentile, and we can clearly observe our model is significantly better than chance (*p<0.0001*).

———————

Progress prediction model:

Parameter selections, $\alpha = 0.7437333$, with penalty $\lambda = 0.001045726$, giving a *mean error: 0.003908549*, see 7.8.

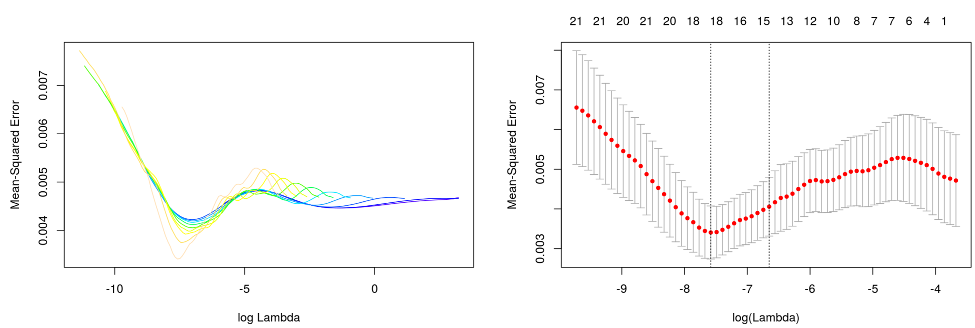


Figure 7.8: Upper figure: Mean-Squared Error of *10* α values (10 colours). Bottom figure: Such $\alpha = 1$ is selected for which λ has minimum error; there are 2 proposed λ values (gray vertical lines), the left one giving minimum error, and the other one is more regularized (selects less factors). Values presented above the bottom figure are the numbers of selected factors for each λ. The λ giving minimal error selected 18 factors.

Our model mean error is smaller then the 5^{th} percentile of the mean error of the random model, thus better than chance, see figure 7.9.

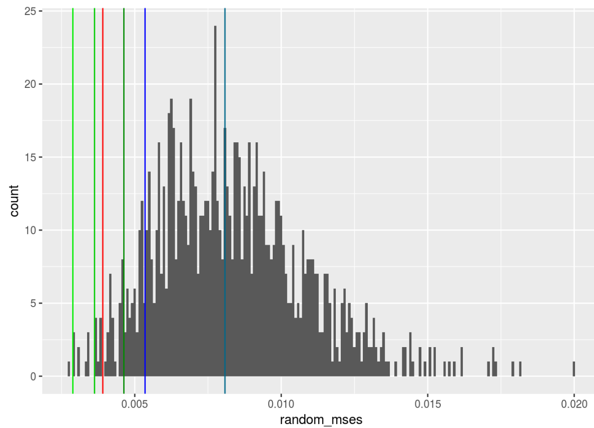


Figure 7.9: Histogram of mean errors. Mean squared error values (denoted as *random_mses*) are in *x-axis*. Our model mean error (30 iterations, in red), and random mean error (1000 iterations) of which blue and green colours represent different percentile values (from right to left are: median, *10 percentiles*, *5 percentiles*, *1 percentiles* and *0.1 percentiles*). Our model mean error is between *5 percentiles*, and *1 percentiles*.

Appendix: Active Inference

Relative Entropy:

Relative entropy, also called the Kullback-Libeler divergence, D_{KL} of 2 probability density functions Q and P : $D_{KL}(Q\|P)$ is a measure of the information gained when one revises one's beliefs from the prior probability distribution P to the posterior probability distribution Q. In other words, it is the amount of information lost when Q is used to approximate P [Burnham and Anderson, 2002]. In applications, P typically represents the "true" distribution of data, observations, or a precisely calculated distribution, in our case being $P(s_i|o_i, m)$, given the model m. Q typically represents an approximation of P, or in our case $Q(s_i|m)$. In order to find a distribution Q that is "closest" to P, we can minimize the KL divergence and compute an information projection $p^* = \underset{p \in P}{\arg\min}\, D_{KL}(q\|p)$. Viewing the KL divergence as a measure of distance in the space of probability distributions, p^* is the "closest" distribution to q of all the distributions in P. However, note that the KL divergence is not a metric as it is non-symmetric, in general $D_{KL}(P\|Q) \neq D_{KL}(Q\|P)$, and does not satisfy the triangle inequality. The KL divergence is always non-negative $D_{KL} \geq 0$, and is equal to zero if and only if the two distributions are equal. For discrete probability distributions Q (posterior) and P (prior), KL divergence is defined to be [MacKay and Mac Kay, 2003]:

$$D_{KL}(Q\|P) = -\sum_i Q_i \; log \; \frac{P_i}{Q_i}$$

Variational distribution:

As the agent is a Bayesian modeler, at each step it wants to maximize the model evidence or minimize surprise, i.e., to minimize expected prediction error $E_{Q(o_\tau|\pi)}[D_{KL}[Q(s_\tau|o_\tau, \pi)|Q(s_\tau|\pi)]]$. To evaluate surprise is a difficult problem of **exact** Bayesian inference, because we need to minimize the prediction between potentially many future states again given many possible priors. One needs to find a bound for the marginal (i.e., integrated) likelihood, which generally involves an intractable integral over hidden states s_i, i.e., summing out the states from $Q(s_i, o_i)$. So we need approximations or a bound to solve it (for more information, see [Blei et al., 2017]). Thus, if we add the same fixed, variational approximate distribution Q in the surprise, we get an approximate solution to the marginal likelihood and we get the expectation of surprise within a bound. Such minimization of surprise is also called the variational (approximate) free energy.

Investigating ElectroGastroGraphy for assessing Emotions

Abstract

Recent research in the enteric nervous system, sometimes called the second brain, has revealed potential of the digestive system in predicting emotion. Even though people regularly experience changes in their gastrointestinal (GI) tract which influence their mood and behavior multiple times per day, robust measurements and wearable devices are not quite developed for such phenomena. However, other manifestations of the autonomic nervous system such as electrodermal activity, heart rate, and facial muscle movement have been extensively used as measures of emotions or in biofeedback applications, while neglecting the gut. We expose electrogastrography (EGG), i.e., recordings of the myoelectric activity of the GI tract, as a possible measure for inferring human emotions. In this paper, we also wish to bring into light some fundamental questions about emotions, which are often taken for granted in the field of Human Computer Interaction, but are still a great debate in the fields of cognitive neuroscience and psychology.

Introduction

Recent developments in Human Computer Interaction (HCI), and physiological and affective computing brought to light the necessity for wearable and robust physiological sensors. So far, using physiological sensors a person can: (1) consciously monitor/regulate their bodily functions through biofeedback for well-being [McKee, 2008], (2) (un)consciously adapt an environment or task, which can for instance increase immersion in gaming [van de Laar et al., 2013b], or (3) consciously manipulate an external device with only physiological (neural) activity, as in active Brain-Computer Interfaces, to control wheelchairs or for communication for example[Wolpaw et al., 2002a]. Measures of electrodermal activity (EDA), cardiac function, facial muscles activity, and respiration have been used frequently to assess emotional states [Mayer and Saper, 2000]. Nowadays there are wearable devices developed for measuring EDA and heart rate, such as the Empatica E4 smartwatch. Remarkably however, the gastrointestinal system has often been neglected by affective research. Even though humans regularly experience having a "gut feeling" or "butterflies in the stomach", they often overlook the importance of such phenomenon as an actual physiological process. However, studies have shown that indeed the gut could have an important role in affective disorders [Bennett et al., 1998]. Still, non-invasive, robust physiological measurements or wearable devices for such phenomena are not yet developed. The possibility of assisting users in regulating the internal processes of the gut, and thus regulating the emotions that arise with such physiological processes are not yet taken seriously into consideration.

In this paper we briefly explain what the gut signal is, and the usefulness of such modality for inferring and regulating emotions, using a biofeedback. We also tackle some fundamental questions about emotions which are often taken lightly in the HCI community.

Gastro-Intestinal tract

The gastro-intestinal (GI) tract comprises of the mouth, esophagus, stomach and intestines. The GI tract has a bidirectional communication with the Central Nervous System (CNS) through the sympathetic and parasympathetic systems [Sudo et al., 2004], thus researchers often refer to the gut-brain axis. The GI tract is governed by the enteric nervous system which can act independently from the CNS and contains over 500 million nerves, which is why it is also called the "second brain". Moreover, today there has been many interest in the gut microbiota or microorganisms that inhabit the gut and have shown to have a role in the stress regulation in mice [Sudo et al., 2004].

The electrogastrogram (EGG) is a reliable and noninvasive method of recording gastric myoelectrical activity [Nelsen and Kohatsu, 1968]. The gastric myoelectrical activity paces the contraction of the stomach. The normal frequency of the electrogastric wave is 3 cycles per minute (cpm), and is termed normogastria [Koch and Stern, 2004]. It is worth nothing that amplifiers typically used for electroencephalography (assessing brain activity) have shown to be equally useful for EGG, for example in [Gharibans et al., 2018] using an affordable and open-source device, OpenBCI. Recent studies showed that EGG could be a valuable measure of emotion [Vianna and Tranel, 2006]. Individuals often report a "nervous stomach" for too frequent contractions (tachygastria, 4-9 cpm) during stressful experiences [Vujic, 2018]. Participants reacted with tachygastria during horror movies, but a reduced frequency of gastric waves during a relaxation session [Yin et al., 2004]. It is also shown that gastric slow waves can be useful for predicting the experience of disgust [Harrison et al., 2010].

Individuals clearly react emotionally with their gut, as well as the gut influences their emotions. As such, we advocate that it could be interesting to propose biofeedback specifically aimed at regulating a "nervous stomach".

Biofeedback for gut awareness

Biofeedback is a system that externalizes one's internal bodily activity, for example in visual, audio or haptic modalities. It assists people to be aware of their internal processes or physiological activity, as a technique of interoception, known to be beneficial for well-being [Farb et al., 2015]. Notice that biofeedback is built under the assumption that being aware of one's physiological processes creates or modulates an emotion. In other words, the perception of physiological changes contributes to the content of conscious experiences of emotion [Tsuchiya and Adolphs, 2007]. Biofeedback thus externalizes such phenomena and enables people to consciously examine and regulate their internal states and their experience of emotions. As the gut clearly has an important role in human emotion, we believe it could be beneficial to build an EGG wearable device which could record and process feedback to one's gut contractions, as depicted in Figure 7.10. Interestingly, the use of biofeedback could also expose the relationship between experiencing bodily activity and experiencing an emotion. In experiments where people are given a fake biofeedback to manipulate their emotions toward images of individuals, the perception of external audio stimuli dominated over their autonomic perception [Woll and McFall, 1979]. This leads us to ask whether the perceived physiological process is more important than the actual one.

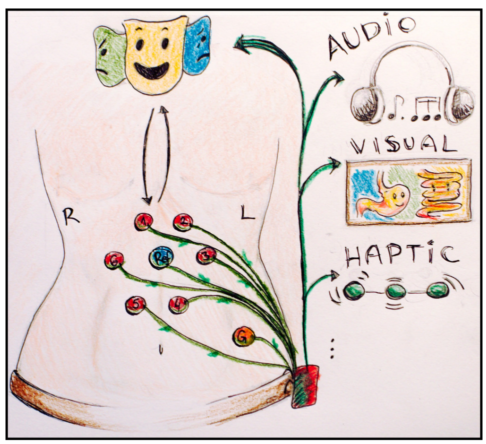


Figure 7.10: Depiction of a potential gut biofeedback for regulating emotion through various modalities out of which we expose audio, visual and haptic. The electrode positioning is from [Gharibans et al., 2018].

Relation between physiology and emotion

Sympathetic nervous system, governing the fight or flight mechanisms, influences sweat secretion, increases heart rate, constricts blood vessels in gastrointestinal organs or inhibits contractions in the digestive tract, and much more. These physiological changes are recognized as measures of emotion and expressed as stress, anxiety, fear etc. This assumption follows the James' theory [James, 1884] in which feeling (emotion experience) exists due to physiological changes in one's own body. James argued that seeing a fearful stimulus would first trigger emotional responses (increases in sympathetic activity), and that the perception of these physiological changes would form the basis for our conscious experience of emotion. Today, in affective neuroscience, the James theory is revised and updated, e.g. acknowledging the role of emotions in decision-making [Bechara et al., 2000]; or distinguishing "the conscious experience of an emotion (feeling), its expression (physiological response), and semantic knowledge about it (recognition)" [Tsuchiya and Adolphs, 2007]. Taking more often into consideration the role of the GI tract might help to reconcile antagonist views of emotion. For example, in [Johnsen et al., 2009] authors described the dissociation between the autonomic response and affect through the study of patients with brain lesions. In this experiment, patients without automonic responses would not sweat but would still be able to experience emotions related to music excerpts, while patients with different lesions, incapable of judging music, displayed EDA responses. As such, without a link between physiology and emotions, authors "opposed" James' theory. Nevertheless, we believe, as the enteric nervous system can function independently from the autonomic system, it could be that the physiology still contributed to the emotional perception of music.

Conclusion

With this paper we hope to foster discussions among HCI practitioners about the study of gut signals. To discover further how the body contributes to the experience of emotion and *vice versa*, it can be useful to include EGG as an additional tool for emotion recognition. Also, affordable and mobile biosignal amplifiers could enable the creation of a new biofeedback mechanism, in which individuals could learn how to regulate their emotion related to the gut.

Dishimo: Anchoring Our Breath

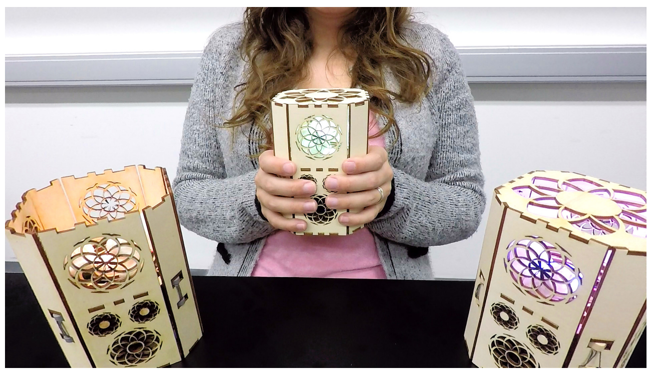


Figure 7.11: Dishimo: an ambient and shared biofeedback about heart rate variability.

Abstract

We present a system that raises awareness about users' inner state. Dishimo is a multimodal ambient display that provides feedback about one's stress level, which is assessed through heart rate monitoring. Upon detecting a low heart rate variability for a prolonged period of time, Dishimo plays an audio track, setting the pace of a regular and deep breathing. Users can then choose to take a moment to focus on their breath. By doing so, they will activate the Dishimo devices belonging to their close ones, who can then join for a shared relaxation session.

Introduction

Over the last decades, the increasing availability of physiological sensors enabled new ways to mediate with the body. In human-computer interaction, while physiological activity has been used as another explicit input modality, researchers also investigated how presenting biofeedback to users could alter self-awareness and prompt for better habits. In [Moraveji et al., 2011], a widget on a desktop computer was used to help people breathe better. This feedback was effective, but was occurring somehow intrusively, and the locus of attention was still on a computer device. Recent works such as [Roo et al., 2017] have started to explore how an ambient display with multimodal biofeedback could leverage physiological sensors to propose a calm experience focus on the body. In the present work, we take this idea further, incorporating real-time monitoring and exploring how a cluster of users can become an incentive for relaxation.

Dishimo ("we breathe" in Slavic languages) is a portable device that acts as a gentle and ambient reminder of one's state. It can be used not only to regulate oneself over the course of the day by breathing exercises, but several devices can be connected remotely in order to display those relaxation sessions to close ones.

We contribute to the field by leveraging behavior change with an ambient biofeedback which can be shared among a cluster. Not only the manifestation that a close one is using Dishimo could be an incentive to use the device and increase self-awareness, but joining a relaxation session could create an alternate way to empathize with other, by sharing explicitly physiological activity.

Scenario

When used in conjunction with a smartwatch capable of measuring heart rate, it will sense a decrease in heart rate variability (HRV) as a sign of stress or cognitive workload [Fairclough and Houston, 2004]. After a certain period of time, if the HRV does not improve, Dishimo will play a sound as a gentle reminder to breathe. The user can then choose to take a break from the current task and use Dishimo to focus on breathing for his or her well-being. They can also choose to ignore it, in which case Dishimo will automatically stop playing the sound. If the person's state does not improve, after a little while, the sound will resume. In cases where users do not wear a heart rate sensor, the device could be connected to a computer and be triggered when the user stares at the monitor for too long.

If users decide to take a break and grasp Dishimo, the device illuminates itself and the sound will fade to let them breathe at their own pace. Then, if they manage to regulate their breathing and increase their HRV, physical particles embedded inside Dishimo will start to flutter and produce harmonious tones when hitting the enclosure. This later feedback serves as a physical manifestation of cardiac coherence, a state known to be correlated with well-being [McCraty et al., 2009]. In future version, the device itself can be equipped with sensors to monitor heart rate by the mean of electrocardiography (ECG) when users grasp its edges.

During the demonstration, we propose to show how several devices could be used to orchestrate a co-located relaxation session. Up to 3 attendees will be able to use Dishimo. Their heart rate will be monitored, either by being equipped with a smartwatch or by direct contact with the device. Then, guided through audio with the modulation of a pink noise, within a couple minutes they will increase their HRV. Should an attendee manage to reach this state, their particles will flutter. Should all attendees increase HRV, the light of each device will brighten, an indicator of synchronization and shared relaxation.

Description of the system

Dishimo possesses two main features: it can sense the user and provide for a multi-modal feedback through light, sounds, and the actuation of physical particles. The bottom part of the device comprises its electronic components: an Adafruit Feather with a custom shield to power a speaker and detect when a user is grasping the device through capacitive touch – a conductive thread being woven around the edges (Figure 7.5). A step-up voltage regulator is also present in order to power up a 12V fan (Noctua NF-A8/R8 PWM) which is enclosed in the center of the device.

Figure 7.12: Dishimo Schematics: multimodal feedback is provided via sound, light, and fluttering particles.

The upper part of the device embeds LEDs (Adafruit Jewel) and a dome to diffuse their light. The upper section also serves as a "chamber" where particles can bounce when the fan is activated. Those particles are made of expanded polystyrene (Storopack Pelaspan). While they were meant to fill boxes and protect goods, they are light enough to fly with a modest airflow (from $\approx 34.8m^3/h$) and, more importantly, because of their material and shape, they happen to create a nice sound when they hit a surface, a sound reminiscent of wooden wind chimes. To provide for another sort of biofeedback, that is the manifestation of air flowing, is one of the core design idea of the project. The device underwent several iterations in order to find the right combination of shape and material in order to accommodate this particular type of feedback, which is triggered once HRV increases (Figure 7.13).

The Adafruit Feather board can connect to a host computer through Bluetooth BLE in order to retrieve HRV when the user is wearing a device capable of measuring heart rate, such as the Mio Alpha 2 (used in the current prototype). It can also be paired with an OpenBCI board, an amplifier dedicated to the recording of physiological signals such as ECG. The OpenBCI board fits inside the device and is sensitive enough to measure ECG upon contact with the conductive material placed around the edges of Dishimo, which then serve as electrodes connected through a bipolar montage.

Whenever measurements are made continuously with a smartwatch or discreetly with the OpenBCI board, signals are processed in real-time on a host computer running OpenViBE. To asses HRV, we measure the range of instantaneous heart rate over a 15s sliding time window, with thresholds HRV_{low} < 2 beats/min and HRV_{high} > 5 beats/min. Upon detection of a low HRV for 10m, the breathing guide played through the speaker is a modulated pink noise, as in [Roo et al., 2017], which reminds of the sound of waves. The synthesized breathing is ample and slow enough to induce an increase in HRV, with a frequency of 7.5 breaths per minute. We also used the results from [Frey et al., 2018] and increased the amount of time spent exhaled since such breathing feature was associated with positive emotions. The resulting sequence is $3\frac{1}{3}s$ breathe in, $3\frac{1}{3}s$ breathe out and finally a pause of $1\frac{1}{3}s$, that is repeated to form the guiding pattern.

The audio guide is played for 30s (4 breaths), after which the device will go silent. The volume of the audio guide is low enough so as not to compete with the attention level of users, avoiding being a push notification which would disturb them. It is eventually up to the user to decide whether they want to take a break or not. If they decide to use the device, upon grabbing, the audio guide will play again for 30s. It is not played continuously as the synthesized pattern only serves as example, and each user might have a slightly different pace of breathing.

Figure 7.13: Various iterations were necessary in order to find a material which would be pleasing to hold (wood vs plastic), a structure that lets enough air flow toward the particles, and a shape which would create harmonious sound when the latter are fluttering (faces vs curves).

When the device is touched, it is formally activated and it lights up with a color previously picked by the user. Among a cluster of users, the color of active users are mixed together (average of each RGB channel). The global brightness of the light is mapped to the ratio of active users who increased their HRV. In order to be as non-judgmental as possible, we purposely avoided to give information about who specifically reached a higher HRV. Dishimo is not meant to foster competition, that would defeat the purpose of improving well-being, instead it is an aid and a mediator.

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