31 A Generic Framework for Adaptive EEG-Based BCI Training and Operation

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CONTENTS

Abstract

Adaptive BCIs have shown promising results by reaching higher performances and robustness. However, existing methods lack guidelines in their manner of addressing the problem. Most of the current adaptive techniques simply handle challenges at hand by dynamically adjusting the machine to signal variability, often not entirely taking into account the human factors. To our knowledge, there has not been any work done in creating a taxonomy for adaptive BCIs, one that acknowledges and arranges known BCI components in a comprehensive and structured way. We propose a conceptual framework that encompasses adaptation approaches for both the user and the machine, that is, using instructional design observations as well as the usual machine learning techniques. This framework not only provides a coherent review of such extensive literature but also allows the readers to clearly visualize which component is being adapted and for what reason. Moreover, it enables the readers to perceive gaps in current BCIs

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and grasp the adaptive system in its entirety. Our proposal hopefully contributes as a guideline for a computational implementation of a fully adaptive BCI and an overall improvement.

31.1 INTRODUCTION

Thanks to the technological advancements, the interest in brain–computer interfaces (BCIs) has grown immensely during the last decades. BCIs are mainly used to facilitate the interaction between people with different disabilities and their environment (Millán et al. 2010; Perrin 2012). However, there has been outreach in nonclinical domains such as gaming and art (Lotte 2013a; Tan and Nijholt 2010).

There are two main paradigms in BCI, depending on the type of extracted physiological markers. (1) Spontaneous BCIs (synchronous or self-paced) paradigms typically measure oscillatory EEG activity, and the event-related desynchronization/synchronization (ERD/ERS) in sensorimotor rhythms (SMRs) (Pfurtscheller 2006). They are mainly related to motor imagery (MI) BCI, for instance, imagining left or right hand movements (Pfurtscheller 2006), and to mental imagery, such as mental object rotation or calculations (Faradji 2009). Spontaneous BCI paradigms may also rely on slow cortical potentials (Birbaumer and Kübler 2000). (2) Evoked responses or ERP (event-related potential)-based BCI paradigms are based on the attentional selection of an external stimulus among many. 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 (Donchin et al. 2000) or steady-state sensory evoked potentials (SS(V/A/S)EP) (Middendorf et al. 2000). Those BCIs follow the same rationale; they typically consist of (i) a calibration phase, in which the classifier "learns" to discriminate and translate signal features into commands, (ii) a training phase, in which the user learns to manipulate the system and to regulate his or her EEG patterns, and (iii) the application, in which the user has hopefully control over the system. A general opinion is that there is very little need for user training with ERP-based BCIs (Fazel-Rezai et al. 2012), even though the user can improve his or her P300 marker with training (Baykara 2016). However, the system calibration is often mandatory (Fazel-Rezai et al. 2012) and lasts about 10 min. Furthermore, 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 2014; Shenoy and Carmena 2014). Also, SMR with higher signal-to-noise ratio have been observed as a consequence of learning during such training (Gaume et al. 2016; Kober et al. 2013).

There are two main approaches engaged in improving BCI systems: (i) improving the machine learning techniques (Makeig et al. 2012; Müller et al. 2008) and the newly introduced (ii) improving human learning, by using the knowledge from instructional design and positive psychology (Lotte 2013b; Lotte and Jeunet 2015). 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 nonstationary brain signals, while human learning approaches assist in the production of 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. Including both aspects of adaptation, a symbiotic coadaptation (Sanchez et al. 2009) could give rise to a system ready to be used in real-life conditions.

However, 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, and so on (Maby 2016) to (ii) the fluctuations in the user's psychophysiological states, as a result of fatigue, motivation, attention, and so on (Jeunet et al. 2016). For these reasons, a BCI has not yet proven to be reliable enough to be used outside the laboratory (Wolpaw and Wolpaw 2012). In particular, it is still almost impossible to create one BCI design effective for every user, owing to large intersubject variability (Allison and Neuper 2010). Therefore, 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 (Lotte 2013b; Wolpaw and Wolpaw 2012). This calls for adaptive BCI training and operation.

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 that 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, that is, referring to instructional design observations as well as the usual machine learning techniques. It not only provides 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. BCIs, which use noninvasive electroencephalography (EEG) as a measuring tool, will be 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 organized as follows. Section 31.2 discusses the reasoning behind creating adaptive BCIs; it will guide the reader through the aspects of human and machine learning that call for adaptive methods. Section 31.3 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 31.4, we describe the challenges and future work. Finally, Section 31.5 is the concluding section of this chapter.

31.2 ADAPTIVE BCI SYSTEMS—MOTIVATIONS AND PRINCIPLES

For the sake of understanding the reasons for adaptation, we develop prominent variabilities that cause low BCI performance and present the main principles used for adaptation.

31.2.1 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 2013b).

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 help design more advanced and more robust approaches. 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 somewhat used to describe the user, environment, and equipment "variability" and, more frequently, the signal variability. These two variabilities are often confounded, as one being the cause and the other being the effect, respectively. Throughout this chapter, we mostly address the user variability as the main cause and denote its various expressions as *components*.

31.2.1.1 Causes of Signal Variability

Variability can be distinguished as (1) short term (Schlögl et al. 2010), that is, signal variabilities within trials or runs caused by, for example, fluctuations in attention, mood, and muscle tension (Jeunet et al. 2016; Schumacher 2015), or (2) long term (Schlögl et al. 2010), such as regulations of SMRs over sessions because of learning (Kober et al. 2013). EEG variability can be provoked by many causes, as follows:

The equipment and experimental context:

1. Equipment sensitivity or magnetic field present in the environment (Maby 2016; Niedermeyer and da Silva 2005)
2. Quality of the instructions given to the user to follow through the task (Neuper et al. 2005)

Short-term user *components*:

1. Attention, mood (Jeunet et al. 2016; Nijboer et al. 2008), and muscle tension (Schumacher 2015), naturally evolving during, and somewhat driven by, the interaction with a BCI system.
2. In the case of no specific instruction, user's mental command itself can be a cause of signal variability. For instance, during a MI task, the user may be using kinesthetic or visual MI as strategy for mental commands (Neuper et al. 2005).

Long-term user *components*:

1. The user's learning capacity to control the machine depending on memory span, intrinsic motivation, curiosity, user profiles, and skills (Jeunet et al. 2016).

A negative or positive loop in learning progression could occur (see instructional design—Keller 2010; Oudeyer et al. 2016). For instance, a positive loop concerns a motivated user in 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. 2014).

31.2.2 Main Principles of Adaptation

When considering adaptation, 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 by simplifying the layout or diminishing the task difficulty if the user is in a state of fatigue (Hattie and Timperley 2007; Sweller et al. 1998). Ideally, the BCI system should be (i) set *a priori* for each subject, for instance, based on their stable characteristics (skills or profile), and also (ii) dynamically readjusted during the usage, according to their evolving cognitive and affective states.

31.2.2.1 Machine Learning

The BCI community has long been aware of the need for adaptive signal processing and classification (Krusienski et al. 2011; Schlögl et al. 2010). Experimental results have confirmed that using adaptive features and classifiers significantly improves BCI performances, both offline and online (Mattout et al. 2014; McFarland et al. 2011). Signal processing adaptation appears to be particularly useful for spontaneous BCI such as MI (McFarland et al. 2011). However, they 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. 2014).

31.2.2.2 Human Learning

It is shown that one's capacity to create distinct EEG patterns depends, among others, on one's psychological *components* as motivation, mood, skills, personality traits, and so on (Hammer et al. 2012; Jeunet et al. 2016). In that way, those patterns are more or less detectable and as such influence the BCI performance accuracy (Wolpaw 2002). To assist the users to produce clear EEG patterns is to assist in their learning. To do that, we consider adapting the BCI output (feedback and instructions) by considering a specter of users' psychological *components* in order to keep them motivated and for them to perform well and to be efficient and effective. As in any discipline, a well-designed and well-adapted feedback on one's progress from a tutor is what enables further development, intrinsic motivation, and learning (derived from cognitive developmental theories with Vygotsky 1978, and refined through instructional design theories [Keller 2010]). It is important to design a feedback that would encourage motivation and learning (Lumsden et al. 2016) and thus good BCI performance. Moreover, 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).

In order to minimize fatigue and induce motivation in BCI, we should investigate the instructional design theories (Lotte 2013b). These theories could be useful for finding and guiding the adaptation of tasks to users' skills, profiles, and cognitive abilities. Indeed, it has been shown that, for instance, visual–motor coordination and the ability to concentrate (Hammer et al. 2012); age, gender, practicing sports, gaming, or playing a musical instrument (Randolph 2012); moods and motivation (Nijboer et al. 2008); or spatial abilities (abilities to create, manipulate, and transform mental images) (Jeunet et al. 2016) were all positively correlated to MI BCI performances (classification accuracy). It is likely that some other factors may affect BCI performances, e.g., mental workload, which is known to affect learning in general (Sweller et al. 1998). Accounting for the variety of users' psychological *components* would lead to a better BCI feedback design and task adaptation, further assisting them in learning to control a BCI. This way, the EEG patterns would be regulated, which implies that to assist in the user's learning also means to assist in the machine learning techniques.

31.3 FRAMEWORK

We introduce a conceptual framework that can be used as a tool for a clear visualization of the elements being adapted, as well as of the missing methods that could possibly lead to optimal adaptive BCI design. It emphasizes existing solutions encompassing all the information possibly used for creating a fully adaptive BCI system. The framework (see Figure 31.1) has a hierarchical structure,

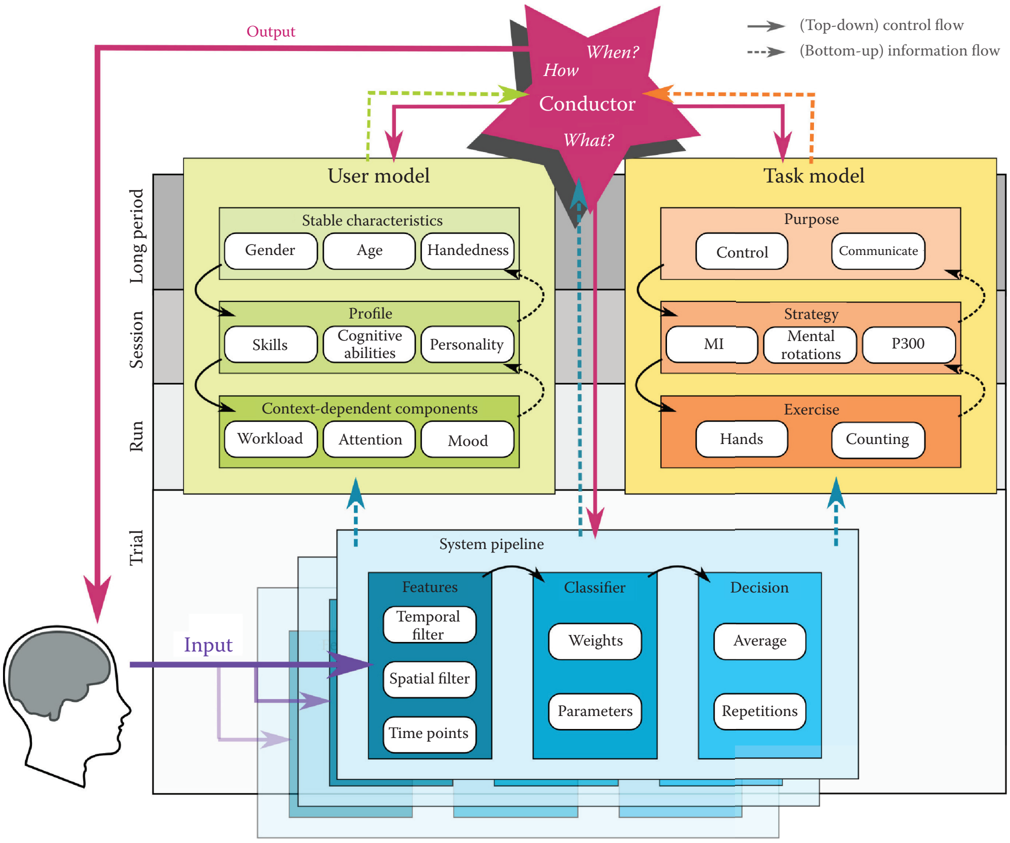

FIGURE 31.1 Multiple signals (input) may be observed and processed in parallel in order to infer complementary states or intents, at the trailwise time scale. All the information extracted from these parallel pipelines may trigger the updating of the user or task model, which, in turn, might yield a decision from the conductor to take action, such as adapting one of the systems or the output, or modifying the task or the user model.

from the lowest-level elements that endure rapid changes to the highest-level elements that change at a much slower rate.

It is composed of four major elements, presented bottom-up: (1) the **system pipeline** presents the path that 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 a detailed representation of the BCI task; (3) the **conductor** masters the adaptation process by deciding the moment, the manner, and the elements of the whole system (pipeline, task, user, output) to adapt. The input of the system pipeline comes from (neuro)physiological activity patterns measured on the user, while the output of the system (feedback and instructions) 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 31.1.

To our knowledge, for the first time, we conceptualize a possibility of having an intelligent agent that could eventually replace the experimenter. For the sake of readability, we introduce step by step each element of the framework, starting bottom-up.

31.3.1 The System Pipeline

The system pipeline, as in Figure 31.2 includes: (1) **EEG features** extracted from the raw signal (the input), possibly passing through

- A temporal filter: to filter noise or to choose an optimal frequency band for instance
- A spatial filter: combining those electrodes that lead to more discriminating signals, such as common spatial pattern (CSP) filter and its variants
- Signal epoching: 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, such as 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 (Kindermans et al. 2014; Mattout et al. 2014).

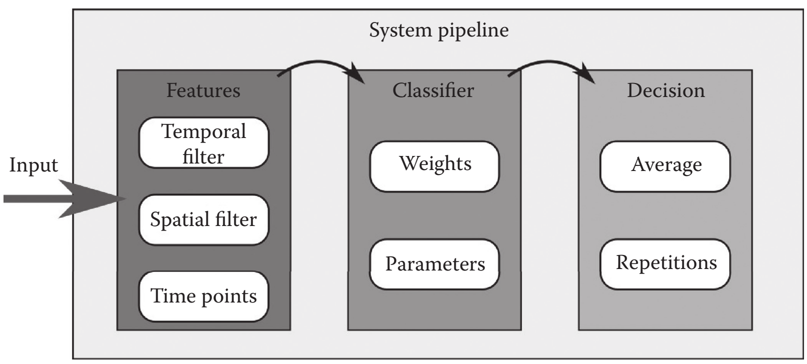

FIGURE 31.2 The system pipeline, acquiring and processing one of the input signals measured with, for example, EEG.

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

- 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, by adjusting the speed–accuracy trade-off for instance

31.3.1.1 Literature Review on Adaptive Signal Processing/Machine Learning

31.3.1.1.1 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; that is, they require the actual EEG class label. Most of the proposed adaptive filters were spatial filters and, in particular, adaptive CSP for MI-based BCI applications. For instance, Sun and Zhang (2006) and Shenoy et al. (2006) proposed to reoptimize the CSP filters as a new batch of labeled data becomes available. Later, Zhao et al. (2008) and Song et al. (2013) proposed new algorithms to incrementally update the CSP spatial filters without the need to reoptimize 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. (2011). In this work, the optimal frequency bands for discriminating MI tasks were regularly re-estimated, and the temporal filters were adapted accordingly. It is worth noting that all these adaptive filter algorithms were evaluated only in offline experiments. Thus, it is unknown how changing the filters influences the users.

Features extracted from EEG signals can also be 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 estimate AR parameters and use them as features for each new EEG sample (Schlögl 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 2000).

Finally, compensating for the features change is possible through the estimation of this change before it is 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 firsts 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.

31.3.1.1.2 Adaptive Classifiers

The majority of the work on adaptive signal processing for BCI was so far on the design of adaptive classifiers, that is, 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 2006), LDA, or quadratic discriminant analysis (QDA) (Schlögl et al. 2010; Shenoy et al.

2006) 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) and Gan (2006) for an LDA classifier with MI data. Another simple unsupervised adaptation of the LDA classifier for MI data was proposed and evaluated both offline and online in Vidaurre et al. (2011a). 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, that is, 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 unlabeled data, that is, adapting this classifier based on these initially unlabeled data. This was explored with SVM and enabled to calibrate P300 spellers with less data than with a fixed, nonadaptive classifier (Li et al. 2008; Lu et al. 2009).

Finally, both offline and online, Kindermans et al. (2014) proposed a probabilistic method to adaptively estimate the parameters of a linear classifier in P300-based spellers, which led to a 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.

31.3.1.1.3 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 nonadaptive version. Even so, combining them both improved the classification accuracy even further.

Online for MI-based BCI, Vidaurre et al. (2007) explored using both AAR 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. 2011b). 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 et al. 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 at the feature extraction, classifier, and decision levels. However, these works often omit the human factors.

31.3.1.1.4 Adaptive Decision Methods

The decision can be adaptive as well, by adapting the speed–accuracy trade-off for wheelchair control (Saedi 2015), or adapting the number of repetitions in a P300 speller (Mattout et al. 2014). While monitoring the user's state, it is also possible to inhibit BCI interaction until specific requirements, such as the user attention level, 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, such as an increase in workload that can affect MI features (Gerjets et al. 2015). Hence, we introduce the user, and the task they have to do, as a guide for adapting the system.

31.3.2 The User and the Task Model

In order to adapt all the elements of the system pipeline with respect to the user skills and states, it is useful to consider a user model (Figure 31.3). 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 three time scales: runs, sessions, and a loosely long time period. Creating a complete automatic adaptation would mean refining the machine to manage more precisely the user's responses. For that purpose, we created a task model (Figure 31.4), containing the necessary BCI task information, whose components follow the same time intervals as the user model.

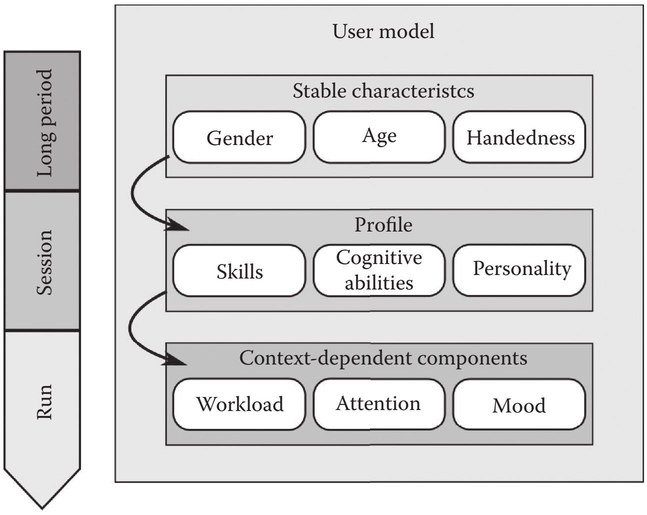

FIGURE 31.3 User model, containing three levels, arranged from the least stable (context dependent) to the most stable components (stable characteristics).

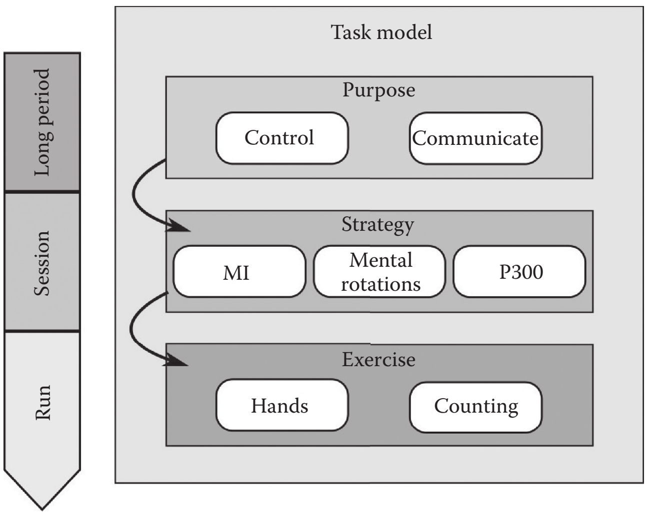

FIGURE 31.4 Task model, arranged within three time scales.

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.

31.3.2.1 User Model

We customized Scherrer's classification of affective states (Martín et al. 2013) for 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.

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

31.3.2.1.1 A Brief Literature Review of "Adaptive Methods" Related to the User Model

There are many attempts to predict the users' performance (predictors) in order to fully customize the system to users' needs. Hence, by knowing that some of their already acquired skills relate to the BCI skills, such as spatial abilities (Teillet et al. 2016), they can be trained and improved beforehand, without using a BCI. This way, by improving those skills, one improves a BCI skill as well. Table 31.1 gathers several predictors and BCI training methods for each element of our user model. For a detailed report on predictors, see Jeunet et al. (2016).

TABLE 31.1
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 et al. 2014) Gender (Randolph 2012)	Acquired skill (gaming, sport; Randolph 2012) Visual–motor coordination (Hammer et al. 2012) Spatial abilities (Jeunet et al. 2016) High θ and low α powers reveal illiteracy (Ahn et al. 2013)	Mood and motivation, confidence (Nijboer et al. 2008) Attention (Hammer et al. 2012) Fear of BCIs (Witte et al. 2013) γ oscillations (Grosse-Wentrup and Scholkopf 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)

31.3.2.2 Task Model

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

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 composed of the following:

- *Purpose of a BCI*: (1) a tool to control: prostheses, wheelchairs, and other devices; (2) a communication device: writing words on a screen, and so on; (3) a tool for rehabilitation: after stroke (Birbaumer and Cohen 2007), for paraplegic patients (Vuckovic et al. 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), and so on.
- *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, for instance, using the MI 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 (between 1 and 20 Hz) on fronto-central, parietal, and occipital regions.
- *Exercise*: it indicates the mental command to be used given a strategy; as for MI strategies, an exercise is chosen between various motor imageries such as feet, hands, or tongue movements.

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. For instance, the user's performance being lower than a certain threshold could indicate the need to change strategy or exercise.

31.3.2.2.1 A Brief Literature Review of Adaptive Methods Related to the Task Model

Purpose: Depending on the purpose of the BCI, the adaptation methods will differ. Rehabilitation will favor methods engaged in learning and self-regulation, communication will favor methods that improve accuracy and speed, while application for entertainment will favor design and innovation, and so on. 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, favoring the one in which the user produces the clearest EEG patterns and has the highest performance. In Müller-Putz et al. (2015) and Pfurtscheller et al. (2010), the use of hybrid BCIs is suggested, that is, switching between or using multiple BCI strategies (e.g., P300, MI, SSEP), combining different measuring techniques (e.g., M/EEG or fNIRS), or using tools apart from those in BCI, such as eye trackers, electrocardiograms, and so on. Accounting for these possible hybrid BCIs is why there are multiple instances of the system pipeline in Figure 31.1.

Exercises: An exercise depends on the chosen strategy. Exercises can be adapted within runs, such as variating between hand and 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, for example, switching from 1D, 2D, to 3D MI BCI tasks (McFarland et al. 2010), changing everything related to it (the instructions and feedback).

31.3.3 Machine Output

Along with feedback, instructions are what the user can receive from the machine. They can be adapted by the conductor based on the information flowing bottom-up, from the various signal processing pipelines or systems, through the user and task models.

31.3.3.1 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 or even necessary for the user's self-regulation process or learning, to be informed on his or her progress when accomplishing the task. There are many different types of feedback, supporting emotional or cognitive states of the user, possibly given in (i) **different modalities**, typically visual (Neuper et al. 2005), but also vibrotactile (Jeunet et al. 2015), a tangible interface (Frey et al. 2014), or an immersive virtual environment (Vourvopoulos et al. 2016); and (ii) **degrees of assistance** (biased feedback—Barbero and Grosse-Wentrup 2010). A feedback could 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 2013) or catching the user's attention with video games (Ron-Angevin 2008).

Adapting feedback could potentially bring benefits that favor ergonomy, minimize fatigue, and optimize learning. This mostly remains to be explored.

31.3.3.2 Instructions and Stimuli

These are, for instance, the stimuli (flashing letters) in P300 spellers or arrows indicating the user to perform left or right hand MI in MI BCI. The instructions could be presented/adapted, independently from the classifier's output in (i) **different modality**: visual, auditive, or tactile; or (ii) **difficulty**:

- Speed—the speed of instruction's appearance might decrease over time, if we assume the user's fatigue (decreasing the task difficulty).
- Order of appearance—it would be interesting to investigate whether presenting a block of instructions for one-class MI (arrow left-hand) and then a block of the other class (right hand) is easier for some users than presenting them in an alternate manner (left–right).

31.3.4 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 framework, which would preferably be created for a global adaptive BCI. It gathers all the information available from the user, the task, and the signal processing pipelines, in order to decide the how, when, and what to adapt. The conductor would need an objective function, upon which it would make its decisions. 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 is the ITS expert (NKambou et al. 2010).

ITS adapt content and activities for the purpose of challenging and guiding students in an optimal way, that is, 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) and (ii) being in flow (Nakamura and Csikszentmihalyi 2014). The first, based on cognitive developmental 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 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).

31.4 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 framework. 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 the following: (i) the user's *stable characteristics*—considering patients with different disorders (paraplegic, after stroke, autistic, etc.), also considering different preferences (between children and adults, women and men, etc.); (ii) the user's *profile*—for individuals who differ in their skills or personality traits; (iii) the user's *context-dependent characteristics*, favoring those methods that increase attention level, motivation, and so on.

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, such as the user's attention or workload level, as monitored with some passive BCI pipeline or with other physiological sensors (e.g., skin conductance).

The challenges we encounter when considering the full adaptation with the conductor are as follows: (1) identifying metrics and criteria to optimize depending on the task, to ensure relevant adaptation, that is, favoring those adaptation methods that most concur to user's needs; (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) propose 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, or 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 favoring 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 coadaptation.

31.5 CONCLUSION

Throughout this chapter, we emphasized the crucial 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 and the task parameters, in order to fully accommodate the user's variability in terms of needs and psychophysiological states. Following that requirement, we created a framework, composed 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; and (iv) the conductor, an intelligent agent that 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. 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 framework are numerous; for one, it enables clear and methodological visualization of all the BCI system components, their possible interaction, and the way and the context in which they could be adapted. Although invasive brain activity recording approaches (e.g., ECoG or intracortical electrodes array) consider different signal processing algorithms from those presented in our pipeline, the same principles for co-adaptivity (Sanchez et al. 2009) and the rest of the framework structure and methods apply for any BCI system, be it invasive or not. Moreover, this framework is also convenient for mapping the literature onto each of its 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 that this framework will contribute to delve possible future research paths and give rise to novel challenges and ventures.

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