



**HAL**  
open science

# Brain-Computer Interaction and Neuroergonomics

Fabien Lotte, Camille Jeunet-Kelway

► **To cite this version:**

Fabien Lotte, Camille Jeunet-Kelway. Brain-Computer Interaction and Neuroergonomics. Flavia Santoianni, Gianluca Giannini, Alessandro Ciasullo. Mind, Body, and Digital Brains, 20, Springer Nature Switzerland, pp.141-156, 2024, Integrated Science, 978-3-031-58362-9. 10.1007/978-3-031-58363-6\_10 . hal-04721871

**HAL Id: hal-04721871**

**<https://hal.science/hal-04721871v1>**

Submitted on 4 Oct 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

# Brain-Computer Interaction and Neuroergonomics

Fabien Lotte\*<sup>[0000-0002-6888-9198]</sup> and  
Camille Jeunet-Kelway\*<sup>[0000-0001-8619-3082]</sup>

\* *both authors contributed equally*

**Abstract** When studying human brains in relation with digital technologies, or digital brains, a relatively recent technology may prove particularly promising to do so: Brain-Computer Interfaces (BCI). Indeed, BCI can decode measures of users' brain activity in real-time, in order to enable direct control of computers via brain activity or to monitor users' mental states when interacting with technologies (so-called neuroergonomics). This chapter presents an introductory overview of this technology, i.e., it describes its motivations, brief history, components, principles of operation and various applications, e.g. for assistive technologies, neurorehabilitation or safety, performance and user experience assessment and optimisation. It also touches on the various current limitations of this technology, which makes it rather different from the science-fiction-like representations it may evoke. Altogether, we hope this chapter can offer a brief but clear glimpse into what BCI can and cannot do, and motivate readers to possibly consider them in their future research and/or developments.

## 1 Introduction

Digital technologies, and especially neurotechnologies, provide breakthrough opportunities i) to enhance one's control over their body and ii) to understand their "mind" (in terms of cognitive, motivational and emotional states).

On the one hand, thanks to neurotechnologies, the brain can be used to send direct commands to digital applications. Indeed, it is now possible to interact with

---

Fabien Lotte  
Inria Center at the University of Bordeaux / LaBRI, 200 avenue de la vieille tour, 33405, Talence  
Cedex, France. e-mail: fabien.lotte@inria.fr

Camille Jeunet-Kelway  
CNRS, EPHE, INCIA, UMR5287, Université de Bordeaux, Bât. 2A- 2ème étage, 146 rue Léo  
Saignat, 33076 Bordeaux cedex, France. e-mail: camille.jeunet@u-bordeaux.fr

our environment without moving: the control intent being directly extracted from the brain activity and translated into a command for an external device. Thus, mobility and communication can be restored in paralysed patients, and even enabled or enhance for all for instance for navigation in a “metaverse”, or in contexts of distant interaction. A whole research field is dedicated to the optimisation of those systems called Brain-Computer Interfaces (BCIs). Among BCIs, two types, named “active” and “reactive” BCIs, are especially relevant for enhancing or restoring communication and control. We provide details on their functioning and association challenges hereinafter.

On the other hand, neurotechnologies can be used to detect, directly from one’s brain, cognitive, motivational or emotional states. This information can then be used to optimise the human-technology interaction, and thereby one’s well-being and safety. Thus, for instance, pilots’ attention levels can be assessed in real-time during critical situations, and the information provided in the cockpit adapted accordingly so that to optimise decision-making. Again, a whole research field is dedicated to the optimisation of this approach, named neuroergonomics (NE), which is based on so-called “passive” BCIs. We also provide more details on the latter in the following sections of this chapter.

We will first introduce the BCI technology: their historical background, their functioning, the different types (active, reactive, passive BCIs). Then, we will provide use-case examples and prospects for i) active/reactive BCIs for communication and control, and ii) passive BCIs for neuroergonomics.

## **2 Brain-Computer Interaction: from history to principles**

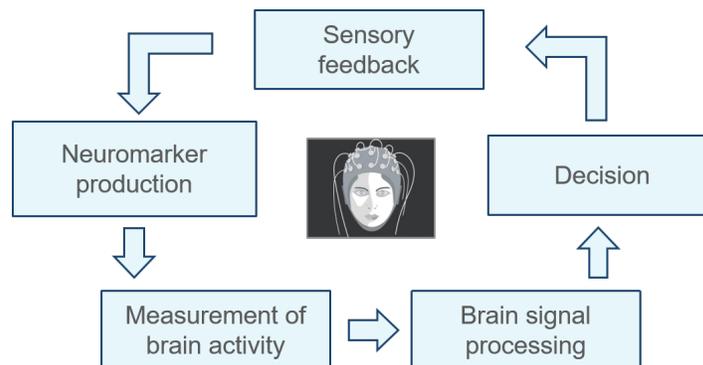
### **2.1 Historical background**

BCIs have been defined in 2002 by Wolpaw et al. [1] as “a communication system in which messages or commands that an individual sends to the external world do not pass through the brain’s normal output pathways of peripheral nerves and muscles”. But the history of BCIs dates back to the end of the 19th century, with Dr. R. Caton, a neurologist from Liverpool, who was the first person to record the electrical activity produced by the brain. Those recordings were performed on dogs [2]. It is in 1924 that Dr. H. Berger (German neurologist and psychiatrist) first succeeded in applying this method to humans: the electroencephalography (EEG) was born [3]. In a nutshell, EEG consists in placing electrodes on the scalp to measure the electrical signals produced by the cortical neurons. H. Berger documented an increased of amplitude of this electrical activity during sleep and a disappearing when people would die. From the nineteen-thirties, after the method was validated by engineers, EEG increasingly developed together with the identification of different types of brain activities called “rhythms” (characterised by the associated frequency band and location) and of their functional roles. In the late fifties, J. Kamiya, psychologist and researcher at the University of Chicago, demonstrated that patients suffering

from anxiety disorders could learn to self-regulate *alpha rhythms* and that this self-regulation ability correlated with an improvement of their clinical symptoms. This is one of the first protocols of *neurofeedback*. Neurofeedback consists in training people to voluntarily self-regulate specific brain patterns in order to improve or restore associated abilities. Since then, clinical neurofeedback has developed, especially for psychiatric (e.g., anxiety disorders, obsessive compulsive disorders) and neurological (e.g., epilepsy, Parkinson's disease). In 1974, with the empowerment of informatics, Dr. J. Vidal, computer scientist at UCLA, suggested for the first time to use people's ability to self-regulate brain patterns in order to send commands to external devices [4]. This is the birth of brain-computer interaction that, since then, have exponentially developed in terms of number of academic specialists and industry, and also in terms of applications (that range from video games to assistive technologies) [5]. Hereinafter is introduced the functioning of BCIs.

## 2.2 Overview of the brain-computer interface (BCI) loop

Designing a BCI system requires setting up a communication loop - an interface - between the user's brain and the computer, see Figure 1. This so-called BCI loop [6], can be described as comprising five main elements, briefly presented below, and detailed in the subsequent sections:



**Fig. 1** Schematic representation of the BCI loop, describing the main components enabling interaction between the brain and the computer.

1. **Neuromarker production:** For users, the first step to control a BCI is to “produce” a specific pattern of brain activity - a so-called neuromarker - that reflects their intentions or mental states. For instance, users can imagine a left or right hand movement, which will change their brain activity in their right or left sensorimotor cortex respectively.

2. **Measurement of brain activity:** Once the user has “produced” this neuromarker, the BCI will measure the user’s brain activity to later be able to identify which neuromarker can be recognised from it. Various neuroimaging sensors can be used to do so, the most used being EEG.
3. **Brain signal processing:** The brain activity being measured, the recorded signals will then be processed in order to identify which neuromarker is present, if any. For instance, this brain signal processing will try to identify whether the users’ EEG signals contain the neuromarker corresponding to a left or right hand imagined movement. To do so, various signal processing and machine learning algorithms are typically used.
4. **Decision:** Once the neuromarker has been identified, a specific decision can be taken, usually associated to an action, e.g., the computer cursor can be moved towards the left if the neuromarker of a left-hand imagined movement was identified.
5. **Feedback:** Finally, the BCI loop can be closed by proposing a feedback to users, informing them about what neuromarker was identified, possibly together with an indicator of the confidence of the BCI system in this recognition. This feedback is essential to enable users to learn to control a BCI. BCI control is indeed a skill that needs to be learned and mastered, and such a learning is only possible with feedback.

The following section will provide more details about these components.

### 2.2.1 Brain activity recording techniques

Various neuroimaging modalities are available to measure brain activity in BCIs [7]. They can be categorised as non-invasive and invasive, depending on whether the sensors are placed below the skull (for the latter) or on or around the skull (for the former). Non-invasive techniques included ElectroEncephaloGraphy (EEG), functional Near-InfraRed Spectroscopy (fNIRS), MagnetoEncephaloGraphy (MEG) and functional Magnetic Resonance Imaging (fMRI). EEG and MEG measure the brain electrical and magnetic activity respectively, while fNIRS and fMRI measure the blood concentration in oxygen in the brain, which reflects which brain areas are the most active. Among these techniques, fMRI and MEG have the best spatial resolution - i.e., they can measure the brain activity of the smallest and deepest brain regions with most precision. Current MEG and fMRI systems are however very bulky, cannot be transported, and very costly (at least around a million euros each). In contrast, EEG and fNIRS are portable and relatively cheap. Note that both fMRI and fNIRS suffer from a low temporal resolution, i.e., they can acquire brain activity measures only once or a few times per second, contrary to EEG and MEG which can do so typically hundreds of times per second. Invasive techniques include mainly ElectroCorticoGraphy (ECoG) and Micro-Electro Array (MEA). ECoG are sensors measuring the brain electrical activity below the skull, on top of the cortex (the external layer of the brain), while MEA measures neuron spiking activity, including possibly single neuron activity, using electrodes penetrating into

the brain. Invasive techniques usually provide a much better signal-to-noise-ratio and a much better spatial resolution than non-invasive methods (with MEA having the best spatial resolution), at the cost of a limited coverage of brain activity (only a few or even a single brain area can be measured) and the need for surgery to implant the sensors. Currently, there is no non-invasive brain activity recording technique that can measure brain activity in the whole brain, with both high spatial and temporal resolution. Thus, currently, EEG is by far the most used techniques (followed by fNIRS), as it is relatively cheap, portable, non-invasive and with a high temporal resolution. In the remainder of this chapter, we will thus focus on EEG-based BCI applications for communication, control and neuroergonomics.

### **2.2.2 Neuromarkers**

Once measured, the brain activity is to be analysed to identify neuromarkers. In EEG, two main families of neuromarkers are typically analysed: 1) Event-Related Potentials (ERPs), which are brain responses to specific events or stimuli, with a specific time course, and 2) oscillatory activity, which corresponds to ongoing changes in EEG oscillations, i.e., changes in the EEG signal power in various frequency bands. The amplitude of the ERPs at different latencies following a stimulus and the power of specific EEG rhythms at different sensor locations have been associated with different mental states or intentions, and can thus be used to decode the latter. In addition to these two most common neuromarker types, additional ones can be used, such as measures of brain signal complexities or measures of synchronisation between the signals from different brain areas (so-called functional connectivity). For an overview of the different neuromarkers that can be exploited in BCIs and the associated BCI paradigms, the interested reader can refer to [8]. We will describe more specific neuromarkers later in this chapter, when describing different BCI types.

### **2.2.3 Signal processing & decision**

In order to automatically infer BCI users' intentions and mental states from their EEG signals, signal processing and machine learning algorithms are typically used. Usually, this signal processing pipeline starts with a preprocessing step, to clean and denoise EEG signals, which are typically affected by various sources of noise and artifacts [9]. Such artefacts include for instance muscle artefacts (electromyography - e.g., from facial muscles) that are also recorded by EEG sensors but are not originating from the brain and thus degrade the EEG signal quality. Then, a step called feature extraction is performed in order to describe EEG by (ideally a few) relevant values, called features, for instance by computing the power of EEG signals in various frequency bands and sensors, when aiming at identifying specific oscillatory activity neuromarkers [10]. Finally, machine learning algorithms are used to automatically identify which features correspond to which neuromarker, for instance, whether the

estimated power in various frequency bands and sensors correspond to a left or right hand imagined movement. Typically, when a BCI is being used for the first time, there is need for a calibration phase, during which the user will “produce” known neuromarkers upon instructions, e.g., by repeatedly imagining a specific hand movement at a specific time. The EEG signals collected during that phase will be used as labelled training data (i.e., labelled with the known intention or mental state in which the user was) to train machine learning algorithms. Once calibrated, the machine learning algorithm will be able to recognise the users’ intention/mental state from features extracted from ongoing (and unlabelled) EEG signals. Typical algorithms used for this purpose include linear classification algorithms such as Linear Discriminant Analysis (LDA) or Support Vector Machine (SVM) [11]. Recently, advanced non-linear classification algorithms such as Riemannian geometry classifiers or Deep Learning are increasingly more explored [12]. Once the users’ intention/state has been estimated by these algorithms, they can be associated with a specific command for the applications controlled by the BCI, e.g., making a wheelchair turn left when an imagined left-hand movement has been recognised.

#### **2.2.4 Feedback**

The last component of the BCI loop is the feedback the users are provided with to help them learn to control a BCI. The most typical feedback type is a visual gauge, e.g., a gauge extending towards the left or right to indicate that the BCI has recognised a left or right imagined hand movement respectively, with the length of the gauge representing the confidence of the BCI in its estimation. However, recent research has shown that different types of feedback can help BCI users learn better and faster, e.g., richer and more realistic feedback (e.g., seeing a virtual hand moving, possibly in immersive virtual reality, when an imagined movement is detected) [13], multimodal feedback combining visual and tactile or audio feedback (the former being usually more effective than the later) [14], or even social feedback with artificial learning companions providing advice and guidance to BCI trainees based on their performance and progression [15]. For an overview of BCI feedback research, the interested reader can refer to [16]. This feedback learning process can enable BCI users to learn BCI control and thus to increase their proficiency: their mental commands can be increasingly accurately recognised by the BCI with such feedback training.

### **2.3 Three main types of BCIs**

Zander & Kothe [17] have suggested a classification of BCIs into 3 main categories characterised by i) specificities in the BCI loop and ii) the applications they are the most relevant for.

### 2.3.1 Active BCIs

**Objective.** The objective of active BCIs is to send voluntary commands to external applications. **Functioning.** The specificity of active BCIs is that they allow *asynchronous* control. In other terms, users decide when they want to send a command—the later being most often emitted through mental imagery. Indeed, as mentioned earlier, mental imagery tasks such as mental calculation, mental navigation or motor imagery (i.e. imagination of movements) are associated with modulations of specific brain oscillations that can be detected using the EEG. Hence, during the calibration of the BCI, users are asked to perform mental imagery tasks (for instance imagining left and right hand motor imagery). The associated brain patterns (here, theoretically, modulations of sensorimotor rhythms over the right and left sensorimotor cortices, respectively) are measured and associated with specific commands, e.g., making a wheelchair turn left and right respectively. After some training, that includes informative (neuro)feedback, users are supposedly able to control the wheelchair through the voluntary, and asynchronous (self-paced), imagination of left and right hand movements. **Challenges.** The asynchronous control of active BCIs assumes a continuous recording of the brain activity and the ability to detect intentional commands and *only* intentional commands. Yet, in real-life settings, when people interact with their environment, a lot of modulations occur in their brains thus making “false positive detection” most likely. A first challenge thus consists in identifying paradigms that minimise the false positives (command sent while not intended) and also false negatives (no command detected while there was an intention to). A second major challenge for this kind of BCIs is the user training. Indeed, users have to learn to self-regulate specific brain activities to produce patterns that are i) stable (the same as the ones produced during the calibration) so that they can be recognised and translated into commands, and also ii) distinct between the commands so that this translation is reliable. Many factors seem to impact those self-regulation abilities, including individual characteristics (e.g., personality, cognitive profile) and the interface and training design (e.g., instructions, feedback) [16]. A main challenge thus consists in adapting the training procedures (and especially the feedback) so that a reliable and efficient BCI control is accessible to as many users as possible.

### 2.3.2 Reactive BCIs

**Objective.** The objective of reactive BCIs is also to send voluntary commands to external applications. **Functioning.** Contrary to active BCIs, reactive BCIs mostly enable synchronous control. Indeed, *reactive* BCIs get their name from the fact that commands are sent through the brain patterns generated automatically as a reaction to stimuli of interest produced by the system, and to which the users pay attention to. Those brain patterns are called event-related potentials (ERPs). Many different ERPs exist. Among them, the P300 and SSVEPs (for steady-state visual evoked potentials) are currently the most used in brain-computer interaction due to the relative ease to measure them using EEG. The P300 is a positive (P) potential

occurring around 300ms after the appearance of stimulus of interest on which one focuses their attention. In the *P300 speller* application for instance, which has been designed to enable severely paralysed patients to communicate, letters/symbols flash the ones after the others. Each time the symbol the patient wants to select flashes, a P300 is triggered. Several flashes are required for smoothing the brain signal (increasing the signal-to-noise-ratio) and enabling a reliable detection of this P300 and a translation into a command. SSVEP-based BCIs rely on the fact that observing a light flashing at a certain frequency will induce an increase of the amplitude of the brain activity at the same frequency in the visual cortex. Thus, equipping for instance different domestic appliances with LED lights flashing at different frequencies could enable switching them on/off simply by looking at them. Despite the constraint of enabling only synchronous control, reactive BCIs have a main advantage being that they are very reliable with performances around 90% of good detection. **Challenges.** The main challenge with reactive BCIs is to prevent the visual fatigue generated by the stimuli, for instance using other sensory modalities (auditory and tactile stimuli can be used).

### 2.3.3 Passive BCIs

**Objective.** The objective of passive BCIs is to measure the mental states of a person in order to adapt an interactive system accordingly, in real-time. Mental states encompasses cognitive (e.g., attention), motivational and emotional (e.g., frustration) states. **Functioning.** Passive BCIs rely on our capacity to identify brain activity patterns (oscillations or ERPs) that specifically underlie mental states of interest and that can be reliably detected using the brain recording method used (i.e., most often, the EEG). Indeed, based on those patterns, it is then possible to infer the mental state of a person and to adapt the system with which they are interacting accordingly, in real-time. For instance, the difficulty of training exercises can be reduced when high mental workload levels are detected. One kind of ERP is especially relevant for passive BCIs, the so-called *error potentials* that are triggered when one *notices* an error in the interaction they are involved in. For instance, when manipulating a mouse, if the cursor stops moving unexpectedly, an error potential will likely be elicited. Error potentials can be used for instance to evaluate user experience: if error potentials are elicited when people click on a button because the page displayed is not the one they expected to see, then the application interface should be revised. **Challenges.** The main challenge here consists in identifying neuromarkers (i.e., brain activity patterns) that are both reliable and specific. Brain activity variability is far from being fully understood, and identifying invariants representing specific mental states whatever the mental/motor task performed is a real challenge, what is more due to the fact that such mental states usually involve multiple brain areas, both at the cortical and sub-cortical levels (the latter being difficult to assess using the EEG).

### 3 BCIs for communication and control: applications, limitations and prospects

Now that BCI principles are exposed, the following sections will present their main application areas, starting by using them for communication and control, which can be notably useful for assistive technologies, entertainment or neurorehabilitation.

#### 3.1 Control of assistive technologies for communication and mobility

**Applications.** Assistive technologies benefit a lot from neurotechnologies and BCIs in particular as the latter enable severely paralysed persons to control external devices, without moving. Two main application areas are developed: mobility and communication [18]. Smart wheelchairs, prosthetics and exoskeletons are certainly the most emblematic applications of active BCIs. Regarding communication, the most relevant paradigm seems to be reactive BCIs with, for instance, the P300 speller introduced earlier that enables a digital spelling. **Limitations.** As mentioned earlier in this chapter, active control through mental imagery is not very reliable yet and requires a lot of cognitive resources. Therefore, most systems are coupled with other paradigms to increase reliability. For instance, BCI-controlled wheelchairs might be equipped with infrared sensors to detect and avoid obstacles and thereby rely on a shared-control paradigm [19]. Active (mental imagery) and passive (error potentials) BCIs can also be combined so that an erroneous recognition of a mental command can be detected thanks to the elicitation of an error potential and corrected. **Prospects.** The reactive BCI-based communication applications are very reliable and increasingly usable thanks to a reduction of the time required to select letters/symbols and thus communicate. Regarding active BCI-based mobility applications, current research and development directions suggest that for them to be sufficiently reliable, EEG should be replaced by electrocorticography or intracortical electrode arrays as the latter provide a better signal-to-noise ratio and more stable data [20]. With those invasive methods, relying on a surgical operation and continuous recordings of brain activity, come multiple ethical concerns including questions of acceptability, accessibility, safety and benefits/risk ratio.

#### 3.2 Enhancing interaction for entertainment applications

**Applications.** BCIs can also be used, for healthy users and motor impaired users alike, as an alternative or additional control modality for entertainment applications, typically video games and virtual reality [21, 22]. Typically active BCIs can be used to navigate virtual environments by using mental imagery, while reactive BCIs, notably P300-BCIs or SSVEP-BCIs, can be used to select virtual objects or to activate virtual buttons that are flashing or flickering. Such BCI-based commands can either replace

classical mice/game pads, to provide a new and original control modality, or be used as a complementary command to classical game pads. For the former, various video game prototypes have been proposed, in which virtual avatars are fully controlled by a BCI [22, 21], whereas for the later, the avatar can be controlled by a game pad and additional in-game super-power can be triggered using the BCI, see, e.g., [23, 24]. Some of such applications are even commercialised now, see, e.g., the NextMind system that is based on SSVEP-like neuromarkers for gaming and virtual reality. **Limitations.** While all such applications are particularly appealing for the general public, it should be mentioned that current BCIs are not reliable, and make frequent mistakes in the mental command recognised. As such, fully controlling a video game using a BCI can be rapidly frustrating and demotivating. While SSVEP-related BCIs are more reliable than active BCIs and thus possibly more useful for this type of application, it should be stressed that game pads and computer mice are still by far the most efficient and effective control devices for video games. **Prospects.** Future research in BCI for entertainment thus needs to either vastly improve the reliability of BCIs, or find new ways to use BCIs for entertainment that are less reliant on reliable control. The former is less likely in the short term. For the latter, it may seem more promising to use passive BCIs (rather than active or reactive ones) for dynamically adapting the game content and/or parameter (e.g., difficulty) to the players' mental states.

### 3.3 Neurorehabilitation

**Applications.** For neurological and psychiatric pathologies associated with well-identified pathological brain patterns, active BCIs and neurofeedback can be used to enhance (neuro)rehabilitation procedures and favour motor and cognitive recovery. For instance, in patients who underwent a stroke and experience motor aftereffects, standard rehabilitation procedures involve mental imagery: patients are asked to imagine movements in order to stimulate their sensorimotor cortex, foster synaptic plasticity (i.e., the reconstruction of connections between the neurons) and thereby favour motor recovery. The main limitation of this approach is that therapists do not know i) when exactly the patient imagines the movement, which results in the impossibility to provide a synchronised feedback, and ii) if the patient actually triggers their sensorimotor cortex (or other brain areas, in which case the impact on motor recovery would be reduced). With BCIs, it is possible to detect modulations of brain activity in the sensorimotor cortex and thereby i) to provide a real-time feedback, synchronised with the imagination, thus closing the sensorimotor loop and fostering synaptic plasticity, and ii) to inform the therapist so that they can guide the patients to identify the most efficient strategies. Beyond stroke rehabilitation, the number of clinical studies investigating the efficiency of BCIs to enhance the efficiency of neurorehabilitation procedures for patients with Parkinson's disease, epilepsy, post-traumatic stress disorders, attention deficits and many others has significantly increased in the last years. **Limitations.** While theoretically more efficient

than standard approaches (especially for attention deficits [25] and stroke rehabilitation [26]), BCI-based approaches remain barely used in clinical settings. This can be explained, at least in part, by acceptability factors: it is not enough to design a technology, the latter then has to be usable by the end-users [27]. Therapists should be trained, hospitals should allocate specific funding, the population (including the clinicians, patients and their family) should be properly informed. **Prospects.** BCI technologies will become increasingly affordable. They are also increasingly publicised. Therefore, if interdisciplinary and intersectoral collaborations arise in the coming years, and if acceptability and organisational constraints are considered, BCIs for neurorehabilitation should develop a lot in the near future.

## 4 BCIs for Neuroergonomics: applications, limitations and prospects

In addition to using BCIs for controlling various interactive systems, BCIs can be used for Neuroergonomics, to study the brain in the wild, notably to assess and optimise safety, performance, learning or user experience directly through brain activity [28]. Hereafter we present three families of BCI-based neuroergonomics applications: 1) for safety critical systems such as aeronautics and transportation; 2) for training and education and 3) for user experience optimisation.

### 4.1 Safety and performance in aeronautics and transportation

**Applications.** In many critical systems with a human-in-the-loop, such as in aeronautics and transportation, there is a need to ensure the safety and performance of the operators across time and situations. Doing so notably requires monitoring those operators' states (e.g., their fatigue or vigilance), to assess the impact of the latter on the critical system operation, and possibly optimise it dynamically so as to improve safety and performance. Interestingly enough, these operators' mental states can be monitored using passive BCIs [29, 30]. For instance, a number of research works have demonstrated the possibility to estimate mental states such as fatigue, attention, vigilance or mental workload in both plane pilots and/or car drivers [31, 29]. In turns, these mental state estimates can be used to dynamically adapt the interaction with the system, e.g., changing the amount of information displayed in a plane cockpit to avoid pilot overload, or to increase the level of automation proposed in autonomous cars if the driver is too tired or not paying attention. The later type of technology would be called a NeuroAdaptive Technology (NAT), i.e., a system adapting its properties based on neural information [32]. **Limitations.** The main limitation of this neuroergonomic approach to safety and performance in aeronautics and transportation lies in the specificity of the neuromarkers used to estimate the operators' mental states mentioned above. Indeed, while many proof-of-concepts

have been made, they were often made in a single context and for studying a single operator's mental state. As such, it is unclear whether the identified neuromarkers and associated BCIs to identify them would still work if used when other mental states are also varying (e.g., does fatigue also impact the identified neuromarker of mental workload?). In other words, it is still unclear how specific these neuromarkers are, and how much they can be confounded by other states. **Prospects.** Future research in this area will thus need to study the specificity of the various neuromarkers identified, and possibly identified new neuromarkers, representing mental states that can be useful to also monitor in this context (e.g., information overload or attention tunnelling). Estimating such neuromarkers and mental states from EEG is also not enough to ensure useful NATs. Indeed, there is also a need to build models (typically computational models) describing how changes in the monitored mental states affect the operation of the critical system targeted, so as to be able to provide suitable and timely interventions (e.g., when to increase or decrease the system autonomy?), in order to optimise safety and performance.

## 4.2 Intelligent tutoring systems for training and education

**Applications.** As mentioned earlier, passive BCIs can also be used to facilitate/improve learning. Intelligent tutoring systems [33] consist in computerised tutors that adapt in real-time in order to optimise users' learning. To do so, they include a "student model" that makes use of behavioural (posture, number of clicks, ...) and sometimes physiological (eye pupil size, skin conductance) to infer the mental state of the student (cognitive workload, frustration, attention, ...). With BCIs, it is now possible to design "neuroadaptive" tutoring systems that make use directly of the student's brain activity to infer their mental states. Brain activity information might be more specific than physiological data. For instance, variations of skin conductance can be related to emotions, but also to room temperature or circadian rhythm. **Limitations.** While promising, it should be noted that we are still far from the identification of stable and fully reliable neuromarkers of humans' cognitive states. Given the complexity of brain activity and the low signal-to-noise ratio of EEG activity, we should all be careful when claiming that we can infer one's mental state. **Prospects.** The most relevant approach seems to combine different indicators (self-reported, behavioural, physiological, neurophysiological) in order to define models of mental state indicators that are as precise and reliable as possible. Then, a compromise should be determined as precision (using multiple sensors) should not come at a cost of usability and acceptability. For those systems to be useful, they first have to be used. And multiple, expensive sensors might discourage stakeholders to adopt those promising technologies.

### 4.3 Measuring and improving user experience in interactive set-ups

**Applications.** Beyond aeronautics, transportation and education/training, and maybe more generally, BCI and Neuroergonomics can be used to assess User eXperience (UX) with interactive systems in general. Typically, passive BCIs can be used to monitor UX with various input devices (e.g., mice, haptic or tactile devices) - to assess and compare these devices - but also to monitor UX with output devices (e.g., various displays), to monitor users' perception [34, 35]. For instance, it has been shown that mental workload could be monitored from EEG during 3D object manipulation tasks or 3D navigation tasks (input devices) [36] - to assess when and where an input can be too cognitively demanding to use; while EEG can also be used to assess visual comfort with stereoscopic displays [37] or to detect users' perception with system errors displayed in virtual reality [38] (output devices). These types of assessment can be used in complement to traditional UX assessments methods (e.g., questionnaires or interview), to obtain better insights into the UX with a given system, and thus to design a better system. Like for aeronautics and transportation, such BCI-based UX assessments can be used to design NATs, that will use these assessment to dynamically reconfigure the user-interface, in order to optimise UX on the fly, e.g., by correcting errors detected in the users' EEG (see [39] for a review). **Limitations.** The limitations here would be similar to that of safety-critical systems (although to a lesser extent as safety is usually less an issue in the present contexts) and to intelligent tutoring systems, i.e., the neuromarkers identified for various UX metrics may not be very specific, and thus the UX assessment should be considered carefully. Moreover, while EEG is suitable to be used in the design and testing phase of interactive devices with testers in the lab, it is currently not so usable and comfortable for everyday prolonged use. **Prospects.** Future works will thus need to focus on assessing the specificity of UX neuromarkers in complex real-life situations, and possibly to design EEG sensors that are more transparent and wearable, and passive BCIs that are more usable and acceptable altogether, so that NATs optimising UX could be used outside the lab.

## 5 Conclusion

Overall, this chapter presented a brief and introductory overview of the current state of BCI technology and neuroergonomics. It presented the motivations for BCI research and how they work, notably regarding their main components that are neuromarkers, brain imaging modalities, signal processing and feedback. It also described what are the main applications and usages of BCIs, either for communication and control, which includes assistive technologies, entertainment and neurorehabilitation, or for Neuroergonomics, notably for assessing and optimising safety and performance in aeronautics and transportation, for education and training, or for optimising user experience with interactive systems. Altogether BCIs and Neuroergonomics are thus very promising to study human brains in relation with digital technologies, i.e., dig-

ital brains, and possibly to enhance this relationship using NATs. However, beyond science fiction and beyond unfortunately too-often exaggerated media representations, BCIs are (fortunately) far from being able to read minds, and currently still suffer from various limitations. There are notably not reliable enough, may lack specificity in the mental states they can recognise, and are uncomfortable, tedious and inconvenient to use in real-life, among other [40]. Consequently, there is still a lot of research needed before they can be used in daily life outside laboratories. The research community is working hard in that direction.

## References

1. Jonathan R Wolpaw, Niels Birbaumer, Dennis J McFarland, Gert Pfurtscheller, and Theresa M Vaughan. Brain–computer interfaces for communication and control. *Clinical neurophysiology*, 113(6):767–791, 2002.
2. Richard Caton. Electrical currents of the brain. *The Journal of Nervous and Mental Disease*, 2(4):610, 1875.
3. Hans Berger. Über das elektroenkephalogramm des menschen. *Archiv für psychiatrie und nervenkrankheiten*, 87(1):527–570, 1929.
4. Jacques J Vidal. Toward direct brain–computer communication. *Annual review of Biophysics and Bioengineering*, 2(1):157–180, 1973.
5. Fabien Lotte, Chang S Nam, and Anton Nijholt. Introduction: evolution of brain–computer interfaces, 2018.
6. Marcel Van Gerven, Jason Farquhar, Rebecca Schaefer, Rutger Vlek, Jeroen Geuze, Anton Nijholt, Nick Ramsey, Pim Haselager, Louis Vuurpijl, Stan Gielen, et al. The brain–computer interface cycle. *Journal of neural engineering*, 6(4):041001, 2009.
7. Jonathan R Wolpaw, Gerald E Loeb, Brendan Z Allison, Emanuel Donchin, Omar Feix do Nascimento, William J Heetderks, Femke Nijboer, William G Shain, and James N Turner. Bci meeting 2005–workshop on signals and recording methods. *IEEE Transactions on neural systems and rehabilitation engineering*, 14(2):138–141, 2006.
8. Reza Abiri, Soheil Borhani, Eric W Sellers, Yang Jiang, and Xiaopeng Zhao. A comprehensive review of eeg-based brain–computer interface paradigms. *Journal of neural engineering*, 16(1):011001, 2019.
9. Md Kafiul Islam, Amir Rastegarnia, and Zhi Yang. Methods for artifact detection and removal from scalp eeg: A review. *Neurophysiologie Clinique/Clinical Neurophysiology*, 46(4-5):287–305, 2016.
10. Ali Bashashati, Mehrdad Fatourehchi, Rabab K Ward, and Gary E Birch. A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals. *Journal of Neural engineering*, 4(2):R32, 2007.
11. Fabien Lotte, Marco Congedo, Anatole Lécuyer, Fabrice Lamarche, and Bruno Arnaldi. A review of classification algorithms for eeg-based brain–computer interfaces. *Journal of neural engineering*, 4(2):R1, 2007.
12. Fabien Lotte, Laurent Bougrain, Andrzej Cichocki, Maureen Clerc, Marco Congedo, Alain Rakotomamonjy, and Florian Yger. A review of classification algorithms for eeg-based brain–computer interfaces: a 10 year update. *Journal of neural engineering*, 15(3):031005, 2018.
13. Maryam Alimardani, Shuichi Nishio, and Hiroshi Ishiguro. Brain–computer interface and motor imagery training: The role of visual feedback and embodiment. *Evolving BCI Therapy-Engaging Brain State. Dynamics*, 2(64), 2018.
14. Léa Pilette, Bernard N’kaoua, Romain Sabau, Bertrand Glize, and Fabien Lotte. Multi-session influence of two modalities of feedback and their order of presentation on mi-bci user training. *Multimodal Technologies and Interaction*, 5(3):12, 2021.

15. Léa Pillette, Camille Jeunet, Boris Mansencal, Roger N'kambou, Bernard N'Kaoua, and Fabien Lotte. A physical learning companion for mental-imagery bci user training. *International Journal of Human-Computer Studies*, 136:102380, 2020.
16. Aline Roc, Lea Pillette, Jelena Mladenovic, Camille Benaroch, Bernard N'Kaoua, Camille Jeunet, and Fabien Lotte. A review of user training methods in brain computer interfaces based on mental tasks. *Journal of Neural Engineering*, 18(1):011002, 2021.
17. Thorsten O Zander and Christian Kothe. Towards passive brain-computer interfaces: applying brain-computer interface technology to human-machine systems in general. *Journal of neural engineering*, 8(2):025005, 2011.
18. José del R Millán, Rüdiger Rupp, Gernot Mueller-Putz, Roderick Murray-Smith, Claudio Gugliemina, Michael Tangermann, Carmen Vidaurre, Febo Cincotti, Andrea Kubler, Robert Leeb, et al. Combining brain-computer interfaces and assistive technologies: state-of-the-art and challenges. *Frontiers in neuroscience*, page 161, 2010.
19. Tom Carlson, Guillaume Monnard, and José del R Millán. Vision-based shared control for a bci wheelchair. *International Journal of Bioelectromagnetism*, 13(ARTICLE):20–21, 2011.
20. Alexandre Moly, Thomas Costecalde, Félix Martel, Matthieu Martin, Christelle Larzabal, Serpil Karakas, Alexandre Verney, Guillaume Charvet, Stephan Chabardes, Alim Louis Benabid, et al. An adaptive closed-loop ecog decoder for long-term and stable bimanual control of an exoskeleton by a tetraplegic. *Journal of Neural Engineering*, 19(2):026021, 2022.
21. Bojan Kerous, Filip Skola, and Fotis Liarokapis. Eeg-based bci and video games: a progress report. *Virtual Reality*, 22:119–135, 2018.
22. Anatole Lécuyer, Fabien Lotte, Richard B Reilly, Robert Leeb, Michitaka Hirose, and Mel Slater. Brain-computer interfaces, virtual reality, and videogames. *Computer*, 41(10):66–72, 2008.
23. Anton Nijholt, Danny Plass-Oude Bos, and Boris Reuderink. Turning shortcomings into challenges: Brain-computer interfaces for games. *Entertainment computing*, 1(2):85–94, 2009.
24. Marius Klug. Real virtual magic-modifying a vr game with a bci to enhance immersion. *Proc. of NeuroAdaptive Technologies (NAT) conference*, 2022.
25. Mohammed Gamil Mohammed Saif. Clinical efficacy of neurofeedback protocols in treatment of attention deficit/hyperactivity disorder (adhd): A systematic review. *Psychiatry Research: Neuroimaging*, page 111723, 2023.
26. Zhongfei Bai, Kenneth NK Fong, Jack Jiaqi Zhang, Josephine Chan, and KH Ting. Immediate and long-term effects of bci-based rehabilitation of the upper extremity after stroke: a systematic review and meta-analysis. *Journal of neuroengineering and rehabilitation*, 17:1–20, 2020.
27. Elise Grevet, Killyam Forge, Sebastien Tadiello, Margaux Izac, Franck Amadiou, Lionel Brunel, Léa Pillette, Jacques Py, David Gasq, and Camille Jeunet-Kelway. Modeling the acceptability of bcis for motor rehabilitation after stroke: A large scale study on the general public. *Frontiers in Neuroergonomics*, 3:1082901, 2023.
28. Hasan Ayaz and Frédéric Dehais. *Neuroergonomics: The brain at work and in everyday life*. Academic Press, 2019.
29. Gianluca Borghini, Laura Astolfi, Giovanni Vecchiato, Donatella Mattia, and Fabio Babiloni. Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews*, 44:58–75, 2014.
30. Fabien Lotte and Raphaëlle N Roy. Brain-computer interface contributions to neuroergonomics. In *Neuroergonomics*, pages 43–48. Elsevier, 2019.
31. Frédéric Dehais, Alban Duprès, Sarah Blum, Nicolas Drougard, Sébastien Scannella, Raphaëlle N Roy, and Fabien Lotte. Monitoring pilot's mental workload using erps and spectral power with a six-dry-electrode eeg system in real flight conditions. *Sensors*, 19(6):1324, 2019.
32. Stephen H Fairclough and Thorsten O Zander. *Current Research in Neuroadaptive Technology*. Academic Press, 2021.
33. Roger Nkambou, Riichiro Mizoguchi, and Jacqueline Bourdeau. *Advances in intelligent tutoring systems*, volume 308. Springer Science & Business Media, 2010.

34. Jérémy Frey, Christian Mühl, Fabien Lotte, and Martin Hachet. Review of the use of electroencephalography as an evaluation method for human-computer interaction. In *International Conference on Physiological Computing Systems*, volume 2, pages 214–223. SCITEPRESS, 2014.
35. J Frey 1 2, M Hachet 2, and F Lotte 2. Eeg-based neuroergonomics for 3d user interfaces: opportunities and challenges. *Le travail humain*, 80(1):73–92, 2017.
36. Jérémy Frey, Maxime Daniel, Julien Castet, Martin Hachet, and Fabien Lotte. Framework for electroencephalography-based evaluation of user experience. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems*, pages 2283–2294, 2016.
37. Jérémy Frey, Aurélien Appriou, Fabien Lotte, and Martin Hachet. Classifying eeg signals during stereoscopic visualization to estimate visual comfort. *Computational intelligence and neuroscience*, 2016:7–7, 2016.
38. Hakim Si-Mohammed, Catarina Lopes-Dias, Maria Duarte, Ferran Argelaguet, Camille Jeunet, Géry Casiez, Gernot R Müller-Putz, Anatole Lécuyer, and Reinhold Scherer. Detecting system errors in virtual reality using eeg through error-related potentials. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, pages 653–661. IEEE, 2020.
39. Erin T Solovey, Felix Putze, et al. Improving hci with brain input: Review, trends, and outlook. *Foundations and Trends® in Human-Computer Interaction*, 13(4):298–379, 2021.
40. Stephen H Fairclough and Fabien Lotte. Grand challenges in neurotechnology and system neuroergonomics. *Frontiers in Neuroergonomics*, page 2, 2020.