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Augmenting Attention with Brain–Computer Interfaces

Mehdi Ordikhani-Seyedlar and Mikhail A. Lebedev

Abstract

Brain–computer interfaces (BCIs) are rapidly gaining popularity. They can be employed in a clinic to treat neurological disorders and even to augment brain functions. Among clinical applications, BCIs can be used to treat disorders of attention. In this chapter, we review current attention-based BCIs, in particular the ones that operate in the domain of visual attention. Patients with attention deficits utilize such BCIs to improve their control of attention. We highlight the approaches for extraction of neural features relevant to attention-based BCIs. The efficiency of current clinical BCIs for augmenting attention is discussed. We conclude that although considerable advances have been made in attention-based BCIs, fundamental challenges for the optimization of such systems and their practical applications in the clinical world remain mostly unresolved.

28.1 INTRODUCTION

This chapter describes BCIs that operate in the domain of attention, a complex cognitive function. While attention has distinct neural manifestation, utilization of attention-related neural signals in BCIs is a difficult task because relevant signals may be obscured by irrelevant neural activities. A good understanding of neurophysiology of attention is needed to build better BCIs. Among them, extraction of relevant features is of high importance. This chapter delves into the basic neural mechanisms of attention, the ways they are manifested in the brain recordings, such as electroencephalography (EEG), features that can be extracted from these recordings, and their utilization in BCIs.

We focus mostly on visual attention because of the abundance of neurophysiological and BCI studies in this field. The visual system translates very complex input information from the external world into a stable neural representation. The emergence of such a representation can be described as a process of information reduction, where only behaviorally relevant visual inputs are processed (Sprague et al. 2015). For instance, for a driver moving toward a crossing point, it is essential to have...
the capacity to recognize traffic lights while disregarding insignificant light sources. Attention is the ability of the brain to suppress the superfluous sources of information and select only the relevant ones. This key brain function can suffer because of neurological conditions. Patients with disorders of attention have difficulty focusing on the relevant pieces of information and get easily distracted. Attention-deficit/hyperactivity disorder (ADHD) is a mental condition characterized by deteriorated attention, hyperactivity, and impulsivity (Biederman et al. 2000; Faraone et al. 2006). Treatment approaches to ADHD have been mostly pharmacological, such as the usage of psychostimulants. However, pharmacological treatment is often associated with unwanted side effects (Conners et al. 2001; Greenhill et al. 2001). There is also an associated substance abuse problem (Kollins 2008; Steiner et al. 2014a). Psychological therapy can be used as an alternative treatment for ADHD, but it is effective only in 30% of cases (Zarin et al. 1998).

BCIs offer a novel and potentially very effective strategy for treating attention deficits (Arns et al. 2009; Lim et al. 2010, 2012). BCIs link the brain and external devices in uni- or bidirectional ways (Donoghue et al. 2004; Lebedev 2014; Lebedev & Nicolelis 2006, 2017; Nicolelis & Lebedev 2009; Schwarz et al. 2014; Wolpaw et al. 2000). During BCI operation, neural signals are first recorded and then analyzed using mathematical methods. Following the analysis, certain features of the signals are selected and compared to template features based on control experiments in healthy subjects. Depending on how different the neural features are from the templates, the computer delivers an appropriate feedback to the person. In this context, the terms “neurofeedback,” “neurofeedback therapy,” “BCI,” and “BCI therapy” are often used interchangeably. While many neural recording methods can be utilized by BCIs, EEG has been by far the most popular recording technology utilized in such applications (Bamdadian et al. 2014; De Vos et al. 2014; Kashihara 2014; Kus et al. 2013; Tonin et al. 2013; Yang et al. 2014). A distinct class of BCI/neurofeedback applications strives to improve attention in ADHD patients (Christiansen et al. 2014; Heinrich et al. 2014; Holtmann et al. 2014a,b; Micoulaud-Franchi et al. 2014; Steiner et al. 2014b). Optimizing attention-based BCI and making them practical is, however, quite challenging because the brain mechanisms of attention are highly sophisticated (Ming et al. 2009; Rossini et al. 2012) and it is not easy to dissociate attention-related neural activity from the other activities in the brain circuits (Sanéi & Chambers 2008).

In this review, we first highlight the key findings of the neuroscience studies of attention. Next, we explain how BCIs could be used to treat attention deficits. We deliberate on several neural features that have been utilized in attention-based BCIs: neural oscillations, evoked potentials, and steady-state potentials. These considerations lead to the discussion of the problems in implementing attention BCIs and the ways these problems could be solved in the future.

### 28.2 NEUROSCIENCE OF ATTENTION

In our daily life, we constantly receive multiple sensory inputs from the external world; the amount of incoming sensory information is huge. The only way for the brain to process this information stream and generate proper behavioral responses is to filter out irrelevant incoming signals and leave only the important ones. As a result of such attentional filtering, only a tiny amount of the initial sensory information reaches higher-order areas of the brain (Posner 1994, 2012). The signals that are filtered out are still represented by neural modulations, especially at the early processing stages, but they are usually not perceived consciously. On the other hand, the relevant signals are selected by the brain attentional mechanism, and they enter the conscious processing stage. Such attentional selection is governed by a network of interconnected brain areas. One of these areas, the prefrontal cortex (PFC) has a particularly important role in the mechanisms of selective attention. PFC is activated during attentional tasks, and lesions to this area lead to attentional deficits (Ferrier 1876). Posner’s laboratory has conducted a series of studies to identify the brain areas involved in attention (Fan et al. 2005; Petersen & Posner 2012; Posner & Rothbart 2007). These studies have demonstrated that multiple brain areas govern attention, and the same areas are also
engaged in oculomotor control. In addition to PFC, the attentional brain network includes parietal cortical areas, the frontal eye field (FEF), subcortical nuclei, and, importantly, the superior colliculus.

Several types of attentional mechanisms have been defined in the literature. Overt and covert attention refer to attentional reactions performed with and without eye movements, respectively. According to Rizzolatti’s premotor theory of attention (Rizzolatti et al. 1987), spatial attention (both overt and covert) is controlled by the same brain regions that move the eyes. The premotor theory of attention explains such overlap between the oculomotor and attentional areas in the following way: to produce overt shifts of attention, eye movements are first prepared and then executed; covert shifts of attention are also prepared by the same areas but not executed. Rizzolatti’s theory gained some support from the functional magnetic resonance imaging studies that demonstrated an overlap between the cortical regions activated during both covert and overt shifts of attention (de Haan et al. 2008). Moreover, neurons in the superior colliculus, the area responsible for generation of saccades (rapid eye movement from one fixation point to another), have been shown to be involved in both overt and covert shifts of attention (Ignashchenkova et al. 2004).

Although the orientation of attention, the location of the target of movement, and gaze direction often coincide, the spatial location of attention focus can be disengaged from gaze direction (as in overt attention) and motor goals. Lebedev, Wise, and their colleagues investigated cortical representation of attention using experimental conditions that required monkeys to attend to one spatial location and also neutrally process the other as a potential target of movement. Two studies were conducted with this design. In the first study (Lebedev & Wise 2001), attention-related neuronal activity was recorded in dorsal premotor cortex (PMd). In this study, a robot served as an attention attractor, since its movements instructed monkeys when to initiate an arm-reaching movement. The arm movements were directed either to a feeder attached to the robot or a stationary feeder positioned differentially from the robot. It was found that close to 20% of PMd neurons represented spatial attention instead of representing motor preparation or gaze direction. Such neurons could be involved in covert attentional shifts. In the second study (Lebedev et al. 2004), the researchers investigated how neurons in PFC represented attention and how this representation was different from the encoding of spatial locations in working memory. Monkeys were trained on an oculomotor task that required them to attend to one spatial location while remembering the other. A sizeable population of PFC neurons represented mostly attention, not the working memory. Taken together, these two series of findings indicate that a large number of frontal cortex neurons are tuned to the orientation of spatial attention.

In agreement with these findings in monkeys, human studies have shown that abnormalities of the frontal cortex have a key role in ADHDs (Dirlikov et al. 2015; Praamstra et al. 2005). In a brain imaging study by Dirlikov et al. (2015), the cortical structure was examined in 93 children with ADHD. Reductions in cortical surface were found in the PFC and premotor cortical areas (Dirlikov et al. 2015). The other neuroimaging studies demonstrated that, in ADHD, gray matter is affected in the FEF and the network of areas interconnected with it, particularly dorsal and ventral PFC, the inferior parietal cortex, and the dorsal anterior cingulate area (Szuromi et al. 2011; Valera et al. 2007). It has been suggested that the frontal lobe is involved in selective filtering of sensory information, since damage to this brain region causes ADHD (Jonkman et al. 2004). A study of resting-state EEG patterns in ADHD patients showed that frontal cortex abnormalities play a role in this disease (Keune et al. 2015).

### 28.3 EMERGENCE OF ATTENTION-BASED BCIS

After the emergence of the neurofeedback approach in the 1960s, many authors have proposed that neurofeedback could be utilized to treat attentional disorders (Elbert et al. 1980; Lutzenberger et al. 1980; Wolpaw et al. 1991). Modern attention-based BCIs employ advanced computer algorithms to decode neural signals associated with attention. In a typical BCI arrangement, subjects
focus their attention on a video game. While they do so, the BCI extracts attention-related neural activities, processes them, and delivers the processed signals back to the subject, typically using visual feedback. Therapy sessions with such a BCI repeat several times, engage brain plasticity, and eventually normalize attention (Dobkin 2007; Rossini et al. 2012). Although attention-based BCIs have experienced a steady development, the outcomes of such treatment are not without controversy (Ordikhani-Seyedlar et al. 2016). Several reports described BCI training of attention as efficient (Gevensleben et al. 2009; Leins et al. 2007; Steiner et al. 2011; Wangler et al. 2011), but several other publications questioned this conclusion. Arns et al. (2009) called neurofeedback therapy for attention “efficient and specific” based on their literature analysis (Arns et al. 2009). Lofthouse et al. (2012) examined neurofeedback studies conducted from 1994 to 2010 and concluded that this approach was “probably efficacious” (Lofthouse et al. 2012). However, a different conclusion was reached by Vollebregt et al. (2014a) based on a systematic review of BCIs for ADHD. They concluded that this approach had no effect on any neural functions affected by ADHD (Vollebregt et al. 2014a). Clearly, there is a need for further investigation into attention-based BCIs.

28.4 NEURAL FEATURES FOR ATTENTION-BASED BCIs

28.4.1 Importance of Feature Selection

Selection of neural features is an important part of BCI design (Shahid & Prasad 2011). During this signal processing stage, specific characteristics of neural activity are chosen, which are then sent to the decoding algorithm to produce neurofeedback. Depending on the BCI’s principles of operation and recording method utilized, different features can be extracted from brain activity. Neuronal spikes recorded with implanted electrodes are usually converted into time-dependent discharge rates. EEG recordings are typically converted into spectral bands or event-related potentials (ERPs). The feature selection also depends on whether the BCI is endogenous (self-controlled) or exogenous (driven by an external stimulus). Subjects generate neural patterns at their will when operating endogenous BCIs, for example, using mental imagery (Nicolas-Alonso & Gomez-Gil 2012). In exogenous BCIs, external stimuli (e.g., objects shown on a screen) evoke neural responses, and subjects control these responses by directing attention and/or gaze to the stimulus of their choice.

28.4.2 Neural Oscillations

Analysis of oscillatory neural activity, for example, EEG rhythms sampled over different cortical areas, is a common method to extract neural features for endogenous BCIs. For example, EEG time-frequency analysis detects transient occurrences of neural oscillations, which in turn could be used to detect attentional shifts (Sanei & Chambers 2008). High-frequency oscillations (with a frequency greater than 30 Hz) indicate increased attention, as evident from EEG studies in humans (Kaiser & Lutzenberger 2005; Koelewijn et al. 2013; Musch et al. 2014) and intracranial recordings in monkeys (Fries et al. 2001).

Attention-related oscillations occur in the γ-band (30–80 Hz) and even higher-frequency bands (Crone et al. 2006). Ray et al. (2008) observed high-γ activity (80–150 Hz) in subjects presented with a sequence of auditory and tactile stimuli and instructed to attend to one of these modalities. Attentional shifts between the modalities resulted in high-γ activity in the cortical areas that correspond to the chosen modality, that is, auditory cortex for sounds and somatosensory cortex for tactile sensations. Furthermore, high-γ activity was elevated in PFC when subjects attended to any modality, which agrees with the suggestion that PFC is a part of the supramodal attentional system (Dirlikov et al. 2015; Keune et al. 2015). Oscillations at 350 Hz were reported in human frontal and centro-parietal regions, where they occurred in response to somatosensory stimulation (Ozaki et al. 2006). Several explanations have been proposed for the function of high-frequency oscillations during attentional shifts. According to one hypothesis, ultrahigh-frequency oscillations represent
noise that has a modulatory function in neural processing (Benzi et al. 1982). Adding moderate amounts of noise to the activity of a brain circuit increases neural synchrony and decreases stimulus detection threshold (Ward et al. 2006), the effect known as stochastic resonance (Benzi et al. 1982). Similar modulations of brain circuits can be produced by adding noise to the brain activity using microstimulation (Medina et al. 2012).

Various EEG spectral bands have been utilized in the BCIs for controlling attention. For instance, human subjects can learn to modulate γ-oscillation in their superior parietal cortex by alternating between the rest state and attentive state (Grosse-Wentrup & Scholkopf 2014). In addition to using a single spectral band, attention-controlling BCIs have utilized the ratio of power in different bands as neural feature. Several BCI studies used the ratio β/(α + θ) that increases with elevated attention (Nagendra et al. 2015). The ratio θ/β that decreases with elevated attention has been used as well (Clarke et al. 2013; Dupuy et al. 2013; Heinrich et al. 2014; Vollebregt et al. 2014b). In general, the slower waves such as θ and α rhythms are prominent in inattentive states and drowsiness, and β rhythm increases in attentive states. In addition to EEG spectral bands, attention-based BCIs can utilize instantaneous phase of EEG oscillations as their feature (Busch et al. 2009). Busch et al. (2009) instructed subjects to detect a brief light flash that occurred either in an attended or unattended part of space. The performance on this task depended on the EEG phase at the time of stimulus occurrence. Additionally, detection errors increased in the presence of strong α activity, a finding that is consistent with several previous studies (Babiloni et al. 2006; Ergenoglu et al. 2004; Hanslmayr et al. 2007; Thut et al. 2006).

Several studies employed BCIs based on EEG rhythms as a treatment of ADHD. Lubar et al. (1995) treated children and adolescents with ADHD using a neurofeedback protocol that required increasing β rhythms (16–20 Hz) and suppressing θ rhythms (4–8 Hz). Both parent ratings of their children and the performance on attention-demanding tasks improved following the training. More recently, Gevensleben et al. (2009) conducted a randomized controlled trial that assessed the efficacy of several neurofeedback protocols (based on θ and β rhythms and slow cortical potentials) as a treatment for children with ADHD. The neurofeedback protocols were found to be more efficient compared to computerized attention skills training. In a meta-analysis study from five different studies, a total of 146 children with ADHD were considered, all trained using EEG-neurofeedback (Micoulaud-Franchi et al. 2014). This meta-analysis showed that ADHD symptoms were improved substantially after neurofeedback therapy.

### 28.4.3 Event-Related Potentials

ERPs consist of several deflections of an EEG trace after stimulus presentation; several of these deflections have been linked to attentional processing (Cohen 2013). Accordingly, ERPs have been used in numerous studies on neural mechanisms of attention (Gherri & Eimer 2011; Jones et al. 2013; Matheson et al. 2014; Wu et al. 2009; Zheng et al. 2014). ERPs recorded from cortical sensory areas increase in amplitude when the stimulus of the corresponding modality is attended to (Harter et al. 1984). For an ERP-based BCI to attain high performance, it is essential to select the optimal ERP components and scalp locations. Farwell and Donchin pioneered ERP-based BCIs in 1988 (Farwell & Donchin 1988). The participants of their experiments looked at a matrix of alphanumeric characters in a 6 × 6 arrangement. EEG activity was sampled with a single Pz electrode. The participants attended to one of the characters while the matrix columns and rows flashed. When the attended character flashed, an ERP, called P300, was evoked. Accordingly, the character could be recognized as the one that evoked the strongest P300. Approximately 30 repetitions of the character were needed to achieve good recognition accuracy.

ERP-based BCIs have a relatively slow performance, evaluated as information transfer rate (ITR). In Farwell and Donchin’s experiments, the ITR of approximately 12 bits min⁻¹ was achieved (or 2.3 character per minute). Despite the advantage of requiring very little training time, surprisingly, P300-based BCIs have not yet been used for treatment of ADHD subjects. This is because
the P300 characteristics substantially vary across trials conducted in the same subjects, as well as across different subjects. This variability is related to such factors as fatigue, mental state, motivation, and other nonstationary processes in the brain (McFarland & Wolpaw 2011). To cope with the variability, individualized calibration is needed for each subject and, additionally, calibration for different mental states of the same subject (Fazel-Rezai et al. 2012). Overall, fluctuations in P300 characteristics hinder their utilization for ADHD treatment (Furdea et al. 2009; Gonsalvez & Polich 2002; van der Waal et al. 2012).

28.4.4 Steady-State Visual Evoked Potentials

Steady-state visual evoked potentials (SSVEPs) are another popular protocol used in exogenous BCIs (Lesenfants et al. 2014; Palomares et al. 2012; Reuter et al. 2015; Wu & Su 2014; Zhang et al. 2010). SSVEPs are evoked by flickering stimuli, for example, a flickering checkerboard (Punsawad & Wongsawat 2012). Such stimuli produce cortical responses that are entrained to the stimulus frequency. In BCIs, SSVEPs are typically recorded from the visual and parietal cortices. Such BCIs require a few seconds for the recognition of attended stimuli (Dmochowski et al. 2015). Several targets would flicker on a computer screen, each at a unique frequency, while a subject looks at one of the targets, and then the target with the strongest response would be identified using the analysis of the EEG spectral peaks (Bakhshayesh et al. 2011; Leins et al. 2007; Lim et al. 2010, 2012).

The performance of SSVEP-based BCIs is considerably better compared to the ERP-based BCIs (Muller-Putz & Pfurtscheller 2008). Bin et al. demonstrated an SSVEP-based BCI with an ITR of $58 \pm 9.6$ bits min$^{-1}$ and an accuracy of 95.3% (Bin et al. 2009). Flickering frequency of 6 Hz and higher is needed to achieve this level of performance. Recently, visual flicker of up to 100 Hz was implemented in a BCI demonstrated by Dreyer and Herrmann (2015). Subjects are comfortable with such high-frequency stimulation because they do not perceive flicker of 40 Hz and higher (Lin et al. 2012). Sakurada et al. (2015) reported that an SSVEP-based BCI with the frequency above 50–60 Hz eliminated visual fatigue while improving the performance (Sakurada et al. 2015). Training time also improves, notably in ADHD patients for whom the flicker is especially irritating (Kooij & Bijlenga 2014). In some cases, harmonics of the flicker frequency provide a better readout compared to the spectral band at the stimulation frequency (Allison et al. 2010; Muller-Putz & Pfurtscheller 2008; Ordikhani-Seyedlar et al. 2014). Additionally, SSVEP-based designs can be combined with ERP-based designs to improve the performance further. For example, Muller and Hillyard (2000) designed such an experiment where SSVEP and ERPs were captured at the same time. This study showed that there is a significant correlation between N1 and N2 components of ERP with SSVEP, whereas no such correlation was found between the P300 component.

An SSVEP-based BCI has been proposed as a potential method for training attention in ADHD patients (Ali & Puthusserypady 2015). The BCI settings incorporated a 3D classroom environment with 2D games played on the blackboard, and SSVEP features. Tests in healthy subjects showed that the attentional demands could be increased by changing the difficulty level of the game.

28.5 Future Directions

The development of the BCI field has been quite spectacular during the last decade. While the focus of many BCI studies has been on the enabling motor and sensory functions to disabled patients (Lebedev & Nicolelis 2006, 2017), the interest in BCIs that operate in the higher-order, cognitive domain has been steadily growing (Andersen et al. 2004; Mirabella & Lebedev Mcapital A 2017). Here, we reviewed the research on BCIs that work in the cognitive domain and strive to decode neural signals related to attentional control. Such attention-based BCIs have been already employed as an approach to treat ADHD, with positive results (Gevensleben et al. 2009; Leins et al. 2007;
Steiner et al. 2011; Wangler et al. 2011). In our opinion, the key future challenges for BCIs that treat attention disorders include the following:

1. Reducing noise and eliminating artifacts: Noise is common in EEG-based BCIs. It can be caused by electrical and mechanical artifacts, and it can be related to scalp muscle EMGs. Neural signals irrelevant to the targeted function can also be considered as noise because they hinder BCI operations. Dealing with noise is especially important for therapeutic BCIs because noise interference may result in unwanted functions being enhanced instead of the intended ones. As an example, the $\alpha$-band is thought to be associated with the suppression of irrelevant inputs in attention tasks. However, drowsiness state also enhances the $\alpha$-band, so the BCI based on this feature could increase drowsiness instead of improving attention. This issue can be handled by adding topographical information about the $\alpha$-sources.

2. Improving the measurements of BCI training effects: The effectiveness of BCI-based therapy is typically evaluated using a comparison of neural features before and after the BCI training. However, such changes in neural features do not necessarily guarantee a functional improvement. For example, $\beta$-band power is often used as an indicator of a high attention level. However, different factors unrelated specifically to attention can cause an increase in $\beta$-band power, for example, suppression of voluntary movements (Zhang et al. 2008). Because of this possible confound, we suggest that the outcome of neurofeedback therapy should be evaluated using both EEG-derived measures and the measures of behavioral performance.

3. Taking individual variability into account: EEG data are variable across subjects. Variability can be manifested as intersubject differences in mental states, nonstationary EEG activity (Vidaurre et al. 2011), and variable responses to task events (Iturrate et al. 2013). Ideally, BCI algorithms should account for individual characteristics of subjects, including the way they respond to BCI training.

4. Ease of use: BCI-based training is currently conducted by an expert in EEG recordings and running BCI trials. In the future, more user-friendly ones need to be developed.

### 28.6 CONCLUSIONS

BCIs have significantly improved in recent years. They currently offer exciting opportunities not only as enablers of motor, sensory, and cognitive capabilities, but also as therapies for neural disorders. In particular, BCIs hold promise as a treatment for disorders of attention. While several BCI-based protocols for training attention have been already tested, there remain many challenges. We envision the development of BCIs for attention disorders as a multidisciplinary venture, where technical knowledge of BCIs is combined with Neuroscience and psychology expertise.

### REFERENCES


