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Brain-Computer Interface in Neuropsychological Rehabilitation

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ABSTRACT

Brain-computer interface (BCI) is a new frontier of neuropsychological rehabilitation. Neuroscientists have long visualized the possibility of using brain signals to control artificial devices. There are promises as well as challenges involved in it. The present article examines the concept of BCI through its function-based classification and its various operational paradigms such as P300, steady state evoked potentials, sensorimotor rhythms, and slow cortical potentials, which are used as means of BCI. In this context, Hebb's theorem of long-term potentiation (LTP) was discussed to explain the mechanism of behaviour change. While describing the stages of signal acquisition, this article describes procedures for artifact reduction. It provides a kaleidoscopic view evidence-based practice of BCIs various clinical conditions, with hope that in coming years BCI will provide new avenues of applied research and insight for neuropsychological intervention.

Keywords *Brain-Computer Interface, P300, Steady State Evoked Potential, Sensorimotor Rhythm, Slow Cortical Potentials, Long-Term Potentiation*

INTRODUCTION

Brain is an immensely complex, self-organizing and self-modifying 'super organ', that has always remained an enigma. Its learning, memory and categorization capabilities make it possible to self-recruit the sensory and motor systems to identify patterns and features in the real world, which in turn, helps it in modeling and modifying the external world for its best use. Its capability to directly alter its own circuitry and neural activity even offers promises for treatment of brain damage. However, this capacity for self-recovery (plasticity) is limited. Therefore, the existing functions need to be augmented through assistive technology—neuroprosthesis, the devices, which are linked to the peripheral or central nervous system to enhance the cognitive, motor or sensory abilities (Medical Dictionary, 2009). In a broader sense, such devices—most often computers, used for restoring and enhancing the functions lost due to brain damage is called the brain-computer interface (BCI). Vidal coined this term in 1973 describing it as "utilization of the brain signals in a man-computer dialogue" (Vidal, 1973). BCI is primarily a communication system in which an individual sends messages or commands to the external world without passing through the brain's normal output pathways of peripheral nerves and muscles (Wolpaw et al, 2002). The CBI system uses devices that enable their users to interact with computers and machines by using brain activity (Nam, Nijholt, & Lotte, 2018). Nicolelis (2001) predicted that real-time interfaces between the brain and electronic and mechanical devices could one day be used to restore human sensory and motor functions. The present article attempts to track some of the significant developments in the field that has created convergences in closer inter- and cross-disciplinary approach and expanded the field of neuroscience enormously.

The earliest development of BCI came with Hans Berger's path-breaking discovery of electroencephalogram (Berger, 1929), which translated the brain signals into electrical signals to study cognitive functions and their neural correlates. The technology opened floodgates for research and applications. Joseph Kamiya (1968) on the other hand used alpha waves in neurofeedback training and demonstrated that human action can control the brain waves such as alpha is possible by receiving real time feedback, based on the principle of operant learning. Another remarkable innovation was Farwell and Donchin's (1988) 'P300 Speller' a form of mental prosthesis, based on event-related potential (ERP). It was a 6 x 6 grid of letters and digits, from which the user can select letters as well as digits to spell. It became possible to detect and predict which row and which column contains the letter that the user would select to spell. Although, designed for healthy users, could be used successfully for people with brain injury. Childers and associates (1989) developed a 'cortical mouse', based on event-related potentials, which enabled the user to select one command among the two. This was based on the N400 response to a congruent or incongruent stimulus sentence (Konger et al. 1990, Principe, 2013). Thereafter, researchers developed BCI-based parameters such as sensorimotor rhythms (SMR) (Wolpaw et al. 1991). Since end of the last century there has been a bloom of research in the field, as a result of which BCI has become a distinct field itself. For comprehensive and detailed review of the historical development, readers may refer to Nam, Nijholt, & Lotte, (2018).

Types and Paradigms of BCI

The BCIs are classified under three different categories (Zander, et al, 2008): active, reactive and passive. *Active BCIs* are based on brain electrical patterns of activities, identified in terms of specific frequency bands at a

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specific electrode location. The user actively generates the electrical changes by use of limbs movements or through cognitive performance (e.g. mental arithmetic, speech imagery, visualization or mental rotation). *Reactive BCIs* are the brain responses to certain stimuli (cues that the user uses and the ones he/she ignores). Apart from discrimination and feature detection, it also reveals the emotional state of the individual user such as frustration, attention, workload, and drowsiness. which are measured through event-related potentials (ERPs) of Steady State Evoked Potentials (SSEP). The third group, *Passive BCIs* use information about the user's cognitive or emotional states as neural correlates of cognitive and affective states in order to improve performance. These are further explained through its paradigms.

Few paradigms of research have been discusses in the next section, which focuses on some of the major paradigms of BCI.

P300 based BCI Paradigm

P300 is a positive deflection in human event-related potential (ERP), most commonly elicited by "oddball" paradigm in which an occasional "target" stimulus appears in a regular train of standard stimuli. The peak P300 is generally seen in adults while making a simple discrimination at 300 ms. and its amplitude varies with the chance of occurrence of a target (infrequent) stimulus, whereas the latency varies with difficulty in distinguishing a target stimulus from the standard ones (i. e simple discrimination). People, with decreased cognitive abilities (as in epilepsy) tend to have smaller and later waves than in age-matched normal participants. It reflects the amount of attentional resources allocated to a task as well as degree of information processing of an individual. Although the origin and role of P300 is not adequately understood, the wave is expected to occur only if an individual is actively engaged in detecting the target. It is generated naturally without any conscious effort in response to target trial, therefore, unlike many rhythm-based neurofeedback tools, the ability to control the proposed P300-based neurofeedback training is obtained after a short calibration, without undergoing tedious trial and error sessions. This can be the basis for input for performance-enhancing assistive devices for patients suffering from brain damage or impaired neurological functioning for improving their quality of life (Arvaneh, Robertson, & Ward, 2019).

Steady State Visual Evoked Potentials (SSVEP) based BCI Paradigm VEPs are elicited by changes in the visual field, which are strongly generated in the occipital area of the brain and there are two types of visual evoked VEPs: Steady State Visual Evoked Potential (SSVEP) and Transient State Visual Evoked Potential (TSVEP). The former is elicited by the change in the visual field, which is higher than 6 Hz (Wu, He & Tian, 2012) and the later is lower than 6 Hz, and can be caused by events such as visual stimulus applied to the subject via a computer screen. 'Steady state' is vibratory in nature. When a participant is presented with a steady state stimulus (visual, auditory or vibrotactile), rhythmic brain activity associated with cortical areas will be generated similar to the frequency of the stimuli. Currently, the most popular one is Steady-State Visual Evoked Potentials (SSVEP) in BCI operations. This is elicited by visual stimuli, whereas, auditory stimuli elicit Steady-State Auditory Evoked Potentials (SSAEPs)(Hill, et al. 2012). These evoke potential are useful for training patients suffering from brain damage that affects their communication significantly and those who are in 'lock-in' condition.

Sensorimotor Rhythms (SMR) Paradigm

SMR the rhythm is typically picked up from sensorimotor part of the cortex, notably, the Mu band or Mu rhythm (~7-13 Hz, alpha band) mostly picked up at sensorimotor part of the cortex (somatosensory and motor cortices) and also the Beta band 14-30 Hz). The participants are trained to control the amplitude of the SMR, so that they can self-regulate in order to activate an assistive device (e.g. 1D cursor). These wave patterns may change due to either actual or imagined movements, which create event related desynchronization (ERD) i. e increase in the frequency band amplitude immediately in the sensorimotor area (Graimann et al. 2010). The event-related synchronization (ERS) is significant for BCI studies on patients who have neurological disorders affecting motor co-ordination. Pfurtscheller, Flotzinger, and Kalcher (1993) developed an imagery-based BCI in which the user had to explicitly imagine left- or right-hand movements. The SMR generated from this motor imagination was translated into command for a computer by using machine learning that focuses on the use of data and algorithm to improve its own performance, which is similar to human learning that improves gradually by accuracy. It allows making accurate prediction of the outcomes. Tariq and his associates (Tariq, et al., 2018) studied the use of SMR for improving the gait disturbance of people suffering from spinal cord injuries (SCI) and found that the action imageries obtained through SMR could improve the functioning of an individual. In other words BCI could be used to build new communication channel between the brain and other output devices.

Slow Cortical Potentials (SCP) Paradigm

Slow Cortical Potentials (SCP) is the third type of paradigm, which refers to very slow shifts in electrical activity of the brain lasting from several milliseconds to several seconds. SCP takes anywhere from 1 second to several seconds to develop. It suggests that the information transfer rate is quite slow compared to

SSVEP and visual P300. A change of the direction of negative polarity is associated with increased cortical activity or movement and a change in the positive polarity is associated with decreased cortical activity and calm (Nam, Choi, Wadeson, & Whang, 2018). These changes in neural activity are assumed to be related with excitability of the neural network that is linked with mental functioning such as executive functions, especially attention (Banaschewski and Brandeis, 2007, Calderone et al., 2014). These negative or positive polarizations, can be externally triggered or self-induced. The amplitude of this low frequency variation of can be voluntarily increased or decreased through neurofeedback training. For instance, among the neurofeedback protocols applied for Attention Deficit-Hyperactivity, SCP-training is considered as the best validated approach (Mayer et al, 2013). SCPs have moderating impact on information processing. This has been demonstrated in a number of studies (e.g. Bauer & Nirnberger, 1981; Birbaumer, et al., 1992; Schupp et al. 1994). Similar to SMR BCIs, SCP BCIs do not rely on external stimuli, such as visual stimuli of SSVEP in order to generate brain wave patterns. Instead of which users control their thought processes in order to interact with BCI. SCPs are generally analysed through Thought Translation. It can select one group of commands or another to increase or decrease the SCP. All the above paradigms of BCI heavily rely on the principles of operant conditioning. Extensive and intensive training is required using individualized cognitive and behavioural strategies (Studer et al., 2014).

Hwang et al. (2013), who conducted a survey of the neurotechnologies used for BCI studies, reported that, according to the published work during 2007-11, EEGs (i. e. P300, SSVEP, SMR) are the most commonly used BCI technologies. At least 68% research articles are based on these technologies, followed by invasive technologies (32%), IMRI (3%), Functional Near Infrared Spectroscopy (fNIRS) (3%) and MEG (2%).

CBI and Neuroplasticity

Neuroplasticity refers to capacity of the brain to self (re) organize after trauma or environmental changes (Gross-Wentru et al. 2011). This innate capacity makes BCIs successful in restoration of brain function. CBI is now designed for neuromdulation that induces plasticity in neural structures. It is suggested that experience–dependent activation of two or more converging inputs strengthens the connectivity of neurons, whereas the connectivity is weakened by uncorrelated activities due to “neural pruning”.

In this context, it is important to understand Hebb’s theorem of long-term potentiation (LTP), the cellular mechanism for memory and learning storage. Hebb (1949) suggested that relearning motor tasks because of motor impairments requires correlated activation of neural cells. Accordingly, relearning of motor tasks in people suffering from motor impairment requires correlated activation of neural cells. Other investigators have extensively investigated this. For instance in one of the *in vitro* experiments this was observed following stimulation of the prefrontal path. LTP was observed in dentate area of the anesthetized rabbit (Bliss & Lomo, 1973). This phenomenon has been extensively studied in hippocampus of rats. The *mu* rhythm changes are quantified in terms of event-related. However, Stefan and colleagues (Stefan, et al., 2000) provided the first proof of LPT-like plasticity in a human experiment. Although LPT is dependent on the extent of brain damage, these observations suggest that BCI designed for neuromodulation, based on known theories of memory storage and learning can benefit the patients who have lost certain adaptive functions due to brain damage.

Stages in BCI

In the previous section, I discussed the most widely used parameters of signals used for BCI. There is always a need for improving signal quality and extract important features. Therefore, the computers have to be designed in a manner to accurately detect and amplify the signals in order to make them perceptible for the user.

There are several stages of implementation of BCI for securing high level of competence, which starts with recording, designing and application in real settings. It involves various stages of processing for effective use in neuropsychological rehabilitation, such as signal acquisition, improving signal quality, feature extraction, classification and application

The raw signals picked up from the targeted cites of the body (e.g. scalp, brain, skin or muscles) whether invasive or non-invasive are inherently “noisy” or contaminated with “artifacts”, which could be endogenous (e.g. eye blink, heart rate, sweating, bodily movements) or exogenous (e. g. power line interference, affecting flow of the current, poor impedance due to electrode contact and electrode drift). A notch filter is applied at 50 Hz to 60 Hz to remove artifacts due to power line data from the incoming signals (Nam, Choi, Wadeson, & Whang, 2018). A good number of artifacts are reduced manually just by organizing the setting by giving appropriate instruction to the participant and others by use of technology. For instance the eye blink, heart rate have certain patterns of electrical activity, which goes unnoticed, and contaminating the data. High correlation of these biosignals (e.g. ECG, EOG, or EMG) with the index signals (e.g. EEG or ERP) reveals the extent of data contamination. Statistical analyses and visual monitoring are used to overcome irrelevant signals from issues with EEG cap. Under circumstance, when the correlation between these sources and the EEG is still high the data is not considered for controlling BCI. Spatial filtering is conducted in order to enhance the sensitivity to a particular cite (brain sources) from which the data is acquired. It improves source localization and suppresses certain artifacts (Krusienski, et al. 2012). Referencing of one of the principal measures of spatial filtering and the simplest measure of bipolar reference, which is a measure of difference between two electrodes placed anteriorly, posteriorly, to left or right of the target position. Spatial filtering can be derived from user's data using statistical methods such as principal component analysis (PCA), independent component analysis (ICA) and common spatial pattern (Nam, Choi, Wadeson, & Whang, 2018). Apart from amplification and filtering original signals there is a need for performing analog to digital conversion to facilitate further processing and storage of data, which is often programmed with the computer.

In order to understand the acquired data in terms of their functionality, the data features are classified according to the nature of activation. For instance, Hidden Markov Model is being used extensively to classify EEG-based BCIs (see Cincotti et al. 2003). Other feature classifiers include, linear classifiers, and artificial neural network classifiers. These classifiers aim at determining the user's intention by extracted brain features.

Application

If EEG and ERP can be obtained reliably in real-time, it is logical to ask how to make use of it in neuropsychological intervention? While the technology has generated considerable interest as a potential tool for rehabilitation, there are critical questions too about which signal to be used in which context or training paradigms.

Neurofeedback

(a) Neurofeedback involves providing feedback in the form of some visual or auditory stimulus, based on some predetermined EEG feature (Micouland-Franchi et al. 2015) and normalize the EEG. This has been used successful treatment in wide range of behaviours including mental health problems, such as treatment resistant obsessive-compulsive disorder (Mantione, et al, 2010), intractable major depression (Mayberg et al., 2005) and other mood disorders (Downar, & Daskalaakis, 2013), anorexia nervosa, (Lipsman, et al., 2013), learning disability (Kaushik, & Jena, 2022); autism (Friedrich et al., 2015), attention-deficit /hyperactivity disorder (ADHD) (Lubar & Shouse, 1976), depression (Hammond, 2005). This is also used extensively in the filed of disability such as sound perception (Eisen, 2003), word recognition (Henkel, 2013), word recognition (McGee, 1965) in deaf, cognitive restoration and augmentation (Serruya, & Kahana, 2008), and substance use disorder (Trudeau, 2005). In neurorehabilitation, epilepsy is one such condition where this is used effectively in many cases who simply do not benefit from anti-epileptic drugs. They have distinct pattern of neurological activity associated with the initiation and establishment of seizure attacks. Recently, few labs have introduced automatic seizure-production algorithms that can be applied to intracranial and scalp recording to forecast the occurrence of seizures.

Imagery Enhancement

Imagery-based BCI helps in use of mental imagery, and the purpose being reinforcing mental imagery in order to enhance performance of the individual client. A majority of researches have been conducted in this area of restoration of motor control. The fundamental parameters of motor control emerge by collective activation of population of motor neurons in primary motor cortex (M1). These neurons are broadly turned to the direction of force required to generate a reaching arm movement (Georgopoulos, Schwartz, & Kettner, 1986). Even if these neurons fire maximally, before the onset and execution and of the arm of a movement (activity). They also fire significantly before the movement in broad ranges of other directions. It suggests that one can design algorithms capable of extracting motor control signals from these ensembles, for their clinical use. Hundreds and thousands of people suffer from motor impairment in which intact movement-related areas of the brain cannot generate movement because of damage to the spinal cord, nerves and nerves to the muscles. They can benefit from BCI-based muscle activation.

Close Sensorimotor Loop

The ability to learn, adapt, and refine motor skills are the key features of sensorimotor control. Cognitive control employs cognitive processes such as prediction, learning and multisensory integration. The neural processes behind these cognitive processes even in one of the simplest acts like arm reaching, is quite intricate. The action involves a nonlinear dynamics and multiple modalities. A BCI is a well-defined sensorimotor loop with key simplifying advantages that address each of these challenges, while engaging similar cognitive processes. As a result, it is becoming recognized as a powerful tool for basic scientific studies of sensorimotor control (Golub, Chase, Batista, & Yu, 2016).

The key aspect of this approach is re-establishing the disrupted sensorimotor feedback loop. This is about determining the intended movement using a BCI and helping the individual with impaired motor function (Gomez-Rodriguez, et al., 2010). This is a valuable tool for neuro-rehabilitation and has been used in cases with severe hemiparetic syndromes due to stroke (crebrovacular brain damage) and other conditions. Haptic feedback helps to improve motor coordination.

Close sensorimotor loop is also used in the context of control of orthosis. The purpose was to associate intention with haptic feedback control of orthosis. Badakva and associates (2016) suggested that BCIs have to be based on bidirectional system involving tactile, proprioceptive and other useful feedback.

Neuroergonomics

A key aspect of this approach is re-establishing the disrupted sensorimotor feedback loop, i.e., determining the intended movement using a BCI and helping a human with impaired motor function to move the arm using a robot.

Neuroergonomics applications

BCI also has a neuroergonomics applications, that is use of brain signals to control external devices without need for motor output. Neuronal ensemble control of prosthetic devices by patients, in other words called 'neuromotor prostheses' (NMPs) is a challenging area. The aim is to replace or restore motor functions in paralyzed patients. This is made possible by routing movement-related signals from brain, around damaged areas of the neural systems, to external affectors (Hochberg, 2006). This would help individuals who have limited or no need for motor output, as in case of 'locked-in' patients who are confined to their beds with amyotrophic lateral sclerosis (ALS) who have virtually no motor control (Kramer, & Parasuraman, 2007). Noninvasive BCIs have been used successfully with a wide range of clinical population such as chronic pin (Coffey, 2001), Ischemic stroke (Bearden et al., 2003; Buttaro, 2012), Tourette's syndrome (Kaido et al, 2011; Wardell, et al., 2015), hypertension (Das, 2010).

CONCLUSION

To sum up, undoubtedly, the field of BCI is expanding rapidly and the achievements are remarkable. Looking at the advances in neuroscience, we expect that, could one day we shall allow our patients to use their brain activity to control sophisticated electronic, mechanical and even virtual devices to their fullest extent? Although, this has remained a very distant dream, the success stories are many. There is accumulating evidence that BCI has been quite useful with patients suffering from a wide range of neurological, psychological and behavioural disorders. In recent years, sensitivity of the instruments used for this purpose have been remarkably enhanced, making them more sophisticated and sensitive to neural activity in the brain. For instance, when repeated or continuous monitoring of brain activity obtained from surface scalp electrodes, it is found to be contaminated with increased artifacts due to muscle and electronic artifacts, therefore now subdermal electrodes are used as non-invasive alternatives, particularly for low frequency waves (8-30 Hz) (Smith, Olson, Darvas, & Rao, 1928). There has been revolutionary change in biomedical engineering, particularly in acquisition, classification and processing of neural signals. In view of these developments, now BCIs can facilitate much more natural, seamless and intuitive interaction. This has opened up several modalities including Virtual Reality (VR) and Augmented Reality (AR) to explore its use further.

However, there are still methodological questions. The researches are plagued with methodological issues such as small sample size, unavailability of control group, and lack up long-term generalization beyond the hospital settings (very few follow-up studies). Randomized control designs considered as 'gold standards' of intervention research, are rare to find. Unlike pharmacological studies on drugs, the process of research is slow. Some of these difficulties are due to the cost of the instrument, training time and other logistic issues. Future searchers should look into these limitations of methods and improvisation of the technology in use.

While conceptualizing the complex movements of a classical dancer or a gymnast, we always admire the amazing co-ordination that results in such exquisite accomplishment. Can this again happen to a performer paralyzed by traumatic brain injury? Although the question is too difficult to answer at the moment, possibilities and promises of BCI are immense.

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