EEG BRAIN-COMPUTER INTERFACE AS AN ASSISTIVE TECHNOLOGY: ADAPTIVE CONTROL AND THERAPEUTIC INTERVENTION

Qussai M. Obiedat, Maysam M. Ardehali, Roger O. Smith
Rehabilitation Research Design & Disability (R2D2) Center, Department of Occupational Science & Technology, University of Wisconsin-Milwaukee, Milwaukee, WI

ABSTRACT

Recently, there has been an increasing interest in developing brain-computer interface (BCI) technology. BCI technology is a promising venue to overcome the shortcomings of the available rehabilitation methods of restoring normal motor function in people with disabilities. BCI have the potential to improve the quality of life and aid motor recovery of people with severe motor impairments through the development of both adaptive control and therapeutic intervention BCI systems. This paper reviews several affordable EEG systems that have been developed recently, provides an example of an EEG-BCI-FES system, and discusses several factors that both rehabilitation engineers and therapists have to fulfill in order to facilitate the adoption of BCI systems in the rehabilitation field and clinical practice.

INTRODUCTION

In the past couple of decades, there has been an increasing interest in developing brain-computer interface (BCI) technology in gaming, military control of equipment, and in biofeedback systems. In the rehabilitation field, BCI technology was developed to improve the quality of life and aid motor recovery of individuals with various types of disabilities (Daly & Wolpaw, 2008). The need for such innovative technology comes from the shortcomings of the available rehabilitation methods to restore motor function for individuals suffering progressive diseases, such as multiple sclerosis (MS), amyotrophic lateral sclerosis (ALS), or Parkinson's disease, or for many individuals with severe motor impairments due to stroke, cerebral palsy, or injuries to the brain or spinal cord. The applications of BCI technology in rehabilitation can be classified into two main categories: Adaptive control and Therapeutic intervention. The first category focuses on enabling people with disabilities (PWD) to control and interact with their surrounding environment. Communication programs, such as P300 speller (Cecotti, 2010), are good examples of BCI systems in this category. The second category aids in restoring impaired motor functions of both upper and lower extremities, such as the restoration of motor function through using brain guided functional electrical stimulation (FES) (Teo & Chew, 2014).

The purpose of this paper is to review the different components of BCI systems and their working process. Compare some of the available electroencephalography (EEG) systems, provide an example of a BCI system to guide the delivery of functional electrical stimulation (FES), and discuss additional requirements that need to be implemented in order to facilitate adoption of BCI systems in clinical practice.

A review of BCI Systems

Generally, BCI systems are responsible for translating brain-generated electrophysiological signals to control signals, which in turn are used to drive external devices or applications. The general working process of a BCI system can be broken down into steps shown in Figure 1. Acquiring brain electrophysiological signals via proper electrodes is the first step. Then the signal is processed and classified. Finally, the signal classification component which is composed of the brain signal feature extraction and the translation of these signals into output commands for a certain device or application (Schalk, McFarland, Hinterberger, Birbaumer, & Wolpaw, 2004).

Electrophysiological Brain Signals

Electrophysiological signals of brain can be acquired either invasively or through non-invasive methods. Invasive acquiring of signals is performed through direct implantation of electrodes in the individual's brain either at the cortical surface (electrocorticographic [ECoG] activity), or within the brain (local field potentials [LFP] or neural action potentials [spikes]) (Daly & Wolpaw, 2008). Brain signals can be acquired non-invasively by EEG through placing electrodes on the scalp. EEG signals consist of different frequency bands, each with its own characteristics (Subasi, 2007).

Although acquiring signals using invasive methods results in a better topographical resolution and wider frequency ranges, but implantation of electrode arrays within the brain arises several safety concerns. On the other hand, EEG is simple and non-invasive, but has limited topographical resolution and frequency range, and is prone to contamination from electro-oculographic or electromyographic activity from cranial muscles (Daly & Wolpaw, 2008). However, recent advancement in technology and signal processing resulted in the development of more efficient EEG systems.

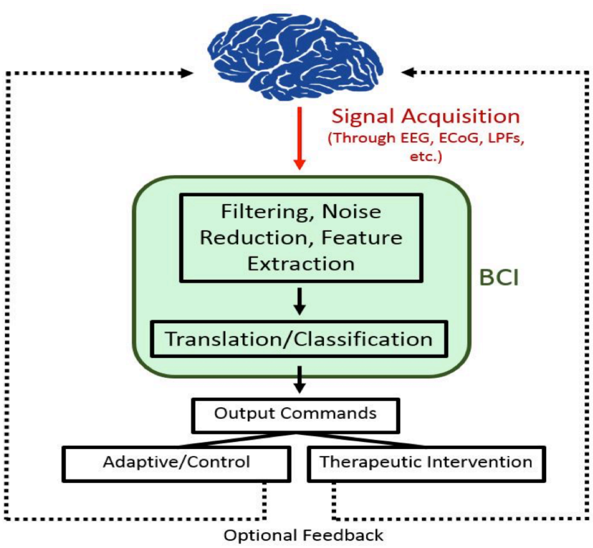

Figure 1: Overview of BCI Systems

EEG systems

Wide variety of EEG systems have been developed recently. G.tec® Medical Engineering is one of the leading companies that provides advanced, research grade EEG systems (Figure 1). However, these systems are expensive. Emotive, Inc. (Figure 2) and OpenBCI group (Figure 3) recently developed an affordable and portable EEG acquisition system. Such systems provide the ability to study brain activities while the individual engages in daily activities, and a practical solution for operating different BCI applications in different contexts and settings. Different characteristics of the three systems are described in Table 1.

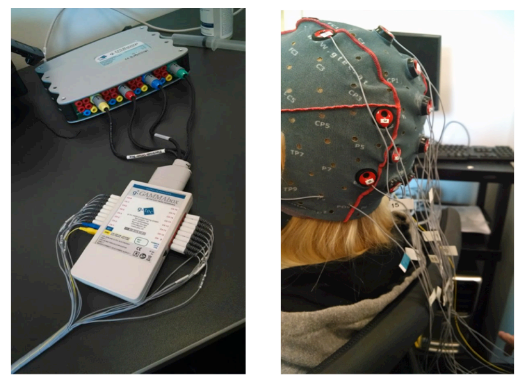

Figure 2: G.tec® g.USBamp & g.GAMMAbox

EEG-BCI system process

Most EEG-BCI systems, if not all, use the same general process. When EEG electrodes are optimally selected and placed over subject scalp, signals associated with the predefined task can be extracted. In neurological rehabilitation, most of the available BCI applications target either the motor cortex area or the visual cortex in the occipital region. In both cases, individuals use a particular mental strategy to focus their attention either on a specific body movement or on an external stimulus in order to generate a specific response. While signal acquisition from the brain is in session, this signal needs to go through the process of feature extraction and classification in order to be meaningful to the application. The classification strategy depends on the response to detect one of the following potentials: event-related potentials (ERP), steady-state evoked potentials (SSVEP), motor imagery (MI) or slow cortical potentials (SCPS). These responses can be provoked by an external stimulus (visual or auditory), or through movement imagination (Cecotti, 2010; Pfurtscheller, Müller-Putz, Scherer, & Neuper, 2008). In the case of imagination of movement, this means that the BCI system should be able to train itself to recognize patterns associated with imagination of movement of right/left hand, for example.

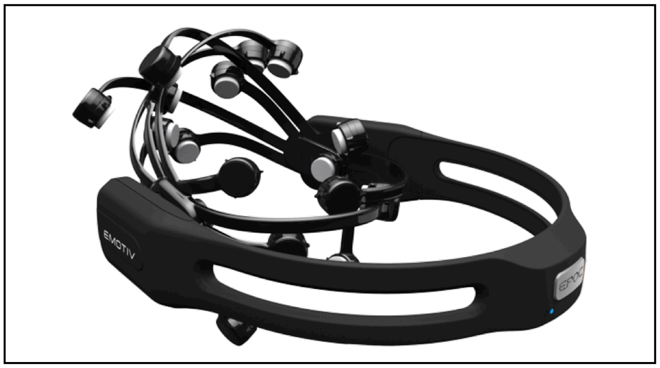

Figure 3: Emotive EPOC+

In order for the BCI system to be able to train itself, the EEG signal must be processed first, and in real-time in most cases. Signal processing usually entails 1) noise reduction, 2) feature extraction, and 3) classification (Roman-Gonzalez, 2012). Noise reduction phase utilizes filters (low-pass, high-pass, mid-pass, and notch) to provide a "clean" signal to its output.

After the EEG signal is devoid of contamination to the best possible extent, the feature extraction phase begins. In this phase, the goal is to separate useful values (features) of the signal from the rest. Sometimes noise reduction is also embedded in this phase. These values or features should be representative of different mental states. Usually, after the features are extracted, they are arranged in a vector, known as a feature vector (Lotte, 2014). Classification phase is concerned with assigning a class to a feature vector, corresponding to the identified mental state. Algorithms responsible for classification are called "classifiers". In other words, this step acts as an interface between features and commands. Classifiers use pattern recognition and machine learning in order to learn how to classify different feature vectors (Lotte, 2014; Lotte, Congedo, Lécuyer, Lamarche, & Arnaldi, 2007). This means that classification methods are unique and tailored for each subject, as the same mental tasks do not usually evoke the same responses in different individual's brains. The patterns by which the classifier learns how to classify different feature vectors, are usually acquired during the training phase.

EEG-BCI Guided FES

FES provides muscular contraction and produces a functionally useful movement via providing electrical stimulation for muscles deprived of nervous control (Liberson, Holmquest, Scot, & Dow, 1961). It has been found that this method enhances post-stroke motor recovery (Kralj, Aˇmović, & Stani, 1993), reduces spasticity (Alfieri, 1981), strengthen muscles, and increases the range of motion of affected joints (Baker, Yeh, Wilson, & Waters, 1979). FES has been found to be most effective when combined with MI (Reynolds, Osuagwu, & Vuckovic, 2015). Such combination can lead to an increase in neuroplasticity, which in turn, improves motor learning (Celnik & Cohen, 2004; McDonnell & Ridding, 2006). Mental imagination of movement can be detected using a BCI system, and, if detected, in combination with FES, can provide a solid means to influence brain plasticity processes that could induce recovery of normal motor functions.

Table 1: EEG Systems

EEG System	Channels	Electrodes	Connection	Portability	Cap	Cost
G.tec® Medical Engineering g.USBamp & g.GAMMAbox	16	Wet/gel	Wired	No	Fabric	~ $30,000
Emotive Inc. EPOC+	14	Saline soaked felt	Wireless	Yes	Headset	$799

		pads				
OpenBCI	8-16	Dry	wireless	Yes	3D printable	~ $1,300

In EEG-BCI-FES application, imagination of a particular movement is the task for which the features need to be extracted and then classified to translate the intention of movement to trigger electrical stimulation. Electrodes are placed on and around the motor cortex area to detect sensorimotor rhythms from both hemispheres.

Features to be extracted from the raw EEG signal are band powers of frequencies associated with MI from motor cortex, which are typically in μ and β rhythms (Pfurtscheller & Neuper, 2001). The BCI system learns which frequencies are dominant when the individual is imagining a particular movement (e.g. right/left hand movement). Then the system trains itself to recognize those features and classify them, and then sends an activation command to the FES system to stimulate the corresponding muscles.

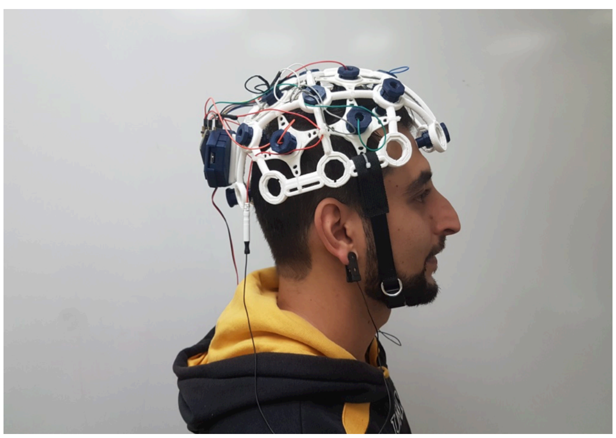

Figure 4: OpenBCI

DISCUSSION

With the advances in technology over the past decade, brain-computer interface (BCI) stands as a promising technology with the potential to restore lost motor functions in patients with devastating neurological conditions, such as stroke, and empower PWD to regain control of their bodies and environment. The development of cost-effective EEG systems can have a great impact on the adoption of BCI technology for improving the quality of life and restoring function for people with severe motor disabilities. These systems may open new venues of research and development around PWD in their natural environments. However, further research is required in order to validate

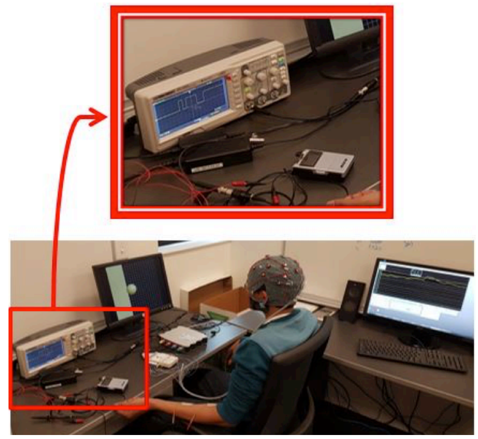

Figure 5: EEG-BCI-FES System

the efficacy and the quality of the acquired EEG data, from the newly developed cost-effective EEG systems. Advancements in research and adoption of BCI systems in the rehabilitation field is contingent on decreasing the overall cost of the system to less than 500$, producing a system that does not require therapists to have intensive technical backgrounds, providing sufficient professional training modules, conducting further research to document evidence for use and reimbursement. Both rehabilitation engineers and therapists have their responsibilities to fulfill these needs.

REFERENCES

Alfieri, V. (1981). Electrical treatment of spasticity. Reflex tonic activity in hemiplegic patients and selected specific electrostimulation. *Scandinavian journal of rehabilitation medicine*, *14*(4), 177-182.

Baker, L. L., Yeh, C., Wilson, D., & Waters, R. L. (1979). Electrical stimulation of wrist and fingers for hemiplegic patients. *Physical Therapy*, *59*(12), 1495-1499.

Cecotti, H. (2010, August). Spelling with brain-

computer interface-current trends and prospects. In *Cinquième conférence plénière française de Neurosciences Computationnelles," Neurocomp'10"* (pp. 215-220).
Celnik, P. A., & Cohen, L. G. (2004). Modulation of motor function and cortical plasticity in health and disease. *Restorative neurology and neuroscience*, *22*(3-5), 261-268.
Daly, J. J., & Wolpaw, J. R. (2008). Brain–computer interfaces in neurological rehabilitation. *The Lancet Neurology*, *7*(11), 1032-1043.
Kralj, A., Aˇmović, R., & Staniˇ, U. (1993). Enhancement of hemiplegic patient rehabilitation by means of functional electrical stimulation. *Prosthetics and Orthotics International*, *17*(2), 107-114.
Liberson, W. T., Holmquest, H. J., Scot, D., & Dow, M. (1961). Functional electrotherapy: stimulation of the peroneal nerve synchronized with the swing phase of the gait of hemiplegic patients. *Archives of physical medicine and rehabilitation*, *42*, 101-105.
Lotte, F. (2014). A tutorial on EEG signal-processing techniques for mental-state recognition in brain–computer interfaces. In *Guide to Brain-Computer Music Interfacing* (pp. 133-161). Springer London.
Lotte, F., Congedo, M., Lécuyer, A., Lamarche, F., & Arnaldi, B. (2007). A review of classification algorithms for EEG-based brain–computer interfaces. *Journal of neural engineering*, *4*(2), R1.
McDonnell, M. N., & Ridding, M. C. (2006). Afferent stimulation facilitates performance on a novel motor task. *Experimental Brain Research*, *170*(1), 109-115.
Pfurtscheller, G., & Neuper, C. (2001). Motor imagery and direct brain-computer communication. *Proceedings of the IEEE*, *89*(7), 1123-1134.
Pfurtscheller, G., Müller-Putz, G. R., Scherer, R., & Neuper, C. (2008). Rehabilitation with brain-computer interface systems. *Computer*, *41*(10).
Reynolds, C., Osuagwu, B. A., & Vuckovic, A. (2015). Influence of motor imagination on cortical activation during functional electrical stimulation. *Clinical Neurophysiology*, *126*(7), 1360-1369.
Roman-Gonzalez, A. (2012). Eeg signal processing for bci applications. In *Human–Computer Systems Interaction: Backgrounds and Applications 2* (pp. 571-591). Springer
Schalk, G., McFarland, D. J., Hinterberger, T., Birbaumer, N., & Wolpaw, J. R. (2004). BCI2000: a general-purpose brain-computer interface (BCI) system. *IEEE Transactions on biomedical engineering*, *51*(6), 1034-1043.
Subasi, A. (2007). EEG signal classification using wavelet feature extraction and a mixture of expert model. *Expert Systems with Applications*, *32*(4), 1084-1093.
Teo, W. P., & Chew, E. (2014). Is motor-imagery brain-computer interface feasible in stroke rehabilitation?. *PM&R*, *6*(8), 723-728.