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Brain Computer Interface Design and Applications: Challenges and Future

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Abstract: For many decades, instrument control by just thinking, using brain waves, has been accepted in science fiction. However, it is only in the last ten years that these systems have been shown to be feasible in laboratories. Successful Brain Computer Interface (BCI) systems have many potential applications, especially for patients who are paralyzed. Although extensive research has been done in this area, to date, BCI systems have not been implemented successfully outside of laboratories. The problems that impede transferring the successful research results to the outside world are highlighted in this paper. The main problems can be classified into two distinct parts, first, the sensory interfacing problems and, second, the reliability of the different classification algorithms for the ElectroEncephaloGraphic patterns. Potential future applications for this technology have been addressed.

Key words: Brain Computer interface · BCI · EEG

INTRODUCTION

The brain controls our actions, beginning with a free will decision that originates in the mind. That decision is performed by modulating specific brain waves in the area specialized with that task. Complex network activity precedes the order of the brain to our muscles, which requires a healthy brain, nerves and muscles. A BCI system serves as a communication channel between the brain and the outside world directly. It has been estimated that more than one million people in the United States have some form of spinal cord injury [1]. It is the hope of this large population to find a way to restore their limb functions or control an artificial limb using their thinking process. Developing a robust BCI system is one of the main challenges of the twenty-first century.

The main function of BCI is to convert the person's intent into an outside action. According to the work of Mason and Birch, the BCI system can be divided into various functional components [2]. They proposed a general functional model for BCI systems and a universal vocabulary, which enabled different BCI systems to be compared in a unified framework. We will depend on this framework in this article.

The main parts of any BCI system (Fig. 1) are:

- Signal acquisition system: involves the electrodes, which pick up the electrical activity of the brain and the amplifier and analog filters.
- The feature extractor: converts the brain signals into relevant feature components. At first, the EEG raw signals are filtered by a digital bandpass filter. Then, the amplitude samples are squared to obtain the power samples. The power samples are averaged for all trials. Finally, the signal is smoothed by averaging over time samples.
- The feature translator: classifies the feature components into logical controls.
- The control interface: converts the logical controls into semantic controls.
- The device controller: changes the semantic controls to physical device commands, which differ from one device to another depending on the application.
- Finally, the device commands are executed by the device.

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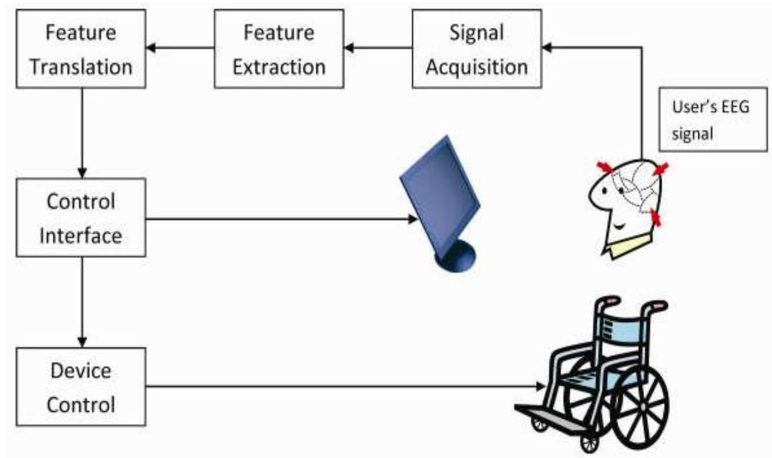

Fig. 1: Functional components of Brain Computer Interface

Types of BCI: The early work of BCI was done by *invasive* methods with electrodes inserted into the brain tissue to read the signals of a single neuron. Although the spatio-temporal resolution was high and the results were highly accurate, there were complications in the long term. These were mostly attributable to the scar tissue formation, which leads to a gradual weakening of the signal and even complete signal loss within months because of the brain tissue reaction towards the foreign objects.

A proof of concept experiment was done by Nicolelis and Chapin on monkeys to control a robotic arm in real time using the invasive method [3].

Recently, less invasive methods have been used by applying an array of electrodes in the subdural space over the cortex to record the Electrocorticogram (ECoG) signals. It has been found that ordinary Electro-encephalogram pickup signals are averaged over several square inches, whereas ECoG electrodes can measure the electrical activity of brain cells over a much smaller area, thereby providing much higher spatial resolution and a higher signal to noise ratio because of the thinner barrier tissue between the electrodes and the brain cells. The superior ability to record the gamma band signals of the brain tissue is another important advantage of this type of BCI system. Gamma rhythms (30-200 Hz) are produced by cells with higher oscillations, which are not easy to record by ordinary EEGs [4]. The human skull is a thick spatial filter, which blurs the EEG signals, especially the higher frequency bands (i.e. gamma band).

Noninvasive techniques were demonstrated mostly by electroencephalographs (EEG). Others used functional Magneto-Resonance Imaging (fMRI), Positron Electron Tomography (PET), Magnetoencephalography (MEG) and Single Photon Emission Computed Tomography (SPECT). EEGs have the advantage of higher temporal resolution, reaching a few milliseconds and are relatively low cost. Recent EEG systems have better spatiotemporal resolution of up to 256 electrodes over the total area of the scalp. Nevertheless, it cannot record from the deep parts of the brain. This is the main reason why the multimillion dollar fMRI systems are still the preferred method for the functional study of the brain. However, EEG systems are still the best candidate for BCI systems as they are easy to use, portable and cheap.

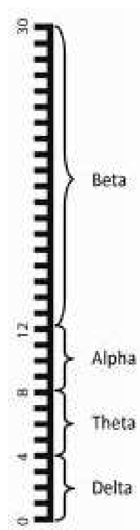

Fig. 2: EEG signal bands (Hz)

EEG Components Used in BCI: Usually EEG signals are divided into four bands: *Delta* band ranges from 0.5 to 4 Hz, *Theta* band 4 to 8 Hz, *Alpha* band 8 to 12 Hz and *Beta* band 14-30 Hz. BCI systems mostly use the alpha and beta band (Fig. 2).

There are four main categories of EEG components used in BCI systems [4]:

Neuronal Potentials: These are the voltage spikes that are generated from a single neuron. They have the advantage that they can control the BCI in two dimensions: the location of the neuron and the firing rate. Until very recently, this method was only used for research purposes in animals because of its high invasiveness, however it has proved that higher accuracy BCI systems that enhance the spatial resolution can be achieved [5, 6].

Slow Cortical Potential (SCP): This is caused by the shifting of the polarization of some dendrites. The higher synchronization between the potential of the dendrites will result in negative SCP, whereas when there is a reduction in the synchronization it will lead to positive SCP. This change usually occurs from 0.5 to 10 seconds from the start of the internal event.

Oscillatory Eeg Activity: This is caused by a network of neurons that create a feedback loop. Whenever the synchronization of the neurons increases the oscillation of the EEG decreases. There are many oscillations but the most important for BCI systems are the Rolandic mu-rhythm (10 to 12 Hz) and the central beta rhythm (14 to 18 Hz). These two types originate from the sensorimotor cortex. During rest, these oscillations occur naturally, however, when the brain performs some cognitive task there will be a significant change in their amplitude and frequency. There is an inverse relationship between the frequency and the amplitude. Whenever the frequency increases the amplitude will decrease and vice versa [4].

Event Related Potentials (ERP): These potentials occur after a fixed time from an external or internal event. Although the exogenous ERP are responses to external physical stimuli that can be of any type, usually visual and auditory stimuli are used in BCI systems. The endogenous ERP are responses to an internal event in the brain. There are many ERP types that the BCI community are interested in, including but not limited to the following:

- Event Related Synchronization/Desynchronization: Events can change the synchronization of specific groups of neurons related to that event. An increase in the synchronization leads to higher amplitude EEG signals in specific frequency bands, which is called event related synchronization (ERS), whereas a decrease in the synchronization results in lower amplitude EEG signals in specific frequency bands, which is called event related desynchronization (ERD).

- Visual Evoked Potentials: This component is the result of seeing a visual stimulus and it is under the control of the user's gaze. One of the most common types used in BCI is the steady state visual evoked potential (SSVEP). It is an exogenous ERP in which the user focuses on one or two flickering images on a computer screen at different frequencies. When the user turns their gaze to another object the SSVEP will be amplified before returning to the normal baseline. The user can control the BCI by switching their focus between different objects on the screen.
- P300: This is an endogenous ERP. The user is subjected to events that can be categorized into two distinct categories. One of the categories is rarely displayed. The user will face a task that cannot be done without categorization into both categories. Whenever the rare event is displayed it will generate a P300 signal. It is a distinct large positive signal that occurs 300 milliseconds after the event onset. The amplitude of the P300 signal is inversely related to the rate of the rare event presented to the user. Although many P300-BCI systems have achieved 100% accuracy [7], the problem with this type of BCI is its dependence on the continuous visual attention of the user, which is usually intolerable for locked-in patients - who are the most important target for BCI technology - especially if used for a long time.

Sellers and Donchin showed for the first time the possibility of using auditory-P300 instead of the visual-P300 stimuli, which is less demanding for the patient, therefore, it is a more tolerable and useful BCI for locked-in patients [8].

Auditory-P300 BCI can be especially useful for patients with extensive neural damage to the degree that they have paralysis in their eye muscles or eye lids [9]. More research should be done to check the usefulness of this type of BCI on patients with extensive neural damage. It should be understood that the accuracy of this technology will be much less for those types of patients compared to healthy population samples. Most of the previous research has been done on healthy individuals due to the lack of interest or tolerance of patients with extensive neural damage such as locked-in patients. One remarkable research that was undertaken to demonstrate the difference in performance and reliability between healthy and paralyzed individuals showed that the usefulness of visual P300-BCI decreases proportionate to the degree of neural damage [10].

Translation: Translation algorithms convert the input features (independent variable) into device control commands (dependent variable). Wolpaw *et al.* suggested that an efficient BCI should have three levels of adaptation [6]. First, is the ability of the translation algorithm to adapt to each user's signal features. The best features are different from person to person. Second, periodic online adjustments should be done as brain signals change according to hormonal levels, environmental changes, illness and spontaneous change over time within the same person for unknown reasons. Third, the algorithm should be able to adapt to the wave changes in the brain because of the feedback effect of an online BCI operation. This feedback should encourage the user to make the BCI more accurate by encouraging the user to produce stronger feature signals in their brain signals [6].

Lotte *et al.* classified the translation algorithms that have been adopted to date into either generative or discriminative, linear or non-linear classifiers, dynamic (takes into account the temporal information of the signal) or static, regularized (by controlling the complexity of the algorithm to provide better generalization and less effect of outliers on performance) or non-regularized [11]. Each algorithm type has its advantages and drawbacks. However, according to the review of Lotte *et al.* Support Vector Machines achieved the best results in most synchronous type BCI.

Challenges and Future: The main problems that reduce the reliability and accuracy of BCI and which prevent this technology from being clinically useful, are the sensory interfacing problems and the translation algorithm problems.

In order to make a clinically useful BCI the accuracy of the detection of intention needs to be very high and certainly much higher than the currently achieved accuracy with different types of BCI [7].

The first important obstacle in designing a robust BCI is the sensory interfacing problem. To date there is no sensory modality that is accurate and safe. Three main types of sensory interfaces have been used previously - the Electro Encephalo Graphic (EEG) sensors, the Electro Cortico Graphic (ECoG) and the implanted microelectrodes. There is a tradeoff between safety and the accuracy of the sensors.

Not surprisingly the most accurate BCI was achieved with the implanted cortical microelectrodes based BCI, which is the most invasive type. The microelectrodes are in direct contact with the neuron, which makes the signal to noise ratio better than the other types of sensors. Nicolelis showed how accurately monkeys can be trained to grasp objects using a BCI based robotic arm controlled by the monkey's neuron firings [12]. The major drawbacks of this type of sensor are that it is highly invasive to the brain tissue and is unstable. The signal will gradually deteriorate because of the defensive mechanism of the brain tissue reacting to these foreign objects. This causes the formation of fibrous tissue, which makes the sensors useless after 6 months [13].

The other type is the EEG based BCI. The sensors of the EEG have the best safety and lowest invasiveness but the accuracy of the brain signal access is the poorest. Despite extensive research on this type of BCI over the last 15 years, the accuracy of EEG based BCI is not promising for a clinically useful aid for patients to provide an artificial prosthesis control. Nevertheless, this type has been shown to be useful as a simple speller which provides patients a slow but effective way of communication [7]. Ordinary EEG sensors need special preparation. Conduction gel should be put beneath each electrode to decrease the impedance of the contacting scalp, which causes discomfort and needs considerable preparation time. These technical issues have recently been solved by the development of a non contact dry EEG sensor that is based on the optical detection of the physiological electrical signals [14]. Notwithstanding this breakthrough in resolving the technical issues that have been identified by the BCI community concerning the EEG sensors, the EEG technique still lacks the spatial resolution needed for a robust and accurate BCI.

The intermediate compromise between accuracy and safety is the ECoG based BCI, which has shown considerable promise. The sensory array of electrodes are less invasive and provide comparable accuracy and high spatial resolution compared to the implanted type. The ECoG based BCI needs much less training than the EEG based BCI and researchers have shown that highly accurate and fast response ECoG based BCI can be developed by experiments done on epileptic patients who need a temporary ECoG implant to identify the exact epileptic foci before surgery. One teenager has been able to play 'Space Invaders', a computer game, using only his thought [15].

The BCI community needs a sensory technological breakthrough to open the door for a very wide area of applications that is currently greatly impeded due to the limitations of the current sensory modalities. To provide safe, non-invasive and accurate access to brain signals we need different sensory technology.

It is known that functional Magnetic Resonance Imaging (fMRI) technology can provide a good non-invasive method with a relatively high spatial resolution. The problem with fMRI technique is its low temporal response. Neural actions can be detected by the previous methods within a few milliseconds, whereas in fMRI it is in a few seconds. The other problem of the fMRI technique is its relative high cost and large size.

By comparing the non-invasive imaging technique (fMRI) with the non-invasive electrical technique (EEG), the first shows much more accuracy in detecting the function of the neurons. Recently, a researcher in the Advanced Telecommunications Research (ATR) Computational Neuroscience Laboratories in Kyoto, Japan, demonstrated the ability to reconstruct 10 by 10 pixel images from the visual cortex of an individual looking at a black and white image by fMRI [16]. The researchers claim that with further research a reconstruction of a color picture or even a dream recording to a video file can be achieved. However, this achievement is far from being successful with the EEG technology due to the EEG sensor's distortion of the brain signals.

Portable fMRI may provide some hope for BCI technology. Cheap, portable, accurate and fast fMRI may be a good candidate for a robust BCI. Researchers at Lawrence Berkeley National Laboratory of the U.S. Department of Energy's have succeeded in developing a portable, cheap and enhanced sensitivity laser based-MRI using atomic magnetometry with better temporal resolution [17]. Nevertheless, to provide a fast BCI that is capable of controlling an artificial prosthesis, this new technology needs to be developed further to increase its temporal resolution.

The other challenge lies in the brain itself. The brain usually has numerous neuron centers that cooperate to produce single smooth limb movements. The question is whether the brain is capable of training specific neurons to act as internetworking neuron centers that control the limbs through the spinal cord way to produce a smooth limb movement. BCI capacity and efficiency depend on the answer to this question. Previous studies indicate that the ability to train specific neuron cells to control an artificial prosthesis smoothly is far more problematic with high variability from trial to trial compared to the usual way of controlling the limbs through the spinal cord. This deficit in the brain's ability is not dependent upon the type of BCI or whether it was done by measuring the activity of cortical neurons or the EEG power spectrum. This suggests that this control deficit cannot be enhanced by developing better recording techniques.

Better translation algorithms will likely emerge in the future, making the control more realistic and more efficient, however, the severity and the nature of this deficit in current BCI research indicates that a more realistic translation algorithm should be developed that decreases the challenge to the extent that the challenge is the same as controlling through normal muscle based control [18].

Applications: Over the past 30 years, many BCI systems have been developed that have targeted different applications. However, the main goal of all of them is to translate the intent of the user into an action without using the periphery nerves and muscles. Because of the number of methods in feature extraction and translation and the increasing target audience, it became difficult to make a universal scoring method to compare different systems. However there have been a few successful trials to make a general framework for BCI design methodologies [2].

Keim and Aunon developed a BCI system for patients with severe physical disabilities that enabled them to spell specific code words. They placed electrodes on the whole surface of the scalp, enabling the system to detect the difference in lateralized spectral power levels [19]. Farwell and Donchin developed a BCI system to type words by making the user select letters and words from a display. The system flashes letters randomly on a 6 by 6 matrix on the screen while the user thinks about the next letter they want to type. They used the P300 signal obtained from several electrodes on the scalp to control the BCI system [20]. Rebsamen *et al.* developed a brain-controlled wheelchair. They adopted the widely used P300 component method. It was claimed in this work that users can navigate inside a typical office or hospital with a BCI controlled wheelchair safely but slowly [21]. Al-Sagban *et al.* used ERP as a forensic tool for lying detection to determine whether a piece of information is significant to a person or not. It was claimed that innocent people were classified correctly (100% sensitivity) and fairly good achievement have been made for positive results (90% specificity) [22].

By enhancing the sensory modalities of BCI systems a wider range of applications of BCI technology will be seen commercially.

CONCLUSION

Although there are dozens of research institutes around the world developing BCI systems, the potential power of this area of research has still not been realized and notwithstanding the fact that industrial applications have emerged, no widely used commercial products can be seen. Accurate brain wave access sensor modalities that preserve the safety and are non-invasive should be invented.

By attracting industrial interest and increasing the target audience, BCI systems will benefit from more research funds and, hopefully, much larger groups of researchers will be involved. Free of charge software for a user friendly BCI design is available [23], in the hope that it will decrease the funding threshold for BCI research and increase the research community involved in this area of research. To achieve higher success in this field, the research teams should be multidisciplinary containing engineers, computer programmers, psychologists and medical doctors.

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