International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 2 Issue 3, March - 2013

A Study Of Brain Computer Interface System

Indu Dokare
Department Of Electronics and Telecommunication Engg., V.E.S. Institute Of Technology, Mumbai, India.

Naveeta Kant
Department Of Electronics and Telecommunication Engg., V.E.S. Institute Of Technology, Mumbai, India.

Abstract

Advances in cognitive neuroscience and brain imaging technologies have started to provide us with the ability to interface directly with human brain. Brain Computer Interface (BCI) is a system that acquires and analyzes neural signals with the aim of creating a communication channel directly between the brain and the external device or computer. The major goal of BCI research is to develop a system that allows people severely affected by motor disorders to communicate with other persons and helps to interact with the external environment. Achievement of greater speed and accuracy of the BCI system depends on improvements in signal processing, translation algorithms, and user training. These improvements depend on increased interdisciplinary cooperation between neuroscientists, engineers, computer programmers, psychologists, and rehabilitation specialists. The objective of this paper is to provide insight into the various aspects of BCI which will help the beginner in this field to understand the basics of BCI.

1. Introduction

A Brain Computer Interface (BCI) is a communication and control system that does not depend in any way on the brain's normal neuromuscular pathways like peripheral nerves and muscles, rather the user's intent is conveyed by recording and analyzing the brain signals. These brain signals do not depend for their generation on neuromuscular activity [1], [12]. BCI establishes a real-time interaction between the user and the outside world. The user receives feedback reflecting the outcome of the BCI's operation and that feedback can affect the user's subsequent intent and its expression in brain signals. A system that simply records and analyzes brain signals, without providing the results of that analysis to the user in an online interactive fashion is not a BCI [1].

Hence, BCI establishes a communication channel between the brain and external devices or a computer for those people who are unable to express their intents to the external world after a severe disablement caused by diseases such as amyotrophic lateral sclerosis (ALS), brainstem stroke, cerebral palsy etc. [1], [12]. Since they do not have enough control of their muscles to voluntarily move their limbs, articulate a word or gaze at a desired location. Beside research on prevention and cure of such diseases, recent efforts are providing a better quality of life to these persons by developing a non-muscular based communication and control system which uses neurophysiological signals as an input.

The central element in each BCI is a translation algorithm that converts electrophysiological input from the user into output that controls external devices. BCI operation depends on effective interaction between two adaptive controllers, the user who encodes his or her commands in the electrophysiological input provided to the BCI and the BCI which recognizes the commands contained in the input and expresses them in device control. Achievement of greater speed and accuracy of the BCI system depends on improvements in signal processing, translation algorithms, and user training. These improvements depend on increased interdisciplinary cooperation between neuroscientists, engineers, computer programmers, psychologists [2],[12].

2. BCI System

Like other communication and control systems, BCIs has an input, an output, and translation algorithm that converts neurophysiological input to the output device control commands.

The main component of the BCI system are:

(i) Signal acquisition & pre-processing: Signal acquisition is the measurement of the neurophysiological state of the brain using the recording interface (i.e. electrodes). The signal are recorded from the scalp (EEG), from the cortical surface (ECoG) or from within the brain (local field potentials (LFPs)) or neuronal action potentials [1],[5],[12]. These acquired brain electrical signals

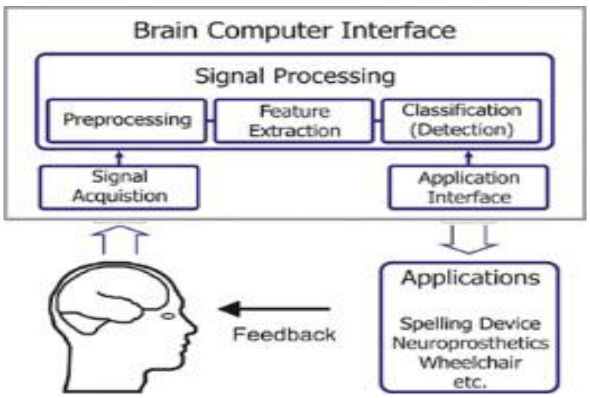

Figure 1. Block diagram of BCI System [4]

are amplified, digitized and pre-processed to increase the signal-to-noise ratio[2],[3].
(ii) Feature Extraction : The (pre-processed) input from EEG contains enormous amounts of information. What actually is needed from this data are features: distinctive characteristics. A feature is that part of the data that gives the best interpretation and most valuable information relating to the users intent. Therefore these characteristics (the best features) must first be found by analysing the data.
(iii) Classification : To recognize patterns from the brain activity, the features that are extracted from the data must be classified into several classes which represents the output. This output can be used to control output device. Several methods exists to classify the features into usable output. The classification algorithm uses linear classification methods (e.g., linear discriminant analysis) or nonlinear ones (e.g., neural networks) [2],[3].
(iv) Application Interface : The signal features thus extracted and classified are translated into device commands that activate and control an assistive technology used for : communication (spelling on a computer screen); movement control (robotic arm); environmental control (e.g. TV, light, temperature etc.); locomotion (e.g. electric wheelchair); or neurorehabilitation [1],[3],[5].

3. Types of BCI

The BCI is a communication system where the on-going brain activities are recorded from the scalp (EEG), cortical surface(ECoG) or from within the brain tissues. Depending on the way of recording the on-going brain activity, the BCIs can be classified as:

3.1. Invasive BCI

Invasive BCIs are implanted directly into the grey matter of the brain during neurosurgery. In general, invasive BCIs provide more accurate signal translation and allow high speed real time control. Being more expensive and risky, invasive techniques are not very popular[4].

3.2. Partially-invasive BCI

In Partially invasive BCI devices, electrode arrays are placed on the cortical surface. They produce better resolution signals than non-invasive BCIs and have a lower risk of forming scar-tissue in the brain than fully-invasive BCIs [1]. Electrocorticography (ECoG) measures the electrical activity of the brain taken from beneath the skull in a similar way to non-invasive electroencephalography.

3.3. Non-invasive BCI

In Non-Invasive technique medical scanning devices or sensors are mounted on caps or headbands placed on scalp of the brain. This technique does not require the expensive surgery and no risk for the users. This type of device has been found to be successful in giving a patient the ability to move muscle implants and restore partial movement. One of the most popular devices to capture the brain activity under this category is the EEG, electroencephalography.

4. Brain waves/rhythms

There are signals of different frequencies that are emanating from the brain. These signals can be classified into different groups as given in Table-1 [7],[9]

Table 1. Brain waves/rhythms

Activity Band	Frequency	State of mind
Beta	13-30 Hz	Alert, Active attention, motor idling
Alpha	8-13 Hz	Relaxed awareness, inattention
Theta	4-7 Hz	Emotional stress, deep meditation
Delta	0.5 - 4 Hz	Deep dreamless sleep, waking state
Gamma	>= 35 Hz	Higher mental activity, including perception and consciousness
Mu	8-12 Hz	Motor activities

5. Brain activity measurement

Many methods are available for imaging brain activity. Following are the most commonly used methods for brain activity measurement [4],[5] :

5.1. Magnetoencephalography (MEG)

It directly measures the cortical magnetic fields produced by electrical currents. This method is non-invasive and has poor spatial resolution and good temporal resolution(about 1 msec). However the equipment is extremely expensive and the field is very small and difficult to measure [4],[5]. The real-time properties for analysis are poor.

5.2. Positron Emission Tomography (PET)

PET indirectly measures metabolism on a cellular level by tracking injected radioactive isotopes. It is based on the principle that in areas of increased activity the metabolism is on a higher level and more isotopes are supplied by the blood flow [4]. Good spatial resolution is an advantage of PET. The really bad temporal resolution (about 1 minutes) is a distinct disadvantage [4]. Moreover ionizing radiation makes this method harmful for the human body and thus unusable for applications like BCI.

5.3. Functional Magnetic Resonance Imaging (fMRI)

It measures small changes in the blood oxygenation level dependent (BOLD) [5]. The advantages are good spatial resolution and the non-invasiveness. But the temporal resolution is poor (about 5 second) [4] and this method requires very expensive equipment.

5.5. Near-infrared Spectroscopy (NIRS)

Infrared light penetrates the human head to sufficient depths to allow functional mapping of the cerebral cortex. Different oxygen level of the blood results in different optical properties which can be measured by NIRS [5]. It has a poor temporal resolution.

5.4. Electrocorticography (ECoG)

It records integrated activity of large number of neurons that are in proximity of the electrodes placed over the surface of the cortex [5]. This has high temporal and good spatial resolution. This technique is invasive and therefore requires expensive surgery and comes with significant safety risks for the patient.

5.6. Electroencephalography (EEG)

It measures the electrical activity of the brain with the help of electrodes placed on the scalp. This is the non-invasive and most commonly used brain activity measurement method in BCI. The prime reason for this is the excellent temporal resolution which is a necessity for real-time BCI. Another advantages of this method are ease of applying it, in expansive and relatively portable as compared to other methods [5].

Configurations of electrodes usually follow the International 10-20 system of placement as shown in figure 2. The 10-20 system of electrode placement, which is based on the relationship between the location of an electrode and the underlying area of cerebral cortex (the "10" and "20" refer to the 10% or 20% inter-electrode distance).

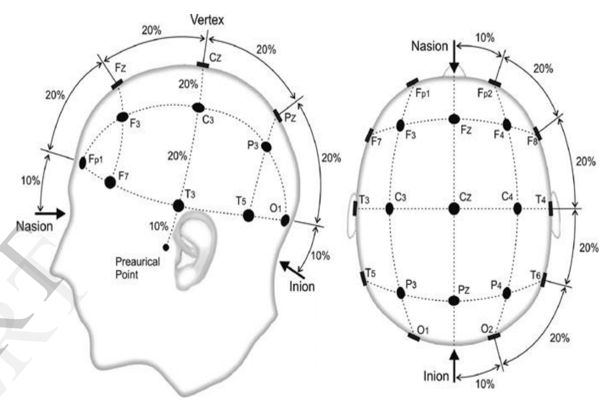

Figure 2. The international 10–20 system: Positioning of Electrodes [5]

6. Control Signal in BCIs

Brain signals involve numerous simultaneous phenomena related to cognitive tasks. However, the physiological phenomena of some brain signals have been decoded in such way that people may learn to modulate them at will, to enable the BCI systems to interpret their intentions. These signals are regarded as possible control signals in BCIs.

The signals measured by the electrodes are called potentials and are measured at multiple locations, and differ in frequency during time. A range of different potential classes are used in BCI. These classes vary, among other properties, in their amplitude, duration, frequency and location. But also by which process they are activated in the brain. The control signals employed in current BCI systems are as follows [3],[5]:

6.1. Visual Evoked Potentials (VEPs)

VEPs are brain activity modulations that occur in the visual cortex after receiving a visual stimulus such as flashing of light. These modulations are relatively easy to detect since the amplitude of VEPs increases enormously as the stimulus is moved closer to the central visual field. 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) in which stimulus changes at frequency 5-6 Hz or greater [3]. 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.

6.2. P300 Evoked Potentials

Infrequent or particularly significant auditory, visual, or somatosensory stimuli, when interspersed with frequent or routine stimuli, typically evoke in the EEG over the parietal cortex a positive peak at about 300 ms after the stimulus is received. This peak is called P300 [3]. P300 responses are elicited about 300 ms after attending to an oddball stimulus among several frequent stimuli. The use of P300-based BCIs require very little training.

6.3. Slow Cortical Potentials (SCPs)

SCPs are slow voltage shifts in the EEG that last a second to several seconds. SCPs belong to the part of the EEG signals below 1 Hz [2]. SCPs are associated with changes in the level of cortical activity. In normal brain function, negative SCPs accompany mental preparation, while positive SCPs probably accompany mental inhibition. These brain signals can be self-regulated by both healthy users and paralyzed patients to control external devices by means of a BCI.

6.4. Sensorimotor Rhythms (SMRs)

Sensorimotor rhythms comprises mu and beta rhythms, which are oscillations in the brain activity localized in the mu band (8–12 Hz) and beta band (13–30 Hz) [12]. Both rhythms are associated in such a way that some beta rhythms are harmonics of mu rhythms, although some beta rhythms may also be independent. The amplitude of the sensorimotor rhythms varies when cerebral activity is related to any motor task although actual movement is not required to modulate the amplitude of sensorimotor rhythms. They are associated with cortical areas most directly connected to the brain's normal neuromuscular outputs. Movement or preparation for movement is usually accompanied by SMR decrease especially to contralateral to the movement. This decrease has been labeled as "event-related desynchronization" (ERD). Its opposite, rhythm increase, or "event-related synchronization" (ERS) occurs after movement and with relaxation [2], [8], [12]. Furthermore, and most pertinent to BCI use ERD and ERS do not require actual movement, they also occur with motor imagery (i.e., imagined movement). People with or without motor disability can learn to control mu or beta rhythm amplitudes in the absence of movement or sensation. This makes it possible to use sensorimotor rhythms for the design of endogenous BCIs, are more useful than exogenous BCIs. Nevertheless, self-control of sensorimotor rhythms is not easy, and most people have difficulties with motor imagery. Motor imagery training is traditionally based on visual or auditory feedback.

7. BCI Performance

The performance of a BCI can be measured in many ways. A simple measure is classification performance i.e. classification accuracy or classification rate. Classification accuracy is the ratio of the number of correctly classified trials (successful attempts to perform the required mental tasks) and the total number of trials [5]. The error rate can be calculated as the ratio of incorrectly classified trials and the total number of trials.

Although classification or error rates are easy to calculate, application dependent measures are often more meaningful. For instance, in a mental type writing application the user is supposed to write a particular sentence by performing a sequence of mental tasks. Again, classification performance could be calculated, but the number of letters per minute the users can convey is a more appropriate measure. Letters per minute is an application dependent measure that assesses (indirectly) not only the classification performance but also the time that was necessary to perform the required tasks.

A more general performance measure is the so-called information transfer rate (ITR) . It depends on the number of different brain patterns (classes) used, the time the BCI needs to classify these brain patterns, and the classification accuracy. ITR is measured in bits per minute. Since ITR depends on the number of brain patterns that can be reliably and quickly detected and classified by a BCI, the information transfer rate depends on the mental strategy employed [5].

8. Applications of BCI

BCIs could provide discrete output like “yes” or “no”, or a particular value out of N possible values. Also it could provide a proportional output like a continuous value within the range of a certain minimum and maximum. BCIs providing discrete output values, or proportional control depends on the mental strategy and on the brain patterns used. A P300 BCI, for instance, is particularly appropriate for selection applications. SMR based BCIs have been used for discrete control, but are best suited to proportional control applications such as 2-dimensional cursor control [5].

BCIs can control any application that other interfaces can control, provided these applications can function effectively with the low information throughput of BCIs [5]. BCIs have been validated with many applications, including spelling devices, simple computer games, environmental control, navigation in virtual reality, and generic cursor control applications. BCI systems allow control of more sophisticated devices, including prostheses, robotic arms, and mobile robots. Because of lack of necessary information transfer rate, BCIs are normally not well suited to controlling more demanding and complex applications.

BCI should allow a combination of process-oriented (or low level) control and goal-oriented (or high level) control. In process oriented control, the user has to manage all the intricate interactions involved in achieving a task or goal, such as spelling the individual letters for a message. And in goal oriented control, the user simply communicate their goal to the application. Such applications need to be sufficiently intelligent to autonomously perform all necessary sub-tasks to achieve the goal [5].

The use of BCI may not be limited to severely disabled people but the healthy people may use. This is possible since there are many ways to increase the “effective bandwidth” of a BCI through intelligent interfaces and high level selection.

9. Scheme of Implementation

It has been proposed to implement extracting feature from EEG signal for motor imagery using wavelet transform and classifying the extracted features into left and right hand movements using support vector machine (SVM) and artificial neural network (ANN) classifiers.

In this motor imagery pattern recognition process, it has been decided to successfully estimate, visualize and represent the ERD/ERS phenomenon[8], [9], [12] in a feature vector using wavelet transform. Several feature extraction techniques exists for feature extraction such as: band power, power spectral density , auto-regressive (AR) and adaptive auto-regressive models (AAR) , windowed and fast Fourier analysis, cross correlation etc.[3],[10].

Since the EEG signal is non stationary, time–frequency signal analysis methods offer simultaneous interpretation of the signal in both time and frequency which allows local, transient or intermittent components to be elucidated. A number of time–frequency methods are currently available for the high resolution decomposition in the time–frequency plane useful for signal analysis like short time Fourier transform (STFT), Wigner–Ville transform (WVT), Choi–Williams distribution (CWD). STFT has a constant resolution at all times and frequencies, whereas the wavelet transform (WT) has a good time and poor frequency resolution at high frequencies, and good frequency and poor time resolution at low frequencies [10], [11]. Hence this method is particularly useful for the analysis of transients, aperiodicity and other non-stationary signal features where, through the interrogation of the transform, subtle changes in signal morphology may be highlighted over the scales of interest. Another key advantage of wavelet techniques is the variety of wavelet functions available, thus allowing the most appropriate to be chosen for the signal under investigation.

The features obtained by wavelet method will be classified in the left/right hand movements using support vector machine (SVM) and artificial neural network (ANN). Then the performance measures in terms of classification accuracy will be obtained.

10. Summary

A brain–computer interface is a communication and control channel that does not depend on the brain’s normal output pathways of peripheral nerves and muscles. BCI operation depends on the interaction of two adaptive controllers, the user’s brain, which produces the input (i.e., the electrophysiological activity) and the system itself, which translates that activity into output commands. A BCI can be invasive or non-invasive, and can be based on electrophysiological signals (EEG, ECoG, intra-cortical recordings) or other signals such as NIRS or fMRI. Control signals used in BCI are slow cortical potentials, P300 potentials, sensorimotor potentials or the action potentials of single cortical neurons. Various linear and nonlinear algorithms are used to translate the input (i.e. EEG features) into output control signals. The most difficult aspect of the translation algorithm design and implementation is the need for continuing adaptation to the characteristics of the input provided by the user.

Evaluation of BCI system are done in terms of classification accuracy, information transfer rate and in terms of usefulness in specific applications.

Brain-Computer Interface research requires a multi-disciplinary approach. There are many possible benefactors of such technology, including rehabilitation, supporting disabled people in everyday activities and the gaming industry. This is a science that has been in the embryonic stage for some years and there has been a recent push to develop the technology for application outside of the laboratory environment.

11. References

[1] Wolpaw JR & Birbaumer N. Brain–computer interfacesfor communication and control. In Textbook of Neural Repairand Rehabilitation; Neural Repair and Plasticity, ed. SelzerME, Clarke S, Cohen LG, Duncan P & Gage FH, pp.602–614. Cambridge University Press, Cambridge, (2006).

[2] Wolpaw J R, Birbaumer N, Heetderks W, et al. “Brain-computer interface technology: a review of the first international meeting,” IEEE Trans Rehab Eng, vol. 8, pp. 164-173 , (2000).

[3] Ali Bashashati, Mehrdad Fatourechi, Rabab K Ward, Gary E Birch,”A survey of signal processing algorithms in brain–computer interfaces based on electrical brain signals, J. Neural Eng. 4 R32– R57, (2007)

[4] Agata Nawrocka, Andrzej Kot,” Brain - computer interface” IEEE, ICCC, 978-1-4577-1868-7/12,2012

[5] Bernhard Graimann, Brendan Allison and Gert Pfurtscheller "Brain -Computer Interfaces Revolutionizing Human Computer Interaction" A Book, Springer (2010).

[6] Boyu Wang, Chi Man Wong, Feng Wan, Peng Un Mak, Pui In Mak, and Mang I Vai, Comparison of Different Classification Methods for EEG-Based Brain Computer Interfaces: A Case Study”, IEEE , International Conference on Information and Automation, (2009).

[7] Avid Roman Gonzalez,” System of Communication and control Based on Thoughts”, IEEE, HCI, Rzeszow, Poland, (2010).

[8] Saugat Bhattacharyya, Anwesha K., Amit Konar, D.N Tibarewala, Atulya K. Nagar "Performance Analysis of Left/Right Hand Movement Classification from EEG Signal by Intelligent Algorithms" IEEE Transaction, (2011).

[9] M. A. Hassan, A.F. Ali, M. I. Eladawy “Classification of the Imagination of the Left and Right hand Movements using EEG" IEEE, CIBEC'08, (2008).

[10] Obed Carrera-Leon, Juan Manuel Ramirez, Vicente Alarcon-Aquino, Mary Baker, David D’Croz-Baron, Pilar Gomez-Gil,“A Motor Imagery BCI Experiment using Wavelet Analysis and Spacial Patterns Feature Extraction”, IEEE, (2012).

[11] Reza Ebrahimpour, Kioumars Babakhani, Morteza Mohammad –Noori, “EEG-based Motor Imagery Classification using Wavelet Coefficients and Ensemble Classifiers”, IEEE, ASIP, (2012)

[12] Wolpaw J R, Birbaumer N, McFarland D J, et al. “Brain-computer interface for communication and control,” Clinical Neurophysiology, vol. 113, pp. 767-791, (2002).