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Instrumentation Electrode Configuration Signal Processing and Applications of Brain Computer Interfacing: A Review

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Abstract—Brain-Computer Interface (BCI) is a fast-emerging technology in which researchers aims to build a direct channel between the human brain and external electronic device. The methods used for this may be invasive (ECoG), or non-invasive (EEG, MEG, fMRI, etc.). EEG-based Brain Computer Interface (BCI) is used to scale the brain movement and convert them into control signals for monitoring and control. These systems are used to develop several applications like Limb Replacements for paralyzed or disabled people, Military Enhancement, Driving Safety, Games and Entertainment, Emotion Classification, etc. Though non-invasive systems have limitations in terms of ability to detect and measure electrical activity of small groups of neurons. However, they can be used for monitoring general cognitive state and brain activity for diagnosis of brain disorders and mental health issues. The review of brain activity mapping techniques, instrumentation, signal processing, and applications of BCI is presented in this paper.

Key Words: Brain Computer Interface, BCI, EEG, Electrode Placement, EEG Classification

I. INTRODUCTION

Brain Computer Interface (BCI) is a technology that enables the human brain to communicate with and control an external device using a brain electrical activity mapping and analysis technique such as EEG, ECoG, fMRI, MEG etc. This technology has helpful applications such as, providing wearer controllable prosthetic limbs to people with disabilities. Detection and diagnosis of mental disorders and health issues has also become much cheaper and faster than before. Brain Computer Interfaces enable humans to control external devices through the use of their brain signals directly. However, this does not make use of the usual channel of communication of signals via the brain to or from the sensory or motor neurons. It measures the combined effect of electric potential change due to synchronous firing of neurons in the brain region to be mapped and generates control signals appropriately to control the connected device. Electroencephalogram (EEG) data is obtained from sufficiently large, observable brain segments and the smaller regions cannot be mapped accurately with this technique. For example, 80,000 neurons firing synchronously can be detected and measured, but electrical signals generated by 400 neurons cannot be mapped accurately. This means that fine-grained information about brain state and activity cannot be measured accurately and hence, the scope of control of the externally connected devices is limited. This paper reviews the various Brain activity mapping techniques, EEG in particular, and explores the research that has been done so far with respect to brain physiology and EEG. We will also discuss the various types of signal processing techniques used for data acquisition and filtering as well as feature extraction methods used for classification of signals into classes.

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II. DEFINITIONS AND FEATURES

A) Brain Computer Interface

EEG measures the observable electrical activity of the brain which can be used to drive external devices or circuits, to perform various tasks depending upon the signal parameters. Large scale changes, i.e. those occurring in the particular lobes are associated with changes in awareness and perception, or a marked change in the consciousness, such as-

The activity in the frontal lobe drops drastically during sleep. Activity in the motor cortex is high when performing tasks involving high levels of physical activity. These signals are parameterized and converted into control signals that are given as control input to actuators or circuits which then produce the required output, i.e. the required movement or output signal respectively.

B) History of BCI

Electroencephalography (EEG) has a rich history that dates back to the 19th century. In 1875, Richard Caton, a British physician, conducted research on the electrical activity in the exposed cerebral hemispheres of rabbits and monkeys, and published his results in the British Medical Journal. Later, in 1890, Polish physiologist Adolf Beck studied the spontaneous electrical activity of the brain in rabbits and dogs by placing electrodes directly on the surface of the brain, leading to the discovery of brain waves. In 1912, Ukrainian physiologist Vladimir Vladimirovich Pravdich-Neminsky published the first animal EEG of a mammal, a dog. Two years later, Napoleon Cybulski and Jelenska-Macieszyna photographed EEG recordings of experimentally induced seizures. Hans Berger, a German physiologist and psychiatrist, invented the electroencephalogram and recorded the first human EEG in 1924. In 1934, Fisher and Lowenback demonstrated epileptiform spikes, and in 1935, Gibbs, Davis, and Lennox described interictal spike waves and the three cycles/s pattern of clinical absence seizures, which laid the foundation for clinical electroencephalography. In 1936, Gibbs and Jasper identified the interictal spike as the focal signature of epilepsy. The study of sleep patterns using EEG began in 1953 when Aserinsky and Kleitman described rapid eye movement (REM) sleep. In 1988, Stevo Bozinovski, Mihail Sestakov, and Liljana Bozinovska published a report on EEG control of a physical object, a robot. In 2018, scientists used EEG to connect the brains of three people and experiment with the process of thought sharing. Five groups of three people participated in the experiment, and the success rate was 81% [1-14].

C) Brain Physiology and EEG

Nervous Signals are transferred within the neurons using electrical pulses. This leads to the formation of an Electric Field within a neuron. However, if many cells are spatially aligned with each other, then these electric fields can be detected and measured. The measurability and accuracy of detected brain signals depends upon the following factors -

1. Electrical activity in small brain regions cannot be captured accurately enough as the voltage across small groups of neurons are too feeble to be measured directly. The disturbances from neighbouring sources are significant and adversely affect the accuracy of measurement. The

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other oscillations occurring in the body such as heartbeat, eye blinking, etc. are of similar frequencies and may interfere with the EEG signal and cause distortions in the measured signal. Thus, the area of the measured region must be large enough for sufficiently accurate data to be collected.

2. Orientation of the neurons in the group relative to other neurons. If the neurons are randomly oriented, then the fields tend to balance each other out and thus, the resulting field value of the group is insignificant.

For example, the fields present in the neurons of the Amygdala do not contribute much to the EEG signal as the orientation of the neurons in this brain region cause the potentials to cancel out giving a net value that is nearly zero. Hence, the representation of various regions in the measured EEG signal is highly dependent upon the nervous structure of the brain region, synchrony in firing, region area and co-orientation of the neurons in the region. The orientation of the neurons relative to the scalp also determines the representation of a region in EEG, as such non-invasive brain activity measurements collect field strength values that are projected onto the scalp. The pyramidal cells are radially oriented and are orthogonal to the scalp surface. Hence, these cells are the most significant contributors to the EEG signal, i.e. the representation of these cells is the highest.

3. Synchronization: A group of neurons firing at random do not produce specific measurable patterns that can be correlated with any brain activity. However, when the neurons fire together, they produce rhythms which indicate the activity of the corresponding region.

The neurons in specific brain regions are connected to each other in feedback. This causes the neurons to constantly follow the activity of the neighbouring neurons and hence, the neurons of a particular brain region fire together in a synchronized manner. This brings us to the last but equally important factor in determining the measurability of the nervous electrical activity and its distribution across various brain regions, i.e. Synchrony. If the neurons do not fire together but at random, then a steady signal cannot be obtained. However, in most brain regions, connected neurons are always synchronized and hence, the obtained field strength at a location is due to the neurons of that region firing simultaneously. The neurons that are aligned with each other are orthogonal to the scalp. These neurons have their ends connected together leading to the synchronization of their electrical activity.

D) Types of BCI

BCI systems are classified into the following types-

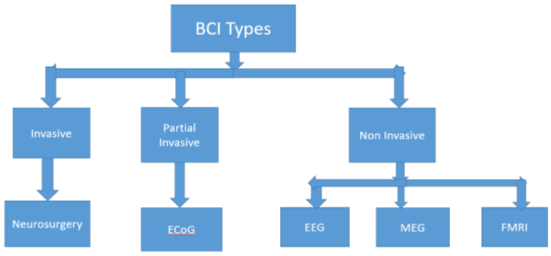

Figure 1. BCI systems classification

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1. Invasive

Invasive brain-computer interface (BCI) systems involve surgically implanting electrodes under the scalp to obtain accurate readings of brain signals. These systems place the electrodes directly into the gray matter of the brain, resulting in high-quality signals. However, there are risks associated with this technique. Scar tissue can form around the implanted electrodes, which may weaken or even eliminate the brain signals. Additionally, since the electrodes are foreign objects, they may trigger an immune response, resulting in medical complications. Research in invasive BCI has primarily focused on repairing damaged vision and providing functional limbs for people with paralysis or other disabilities. Despite the risks associated with invasive systems, they offer more precise and accurate brain signals compared to non-invasive techniques. Therefore, invasive BCI systems have the potential to significantly improve the quality of life for individuals with neurological disorders.

2. Partially Invasive

Partially invasive BCIs are implanted outside the brain but inside the skull, offering better signal resolution than non-invasive systems with lower risk of scar tissue formation. Electrodes in these devices pick up electrical signals from beneath the skull, providing higher spatial resolution and a wider frequency range compared to scalp-recorded EEG. Partially invasive BCIs, like ECoG, have advantages over fully invasive systems, including lower technical difficulty, lower medical risk, and superior long-term stability. They offer promising opportunities for developing more effective brain-computer interfaces for controlling prosthetic limbs or communicating with computers using our thoughts.

3. Non-Invasive

Electroencephalography (EEG) records electrical activity of the brain via electrodes placed on the scalp surface. Functional Magnetic Resonance Imaging (fMRI) detects changes in the blood flow to the brain and uses this data to map the brain activity. Such methods are completely external and do not interfere with the brain activity in any way. Hence, they are much safer and generally suitable for study purposes. However, the signals are of low resolutions and fail to provide precise control or communication.

E) EEG Signal Bands

EEG signals are mainly classified into the following bands based on their frequency -

1. Delta (< 4 Hz):

This band is associated with non-REM deep sleep.

2. Theta (4 - 7 Hz):

Associated with idling and drowsiness and also with repression of an action or desire.

3. Alpha (8 -15 Hz):

Alpha band is associated with a state of relaxation or with closing the eyes.

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4. Beta (16 -31 Hz):

This band is usually observed when the subject is in a state of anxiety or actively focussed on a task.

5. Gamma (32 – 100 Hz):

It is seen when recognized objects, sounds or tactile inputs are sensed.

The general property observed in EEG signals is that the amplitude of lower frequency signal is greater as compared to that of the higher frequency signals. In general, the frequency of the observed signal increases with the increase in focus or awareness, Delta is observed during deep sleep, Alpha is associated with relaxed unfocused state and Gamma is observed during tasks involving intense focus. This can be understood intuitively, as higher frequency means that the neurons are firing more often which is likely to occur during a state of more activity and awareness.

F) Event Related Potentials (ERPs)

The stereotyped brain responses triggered by some specific sensory stimuli, cognitive or motor stimuli are called Event Related Potentials (ERP). They can be measured using Electroencephalography, which measures the electrical activity of the brain using electrodes placed on the scalp. Such non-invasive methods to detect and measure ERPs provide a reliable means to study brain functioning. ERPs which result from external stimulus are called Evoked Potentials.

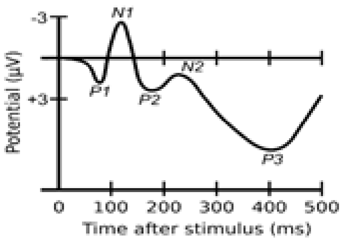

Figure 2. Event related potentials

Sensory Evoked Potentials (SEPs) are a type of Event-Related Potential (ERP) that are measured after stimulating sensory organs. Visual Evoked Potentials (VEPs) and Auditory Evoked Potentials (AEPs) are subtypes of SEPs. ERPs are characterized by their amplitude and latency, and are categorized as positive (P) or negative (N), based on their voltage deflection. The number of milliseconds after the trigger event that the ERP occurs is used to identify it. A well-known example of an ERP is the P300, which is a positive deflection in voltage occurring around 300 ms after the triggering event. ERPs are widely used in neuroscience research to study cognitive processes, such as attention, perception, and memory. By analysing the ERP waveforms, researchers can gain insights into the brain's electrical activity in response to specific stimuli.

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G) Signal Acquisition

EEG signals are obtained by measuring the electric potential values on the points on the scalp as defined by the 10-20 systems of Electrode placement. These potentials are measured with respect to the Reference electrode, which are generally connected to earlobes. This can be challenging due to various problems such as,

1. Variation in conductivity
2. Non-brain artifacts
3. Noise signals from muscular, cardiac activity, eye blinking etc.

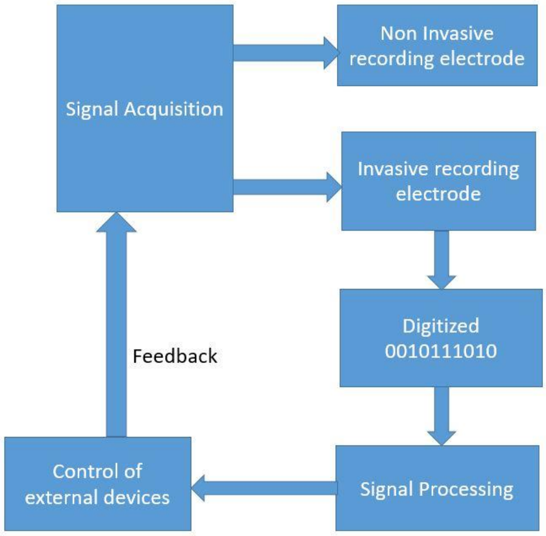

Figure 3. Signal acquisition in BCI system

H) Electrode Placement

In EEG, the brain signals are acquired by electrical activity generated across the scalp. With placing electrodes across scalp voltage fluctuation is measured. The electrode placement for BCI signal acquisition is done by 10-20 EEG System.

10- 20 system:

It is the internationally standardized electrodes placement system. This system is actually based on location mapping of electrodes and underlying area. “10”, “20” signifies distance between electrodes is either 10% or 20% that of the front-back or left-right skull length measures. The front-back markings are done by locating nasion and inion ponts.

It consists of 32 electrodes placed across the skull. Based on the application we can use particular electrodes located on particular brain regions.

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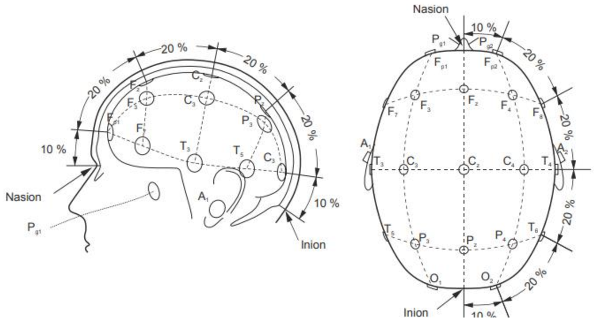

Figure 4. Electrode configuration in BCI system

I) Feature Extraction

Obtaining quantitative features from the signal can be done by observing the signal into spatial domain and frequency domain and finding those parameters of the signal which can be used to differentiate between the signals belonging to different classes. These features can then be used to classify the signals into the required classes. Generally, unsupervised learning algorithms such as K-Means Clustering or K-Nearest Neighbors are used to classify the EEG time waveforms by classes according to the type of activity that the subject is performing.

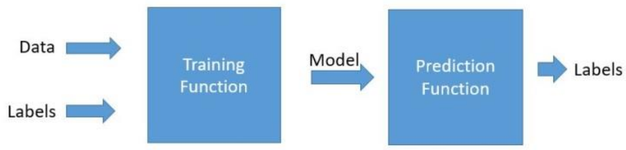

Figure 5. BCI signal classification model

III. BCI APPLICATIONS

Brain Computer Interface has many applications in the areas of Biomedical, Neuroergonomics, Education and Regulation, Games and Entertainment, Security and Authentication, Military Enhancement and much more. Some of the applications are explained below-

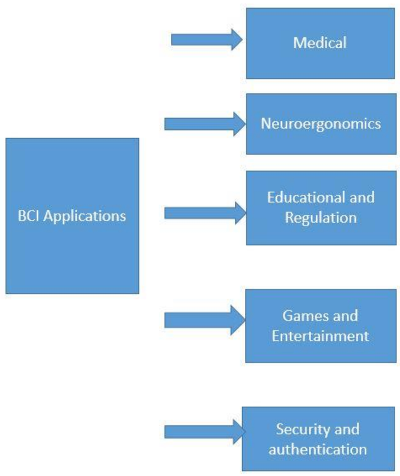

Figure 6. Applications of BCI

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A) Military Enhancement with BCI

BCI technology has opened up new opportunities in military training and operations. Neurosurgeons are now involved in modifying and optimizing military performance through BCI. DARPA has a division that runs the "Silent Talk" program, which aims to develop communication between users on the battlefield using EEG signals. This will allow for communication without the need for vocalization or gestures, which can be beneficial in special operations. DARPA has also proposed a "Cognitive Technology Threat Warning System," which includes a requirement for high-resolution BCI binoculars that can quickly respond to subconsciously detected targets or threats. These biological vision devices have detection ranges of up to 10 km and can expand soldiers' field of view to 120°. Most unclassified DARPA projects are based on non-invasive BCIs, which are similar to the use of night-vision goggles or radio frequency signals and do not pose additional risks. However, the use of invasive or partially invasive BCIs in soldiers raises ethical concerns. This presents a challenging scenario that raises concerns about surgical risks, as well as the issue of neuro-cognitive enhancement. Overall, while BCI technology has opened up new possibilities for military operations and training, its use in soldiers must be carefully evaluated to ensure ethical and safe implementation.

B) Medical Application

Accidents have become a major cause of death and serious injuries in recent times. Studies have been conducted on the concentration levels of individuals who suffer from motion sickness while driving. When motion sickness occurs, the body, ear, and eye generate conflicting sensory information that is sent to the brain. This can cause traffic accidents and decline a person's ability to maintain self-control. Researchers predict that motion sickness could contribute to a driver-state monitoring and alert system using a set of EEG signals. The system collects signals from five different regions of the brain. A BCI-based system that measures human hearing levels, which are part of the sensory information gathering process, has also been developed. In another study, a virtual reality-based motion sickness platform has been designed with a 32-channel EEG system and a joystick to report motion sickness levels in real-time experiments. Overall, these studies show the potential for using BCI technology to monitor and address motion sickness in drivers, which can help improve road safety.

C) Games and Entertainment

Non-medical BCI applications in entertainment and gaming have gained popularity in recent years. EEG signals have been utilized to control game elements like flying helicopters or dropping stress levels in games like Brain Ball. Researchers have also explored the potential for multi-brain gaming experiences using BCIs, where players can collaborate or compete by controlling virtual characters through their brain signals. Games like Mind Balance Video Games and Neuro-Reader challenge players to control virtual characters through balancing weights or imagining movements to achieve higher scores. These applications of BCIs in entertainment and gaming have shown potential for emotional control and neuro-prosthetic rehabilitation.

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D) Emotion Classification by EEG Signals

The proposed system uses EEG signals to classify emotions and involves two steps. Firstly, the original EEG signals are processed using independent component analysis (ICA) and Moving Average (MA) for signal smoothing. Then, natural language processing (NLP) is used to identify and classify the subject's emotions, and the EEG-based rating is combined with sentiment score to improve the overall prediction accuracy.

IV. Signal Processing

A) Drawbacks in BCI using EEG

Whichever technique we use in signal processing the noise in the system is unavoidable. EEG used in BCI not only contains brain electrical signals but also the unwanted signals as mentioned below -

1. Interference due to electromagnetic interference i.e. 50Hz or 60Hz Power signal noise.
2. Electromyography signals – These signals are interfered due to muscular movements.

B) Role of signal processing

BCI is a multi-domain subject where multiple theories from signal processing, Machine learning, Statistics, Neuro-science, Control systems, Information theory are taken into account. Various aspects of BCI can be understood from various theories. No single theory can explain all BCI features.

Figure 7. Block diagram of signal processing EEG signal

The signal obtained from electrodes is the analog signal. The digital signals are convenient for processing and feature extraction. Analog signals then sampled and quantized to get digital signals. Digital signal processing uses various kinds of filters that convert the signal from one state to another. Linear time invariant systems are most commonly used systems in BCI.

In signal processing of BCI the output y(n) is obtained by applying transformation on signal x(n).

$Y(n)=T\{x(n)\}$

BCI systems are actually causal systems as they operate in real time and no future prediction is done. These systems are dynamic so we perform temporal filtering. Some BCI systems are Time Variant and Linear too. The BCI system components can be viewed as Filters. The calculation of various feature parameters is obtained by applying suitable filters.

C) Major filter classes

The various kind of preprocessing techniques that can be applied in BCI are as follows -

Whichever technique we use in signal processing the noise in the system is unavoidable. EEG used in BCI not only contains brain electrical signals but also the unwanted signals as mentioned below –

1. Static Filters -

These filters can be signal squaring filters or logarithmic filters which calculates variance and logarithmic ratios in a signal.

2. Spatial filters -

These are the filters which operate in the spatial domain. The linear mapping in source and sensors can be achieved. Re-referencing, Surface Laplacian, Independent Component Analysis are some of its applications.

3. Temporal filters -

These filters operate in the time domain where yi(n) depends only upon xi(n). This is obtained by time windowing, wavelet transform etc. These are conceptually orthogonal to spatial filters. Example moving average filters.

4. Spectral filters -

The DFT is used to transform time domain signal to frequency domain. The signals are then analysed in the frequency domain.

$$X(k) = \sum_{n=0}^{N-1} x(n)e^{-j2\pi kn/N}$$

The spectrum of the signal is a linear combination of various sinusoidal signals. The signal representation is in terms of frequency and amplitude. These are majorly FIR finite impulse response filters.

$$s(n) = \sum_{k=0}^{N-1} A_k e^{j2\pi kn/N}$$

The classification of signal is done using cut-off frequency. The examples are Low Pass, High Pass, Band Pass, Notch filter. The 50 Hz or 60 Hz power signal noise can be removed by applying band-stop filter which inhibits the certain range of frequencies to pass through. But artifacts such as EMG signals are difficult to remove. One of the methods is to use bandpass filters of particular range in EEG i.e. 4-8 Hz (theta), 8-12 Hz (alpha), 12-30 Hz (beta), 30-100 Hz (gamma).

V. Conclusion

In this paper briefly presented the basics of brain computer interface (BCI) instrumentation, signal processing and the applications of BCI. This topic has more scope to explore and appreciate along with artificial intelligence and machine learning vertical to develop modern assistive tools.

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