Brain-Computer Interface: Systems and Interacting Devices

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Abstract- *In the past, mind control was thought to be a fantasy beyond human intelligence. Over the last few decades, significant advances have been made, such as the invention of novel devices for enhancing information flow into computers through multimodel devices. Brain-Computer Interface (BCI) was initially developed to build communication between paralyzed people and the environment. BCI variously improves human life in the field of medicine, entertainment, security and etc. This paper focuses on the technologies and principles behind the BCI. The paper also discusses the various steps in the BCI system: signal acquisition, preprocessing, feature extraction, and classification. The key challenge in BCI signal processing is the curse of dimensionality in the feature vector. Further, the paper focuses on the BCI communication methods, such as invasive, semi-invasive, and non-invasive BCI, advantages, and limitations.*

Keywords: Brain-Computer Interface, BCI Feature, BCI Devices

I. INTRODUCTION

The Brain-Computer Interface (BCI) is a groundbreaking advancement in the field of Human-Computer Interaction (HCI). The aim of BCI is to use directly generated commands and messages to link the human brain to external devices. The same way devices connecting to the BCI can send and receive messages to the brain. The human brain is a complex structure of over 100 neurons and is responsible for performing a variety of complex functions (Papanastasiou et al., 2020). Different parts of the brain are responsible for these various functions. As a consequence, for different functionalities various regions of the brain are activated, emitting a variety of signals. Therefore, BCI system is intended to identify the various signals generated by the brain's various parts. Electromagnetic signals are generated during brain activity. BCI will use the signals produced to process, recognize and measure this brain activity and transmit control signals that reflect the user's decision.

After observing the electrical activity of the human brain, Hans Berger (1931) invented the Brain-Computer Interface. Electroencephalography (EEG) was the first technique used; it can monitor the electrical activity of the human brain. Brain-computer interface system could be used to recognize human brain expressions. BCI techniques are not a cure for any disease; rather, BCI is assisting disabled people in greatly improving their lives by providing an efficient means of expressing their thoughts, emotions and needs. Via neuron silicon interfaces, BCI allows paralyzed people to interact with their community. Brain imaging techniques use detecting brain activity in a variety of ways. Some of the examples for brain imaging techniques are Functional Magnetic Resonance Imaging (fMRI), Electroencephalography (EEG), Magnetoencephalography (MEG), Electrocorticography (ECoG0, and Near-Infrared Spectroscopy (NIRS). (Ellenbogen and Lucas, 2006)

BCI can be applied in several areas such as medical, system management, security and authentication, entertainment and gaming, education and self-regulation, user monitoring, training, neuromarketing and advertisement etc (Abdulkader, Atia and Mostafa, 2015). Early BCI studies were centered on restoring hearing, vision, and movement defects. BCI is now being used to interact with people who are completely paralyzed by interpreting and analyzing their brain signals. Figure 01 describes the outline of the BCI system.

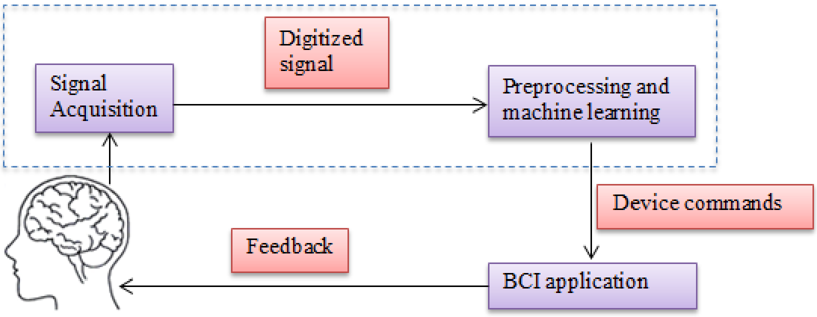

Figure 01: BCI System layout

II. BRAIN AND INTERACTING DEVICES

A. *Human Brain*

Neurons make up the brain. To generate thought and control physical activities, neurons interact with one another. The brain areas divide into the cerebral cortex and subcortical regions. Pattern recognition, reasoning, language comprehension, and other high-level tasks are all handled by the cerebral cortex. Preparing this area of the brain is of particular interest to BCI. The sub-cortical zone handles the heart rate, memory, emotional and instinctive response, temperature regulation, and etc.

Neurons can interact by transmitting electrical signals to other neurons through physical links or by exchanging chemicals (neurotransmitters). Neurons interact with one another for different activities. During this time electrical, chemical and blood flow get change in the brain. Using brain imaging technology, these changes can be detected. This technology can be used to create distinguished images of brain function and structure. Relevant brain tasks established during that period can be analyzed using these images (Vidal, 1977; Birbaumer, 2006).

Brain imaging techniques are divided into three groups; invasive, semi-invasive and non-invasive (Berger, 1931). Invasive technology places sensors inside the brain, while noninvasive technology uses external sensors to monitor neuron activity. In semi-invasive method the electrodes are attached to the brain's exposed surface.

B. *Signals Types*

During brain function, the brain generates a large number of signals. There are two main types of signals that can be distinguished. Spikes and field potentials. Spikes are from individual neurons. Invasive BCI devices use microelectrodes to detect these signals. Field potentials are from a group of neurons. Non-invasive BCI instruments can be used to detect these signals (Lotte et al., 2007)

C. *Brain Imaging Technologies*

1) *Electroencephalography (EEG):* It makes use of the electrical potential of brain activity. Electrodes mounted on the scalp are used to test EEG (Grünwald and Kamada, 2018). It detects the weak electric potential produced via the neural system. EEG devices are compact and wearable, and they have a great temporal resolution. However, because of the disturbance generated as the signal passes through bone, fluid, and muscles, it has a poor spatial resolution (Novak, 2018).

EEG tracks signals are divided into multiple bands such as 1. Delta 2.Theta, 3.Alpha, 4.Beta, and 5.Gamma. However, BCI systems are primarily concerned with alpha and beta signals (Birbaumer, 2006). Mansoor et al., (2020) introduced deep learning classification for EEG signals and it provided better real time result compare to other algorithms.

2) *Magnetoencephalography (MEG):* It works by detecting the magnetic fields produced by the neurons' electrical activity. MEG is much more capable and receptive than EEG in terms of brain imaging. Despite the fact that the system is outside the skull, it is vulnerable since the skull is entirely apparent to magnetic fields. However, in order to process the superconductivity of magnetic potentials, bulky and costly devices are needed (Guenther et al., 2009).

3) *Functional Magnetic Resonance Imaging (fMRI):* fMRI assesses the reduction in deoxyhemoglobin to active brain areas through testing the magnetic properties of the brain(Guenther et al., 2009).

4) Functional Near Infrared (fNIR): The optical brain monitoring technique determines the change in blood oxygenation and blood volume associated with human brain activity. This technique uses near-infrared spectroscopy for functional neuroimaging (Guenther et al., 2009).

5) Positron Emission Tomography (PET): It measures gamma-ray emissions to detect the chemical activity of injected radioactive tracers. Owing to the need to inject hazardous material, it is not appropriate for long-term use.

6) *Single Photon Emission Computed Tomography (SPECT):* It functions similar to PET, but instead of measuring photons emitted by gamma rays, it uses photomultiplier tubes.

7) *Electrocorticogram (ECoG):* ECoG is an invasive method. ECoG uses electrodes fixed directly on the cortical to monitor brain electrical field potentials. In humans, ECoG is moslty used to detect seizures in patients with medically intractable epilepsy (He, 2020; Sanjanasri et al., 2020). Figure 02 a) shows the X-ray and Electrocorticography data, where b) #1 and #2 show signals from the left frontal cortex, #3 signals from left temporal cortex.

D. *Invasive Brain Computer Interface*

Invasive BCI instruments are attached to the cortex's surface. To position the sensors inside the skull, a craniotomy surgery is needed. The sensors are permanently implanted within the skull.

The signals from the brain would be recorded by the electrodes, and this form of signal recording is known as Electrocorticogram (ECoG). Since the sensors are close to the brain inside the skull, the signals recorded from the brain would have high quality and spatial resolution, as well as less interference from outside sources. The combined brain function of a large number of brain cells is recorded by ECoG. They are unable to record individual neural activities. ECoG will also record the neuronal activity of the brain closest cells. As a result, recording all of the brain's neural activity is difficult, and placing several electrodes within the brain is a dangerous process. The ECoG technology that was used in the brain neurons will not be harmed by intrusive BCI. The electrode is not capable of penetrating the brain. However, there is a drawback to this method: scar tissue grows on the sensors, posing a risk to the brain while also reducing sensor sensitivity. As a result, surgery is needed on a regular basis, which is harmful to the individual's wellbeing.

Intracortical recording is one more technique used in invasive BCI. The electrodes used in this process will penetrate brain tissues, allowing it to record brain activity (Birbaumer, 2006; Ellenbogen and Lucas, 2006)

E. *Non-invasive Brain Computer Interface*

The noninvasive BCI approach is the safest since the sensors are not implanted by surgery, and the devices are compact and simple to use. The system will be fixed in the human head and it will include a variety of electrodes that will collect signals from various parts of the brain. The sensors that are used by BCI instruments are non-invasive and capable of detecting and interpreting signals released throughout brain activity. Interferences from the bone, fluid, and skin of the brain, as well as external radio and electrical operations are mixed with original signal and create noises. In the presence of weak signals, the devices can successfully recognize the necessary signals

Electroencephelography (EEG), Functional Magnetic Resonance Imaging (fMRI), Magnetoencephelography (MEG), Functional Near Infrared Imaging (FNIR), Positron Emission Tomography (PET) and Single Photon Emission Computed Tomography (SPECT) are some examples for non-nvasive BCI. EEG is the most common one among them and measures the electrical activity of the brain. (Guenther *et al.*, 2009; Neuper *et al.*, 2009)

F. *International 10-20 System*

Different functions are regulated by different parts of the brain. Scientists created an international standard scheme to collect all brain activity signals from those particular areas. The electrodes were precisely placed on the head using the International 10-20 Method. The electrodes in the systems are evenly spaced from left to right and front to back. All of the electrodes are symmetrically arranged. The electrodes are named according to their position; T - temporal, O - occipital, C - central, P - parietal, Fp - pre-frontal, F – frontal (Lotte *et al.*, 2007). Figure 03 shows international 10-20 system.

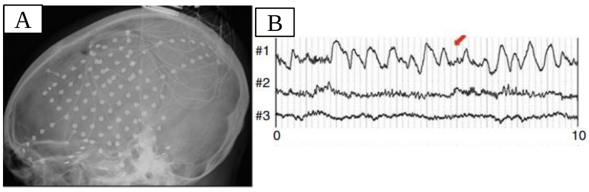

Figure 02: A- X-ray of electr ode placements
B- Electrocorticography (ECoG) data

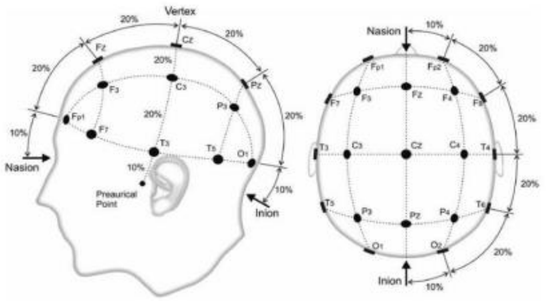

Figure 03: International 10-20 system.

III. SIGNAL PROCESSING, FEATURE EXTRACTION AND CLASSIFICATION

BCI instruments recognize and interpret signals in order to detect brain activity. These are the three steps of signal processing:

1. Preprocessing
2. Feature extraction
3. Feature classification.

The BCI techniques are efficient in capturing and analyzing the electromagnetic signals generated by the human brain (Birbaumer, 2006). The main goal of BCI is to understand brain signals and translate them into computer understandable signals. The two most common approaches used in the literature for this purpose are regression and classification (Lotte *et al.*, 2007). There are few distinct characteristics in the brain signal.

- High dimensionality- the dimensionality of feature vectors is high. The challenge in these data is number of data is smaller than the feature vector.
- Time Information- Neural activity patterns are linked to unique EEG time variations therefore need to have time feature.
- Outliers and noise- Noise and outliers are mixed in with the original signal. Muscle movements are responsible for these noises.
- Non-stationary- Signals change over time and session.
- Small testing set - Training sets are comparatively small.

However, BCI devices are capable to recognize these characteristics and extract them correctly, allowing users to communicate.

A. *Preprocessing*

Preprocessing reduces the amount of time it takes to process data by eliminating noise and other unrelated information from the original signal. Electrodes can detect signals if there is any pattern of neural activity within a time frame. Brain signal processing methods focus the temporal or spatial processing, or a combination of both. EEG is the broadly used technology; however, while recording a neural activity, most of the noises are caused by non-central nervous activities, such as facial muscular movements and eye expression. It is important to reduce the noise in the signal in order to recognize the specific neural activity. The task of identifying and removing these types of noises is critical because they are overpowering and can cause the target signal to be confused when both signals have the same frequency or amplitude causing it hard to separate the noise from the original signal. Independent Component Analysis (ICA) method is used to filer the noise from the such signals(Abdulkader, Atia and Mostafa, 2015).

B. *Feature Extraction*

When designing a BCI system some necessary features are to be considered such as: Band Powers (BP), Auto Regressive (AR) and Adaptive Auto Regressive (AAR) parameters, Time-frequency features, amplitude values of EEG signals, Power Spectral Density (PSD) values and inverse model-based features (Lotte *et al.*, 2007).

1) Characteristics of Feature Extraction Methods: To extract the target signal from the noise, it employs heuristic search techniques. Heuristic search examines a vast volume of data in order to separate the original data from the noise. Heuristic search has a beginning point that will decide the search path, then it will delete irrelevant data and search in a structured manner using a scoring feature. Following that, it will evaluate all possible subsets of the function. It will continue to look for relevant information until it finds it (Birbaumer, 2006).

2) Types of Feature Extraction Methods: For feature extraction, there are three types of methods available.

1. Filter algorithm: These algorithms operate by eliminating unnecessary features from the translation algorithm before it is trained. This can be done by computing entire features correlation along with respect to the target function and selecting higher score features. Next approach, discovers the feature derivation based on features extracted from raw data, sorting these data features based on the amount of variance and selecting a fixed number of top scoring features.

2. Embedded algorithm: Once novel training set is introduced the feature selection process add or eradicate features to counter prediction.

3. Wrapper algorithm: The features will be chosen by evaluating the consistency or uncertainty of a collection of features using the translation algorithm (Birbaumer, 2006).

C. *Feature classification*

Main challenge in the BCI classification is the curse of dimensionality. Usually the feature vectors increase exponentially with the increase in data needed for the classification. Unfortunately BCI training datasets are smaller than the feature vectors *(Lotte et al., 2007)*. Following are the classification algorithms used in the BCI system.

1. Linear Classifiers: Linear classifiers classify various data groups by using linear functions. This technique is the easiest and popular in BCI systems. It uses Support machine Vector (SVM) and Linear Discriminant Alalysis (LDA) techniques (Lotte *et al.*, 2007).

2. *Artificial Neural Networks:* Neural networks along with linear classifiers is the most used classifier in the BCI system. Artificial neural network is a set of artificial neurons. It allows for the development of nonlinear decision boundaries. The Multi-Layer Perceptron (MLP) is a neural network used to classify data in BCI systems(Lotte *et al.*, 2007).

3. *Nonlinear Bayesian Classifiers:* Nonlinear decision-making is performed by this classifier. This is the power of generative algorithms; they can more and reject suspect samples quickly classify. Bayesian classifiers can be divided into two types: Bayesian Quadratic and Hidden Markov Model (HMM)(Lotte *et al.*, 2007)

4. *Nearest Neighbor classifiers:* These are non-linear discriminative classifiers. These classifiers allocate a class based on its nearest class. The neighbor might be a class prototype or feature vector of the training set (Lotte *et al.*, 2007).

5. *Combinations of Classifiers:* This employs a variety of classifiers that are combined in various ways. Some of them are:

Boosting: Boosting entails using a series of classifiers in a cascade. The errors made by the previous classifiers will be the priority of each classifier. This method allows you to construct a strong classifier from a set of weak classifiers. Ordinary Least Square (OLS) and Multi-Layer Perceptron classifiers are used to evaluate boosting (Lotte *et al.*, 2007).

Voting: In the voting system, each of the combined classifiers assigns a class to the input feature vector. As a result, the final class will be the bulk of them. Therefore majority one is selected as final class. It is the most well-known method in BCI because it is both effective and simple.

Stacking: In stacking, the classifiers combine to identify the input function vector. The results of these level 0 classifiers will be fed into meta-classifiers, which are also known as level 1 classifiers.

The final decision will be made by these meta-classifiers. Hidden Markov Models is used as level 0 and Support Vector Machine (SVM) is used as level 1 classifiers in stacking(Lotte *et al.*, 2007).

By combining similar classifiers, one of the classifiers would outperform the others, lowering error and variance.(Lotte *et al.*, 2007)

IV. CONCLUSION

Brain signals represent the brain's controlled activities and actions, as well as the effect of input obtained from body, such as sensing or internal organs. Brain Computer Interfacing allows communication between the brain and external devices. BCI translates brain signals into outputs that convey a user's intent. The research community is interested in BCI applications. Several studies focusing on improving the BCI application fields such as medical, games and entertainment, organizational, transportation and security and authentication. Further, researchers continuously work improving the different instruments that can be used to capture brain signals. Invasive and non-invasive recording devices are two major groups. Invasive techniques achieve higher accuracy rates either spatially or temporally therefore this is typically required for critically paralyzed situations. Unfortunately invasive techniques involve with implanting surgery. The non-invasive group, on the other hand, has been widely adopted in other application fields due to its advantages over the invasive one. BCI signal processing mainly consists of preprocessing, feature extraction and feature classification. The key challenge in the BCI signal processing is the curse of dimensionality in the feature vector. Possible future directions in the BCI technology will be emotion classification based on brain signals using machine learning techniques. Further studies are needed towards BCI in virtual reality.

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