CHAPTER 1

1 Introduction and Objectives

1.1 Background

The system aims to develop a communication pathway between the brain, and a computer is popularly known as brain-computer interface (BCI) system [1]. Such direct interaction of the brain activities with the computer facilitates a human subject to control electronic devices. In other words, BCI translates the neural responses directly to the computer, which signals the external devices to respond in accordance with the subject's intentions. These capabilities of BCI make it a promising system to be used in many medical applications such as rehabilitation of stroke patients, reinstating motor functions of paralyzed patients, building up communication with locked-in patients, and augmenting cognitive and sensory processing [2]. Besides building an interface, researchers find the scope of BCI systems in diagnosing brain tumors, sleeping disorders, and brain diseases [3].

Apart from medical applications, researchers have widened the scope of BCIs to assist healthy users for faster hand-free control of devices [4]. Using BCI, they can control devices such as a robotic arm, smart home appliances, or a wheelchair using their thoughts and cognitive power. However, designing the BCI for use in the real environment involves challenges like poor information transfer rate (ITR) and long training sessions of the users [5].

From the above discussion, it is notable that BCI research can benefit both abled-body and disabled-body users. However, designing an effective real-time BCI device is still a complex exercise. Electroencephalogram (EEG) is widely used for BCI applications due to its characteristics like high temporal resolution, non-invasive acquisition, and portability [6]. In EEG acquisition, biopotential signals are captured by the electrodes placed over the scalp according to the standard International 10- 20 system, as shown in Figure 3. The silver/ silver- chloride or gold cup electrodes are generally used as they provide good conductivity. An electrolytic gel is used to further enhance the conductivity and decrease the skin-electrode contact impedance.

The brain is divided into six main lobes: pre-frontal, frontal, parietal, temporal, central, and occipital. According to 10-20 system electrodes are placed at a distance of either 10% or 20% of the total nasion-inion or right ear–left ear distance of the skull. As shown in Figure 1.1, each electrode has a label in the form of a letter followed by a numeric value, for example, 'c3'. The letter is the electrode's identity given by the area of the brain where it is placed. For example, the letter' O' stands for occipital lobe, 'F' represents frontal, and so on. There is also 'Z' which represents the midline sagittal plane of the skull (Fz, Cz, Pz). The numbers after the letters define electrode placement on the right or left side of the head. Even numbers are assigned to the right section of the head, whereas odd numbers are used to represent electrodes on the left side of the head.

The amplitude of the EEG signal is in the range of 1-100 uV and needs to be amplified. A bio-amplifier device receives the biopotential signal acquired over the skull. The first stage in the device is a patient protection circuitry to avoid any hazardous current to the

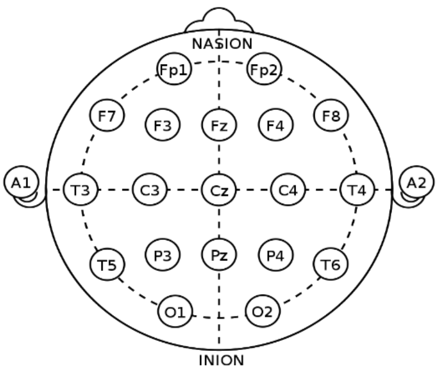

Figure 1.1 International 10-20 system.

skull. In the second stage, an instrumentation amplifier is used for impedance matching. In the third stage, bandpass filters are implemented with the passband frequency range of 0-100 Hz. A 50 Hz notch filter is also designed to avoid power line noise. In the last stage, the main amplifiers are connected with adjustable gain. The output signal of the amplifier module is then fed to an analog to digital converter (ADC) for the digitization of the signal. Thus, the output signal is a time-series signal representing brain activities.

In general, the first step in the BCI system design is to capture EEG patterns that represent the neural responses of a human subject while performing a specific mental task. The second step includes pattern recognition algorithms and machine learning approaches that work to define human intentions. In the third step, researchers generate controlling commands to operate various devices. The commonly used EEG patterns are steady-state visual evoked potential (SSVEP) [7], sensorimotor rhythms (SMR) [8], motor imagery (MI) [9], and event-related potentials (ERP) [10]. These patterns are originated from the different areas of the brain depending on the type of stimulus being provided to the subject.

1.2 Motor Imagery (MI)-based BCI

The imagination of movements of different body parts is known as MI [11]. The human brain originates rhythmic neural waves over different areas of the cortex while performing certain mental tasks [12]. Mu rhythms are one of such rhythms associated with voluntary movement-related mental tasks [13]. These waves are mainly generated over sensorimotor cortex and have a frequency range between 8 and 13 Hz. The homunculus representation explains that each body part's movement is controlled by the contralateral section in the motor cortex. For instance, if the subject is thinking about the movement of left-hand, significant changes in the mu rhythms are observed in the right hemisphere of the motor cortex and vice versa. Therefore, EEG acquired from contralateral section contains information about the movement of that body part. The mu rhythms are explained in [14], where the researcher explains the patterns of mu rhythm in accordance with the movement performed. The power of the mu rhythm gets attenuated when the person imagines or performs the motor movement. This attenuation in the mu rhythm is known as event-related desynchronization (ERD). Another important rhythmic pattern observed is beta rhythm. Unlike mu rhythms, the average power of the beta rhythms tends to increase during MI. The associated improvement in beta rhythms is known as event-related synchronization (ERS). With a sufficient amount of training, a user can control the ERD/ERS patterns of mu and beta rhythms. The learned ability to control ERD/ERS patterns is utilized by the BCI system to control external devices.

The observed variations in the EEG induced the idea of controlling the external devices employing a software module. In practice, signal conditioning of the EEG patterns during the MI task can generate the controlling commands for the devices to take action following the user intention. This is the general idea of an MI- BCI system.

1.2.1 Block Diagram of an MI-Based BCI Device

The block diagram of an MI BCI system is shown in Figure 1.2. The major modules include stimulus generation to provide instructions to the user, signal acquisition device, signal processing unit, and feedback from the external devices. As it can be seen from Figure 1.2 that the MI BCI is a closed-loop system. Feedback is provided to the user in auditory or visual form. The user directly interacts with the device by looking at the function it is performing. If the device is not performing the desired task associated with the thinking of the corresponding limb movement, then the user tries to control it again by focusing more on the MI task. In this way, the user learns to control the device.

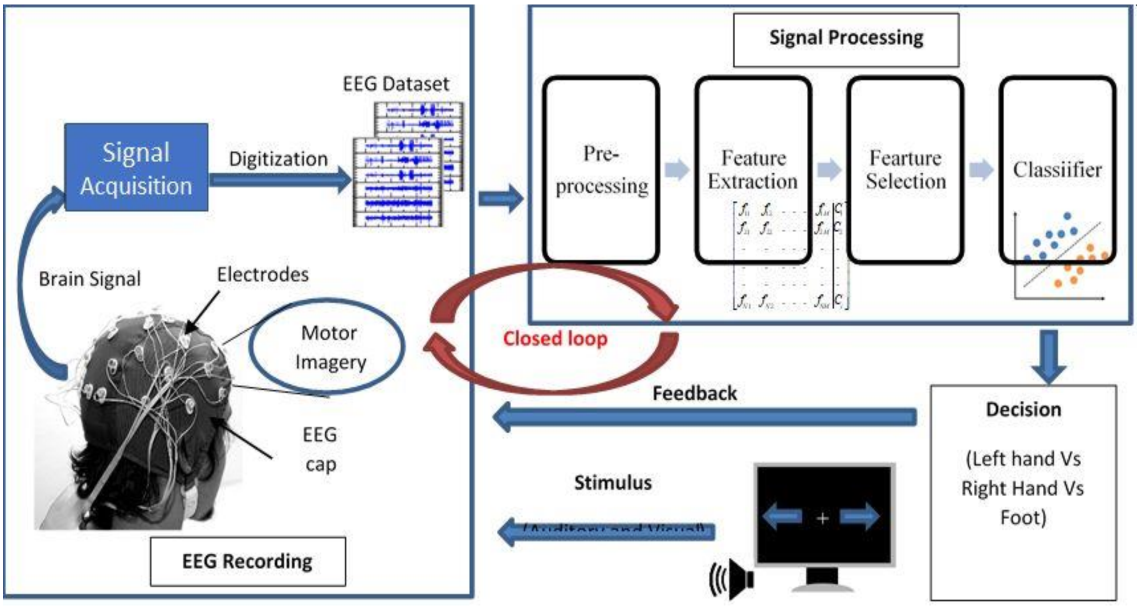

Figure 1.2 Block diagram representing the components of an MI-based BCI Device.

The signal processing unit of MI-BCI system consists of pattern recognition methods such as preprocessing, feature extraction, feature selection, and classification. Pre-processing eliminates the artifacts and improves the signal-to-noise ratio of EEG. Feature extraction is a technique to identify and highlight the most significant information carried by the signal. In the case of MI EEG feature extraction, the selection of an appropriate frequency band is a very crucial step as most of the information lies in a particular band of frequency. Feature selection is used to reduce the dimensionality of a feature vector. The higher dimensionality of the features makes the classification problem a complex exercise and thus causes the classifier to take longer to find true classes. This can be solved by selecting a subset of features from the whole group of features in the feature vector. The selected subset should have the most discrimination properties between the classes to solve the classification problem. Feature selection methods convert the higher m-dimensional feature vector to a lower p-dimensional feature vector by rejecting the irreverent features. The irrelevancy of the feature is measured based on a feature weight numeric value evaluated by a feature selection algorithm. In the last stage of MI BCI system, a decision is made by a classifier to distinguish between the different motor imagery classes correctly. A classifier is an algorithm that learns from the previous data to predict the true class of future data.

1.2.2 MI task

In BCI research, the most commonly used BCI datasets are provided by a series of BCI competitions such as BCI competition I, BCI competition II, BCI competition III, and BCI competition IV. Many of these datasets were recorded for MI tasks [15,16]. They have provided general guidelines to perform MI. In general, during MI task, a user is instructed to think about the closing and opening of his fist of either left hand or right hand at a time. The decision of which hand movement the user has to make is made by a cue presented on a screen. The user sits relaxed on a comfortable armchair and looks at a monitor for instructions. Usually, auditory and visual instructions are given to the user. First, a black screen appears, followed by a beep sound is made indicating the start of MI. After one or two seconds, an arrow pointing either to the right or left is shown on the screen for about 4- 6 seconds. During this period, the subject has to think about the movement of his right or left hand according to the direction of the arrow, i.e., if the arrow is indicated towards the right then, the user thinks about the movement of his right hand and vice versa.

1.3 Steady-state visual evoked potentials (SSVEPs)-based BCI

SSVEP is a resonance phenomenon that is primarily observed in the occipital lobe of the brain when the subject is focusing on a light source flickering at a constant frequency [17]. SSVEP oscillations are close to sinusoidal in nature. The fundamental frequency of the SSVEP is identical to the frequency of the stimulus and its harmonics. For instance,

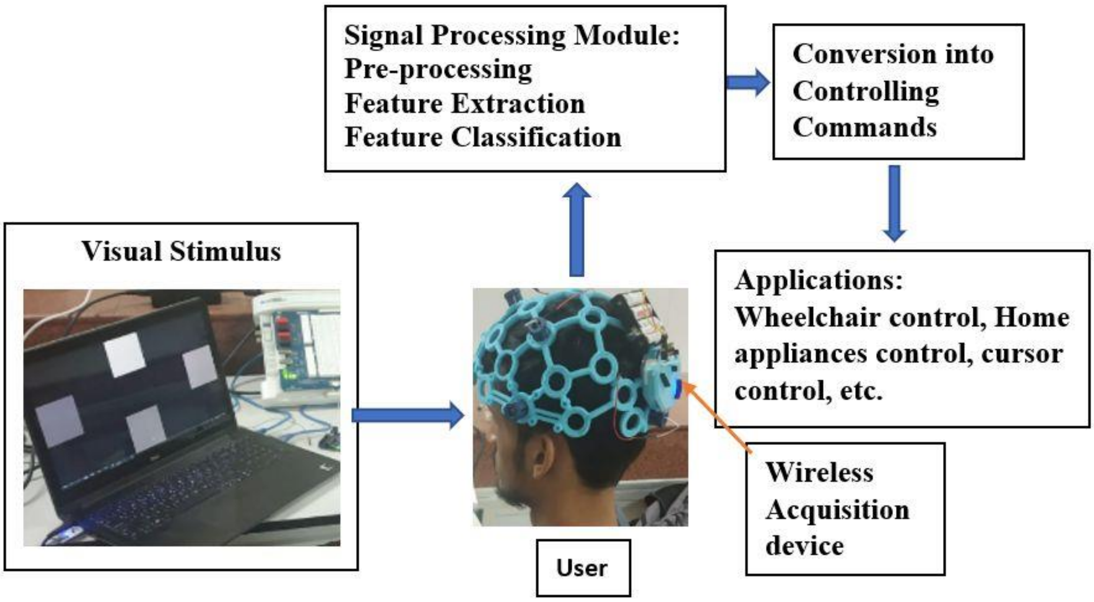

Figure 1.3 Basic building blocks in SSVEP based BCI.

when a visual stimulus, flickering at a specific frequency ranging between 4Hz and 70Hz, is presented to a subject, the brain neural response originates electrical activities of the same frequency as that of the visual stimulus. The SSVEP is widely used in BCI research community because the ITR in SSVEP is high [18].

A Block diagram of an SSVEP-based BCI is presented in Figure 1.2. In SSVEP based BCI framework, the subject is asked to focus on a light source flickering at a constant frequency. During the task, EEG is recorded from the occipital lobe of the brain. The signal processing module detects the SSVEPs using preprocessing and pattern recognition methods. Preprocessing mainly includes bandpass filtering that removes artifacts and noises from the signal. Then, feature extraction finds the spectral information at the stimulation frequency. The extracted information is fed into a classifier. SSVEP performance is generally evaluated in terms of classification accuracy, speed, and the no. of stimulation frequencies. These performance measures are included by a single indicator known as ITR [19].

1.4 Challenges

1.4.1 Removal of Ocular artifacts from single-channel EEG:

While acquiring EEG signal for recording brain activities, we often receive signals from other muscle activities which are added with the brain activity signal, thus resulting in a contaminated EEG signal. Muscle activities such as eyeblink (EB) and eyeball movement are referred as Ocular Artifacts (OAs), which highly affect EEG signal. In BCI systems, removal of OAs is important for correctly converting the brain thoughts into commands in order to control the external device. Various techniques like Independent component Analysis (ICA) and Principal Component Analysis (PCA) are widely used for the elimination of OAs, but these techniques require multi-channel EEG signals for processing.

1.4.2 Feature selection of MI-EEG signals:

In MI-based-BCI signal analysis, mu and beta rhythms of EEG are widely investigated due to their high temporal resolution and capability to define the different movement-related mental tasks separately. Time, frequency, and phase analysis of EEG rhythms extract important MI-related features. However, high feature dimensions of the MI EEG persist the requirement of a suitable feature selection algorithm that can enhance not only the classification performance but also the computational speed of the classifier.

1.4.3 Spectral- Spatial feature optimization of MI-EEG signals:

Common spatial pattern (CSP) is most commonly used for spatial filtering of MI signals. Frequency band optimization improves the performance of CSP in MI task classification because MI-related EEGs are highly frequency-specific. Many variants of CSP algorithm divided the EEG into various sub-bands and then applied CSP to extract MI feature space. However, before feeding the feature space into a classifier, optimization of sub-bands within CSP improves the classification performance. This emerges the need for a sophisticated algorithm that can enhance the CSP performance with optimum computational cost.

Further, the performance of CSP also depends on filtering techniques, and it is recommended to analyze the effect of different filters on the EEG data and then cautiously select the filter.

1.4.4 Multi-view MI-EEG classification

Using a fixed time window of EEG to extract discriminatory features results in suboptimal MI classification performance because time latency during MI tasks is inconsistent between different subjects. Thus, apart from frequency band optimization, time window optimization is equally important to develop a subject-specific MI-BCI. With time windows, extracted feature space becomes a higher-order tensor problem that requires multi-view learning approaches to optimize features.

1.4.5 Improving recognition rate of SSVEP in real-time

In SSVEP-based BCIs, suboptimal ITR is achieved due to the false detection of SSVEP as one of the target classes while the subject does not focus on any target visual stimulus.

1.5 Objectives

This thesis focuses on the signal processing algorithms for MI-BCI and SSVEP-BCI. The objectives of this thesis are to address the following key issues.

1. Removal of Ocular artifacts from single-channel EEG signals and improve signal to noise ratio of EEG signals.

2. Feature extraction using time, frequency, and phase analysis of MI-EEG signals and selecting relevant features to enhance the classification performance of MI signals.

3. MI-EEG spectral-spatial feature optimization and improve EEG filtering techniques.

    i. Frequency band optimization in common spatial patterns.

    ii. Adequate selection of filtering methods.

4. Simultaneous optimization of time window and frequency band for Multi-View MI-EEG classification.

5. Improve Recognition Rate of SSVEP in Real-Time to identify idle state, i.e., when the subject is not targeting any frequency.