REALIZATION OF A CUE BASED MOTOR IMAGERY BRAIN COMPUTER INTERFACE WITH ITS POTENTIAL APPLICATION TO A WHEELCHAIR

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REALIZATION OF A CUE BASED MOTOR IMAGERY BRAIN COMPUTER INTERFACE WITH ITS POTENTIAL APPLICATION TO A WHEELCHAIR

submitted by **BERNA AKINCI** in partial fulfillment of the requirements for the degree of **Master of Science in Electrical and Electronics Engineering, Middle East Technical University** by,

Prof. Dr. Canan Özgen
Dean, Graduate School of **Natural and Applied Sciences** _______________

Prof. Dr. İsmet Erkmen
Head of Department, **Electrical and Electronics Engineering** _______________

Prof. Dr. Nevzat Güneri Gençer
Supervisor, **Electrical and Electronics Engineering, METU** _______________

Examining Committee Members:

Prof. Dr. Murat Eyüboğlu
Electrical and Electronics Engineering, METU _______________

Prof. Dr. Nevzat Güneri Gençer
Electrical and Electronics Engineering, METU _______________

Prof. Dr. Uğur Halıcı
Electrical and Electronics Engineering, METU _______________

Assist. Prof. Dr. Yeşim Serinağaoğlu
Electrical and Electronics Engineering, METU _______________

Assoc. Prof. Dr. Süha Yağcıoğlu
Biophysics Dept., Faculty of Medicine, Hacettepe University _______________

Date: 14.09.2010

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

Name, Last name: Berna Akıncı

Signature :

ABSTRACT

REALIZATION OF A CUE BASED MOTOR IMAGERY BRAIN COMPUTER INTERFACE WITH ITS POTENTIAL APPLICATION TO A WHEELCHAIR

Akıncı, Berna

M.S., Department of Electrical and Electronics Engineering

Supervisor: Prof. Dr. Nevzat Güneri Gençer

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This thesis study focuses on the realization of an online cue based *Motor Imagery* (MI) Brain Computer Interface (BCI). For this purpose, some signal processing and classification methods are investigated. Specifically, several time-spatial-frequency methods, namely the Short Time Fourier Transform (STFT), Common Spatial Frequency Patterns (CSFP) and the Morlet Transform (MT) are implemented on a 2-class MI BCI system. Distinction Sensitive Learning Vector Quantization (DSLVQ) method is used as a feature selection method. The performance of these methodologies is evaluated with the linear and nonlinear Support Vector Machines (SVM), Multilayer Perceptron (MLP) and Naive Bayesian (NB) classifiers. The methodologies are tested on BCI Competition IV dataset IIb and an average kappa value of 0.45 is obtained on the dataset. According to the classification results, the algorithms presented here obtain the 4^{th} level in the competition as compared to the other algorithms in the competition.

Offline experiments are performed in METU Brain Research Laboratories and Hacettepe Biophysics Department on two subjects with the original cue-based MI BCI paradigm. Average prediction accuracy of the methods on a 2-class BCI is evaluated to be 76.26% in these datasets. Furthermore, two online BCI applications are developed: the ping-pong game and the electrical wheelchair control. For these applications, average classification accuracy is found to be 70%.

During the offline experiments, the performance of the developed system is observed to be highly dependent on the subject training and experience. According to the results, the EEG channels P3 and P4, which are considered to be irrelevant with the motor imagination, provided the best classification performance on the offline experiments. Regarding the observations on the experiments, this process is related to the stimulation mechanism in the cue based applications and consequent visual evoking effects on the subjects.

Keywords: Brain Computer Interface, BCI, Wheelchair Application, Movement Imagination, Event Related Desynchronization - Synchronization (ERD - ERS), Electroencephalography, EEG, Short Time Fourier Transform, Common Spatial Frequency Patterns, Morlet Transform, Pattern Recognition, Distinction Sensitive Learning Vector Quantization, Support Vector Machines, Multilayer Perceptron, Bayesian Classification.

ÖZ

İPUCU TABANLI HAREKET DÜŞÜNSEL BEYİN BİLGİSAYAR ARAYÜZÜNÜN GERÇEKLEŞTİRİLMESİ VE POTANSİYEL TEKERLEKLİ SANDALYE UYGULAMASI

Akıncı, Berna
Yüksek Lisans, Elektrik-Elektronik Mühendisliği Bölümü
Tez Yöneticisi: Prof. Dr. Nevzat Güneri Gençer

Eylül 2010, 140 sayfa

Bu tez çalışması, ipucu tabanlı *hareket düşüncesine* (HD) dayanan çevrimiçi bir Beyin Bilgisayar Arayüzü (BBA) sisteminin gerçekleştirilmesine odaklanmıştır. Bu amaçla, bazı sinyal işleme ve sınıflandırma yöntemleri incelenmiştir. Özellikle, Kısa Süreli Fourier Dönüşümü (KSFD), Ortak Uzamsal Frekans Örüntüleri (OUFÖ), ve Morlet Dönüşümü gibi bazı zaman-uzay-frekans yöntemleri 2-sınıflı HD BBA sistemi üzerinde uygulanmıştır. Öznitelik seçme yöntemi olarak Karakteristik Duyarlı Öğrenmeli Vektör Kuantalama (KDÖVK) algoritması kullanılmıştır. Bu yöntemlerin başarısı, doğrusal ve doğrusal olmayan Destek Vektör Makinaları (DVM), Çok Katmanlı Geriye Yayılma Algoritması (ÇKGYA) ve Naif Bayes (NB) sınıflandırıcıları ile değerlendirilmiştir. Yöntemler, 4. BBA Yarışması veri kümesi IIb üzerinde denenmiş ve 0.45'lik bir kappa değeri elde edilmiştir. Sınıflandırma sonuçlarına göre, işlenen yöntemler, yarışmadaki 4. başarılı sonucu vermektedir.

ODTÜ Beyin Araştırmaları ve Hacettepe Biyofizik Bölümü Laboratuarlarında iki denek üzerinde, özgün işaret tabanlı HD BBA paradigmaları ile çevrimdışı deneyler gerçekleştirilmiştir. Bu veri kümelerinde, yöntemlerin 2 sınıflı BBA üzerindeki ortalama tahmin başarısı %76.26 olarak hesaplanmıştır. Bunların yanı sıra, iki adet çevrimiçi BBA uygulaması geliştirilmiştir: ping-pong oyunu ve tekerlekli sandalye kontrol uygulaması. Bu uygulamalardaki ortalama sınıflandırma başarısı %70 olarak ölçülmüştür.

Yapılan deneylerde, BBA sistemlerinin performansının, deneklerin uygulamaya göre eğitimi ve bu uygulamalardaki tecrübelerine oldukça bağlı olduğu gözlemlenmiştir. Deney sonuçlarına göre, literatürde hareket düşüncesi ile ilgisi olmadığı kabul edilen P3 ve P4 EEG kanalları, çevrimdışı veri kümelerinde en iyi sınıflandırma başarısını göstermiştir. Bu durum, deneylerdeki gözlemler ele alındığında, işaret tabanlı BBA uygulamalarındaki uyarma ve bunun sonucunda deneklerde oluşan görsel uyarılma etkisi ile bağıntılanmaktadır.

Anahtar Sözcükler: Beyin Bilgisayar Arayüzü, BBA, Tekerlekli Sandalye Uygulaması, Hareket Düşüncesi, Olay İlişkili Desenkronizasyon - Senkronizasyon (OİD – OİS), Elektroensefalografi, EEG, Kısa Süreli Fourier Dönüşümü, Ortak Uzamsal Frekans Örüntüleri, Morlet Dönüşümü, Örüntü Algılama, Karakteristik Duyarlı Öğrenmeli Vektör Kuantalama, Destek Vektör Makinaları, Çok Katmanlı Geriye Yayılma Algoritması, Bayes Sınıfladırıcıları.

To my Family

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CHAPTER 1

INTRODUCTION

The human being is special among all living things because of its superior skills to other living kinds. Communication is one of these features which enables people to interact with each other and express themselves using speech and body language skills. However, this is not the case for all of the people. There are fatal diseases like Amyotrophic Lateral Sclerosis (ALS), brainstem stroke and multiple sclerosis, causing the condition termed as locked-in-syndrome which results in loss of ability in controlling the voluntary muscles. In this condition, the subject is conscious and the brain works properly, however the movement commands are not transmitted through the body limbs. In other words, the subject is aware of everything going around, but is not able to move any part of the body.

Brain–computer interface (BCI) is a developing technology based on the understanding and interpretation of the brain activity. It uses the fact that different intentions correspond to different patterns in the brain, even if they are not realized by the subject. BCI systems try to define some relationship between the brain activity and these intentions and then realize the intention without the contribution of the body. Being an alternative communication way, BCI systems produce a command for an external device from the acquired brain signals by signal processing and classification methods. The technology can be considered to be meaningful for severe motor disabled patients, since they are able to meet the main needs of the living with this technology.

BCI studies can be grouped under three titles, first of which is the high quality signal acquisition. Since the measurement of brain signals is an important step, different techniques employing invasive or noninvasive methods have been investigated [14]. The second one is the signal processing and pattern recognition, which are used for analysis and interpretation of the brain signals. Beyond all these techniques, it is necessary to understand the underlying functions of the brain and relate them with the cognitive activity. For this reason, neuroscience is the third branch of the BCI studies.

Development of BCI systems has led to further studies improving the success of these systems. Considering the needs of the patients, in order to adapt the BCI technology to daily life use, it is highly necessary to develop accurate and practical systems. For this reason, current studies focus on enhancing the quality of the acquired brain signals and investigating new signal processing and classification algorithms. In order to increase the accuracy and the speed of these systems, it is aimed to find the optimum algorithms for these applications and extend the capabilities of this technology by introducing new applications.

One can find various application areas of BCI as it is an alternative communication method between the computer and the subject. However, the priority of the studies is mainly on the biomedical use. There are already existing BCI applications like wheelchair control, neuroprosthetic robotic arms, spelling applications, intelligent house control systems and simple cursor control based game applications which are specifically designed for disabled people. Nevertheless, the fundamental objective is to develop more useful systems and new ideas for the disabled people to make their life easier.

1.1 Scope of the Thesis

This study focuses on one type of BCI system which is based on motor imagination. In this BCI system, movement intentions are classified according to the limbs they correspond. The result of the classification can be used as a command in several applications like controlling a mobile object.

In the scope of this thesis, it is aimed to design online BCI applications based on left and right hand movement imagination. For this purpose, two 2-class BCI applications are developed. One of these is a ping-pong like game to be played on a computer in which the player either controls the ball or the rackets. The other one is the wheelchair application, the control of which can be performed in either forward or backwards. In these two applications, the classification output is designed to be almost real-time.

Since the implementation of an online system requires both high accuracy and speed; the thesis primarily focuses on finding simple but effective methods providing more accurate classification in shorter time. For this purpose, several signal processing and classification methods in the literature are applied to the MI BCI paradigm. The performances of these methods are first evaluated in publicly available BCI datasets [2] and an online BCI system design is performed afterwards.

For the designed BCI applications, Electroencephalography (EEG) is preferred for signal acquisition due to its ease of use and noninvasive application procedure. Therefore, the study also includes the integration of the aforementioned applications with the existing BCI system developed in METU Brain Research Laboratories.

1.2 Outline of the Thesis

The thesis starts with two introductory chapters explaining the BCI research and technology. Chapter 2 provides a brief introduction to BCI systems discussing the building blocks of a BCI system. Signal acquisition methods, the neurophysiologic background and common procedures employed in these systems are presented in this chapter.

In chapter 3, *Motor Imagery* (MI) BCI systems are introduced explaining the motor activity and its use in BCI systems. Furthermore, a review of the signal enhancement, feature extraction and classification methods are presented in this chapter.

Chapter 4 is reserved to the explanation of the methodologies used in this study. As signal processing and feature extraction algorithms, the Short Time Fourier Transform (STFT), Common Spatial Frequency Patterns (CSFP), Morlet Transform and Distinction Sensitive Learning Vector Quantization (DSLVQ) methods are introduced in here. Furthermore, a brief explanation of linear Support Vector Machines (SVMs) is given as it is used as the main classification tool for the online BCI system.

The designed BCI applications are presented in chapter 5, providing necessary information on the equipment used and the integration of the developed applications with an existing BCI system. The adaptation of the designed BCI system to a wheelchair application is explained also in this chapter with the necessary modifications for software and hardware parts.

Chapter 6 provides the results of the algorithms on one of the BCI Competition datasets and online and offline MI BCI experiments performed in this study. The evaluation criteria for these systems are defined prior to the results.

Finally, in chapter 7, a summary of the study is presented providing the performance evaluation of the methods, emphasizing the observations obtained from the experiments and conclusions to these. A section of future studies is also included in this chapter.

CHAPTER 2

INTRODUCTION TO BRAIN COMPUTER INTERFACES

As explained in chapter 1, Brain Computer Interface (BCI) can be described to be an alternative way of communication in which there is no need for any perceptible body sign such as speech or movement. In this system, the communication is provided via brain signals. Brain is the control and command center of all voluntary / involuntary functions in the body. Therefore, it has a deep and complex structure where complete decoding of such functions seems to be nearly impossible. However, today, activations in the brain corresponding to several voluntary body functions can be observed by different techniques which help to understand the basic processes of this complex structure. In BCI studies, it is aimed to analyze and interpret the electrical brain signals and convert them into commands to be fed to an external system. Being a developing technology, BCI systems can find several application areas from entertainment to military use but the prior aim is to help the locked-in people by providing an alternative way of communication with the outside world.

In the scope of the BCI studies, developed systems are highly dependent on the brain activity measurement tools. This means that proper and accurate acquisition of brain signals is the essential requirement of the BCI system at the very beginning step. In further stages, collected brain signals are analyzed with several signal processing and classification techniques, and are interpreted as a command for an external device. In Figure 2-1, the main blocks of a BCI system flow is visualized.

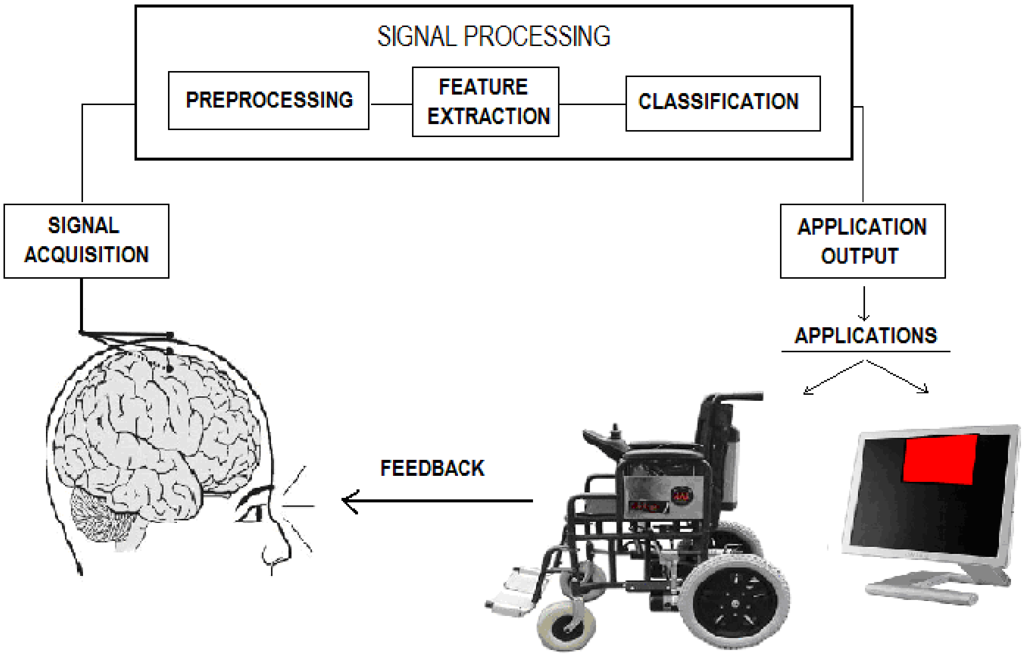

Figure 2-1: The building blocks of a BCI system (modified from [45]). The brain signals acquired from the signal acquisition phase is enhanced and interpreted in the signal processing stage. Finally, the classification output is fed to the BCI application which can be a computer based application or a wheelchair device.

In this chapter, a general review of the main concepts in a BCI system is given. First of all, commonly used signal acquisition methods and neurophysiologic background of the systems are explained in detail. Then the processing steps of BCI systems are clarified with the present applications.

2.1 Signal Acquisition

In order to communicate via brain signals, a BCI system has to measure the brain activity accurately. For this purpose, there are different ways of signal acquisition from electrical to magnetic, invasive to noninvasive, etc. Each technology has its own particular advantages and limitations such as signal quality, cost, ease of use and harm to the user. Depending on the application or purpose, a proper method should be chosen taking these features into account. In this section, these attributes are explained and compared with each other for Electroencephalography (EEG), Magnetoencephalography (MEEG), Electrocorticography (EcoG), and some other brain activity measurement methods used in BCI.

2.1.1 Electroencephalography (EEG)

Electroencephalography is the most common acquisition method used in BCI systems [76]. In this method, the electrical activity of the brain is measured by the electrodes placed on the scalp, i.e. the skin surface of the head. Being non-invasive, portable and relatively cheap, it is used in most of the BCI studies. In order to understand how EEG measures the electrical activity of the brain, it is necessary to look over the structure and functioning of the brain.

EEG reflects the correlated synaptic activity caused by cortical neurons located radial to the scalp. Therefore, it measures the summation of the synchronous activity of thousands of neurons which are close to the corresponding EEG electrode [3].

Amplitude of the brain signals on the scalp surface is on the order of hundreds of microvolts. Thus it is hard to detect these with usual data acquisition systems other than biomedical instrumentation. Furthermore, during the amplification stage in the instrumentation, they can easily be affected by the external disturbances like 50-60 Hz mains supply noise, the movement of the electrodes in contact with the scalp or even by the internal factors such as eye blink, muscular and cardiac artifacts. A high quality EEG system amplifies the related brain signals while suppressing these disturbances. In order to decrease the effects of disturbances; first of all, contact area between the scalp and electrodes are filled with a conductive gel to reduce the contact impedance. After that, the signal obtained from the scalp is subjected to an analog filter in the amplification part to decrease the power line noise and unwanted frequencies. Final corrections may be performed digitally in the signal processing part.

2.1.2 Electrocorticography (ECoG) and Microelectrodes

Electrocorticography and microelectrodes are the invasive techniques in which an array of electrodes is placed surgically beneath the skull. In electrocorticography, the electrodes are placed on the cortex whereas microelectrodes are placed underneath the cortex. Being closer to the source of the brain activity, the signal to noise ratio is higher due to both higher signal amplitude and less contamination with artifacts.

On the other hand, a medical surgery is required to implant the electrodes inside the brain at some risk to the patient. Finding the suitable biocompatible material and possibility of infection are the main problems of this technique. However, advantages such as improved signal quality, less signal processing, better and faster results, and ease of use make this technology a suitable alternative to EEG in BCI applications [4].

2.1.3 Magnetoencephalography (MEG)

Magnetoencephalography is a non-invasive acquisition technique which measures the magnetic field strength caused by the electrical currents through the neurons in the cortex. It has a temporal resolution close to that of EEG. Because of the low amplitude of the magnetic signals, it is required to use the MEG scanners in a magnetically shielded room for isolation from the earth’s magnetic field. Beside that fact, MEG scanners are expensive and non-portable which makes them unpractical for BCI use.

2.1.4 Other Systems

Near-infrared spectrophotometry (NIRS), positron emission tomography (PET) and functional magnetic resonance imaging (fMRI) are the other techniques used to measure the brain activity. Since PET and fMRI are huge, unportable and expensive systems, they are not practical in BCI use but had advantages in the early stages of BCI determining the informative patterns of brain [5].

2.2 Neurophysiologic Signals

Main idea in BCI systems is the characterization and discrimination of different neurophysiologic signals. There are two categories of neurophysiologic signals, one of which is the event-related potentials (ERPs) and the other one is the oscillatory brain activity. As a simple example, when an audivisual stimulus is presented to the subject, the perception of the subject causes a change in the brain signals. These changes are termed as ERPs. In the second one, when the subject performs a mental task, such as imagination of hand movement, the changes in the oscillatory activity of the brain can be detected. The types of signals resulting from a stimuli are explained in section 2.2.1 and the signals resulting from concentration on the mental tasks are given in section 2.2.2.

2.2.1 Event Related Potentials (ERPs)

ERPs are changes in the brain electrical signals with specific characteristics and time locked to the external stimuli. The presented stimulus usually includes auditory or visual content (or both). ERP signals have specific characteristics that are identifiable in everybody with the presentation of the focused stimulus and, thus, can be utilized successfully in a BCI system [79], [80]. In addition, ERP-based BCI systems are more straight-forward to use. Most popular types of ERP-based systems and applications are given below.

2.2.1.1 P300

P300 is a positive peak in the EEG, observed approximately 300ms after the stimulus presentation. A typical pattern of P300 response can be seen in Figure 2-2.

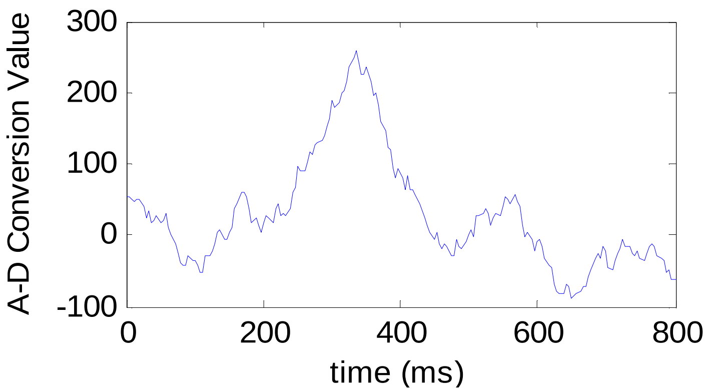

Figure 2-2: A typical P300 signal. A peak occurs nearly 300ms after the presentation of the target stimulus [6]

In P300 applications, there are two types of stimulus, one of which is the target stimulus (odd) and the other is the non-target stimulus (frequent). These stimuli are given in a random sequence and the target stimulus is presented more rarely as compared to the non-target stimulus. In the P300 based applications, subjects are asked to concentrate on each target stimulus and ignore the non-target stimulus. During the concentration, the target-stimulus elicits the P300 response, from which one can identify the time information of the target stimulus by recognizing the P300 pattern from the EEG. In brief, as each stimulus is presented in different time instants, target items can be classified using the time information of the P300 occurrence.

The use of P300 as a tool in BCI systems has the main advantage that P300 is not a subject-dependent response and it can be observed in everybody. Thus, there is no extensive training need for the users which makes this application practical in BCI [79], [81].

2.2.1.2 Steady-State Visual Evoked Potential (SSVEP)

Steady-State Visual Evoked Potentials (SSVEPs) are oscillatory responses of the brain to visual stimulations with specific frequencies. These responses are more detectable in the occipital-parietal regions of the brain. When the subject is excited by a visual stimulus in the range of 3.5 Hz to 75 Hz, the brain generates a response at the same frequency, harmonics and sub harmonics of the stimulus [9]. In SSVEP based BCI systems, several stimuli flickering at different frequencies are displayed on a computer screen. These stimuli are presented simultaneously so that different targets can be assigned to these frequencies. When the subject focuses on one target, corresponding oscillatory signals are quantifiable in the frequency domain and the target (where the subject is looking at) can be recognized by the processing methods [7], [8].

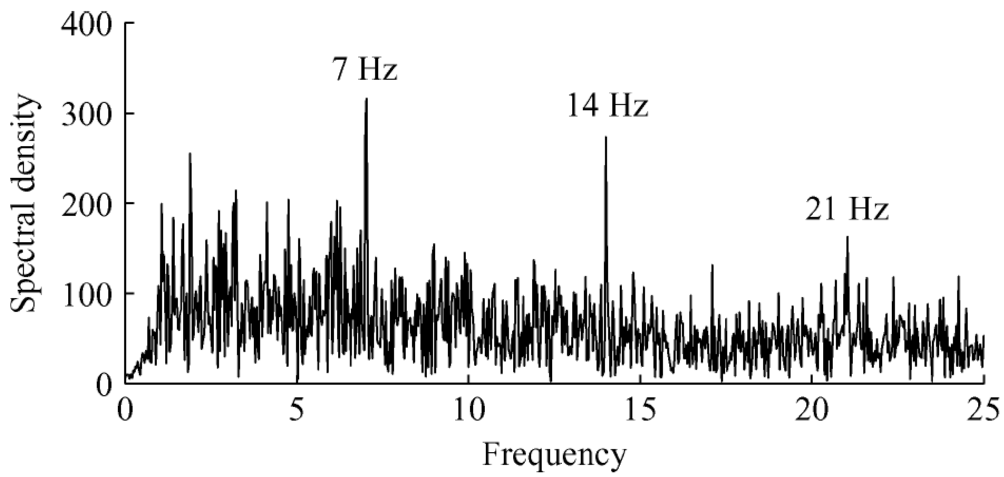

Figure 2-3: Power spectrum of EEG when the subject is stimulated with a flickering light of 7 Hz. One can note that the response also includes the harmonics at 14 Hz and 21 Hz [64].

Being subject-independent systems, both SSVEP and P300-based systems work for all people with the same structure which removes the requirement of subject training. Thus, it is easy to adapt the system to a new user and the user to the system as well. Beside this advantage, the major drawback of the ERP based BCIs is the necessity of stimulation. This requires a proper eye control to choose the target stimulus. The patients in the late stages of ALS or other locked-in situations may lose the control of their eyes which prevents them focusing on the targets properly.

2.2.2 Oscillatory Brain Activity

Oscillatory EEG activity is composed of several frequency band oscillations in particular regions of the brain. The behavior of these oscillations depends on the subject's state such as being awake or in sleep (or in concentration or being idle). These oscillations are usually grouped under several frequency bands namely the delta-δ band, the theta-θ band, the alpha-α band, the beta-β band, the gamma-γ band and the mu-μ rhythm [65]:

- Delta waves are the brainwaves of the lowest frequency (0-4 Hz) and indicate the unconscious state of the subject. They are usually observed during a deep dreamless sleep.

- Theta waves (4-7 Hz) represent the subconscious state. They can be observed during dream sleep (REM sleep), meditation, during peak experiences and creative states. These waves are common in children and people in very spiritual states.

- Gamma waves are the fastest signals in the brain (30-100 Hz) and they are seen in the states of peak performance (both physical and mental), high focus and concentration, but also with anxiety, schizophrenia and hyperactivity.

- Alpha waves are seen in the range of 8-12 Hz when the subject is in a relaxed wakeful state mostly with eyes closed such as before sleeping or daydreaming. These waves are also correlated with tranquility.

- Mu-rhythm is in the range of alpha activity (~10 Hz) which is usually related with the imagination or visualization of the movement. The name comes from the Latin character due to its shape being similar to the μ symbol.

- Beta waves are usually related to the consciousness in the wakeful state, attention and analytical thinking. They are observed in 13-30 Hz frequency range [65].

According to the mental state of the subject, there are observable changes in the amplitude of particular waves in several regions of the brain. In BCI applications, movement imagination is used to observe the changes in mu and beta band activity. According to the temporal, spectral and spatial changes in the mu rhythm and the beta band, the type of imagination is analyzed via several signal processing techniques. In these applications (termed as Motor Imagery BCI systems), the main concern is to identify and classify the energy variations in the mu and beta band over the motor regions of the brain. Detailed explanation will be given in section 3.1.

Being a subject-dependent system, movement imagery BCI systems have some disadvantages. The major problem is the subject training period in which the subject learns how to perform the imagination of the movement. Meanwhile, the system training is performed in which the system adapts itself to the subject's way of thinking. In other words, the system and subject should experience this mutual training phase in order to use the motor imagery BCI. And the problem comes from the fact that, these training durations may take several months until a successful performance is achieved.

2.3 Processes in BCI Systems

In order to run a BCI system, the neurophysiologic signals have to be classified. To perform such discrimination, a classification model has to be constructed. Therefore, the very first step is to acquire a labeled data in which the EEG is marked with some external labels providing time information for several imagination related tasks. After signal enhancement (improving the signal quality by filtering, preprocessing etc.), a learning algorithm is run on the data which performs a mapping from signals to classes. This mapping process consists of sub processes such as feature extraction, feature selection and classification.

2.3.1 Feature Extraction

Feature extraction is a mapping providing the informative features specific to the class attributes. To achieve this, brain patterns can be analyzed in different manners such as temporal, spectral and spatial. The features to be extracted should be appropriate for the application. For instance, for P300 studies, temporal features are meaningful whereas spectral features are discriminative for oscillatory activity based applications and spatial features are effective for nearly all applications.

2.3.2 Feature Selection

Feature selection is basically a transformation of the raw signal (or pre-filtered signal) to a new structure to perform the classification task easily. In other words, the goal is to remove unnecessary information from the input signals, at the same time retaining the discriminative information. In BCI systems, feature selection is essential for finding the most informative features to be used in classification. This is necessary especially in the case of having high dimensional training data because it reduces the dimension of the feature space resulting in reduction of complexity. This also provides higher classification accuracy and time saving. It is shown that with feature selection, classification algorithms perform better than the use of all features in the classification [24], [25].

2.3.3 Classification

Obtained feature set is inserted into a classification algorithm in order to characterize each class data and find the discriminative attributes. First of all, an observation set given with the labels is used to construct a classification model. After that, the constructed classification model is used to classify the unlabeled data. Classification algorithm can be chosen as linear or nonlinear according to the complexity of the problem. For motor imagery BCI problems, it is reported that linear algorithms are more successful than the nonlinear classification methods [10].

2.4 BCI Applications

The most popular P300 based BCI application is the “Spelling Paradigm” introduced by Farnell and Donchin in 1988 [11]. In this application, a matrix of characters is presented to the subject on a computer screen whose rows and columns constitute the visual stimulators. The subject is asked to focus attention on the characters that will be spelled and the words are constructed by predicting each target character. Intensification of the row or column containing the focused character constitutes the target stimuli and evokes a P300 potential in the brain while all other flashes of rows and columns constitute the non-target stimuli and do not evoke a P300. According to this information, chosen character is found and displayed on the screen as a feedback to the user.

As an SSVEP-based BCI application, the roll position of a flight simulator was successfully realized by using two flickering light sources [26]. Also in [27], 13 flickering light sources are employed to develop a multi class BCI application.

Most popular motor imagery based BCI applications are the thought-controlled wheelchair, neuroprothesis with robotic arm, the cursor control on the computer screen and some games like ping-pong and walking in a virtual environment [77]. In these systems, the external device performs the movement that the subject imagines after processing the EEG records. In these applications, the distinguishable movement imagination types are usually restricted to the imagination of main body movements such as right hand, left hand, foot, finger or tongue movements.

CHAPTER 3

MOTOR IMAGERY BCI SYSTEMS

Voluntary movement is one of the most essential needs of human being, lack of which degrades the life quality considerably. Without movement, it is not possible to walk or speak which limits communication and interaction with the others.

Motor imagery BCI systems aim to provide movement without controlling the muscles. The system understands the type of movement the subject intends, only using his/her brain activity and performs the action on behalf of the subject. For this purpose, it is necessary to understand the neurophysiologic phenomena underlying the movement intention and realization.

During normal operation of the brain, there are oscillations in different frequencies which are explained in section 2.2.2. The oscillatory EEG signals in the sensorimotor areas provide understanding on how the movements are generated and controlled in the brain. It is observed that when the subject moves any limb, the oscillations in the mu rhythm and the beta band are destroyed in multiple motor areas of the brain [51]. Furthermore, it is proved that the same change can be seen when the subject imagines the movement [12]. Using this fact, imagined movement can be predicted by interpreting the variations in different areas without performing the actual movement.

3.1 Motor Activity

Motor activity is the neuronal activity observed in the brain as a result of voluntary movement. The activity caused by the movement imagination is termed as *Motor Imagery Activity*. For instance, the changes in the brain signals during right hand movement are also observed when the subject imagines that he moves his right hand [13]. Using this information, it can be concluded that movement intention of a subject can be recognized without execution. In order to achieve this, the functioning of the brain should be investigated during voluntary movement.

Voluntary movement can be categorized into two groups according to the stimulation type of the movement: If the subject does movement whenever s/he wants, it is termed as self-paced (internally-paced). If the timing is performed by an external system and the subject performs movement according to the stimulation signal, the movement is specified as cue-based (externally-paced). For the cue-based case, beside the preparation and execution of the movement, there are additional effects of expectation and perception of the presented audio or visual stimulus [14].

Movement related activity is a part of the oscillatory activity of the brain. As mentioned in section 2.2.2, these oscillations are composed of several frequency bands. The mu rhythm and the beta band carry the most informative context about the movement and are named as sensorimotor rhythms since they are usually better observed in sensorimotor cortex of the brain.

The brain operates via the electrical transmission among the neural networks which consists of several hundreds of neuronal elements. In appropriate conditions, these neuronal elements work in synchrony and the oscillatory behavior is generally related with this synchronous behavior [19].

Electrical activity at the neuron level is on the order of millivolts and it reaches to a macroscopic level in the measurement system (EEG, ECoG, MEG etc.) when the effects of all neurons are combined[1]. The measured activity is mostly the cortical activity since the cortex part of the brain is the closest surface through the scalp. Therefore, the inner region activities are not directly observable, so they have very small contributions to the scalp measurements. Another factor in measurability is the synchrony among the neurons. That is, when the neurons meet in synchrony, the power of the signal in a specific band increases which provides easy detection of those activities from the scalp.

The motor activity can be analyzed in 3 domains, namely the spectral, temporal and spatial domains. In the spectral and the temporal sense, the behavior of the oscillatory activity, and hence the sensorimotor rhythms, can be evaluated.

3.1.1 Spectral Properties

The change in synchronous activity is a spectral concept. It is shown that the preparation, execution and imagination of a movement can cause loss of synchrony over the sensorimotor areas, mostly in the alpha band (mu rhythm) and also in beta band. The loss in synchrony results in a decrease in the signal power which is termed as event-related desynchronization (ERD) [28]. After the movement, the signal recovers itself by providing synchrony again and this ends up with amplitude increase in the signal power. This action is termed as event-related synchronization (ERS) [29]. Evolution of the ERD and ERS patterns can be observed from the EEG data shown in Figure 3-1.

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[1] Although the measurement system such as EEG measures the macroscopic activity of multiple neurons, the amplitude of the signals may degrade due to other effects like volume conduction (the amplitude is on the order of microvolts). Therefore, one should not think that the measured activity will be higher when one uses a macroscopic activity measurement tool.

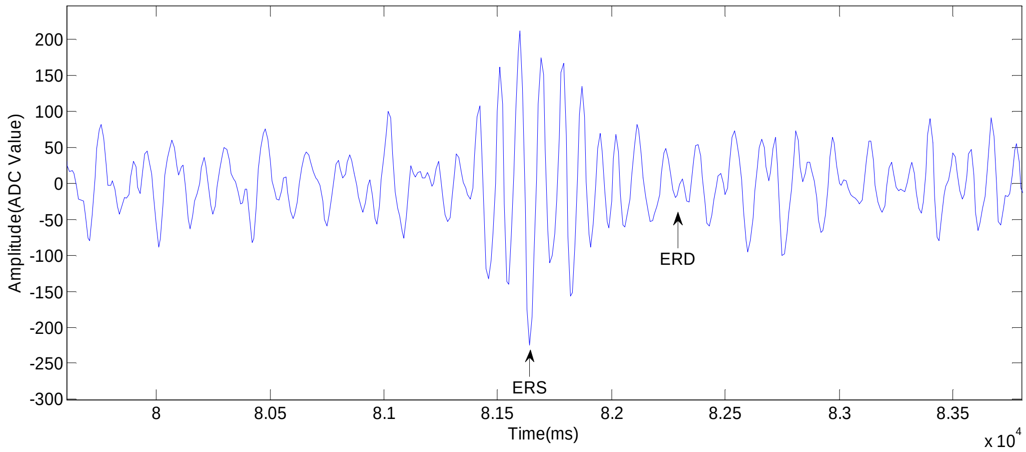


Figure 3-1: The formation of the ERD and ERS patterns

3.1.2 Spatial Properties

Brain is the control center of the body and each control is realized from a particular region in the brain or a combination of these regions. The brain regions that participate during the motor activity can be seen in Figure 3-2.

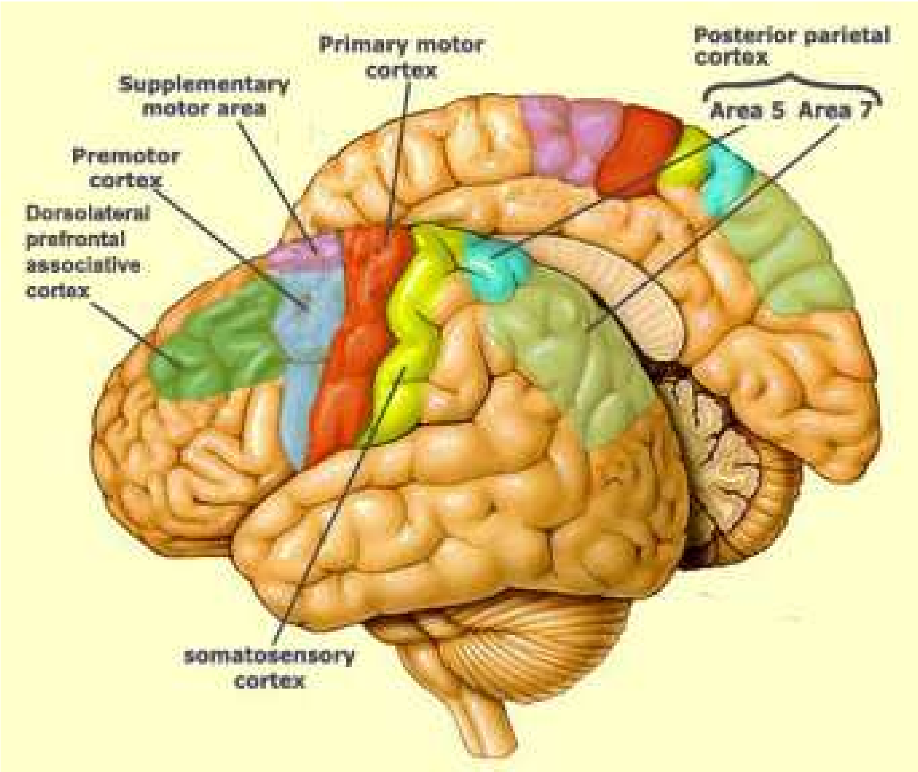


Figure 3-2: The functional regions in the brain [21]

The functions of the regions can be summarized as given below [21]:

- The primary motor cortex is related with the muscle contractions in the body.
- The premotor cortex optimizes the body position that the motor cortex is directing, for any given movement.
- The supplementary motor area is effective on the planning and initiation of movements.
- The somatosensory motor cortex is responsible for reception and reaction tasks.

- The posterior parietal cortex is correlated with the voluntary movements in terms of assessment and decision. The parietal cortex receives somatosensory, proprioreceptive (related with body position), and visual inputs, and then uses them to determine the positions. It also plays role in movement preparation. In the posterior parietal cortex, there are two particular areas. Area 5 receives information from somatosensory areas and Area 7 is the center for processing of visual stimulus [21] (Figure 3-2).

3.1.3 Temporal Properties

Timing of ERD and ERS actions together with the localization are important parameters in detection of the MI patterns. During voluntary movement, there are several phases in which ERD or ERS is observed in particular regions of brain cortex. Preparation for the movement, which is in average 2 seconds before the execution, causes mu and beta ERD in contralateral hemisphere whereas execution results in symmetric mu and beta ERD in both contralateral (more dominant) and ipsilateral sides [66]. After the movement is terminated, the recovery from ERD occurs slowly in a few seconds in mu band, relatively quickly in beta band resulting ERS in the contralateral side. Here, the most significant property is the ERD pattern which occurs just before the movement. Since contralateral ERD starts prior to the movement, even the movement is not executed; the imagination creates ERD due to the intention. This fact is the base for the motor imagery BCI systems. The timing of these motor activities is given with respect to time in Figure 3-3.

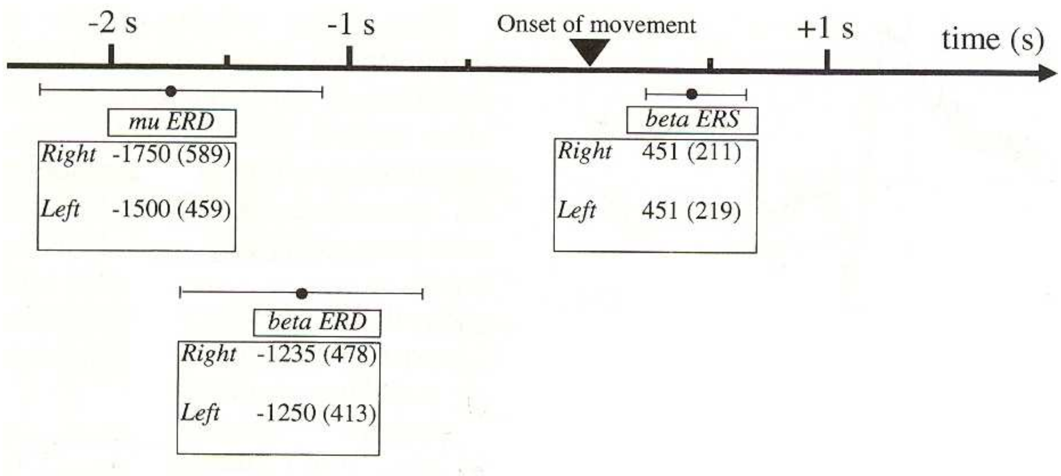


Figure 3-3: Mean (standard deviation) for timing of mu rhythm ERD, beta rhythm ERD and beta rhythm ERS [66].

3.2 Review of the methodologies

The very aim of BCI is to understand the patterns of brain activity and translate the commands for an external device. For this purpose, severel signal processing and classification methods have been used in previous BCI studies. In this section, a review of the common methodologies used in motor imagery BCI studies will be given.

3.2.1 Signal Enhancement

In EEG based BCI systems, preprocessing part is important since the brain signals acquired by EEG are in the level of microvolts and they are highly sensitive to internal and external distortions. Therefore, it is necessary to find a suitable preprocessing technique according to the acquisition system and number of electrodes.

First of all, there is a referencing stage in which the EEG channels are referenced with respect to a point other than the reference electrode used in the recording. Commonly used referencing methods in MI BCI studies are Surface Laplacian

(SL) and Common Average Referencing (CAR) which are spatially high pass filters [30]. For the later processing steps, Principal Component Analysis (PCA) and Independent Component Analysis (ICA) are widespread methods [31], [32]. They are used to solve the blind source separation problem in BCI studies. Common spatial Patterns (CSP) is another method which is again a spatial filtering method that finds a proper combination of spatial information coming from different electrodes based on the covariance among the signals [33].

3.2.2 Feature Extraction

Time and/or frequency methods are popular in BCI applications but frequency methods are widely preferred in motor imagery systems due to its simplicity in use and fast computation. Thus, spectral features have been used in several studies [20]. There are also studies that combine the temporal content with the spectral information forming the time-frequency (TF) analysis [20], [34], [35]. Short-Time Fourier Transform and Wavelet transformation are well-known TF method in motor imagery analysis [35].

Beside TF methods, parametric modelling such as Autoregressive (AR) and Adaptive Autoregressive (AAR) parameters is a common approach in BCI. With these parameters, the signal is expressed as a linear mathematical model in terms of time series [36].

3.2.3 Feature Selection

Principal Component Analysis (PCA) and Common Spatial Patterns (CSP) are also used in feature selection. They perform a linear transformation to find the characteristic of the input data contributing most to its variance [20]. Distinctive Sensitive Learning Vector Quantization is a classifier based feature selection algorithm which was first used by Flotzinger *et al* in 1994 for BCI studies [25]. Genetic Algorithms (GA) is another popular method which minimizes the number of the features to be used in the classification and maximizes the classification performance [25].

3.2.4 Classification

In classification, linear systems are more common in BCI since nonlinear systems have some parameters to adjust properly. However, in the case of having large or small amount of data, complex structures are better in characterization. In these cases, kernel-based and neural network based methods are preferred [20]. Kernel-based classifiers are linear classifiers but the feature space can be transformed to another space (Kernel) with nonlinear functions, thus the classification problem can be linearized. Support Vector Machines (SVM) is one of the Kernel-based classification methods and it is preferred for both linear and nonlinear classification problems [18]. The main idea of SVM is to find the separating hyperplane between two classes with maximum margin, so that it has a good generalization property [46]. It was applied for BCI research by Müller et al [47]. Another widespread kernel-based classifier is the Fisher Discriminant Analysis or Linear Discriminant Analysis (LDA). LDA tries to find the most dicriminative projection direction to have maximum distance between classes and minimum distance in classes. Schlögl et al used LDA to have a continuous output in time and amplitude in BCI systems [48].

Neural networks (NN) are also commonly used in BCI applications which are constituted by several artificial neurons creating a nonlinear decision structure [49]. Multilayer perceptron (MLP) is a popular NN method which is flexible in approximation of any continuous function with sufficient number of neurons. Linear Vector Quantization (LVQ) is another type of NN systems which is based on clustering of data into subgroups. Starting with Kalcher et al, it has been used in two many studies with modified versions such as k-Means and DSLVQ [20], [67].

CHAPTER 4

METHODOLOGIES USED IN THE STUDY

In movement imaginary action, the time instants that ERD and ERS occur are the temporal information whereas the desynchronization and synchronization concepts are spectral ones. The time and frequency characteristics of ERD/ERS are not unique; i.e., they may vary according to the subject or different imagery strategies can be developed by the subjects to induce ERD and ERS patterns [50]. In addition, the time and frequency characteristics of the mu and beta components can also vary such that the beta band shows faster response, whereas the mu band activity takes a few seconds to attenuate and recover [51]. In order to analyze whole these changes successfully, it is necessary to consider the temporal and spectral features together. For this purpose, the time frequency analysis method is preferred in the feature extraction stage of this study.

Applying the time frequency analysis on the EEG signals results in lots of temporal and spectral features. However, they are not all related with the performed motor imagery task. Using all of the features is not contributive to the classification process; but also it is misleading for a classifier to have too many correlated features. Also it is known that different subjects elicit different MI patterns [50]. Therefore, it is necessary to choose the relevant features according to the subject for successful results. For this purpose, Distinctive Sensitive Learning Vector Quantization (DSLVQ) method is used in this study, which finds the most discriminative features for the given classes and for the subject. In order to compare the results of DSLVQ, a simple search algorithm is constructed computing the accuracy for each frequency component.

Combining the spatial information in a proper way is also beneficial such that the channels do not participate equally in the motor imagery activation. For this reason, Common Spatial Frequency Patterns (CSFP), a modified algorithm of Common Spatial Patterns (CSP) is selected as a spatial filtering method. CSP combines the channel information in an optimal manner such that transformed features provide the maximum discrimination among the classes [33]. In addition to spatial features, CSFP considers the spectral features and optimize both of them [15].

After extraction and selection of the features, resulting data is classified with the Support Vector Machines (SVM). In this study, there are also other classification algorithms tried for comparison. All details about these methodologies are explained in this chapter.

4.1 Time-Frequency Analysis

TF analysis provides the time-varying spectral representation of the signal which corresponds to the power spectrum with respect to time. There are different ways to analyze the time-frequency content. One of these methods is the Short Time Fourier Transform (STFT). It is mainly preferred for the applications in this study due to its simplicity and practicality. Morlet Wavelet Transform is another popular method in BCI field which is used as the secondary TF method in this study.

4.1.1 Short Time Fourier Transform – STFT

The Fourier transform refers to the frequency domain representation of a time domain function. It describes which frequencies are present in the function, by decomposing the original function into oscillatory functions [53].

The point where the Fourier Transform is not sufficient is that it does not give any information on the time at which the frequency components occur. However, STFT can give information on the time resolution of the spectrum by analyzing the frequency response at different time instants.

The Short-Time Fourier Transform is really fundamental for analyzing the slowly time varying signals. Originally, it is a continuous-time analysis method due to the continuity of Fourier transform in time domain. Nevertheless, using the Fast Fourier Transform, signal processing systems based on STFT have become practical resulting in a wide application area [54].

4.1.1.1 Continuous-Time STFT

In the continuous-time case, the signal is multiplied by a moving fixed-length window function which is nonzero for a short period of time. Then the Fourier

Transform is applied within the window as the window is moved along the signal, resulting in a two-dimensional representation of the signal [53]. Mathematically, this is written as:

$$STFT\{x(t)\} \equiv X(\tau, w) = \int_{-\infty}^{\infty} x(t)w(t-\tau)e^{-jwt}\,dt \tag{4.1}$$

where $w(t)$ represents the window function, centered around zero and $x(t)$ is the signal to be transformed. $X(\tau,\omega)$ is the Fourier Transform of the windowed signal $x(t)w(t\text{-}\tau)$, which is a complex function representing the phase and magnitude of the signal over time and frequency.

4.1.1.2 Discrete-Time STFT

In the discrete time case, the signal to be transformed is segmented into overlapping intervals and in each interval Fourier transform is applied, resulting in a matrix which includes magnitude and phase for each point in time and frequency [53]. This can be expressed as:

$$STFT\{x[n]\} \equiv X(m, w) = \sum_{n=-\infty}^{\infty} x[n]w[n-m]e^{-jwn} \tag{4.2}$$

where $x[n]$ is the signal and $w[n]$ is the window. In this case, m is discrete and ω is continuous, but in practical applications, Fast Fourier Transform is used in the STFT analysis, so both variables are discrete and quantized.

$$X(m, w) = FFT_w(x[n]w[n-m]) = FFT_w(x \cdot SHIFT_m(w)) \tag{4.3}$$

where $X(m,w)$ is the FFT of windowed signal centered about time m. The overlapping percentage can be chosen and $w[n]$ can vary according to the application. Different windowing function types are applicable such as Rectangular, Hamming, Gaussian, Bartlett, Blackman, etc. For a rectangular windowing and 50% overlapping, STFT analysis can be visualized as in the Figure 4-1.

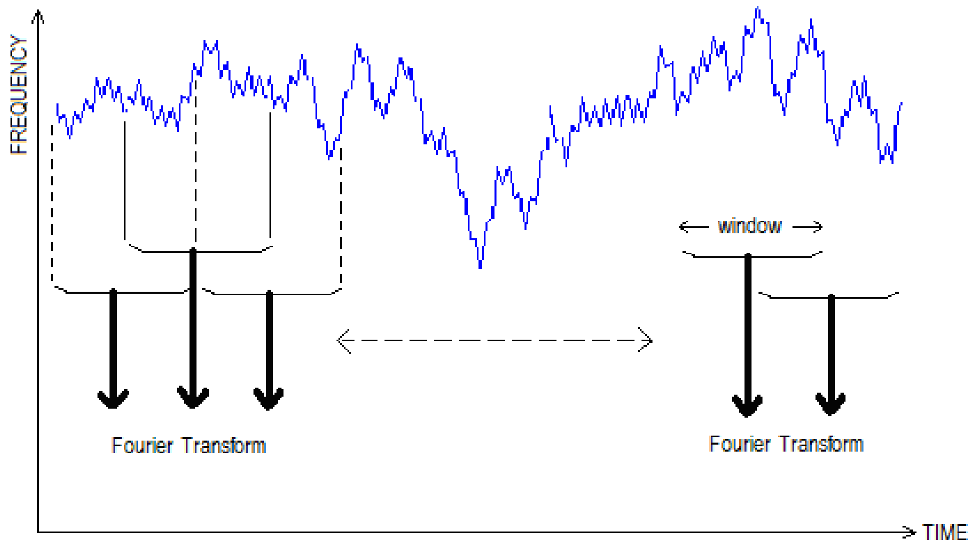


Figure 4-1: STFT method for rectangular windowing with 50% overlapping

In order to obtain the time-frequency spectrum, the power of the signal for each time instant for the specified frequency value should be calculated. Using the magnitude and phase values obtained from STFT of the signal, instantaneous spectrum is expressed as below:

$$spectrogram\{x(n)\} \equiv \left(\mathrm{Re}\{X(n,w)\}\right)^2 - \left(\mathrm{Im}\{X(n,w)\}\right)^2 \tag{4.4}$$

Spectrogram of a signal provides two-dimensional information each row of which indicates the power distribution of a frequency component with respect to time. So that, features to be used in the classification are extracted for any frequency value required and they are combined. The critical point is to know which frequencies are necessary for the best classification that can be achieved by feature selection.

4.1.2 Morlet Wavelet Transform

Fourier transform decomposes the signal into sinusoids. In a similar manner, Wavelet Transform is used to express the signal in terms of wavelets. In contrast with sinusoids, wavelets are localized in both the time and frequency domains [55] which are suitable for non-stationary signals such as EEG MI activity.

In order to extract both time and frequency domain features, STFT is offered as a simple and practical method. More realistic computation of these features can be done by Wavelet transform. As explained before, in STFT, sliding windows of fixed length are transformed to Fourier domain resulting in a fixed time-frequency resolution ratio. However, in wavelet transform, the width of the window varies as a function of frequency providing adaptive time-frequency resolution [55]. The continuous form of wavelet transform can be expressed by the following formula.

$$\gamma(s,\tau) = \int f(t)\psi^{*}_{s,\tau}(t)dt \tag{4.5}$$

Here, $f(t)$ is the signal to be decomposed into a set of wavelets $\psi_{s,\tau}(t)$. The variables s and τ correspond to scale and translation. The set of wavelets, *daughter wavelets,* are generated from a single basic wavelet, the so-called *mother wavelet,* by scaling and translation as following:

$$\psi_{s,\tau} = \frac{1}{\sqrt{s}}\psi\left(\frac{t-\tau}{s}\right) \tag{4.6}$$

There are several types of wavelet in different shapes. The wavelet to be used is selected according to the characteristic of the signal to be processed. Morlet is a kind of wavelet which has a Gaussian distribution in both time and frequency domain and it is suitable for investigating MI patterns [15]. The function of the Morlet wavelet $\psi(t)$ is given with the following expression:

$$\psi(x) = (e^{ik_0 x} - e^{-\frac{1}{2}k_0^2})e^{-\frac{1}{2}x^2} \tag{4.7}$$

where k_0 is the center frequency corresponding to the number of oscillations of the wavelet. A complex morlet wavelet with center frequency of 1 Hz can be seen in Figure 4-2.

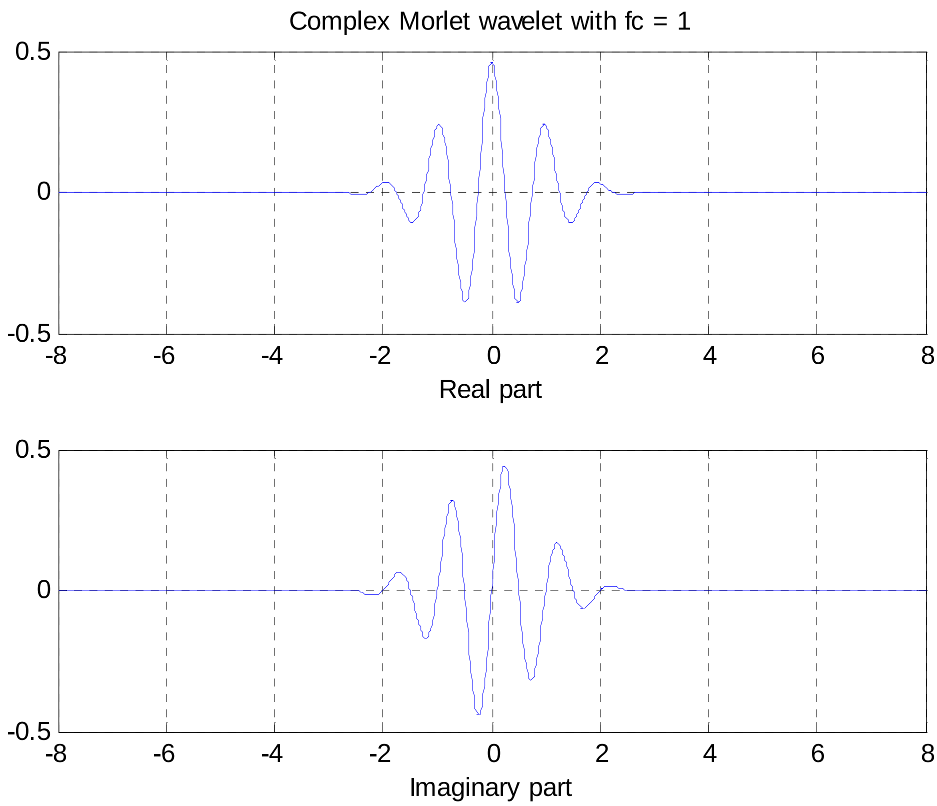


Figure 4-2: Real and imaginary part of a complex Morlet wavelet of 1Hz center frequency

The variance of the Morlet wavelet in frequency-domain is inversely proportional with the variance in the time-domain. These variances determine the time and frequency resolution of the wavelet transform which is the inner-product of the daughter wavelet with the signal.

4.2 Distinctive Sensitive Learning Vector Quantization - DSLVQ

DSLVQ is originally a classification method; however, it is used for feature selection in the MI BCI studies [25], [57]. It is applied to the frequency domain features to obtain effective frequencies for the subjects. It employs supervised learning while weighting the features. DSLVQ finds the most discriminative features for the given classes and for the subject while it searches an optimal linear approximation for the problem. It is modified from Learning Vector Quantization (LVQ) which is a competitive learning developed by Kohonen [16]. LVQ is a neural network based method which finds a good set of reference vectors to be used as a nearest neighbor classifier's reference set. Thus, in order to explain DSLVQ, first of all Nearest Neighbor (NN) classification and LVQ method will be clarified.

4.2.1 Nearest Neighbor Classification - NN

Nearest neighbor is a supervised learning algorithm where the classification of new coming instance is based on nearest neighbor class. The purpose of this algorithm is to classify a new sample according to the attributes of the training samples. Given the training data and labels of each sample, the new sample is classified regarding the closest neighbor from the training data [56].

A set of T sample data $(x_1, x_2, ..., x_T)$ and labels $(\theta_1, \theta_2, ..., \theta_T)$ are given in the training dataset, where the x_t's are N-dimensional (N features for each sample) metric values and the θ_t ‘s are the class labels among K classes in total. Knowing the samples and related classes, when a new sample x is considered, it is desired to estimate θ by utilizing the information contained in the set of correctly classified points. The distance d_t can be defined by the one of the following distance functions:

i) $d_t = \left\| x - x_t \right\| = \sqrt{\sum_{n=1}^{N} (x_n - x_{t_n})^2}$ Euclidean distance (4.8)

ii) $d_t = \sum_{n=1}^{N} (x_n - x_{t_n})^2$ Euclidean squared (4.9)

iii) $\sum_{n=1}^{N} \left| x_n - x_{t_n} \right|$ Cityblock (4.10)

iv) $\max_n \left| x_n - x_{t_n} \right|$ Chebyshev (4.11)

where d_t is the metric distance between new sample x and training sample x_t. Finding the minimum distance among all distance calculations provides the prediction of the class for the sample. The decision is made such that the class of the sample θ is the same as the class of the nearest neighbor which is the closest training data sample [56]. Mathematically, $x_t^{'} \in \{x_1, x_2, ..., x_T\}$ is the nearest neighbor of x if $d(x_t^{'}, x) = \min d(x_i, x)$ for $i = 1,2,...,T$

After finding the nearest neighbor $x_t^{'}$, the label $\theta_t^{'}$ is the predicted label for the new sample x. Figure 4-3 explains NN method visually.

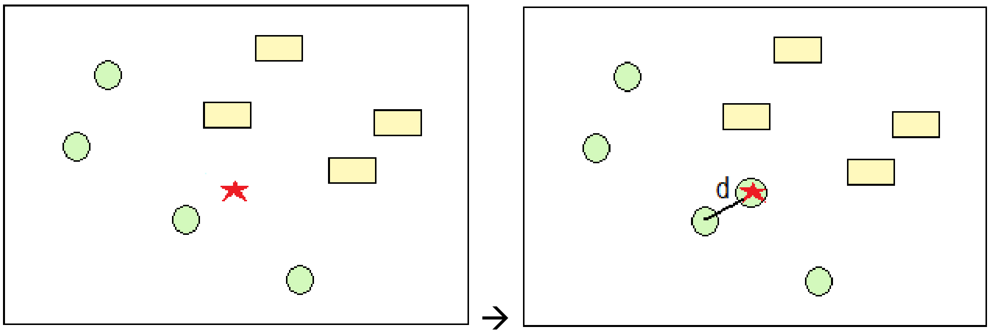


Figure 4-3: Demonstration of the Nearest Neighbor Classification. Circles and rectangles represent different classes. An unknown object (star) is classified as a circle because the closest object is a circle.

For each class, there are samples that can be used to understand the structure of the class, but in this method it is not aimed to find a generalized classification method. Thus, only the closest sample is considered for understanding the class of the new sample instead of using all relevant samples. Due to use of only one training sample, this method is named as 1-NN [56].

4.2.2 Learning Vector Quantization - LVQ

Nearest neighbor classifiers are well known classifiers which are easy to implement and have good classification performance. Learning Vector Quantization (LVQ) is a neural network based classification method aiming to find the proper reference vectors to be used as the nearest neighbor classifier's reference set [16]. These reference vectors are termed as codebook vectors. LVQ is an adaptive learning algorithm proposed for optimization of the positions of the codebook vectors in order to obtain improved classification accuracy. During learning, these vectors are shifted into an optimal position, whereas during classification a nearest neighbor classification method is used. In other words, LVQ is a quantization method, creating clusters of the training data and assigning them to relevant classes. Being a learning algorithm, the goal of LVQ is to find an optimal distribution of the clusters in the n-dimensional vector space.

The codebook vectors $(\bar{\mu}_1 \bar{\mu}_2,...,\bar{\mu}_M)$ represent the centers of the clusters. Total number of clusters or codebook vectors is optional according to the variety of the data; but for each class, it should be equal.

Training part of this method is composed of iterative adjustment of the cluster centers (codebook vectors) until it is stable enough. After that, new coming data can be assigned to the closest cluster and the class of the new data is the class of the cluster.

Adjustment of the codebook vector positions starts with the initialization part in which a vector value is chosen randomly from the dataset or by guess. Then, trials in the dataset are used one by one in order to update the position of the vectors. Based on the updated codebook vectors, the trials are again used for consequent training. This iterative procedure goes on until the change in vector positions is too small which means that all trials are separated into different groups successfully.

The codebook vectors are equally shared among the classes. For a new training sample, distances to each vector are calculated and the nearest vector is found. If both the trial and codebook vector belong to same class, the position of the codebook vector is moved through the trial with the learning rate. If they are from different classes, the position of the closest vector is moved away. Thereby, the vectors are moved closer to the relevant data at the same time moved away from the irrelevant data.

The detailed procedure implemented in this study is summarized as below:

1. The number of codebook vectors is chosen (assume M). If there are K classes in the training dataset, each class has M/K codebook vectors.

2. Initial values for α and μ's ($\overline{\mu}_1, \overline{\mu}_2, ..., \overline{\mu}_M$) are assigned where α is the learning rate and μ's are the codebook vectors. α initially should be smaller than 1 because it is the rate of vector's convergence to the new point and it should decrease monotonically at each iteration. μ's can be assigned to vector values according to the nature of the data or they can be chosen randomly from the input data [16].

3. Distance between input data vector $\overline{x} = (x_1, x_2, ..., x_N)$ and each codebook vector is calculated by the Euclidean distance function:

$$d_m = \left\| x - \mu_m \right\| = \sqrt{\sum_{n=1}^{N} (x_n - \mu_{m_n})^2} \qquad (4.12)$$

where $\overline{d} = d_1, d_2, ..., d_M$ and d_m corresponds to the distance of the data to the mth codebook vector.

The closest codebook vector (μ_C) to the data is found which is termed as the "winning" vector and one of the following actions are performed according to the cases:

4. i) If the class of the closest codebook vector is the same as the class of the input data x, the position of the codebook vector is brought closer to the data by the learning rate.

$$\overline{\mu}_C(t+1) = \overline{\mu}_C(t) + \alpha(t) \geq \left[\overline{x} - \overline{\mu}_C(t)\right] \qquad (4.13)$$

where t represents the iteration number.

ii) If the class of the closest codebook vector is different from the class of the input data, the position of the codebook vector is moved away from the data by the learning rate.

$$\bar{\mu}_C(t+1) = \bar{\mu}_C(t) - \alpha(t)\left[\bar{x} - \bar{\mu}_C(t)\right] \tag{4.14}$$

5. Learning rate α is reduced for the next iteration.

Above steps are performed iteratively, until the change in the vector positions is small enough for two consequent iterations.

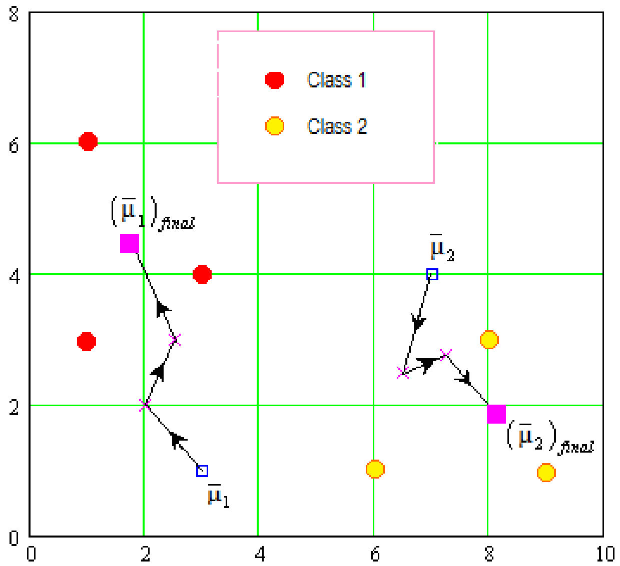


Figure 4-4: Demonstration of the LVQ method [17].

In Figure 4-4, $\bar{\mu}_1$ represents a codebook for class 1 and it is trained with each sample of class 1 data and positioned optimally in the center of class 1 data cluster after the iterations. The same procedure is also valid for the class 2 data and the codebook vector $\bar{\mu}_2$.

4.2.3 Distinction Sensitive Learning Vector Quantization - DSLVQ

As mentioned before, DSLVQ method is the modification of LVQ. In this method, the goal is to find the distinctive features which play a critical role in the success of the classification. For this purpose, a weight vector is assigned to each feature as a scalar indication of the measure of importance. In parallel to learning process of the codebook vectors as in LVQ method, DSLVQ algorithm estimates optimal weights for each dimension through a second learning process [57]. In this learning process, the weight vector is optimized where each weight value keeps the informative value of corresponding feature. Using the most informative features individually or as a combination has a considerable effect on the classification accuracy.

In the learning procedure, the codebook vector positions are optimized by a distance function, in the same manner with the LVQ method. In addition, DSLVQ updates the weights of the features in each optimization step. Thus, double optimization is handled simultaneously. At the end, the amplitude of the weights indicates how informative the features are. In other words, larger weights correspond to more important features.

The Euclidean distance function is used in the codebook vector optimization with a difference, such that the distance between the vector and the sample data is calculated by weighting each feature as shown below:

$$d_m = \sqrt{\sum_{n=1}^{N} \left(\max(0, w_n)(x_n - \mu_{mn}) \right)^2} \tag{4.15}$$

Here $\overline{w} : w_1 w_2 .... w_N$ is an N-dimensional weight vector, w_n is the weight for the n^{th} feature of the training data, and N is the total number of features. The learning algorithm for these weights is similar:

$$w(t+1) = norm(w(t) + \beta(t)(norm(nw(t) - w(t))) \tag{4.16}$$

Here $w(t)$ is the present weight vector and $nw(t)$ is the new weight vector during iteration *t*. By the learning rate $\beta(t)$, the present weight vector is shifted toward the new vector in some extent resulting the consequent iteration $w(t+1)$. Being smaller than 1, $\beta(t)$ provides a rational decision between the present and new weight vector during iteration *t*. Smaller β indicates slower learning which is found to be more reliable as a result of confident learning steps. It is proper to choose β around 0.1 as an initial value and it should decrease through zero within each iteration [57].

In the calculation of the new weight vector,

$$nw_n(t) = \frac{d_{o_n}(t) - d_{c_n}(t)}{\max(d_{o_n}, d_{c_n})} \tag{4.17}$$

is used where d_{c_n} denotes the distance between the nth feature of training example $x(t)$ and closest codebook vector from the correct class and d_{o_n} denotes the distance between the nth feature of $x(t)$ and closest codebook vector among the other classes.

$$norm(y) = \left(\sum_{n=1}^{N} |y_n| \right)^{-1} y \tag{4.18}$$

Function $norm(y)$ is a scaling operation for vector $\overline{y} = (y_1, y_2, ..., y_N)$ to obtain a unit length. Normalization is necessary for the features because during weight learning, being in the correct side of the decision border is more important than the distance to the border [57]. If the closest feature to the corresponding feature of the codebook vector is from the correct class, then the feature is relevant for the correct classification of the training sample. When feature n is found to be relevant for the classification, w_n is increased, otherwise it is decreased. After all iterations, the discriminative features and feature combinations can be selected according to the resulting weight of each feature and low weighted features can be discarded since they are less important.

4.3 Common Spatial Frequency Patterns (CSFP)

In some of motor imagery BCI systems such as the ones that use the left and right hand imagination tasks, it is easy to select the informative channels. However, spatial patterns of the movement imagination are not straightforward all the time. According to the imagination type, subject and number of classes; discrimination of the spatial patterns might become a complicated task. In that case, it is necessary to apply a spatial filter to combine the channel information in the optimal sense.

Common Spatial Patterns (CSP) method is suggested for optimal spatial filtering of two class data [19]. When the discrimination problem becomes more complicated, it is sometimes useful to consider also the spectral patterns. Common Spatial Frequency Patterns (CSFP) is a modified algorithm of CSP which also includes the information in the frequency spectra.

In this section, firstly CSP methodology will be explained for a 2-class problem and then modification to CSFP will be clarified.

4.3.1 Common Spatial Patterns (CSP)

Common spatial patterns (CSP) method was firstly proposed by Ramoser *et al* for classification of multi-channel EEG data [19]. The principal idea is to project the multi-channel EEG data into a low-dimensional data by weighting the signals measured from electrodes such that the discrimination of the 2-class data is maximized.

The idea of CSP is to find a spatial filter such that the projected signals have high power for one class and low power for the other in order to provide separability. The power of a signal can be expressed by the variance in the time domain. Therefore, the CSP algorithm applies a linear transformation that maximizes the variance of one class data while minimizing the variance of the other class data [59]. This problem is equivalent to maximizing one class variance and keeping the total variance of two classes constant. Formally this is expressed by the following optimization problem:

$$\max_{w} \sum_{i::Class1Trials} \mathrm{var}(w^T s_i) \quad , \text{s.t.} \quad \sum_{i:Class1and2} \mathrm{var}(w^T s_i) = 1 \tag{4.19}$$

where var(.) is the variance of the vector and w is the spatial transformation vector. An analogous formulation can be given for the second class.

Using the definition of the variance, the problem is simplified to

$$\max_{w} w^T R_1 w \ \text{ s.t. } \quad w^T (R_1 + R_2) w = 1 \tag{4.20}$$

where R is the covariance matrix of the trials of one class.

This algorithm can be computed by the following steps:

- The auto-covariance matrices for each class are calculated as:

$$R^{(i)} = \sum_{k=1}^{K} \left(x_k^{(i)} - \frac{1}{K} \sum_{k=1}^{K} x_k^{(i)} \right) \left(x_k^{(i)} - \frac{1}{K} \sum_{k=1}^{K} x_k^{(i)} \right)^T \tag{4.21}$$

where $x_k^{(i)}$ is an N-dimensional vector at time *k*. *T* denotes the transpose operator, *i* denotes the class index. The normalized covariance matrice *R* can be expressed as:

$$R = \frac{1}{l}\sum_{l=1}^{l}\frac{R^{(i)}}{trace(R^{(i)})} \tag{4.22}$$

where l denotes the number of trials. *trace(x)* is the sum of the diagonal elements of *x*. The composite covariance matrix is:

$$R = R_1 + R_2 \tag{4.23}$$

The eigenvectors and eigenvalues can be extracted from the matrix R.

$$R = U_0 \Lambda U_0^{\,T} \tag{4.24}$$

where U_0 and Λ are the eigenvector and eigenvalue matrices of *R* respectively. Then the whitening matrix can be obtained as:

$$W = \Lambda^{-1/2} U_0^{\,T} \tag{4.25}$$

In order to extract the common spatial patterns for a 2-class problem, the transformed covariance matrices S_1 and S_2 for both classes are evaluated respectively as below:

$$S_1 = WR_1W^T \quad , \quad S_2 = WR_2W^T \tag{4.26}$$

According to statistics, S_1 and S_2 share common eigenvectors and the sum of their eigenvalues is 1 [60]. Thus;

$$S_1 = U\Lambda_1 U^T \quad S_2 = U\Lambda_2 U^T \text{ and } \Lambda_1 + \Lambda_2 = I \tag{4.27}$$

Multiplication UW gives the resulting projection matrix. The distinctive property of eigenvectors in U lies mostly in the columns corresponding to maximum and minimum eigenvalues. For optimum discrimination, the columns of the eigenvector matrix corresponding to the m largest and m smallest eigenvalues are selected.

Then the final mapping of each EEG trial is:

$$Z_1 = U_m W X_1 \tag{4.28}$$

where $U_m = (U_1, ..., U_m, U_{N-m+1}, ..., U_N)$ and $U_m W$ corresponds to the spatial filter w. For classification, the variance of the filtered features are normalized.

$$f_i^k = \log\left(\frac{\mathrm{var}(Z_{p_i}^k)}{\sum_{p=1}^{2m} \mathrm{var}(Z_P)}\right) \tag{4.29}$$

The aim of the logarithm transformation is to obtain normal distributed elements in f [60]. Here f is the final optimum feature vector.

4.3.2 Common Spatial Frequency Patterns (CSFP)

Considering frequency patterns beside the spatial patterns is contributive to the success. In this part, the common spatial frequency patterns (CSFP) method will be explained which is modified from CSP and provides simultaneous optimization of spatial and frequency features.

In CSP, the information from each channel is inserted into algorithm and weighted to obtain the maximum discrimination. However, the spatial information is not sufficient in some cases, such that the patterns corresponding to different classes might have common active regions on the scalp. In this situation, the scope of the CSP algorithm is extended to take the spectral information into account which forms the method called Common Spatial Frequency Patterns (CSFP) [15].

Using time-frequency analysis, the temporal information for each frequency component can be extracted. Each trial signal acquired from one channel is transformed to the time-frequency domain and at the end each trial is expressed separately for each channel and frequency. In CSP, covariance matrix is calculated for all channel information while CSFP concatenates all channel information for the required frequency components. In other words, the size of the features and the covariance matrix increase by the number of frequencies used. The resulting features to be filtered are the combinations of channel-frequency information. With the same methodology used by CSP, features are weighted and the most distinctive ones are selected from the eigenvector matrix of the whitened covariance matrix [15].

4.4 Classification

In classification problems, there are two main stages. First of all, the learning algorithm is developed in the training part according to the observed data. Then the new coming data is classified according to the decision mechanism of the learning algorithm.

There are basically two types of learning mechanism, being either supervised or unsupervised. In supervised learning, pairs of input data and target outputs are provided. The learning system is trained by the examples in order to achieve a generalization to predict the new coming samples. In the absence of target outputs, the system has to train itself autonomously. This kind of learning is termed as *unsupervised learning* [61]. In this BCI study, supervised learning is used since it is more preferred for the discrimination of motor imagery signals [35]. In this learning type, the set of $\{x_i, y_i\}$ is given where x_i represents the i^{th} observed data and y_i is the corresponding class label. The purpose is to determine y_i with a generalization algorithm. Generalization is performed by searching a suitable transformation $y=f(x)$ between the input data and labels. When a new observation comes, created transformation f predicts the class label of the data. This transformation is the decision part which corresponds to the classification process.

In most of the motor imagery BCI applications, linear classification algorithms such as Support Vector Machines (SVM) and Linear Discriminant Analysis (LDA) are preferred since they are more successful than nonlinear algorithms in discrimination [37]. The methodology of SVM is explained in detail which is mainly preferred in this study due to ease of access to reliable SVM toolboxes and adaptation to nonlinear use. Several concepts used in the classification process are also mentioned here. The other methods used for comparison in this study are given at the end only providing the names and references of the methods.

4.4.1 Support Vector Machines - SVM

Support Vector Machines is a supervised machine learning algorithm which is accepted as a powerful tool for developing pattern classification. In this algorithm, the goal is to separate the classes with a hyperplane which is constructed by the observed examples.

The separating hyperplane can be constructed from observed data by many linear classifiers but the important point is that the hyperplane should have a good generalization property in order to work well for the new samples. In this manner, SVM is different such that it tries to find the separating hyperplane with the maximum margin which is known as the optimal separating plane. In other words, the hyperplane maximizes the distance between the hyperplane and the nearest samples (support vectors) in each class [62].

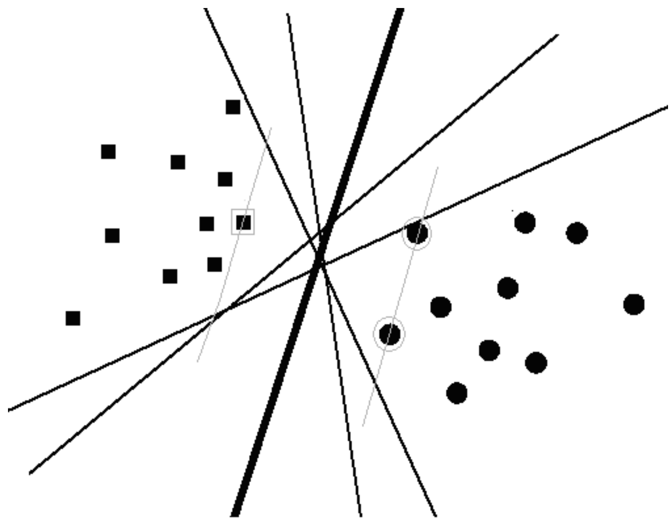


Figure 4-5: Several separating hyperplanes and the optimal separating hyperplane for a 2D data

In Figure 4-5, two-dimensional data from two different classes are shown that can be divided into two groups by several alternative lines. However, there is only one optimum line in the middle trying to be as far as possible to each of the samples.

The nearest samples to the hyperplane are called as support vectors which give the name to the method. SVM is an optimization problem which updates the alignment of hyperplane until the support vectors become furthest to the hyperplane [62]. In this study, the SVM toolbox LIBSVM is used to implement the SVM classification [58].

4.4.1.1 Kernel Functions

The hyperplane function definition above is given for linearly separable case. In other words, the value of the function for a given input is mathematically formed by the usual inner product of the parameters of the function and the input. When the data is not linearly separable, the feature space can be transformed to a higher dimensional space by employing nonlinear Kernel functions [46]. Here, the Kernel operation is expressed as a nonlinear inner product in the feature space. Some of the Kernel functions used in SVM are defined in the following expressions:

Polynomial Kernel: $K(x_i, x_j) = \langle x_i, x_j \rangle^d$ or $K(x_i, x_j) = \left(\langle x_i, x_j \rangle + 1\right)^d$ (4.30)

Gaussian Radial Basis Function: $K(x_i, x_j) = e^{-\frac{\|x_i - x_j\|^2}{2\sigma^2}}$ (4.31)

Sigmoid Function: $K(x_i, x_j) = \tanh\left(\kappa x_i . x_j - \delta\right)$ (4.32)

The Gaussian Radial Basis Function (RBF) is reported to provide the best results with SVM in classification performance [46].

4.4.1.2 Normalization

Normalization is a common technique used in most of the data processing applications. It is used to remove the dependency on the magnitude and variance of the samples in the dataset. It also helps finding the structural similarities among the same class data which is essential for classifier training.

Normalization can be performed both individually and regarding all of the samples in the dataset. In individual normalization, one sample in a dataset is scaled according to its properties. There are several techniques for this kind of normalization. In most cases the data is transformed to the interval [0, 1]. Being a linear scaling operation, it can be performed by various scale factors. The simplest scaling factor is the magnitude of the sample vector such that after the normalization, the sample becomes a unit vector:

$$\hat{x} = \frac{x}{\|x\|} \tag{4.33}$$

In the ensemble normalization, the samples are normalized according to the statistical properties of the whole dataset. For example, each sample can be reassigned according to its difference from the mean of all dataset. Gaussian normalization is a good example for this type. In Gaussian normalization, all data samples are normalized in the structure of the Normal (Gaussian) distribution which shifts the mean of the samples to zero and scales the variance to 1.

$$\hat{x} = \frac{x - \overline{\mu}_x}{\overline{\sigma}_x^2} \tag{4.34}$$

where $\overline{\mu}_x$ and $\overline{\sigma}_x^2$ represent the mean and variance vectors of the samples respectively.

4.4.1.3 Cross-validation

Cross-validation is an assessment for the performance of the classification model obtained by the training process. The idea is to divide the training data into partitions and use some of them for training and the remaining for testing [68]. If this is performed for different combinations and then averaged, it gives an idea about the accuracy of the model. According to the result, some modifications can be done in the feature extraction and classification methods until the best results are obtained.

The most common technique is K-fold cross-validation. In this method, the training dataset is divided into K subsets and (K-1) of them are used for training while the classifier is tested on the remaining subset. This process is repeated for K times until all the subsets are used as a validation. Then all classification accuracies are averaged in order to evaluate the success of the classifier [68].

4.4.2 Other Classification Methods

Beside SVM, three other methods are tried for classification in this study. First of all, linear SVM classifier is adapted to the nonlinear case by using a Radial Basis Function (RBF) as the Kernel operator [58], [69]. Then Naïve Bayesian classifier is applied which is a probabilistic classifier based on the Bayes' theorem. Finally, a neural network model, Multilayer Perceptron, is implemented for the data. These methods are accessed from the Java based classification toolbox Weka 3.6.3 [69].

CHAPTER 5

SYSTEM DEFINITION

General information about BCI systems is given in chapter 3. In this part, the BCI system developed in the scope of this thesis is explained in detail with the software applications and a potential wheelchair application.

In BCI studies, different applications can be obtained by changing the feedback and process type of the system. In this study, the original cue based MI paradigm [13] is implemented on a BCI system [6] to perform the MI related experiments. After that, 2 online BCI applications are developed. One of these is a cue based game application that uses a moving object as a feedback to the subject. The other application is a wheelchair device that can perform movement along 2 directions. In this chapter, the details of these applications are given providing necessary information on the hardware and software designs.

5.1 Hardware Description

Data acquisition is the first step in which the electrical brain activity is measured and transferred to the digital environment to be processed in further steps. Any small deviation in this step may become misleading in the next processes; therefore the acquisition step is crucial in the analysis. The system should be sensitive enough to detect signal changes with high precision. Besides, it should be portable and practical in use for a proper BCI system. Regarding these facts, an EEG device is preferred in this study.

The EEG instrumentation developed for BCI purposes in our laboratory is used in the experiments of this study [6]. The designed cue based MI BCI is adapted on this system with several modifications on the hardware. These are described below after providing a brief summary of the specifications of the EEG system used.

5.1.1 EEG Instrumentation

The EEG system used in this study employs 10 channels (F3, Fz, F4, C3, Cz, C4, P3, Pz, P4, PO7) which are connected to the scalp surface with the electrodes of a standard EEG cap. In this cap, the electrodes are placed according to the 10-20 electrode system that can be seen in Figure 5-1.

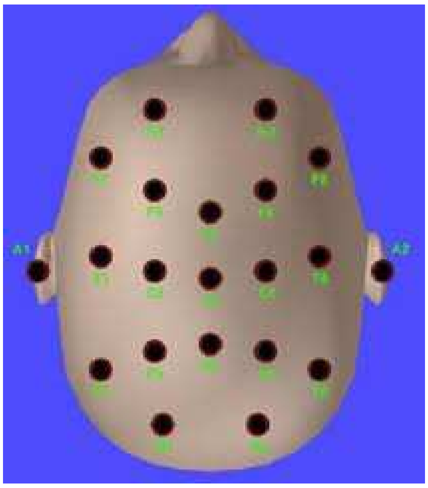


Figure 5-1: The electrode layout for 10-20 system [38]

The acquisition is unipolar which means that the signals acquired from the electrodes are referenced to a predefined point such as earlobe or an unused location of the scalp. As in all standard EEG procedures, the surface between the electrodes and the scalp surface is filled with a conductive gel in order to decrease the contact impedance. The signals from the scalp are amplified with an amplification factor of 10000 in the analog hardware, then filtered by a 0.1 Hz high-pass and 40 Hz low-pass filters. Also there is a band stop (Notch) filter to remove the effect of 50 Hz noise. The amplified and filtered analog signal is digitized with a 12-bit ADC and transferred to the computer in a (adjustable) sampling rate of 100 Hz.

5.1.2 Hardware Modifications on the BCI system

One of the goals of this study is to implement a wheelchair control with a BCI system. Therefore, a wheelchair device has to be integrated with the existing EEG instrumentation [6]. To fulfill this task, a power wheelchair device with a built in VSI controller is used [71], [70]. The pictures of the power wheelchair integrated to our BCI system are shown in Figure 5-2.

Figure 5-2: Pictures of the power wheelchair used to develop the BCI wheelchair application

The type of the VSI controller [70] on the wheelchair was not suitable to control digitally by an external control system. It allows only commands from the analog joystick which implements a complex sensor mechanism inside. To control the wheelchair digitally, an external motor drive circuitry is designed in this study. The main specifications of this motor drive hardware is summarized below:

- The system is electrically isolated from the EEG instrumentation.
- The system acts as a slave device which accepts basic commands like stop, move to main directions and adjust speed.
- The speed of the motors is adjustable up to 8 levels.
- The drives can handle DC currents up to 20 Amps for each motor.

Figure 5-3 shows the main components and the flow diagram of the developed system.

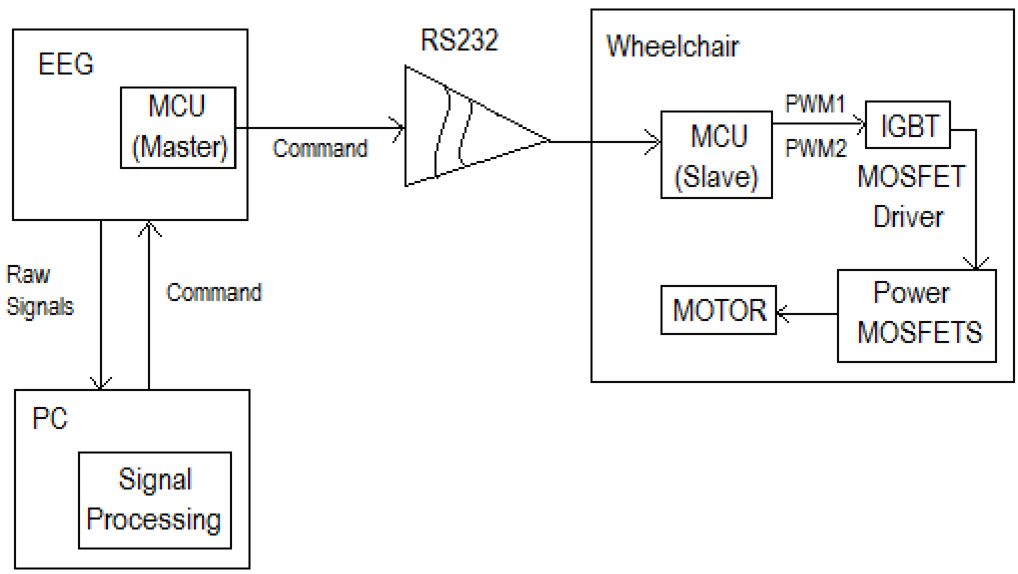


Figure 5-3: Operational flow and control diagram of the developed wheelchair drive and the EEG system.

The control mechanism has been centralized in the microcontroller unit of the EEG such that it handles both the communication of PC with the EEG and the EEG with the wheelchair. The wheelchair control is implemented by the microcontroller PIC16F877 [72] which performs actions according to the commands sent by the master microcontroller in the EEG [6]. The commands are transmitted via RS232.

To drive 2 power motors on the wheelchair, which draw 10 Amps of rated current at 24V, IRF3205 [74] power mosfets are used. These mosfets can handle DC currents up to 110 Amps which is much higher than the rated current of the motors. Each motor is driven by 4 IRF3205's which are controlled by 2 half bridge driver IC's. The mosfet drivers used for this purpose are the IR2111 IC of International Rectifiers [75].

The speed of the motors is controlled with pulse width modulation (PWM) technique whose duty cycle is adjusted by the PIC16F877 microcontroller. The duty cycle can be adjusted from 10% to 80% with increments of 10% which comprises 8 levels of speed control.

Isolation is a necessary process in this design in terms of power supply and signal transmission. The wheelchair draws much more power than EEG system which might cause sudden current changes in the power line of the EEG. This will cause distortion in the EEG signals. Therefore, EEG and wheelchair should be electrically isolated by supplying with different batteries. Furthermore, in the signal transmission line on which the command is sent to the wheelchair, there might occur feedback currents through the EEG. In order to prevent this danger, the transmission line (RS232) is also isolated with the optocoupler IC IL717 [73]. Finally, in case of an emergency, a safety switch is provided to cut off the supply of the motors. The picture of the motor driver hardware is given in Figure 5-4.

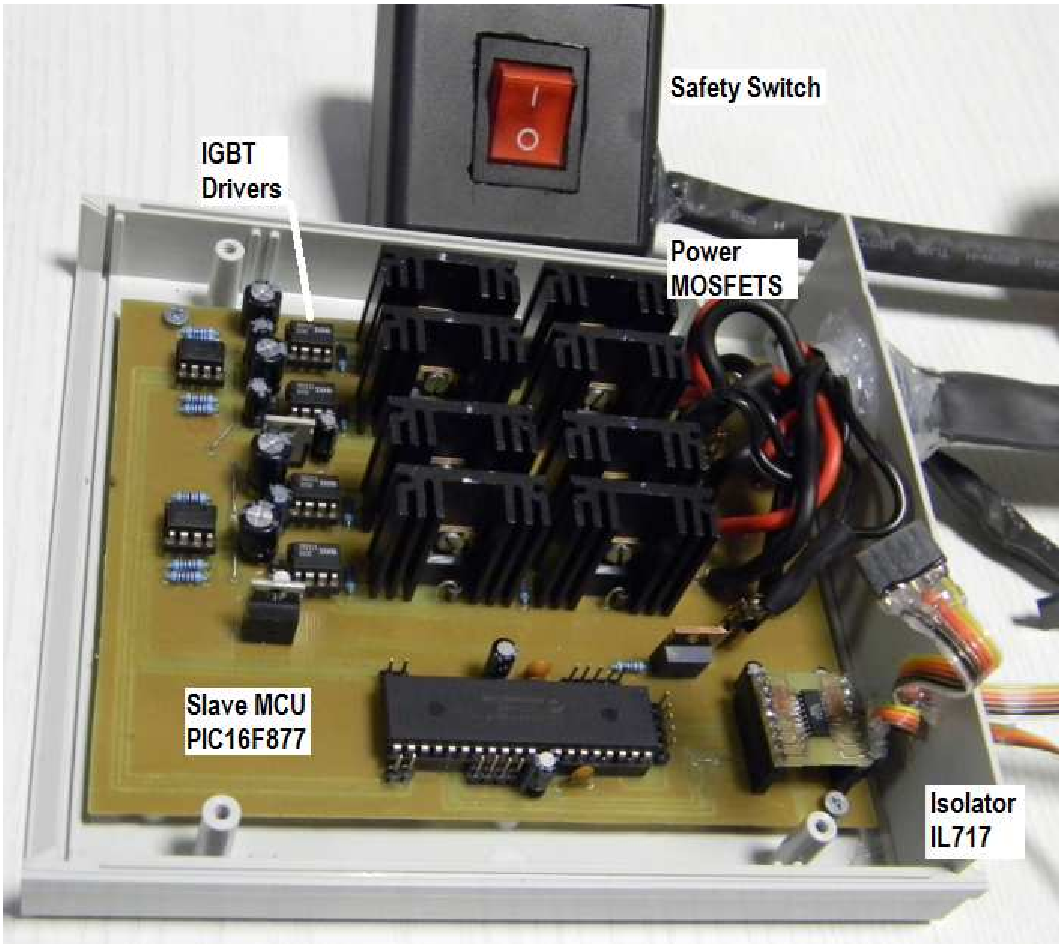


Figure 5-4: Picture of the printed board for the motor driver hardware

5.2 Software Description

Monitoring and recording of the EEG signals are controlled by a computer program. The software of the system is composed of subsystems in which the acquisition of the digitized signal, display of user interface and analysis of the acquired data are carried out simultaneously [6].

In this study, user interface design is performed for the two applications to be developed. In these interfaces, the task to be performed by the subject is displayed on the user screen also indicating the timing of the tasks with both visual and audio cues. This screen is also used to give feedback to the subject in the applications.

The user interface is constructed in Visual Studio .NET 2005 using C# language. The interface varies according to the application and the constructed interfaces are described in the following sections.

5.3 Applications

It is necessary to provide an interface in order to collect the required data for offline analysis. Furthermore, whenever the success of the system exceeds a level in the offline analysis, it can be adapted into an online system where the feedback is provided real-time. For this purpose, two different applications with different interfaces are constructed which will be described here.

5.3.1 Cue-Based Application

In this application, the imagery periods and the feedback instants are adjusted by the computer and the subject is allowed to perform tasks in these periods. In other words, the program is controlled both by the computer and the subject.

There are two screens in the interface, namely, a dataflow screen and a user interface screen. Figure 5-5 and Figure 5-6 show these screens, respectively.

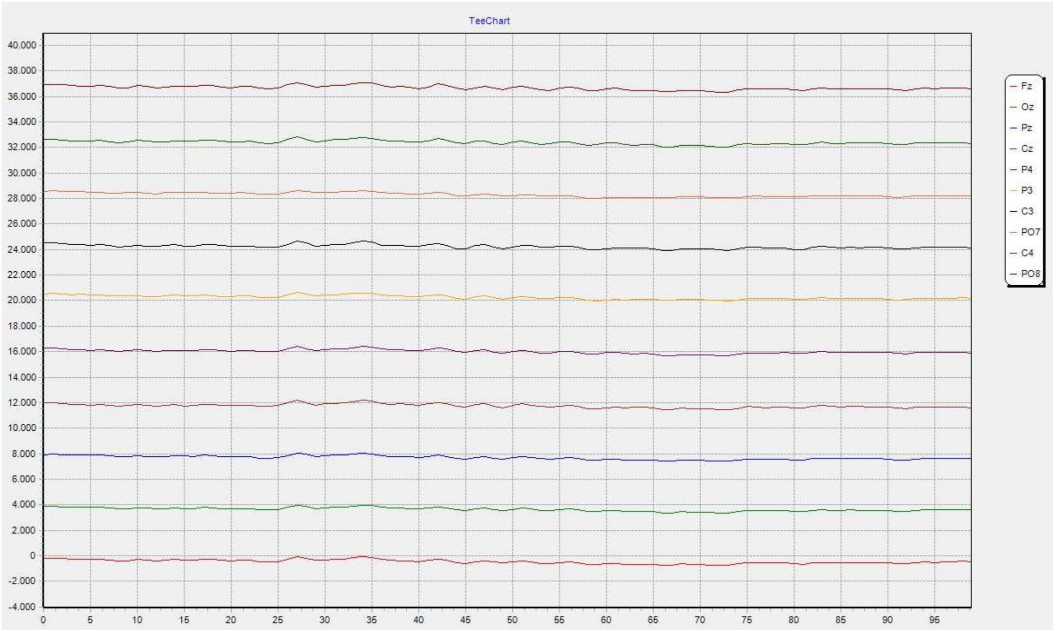


Figure 5-5: Dataflow screen of the cue-based application showing 10 channel real-time EEG data

This screen provides a means to follow the data acquisition from the EEG device. The acquired 10 channel EEG data are displayed real-time on this screen with necessary labels to follow each channel. During the experiments, the status of each channel can be followed from this screen, and in case of technical problems, such as data loss, high noise or poor contact of the electrodes, the user is informed. For instance, the defects in the signals, caused by concentration loss, tiredness or being sleepy, can be observed as alpha-rhythm waves. In this case, displaying the dataflow in one side of the screen is useful in terms of feedback and warning.

The user interface screen enabling the coordination between the computer and the user is constructed to provide a base for the experiments. The training screen given in Figure 5-6 is used to collect training data from the subjects. Including the dataflow screen in the left side, this screen guides to the subject in performing the tasks.

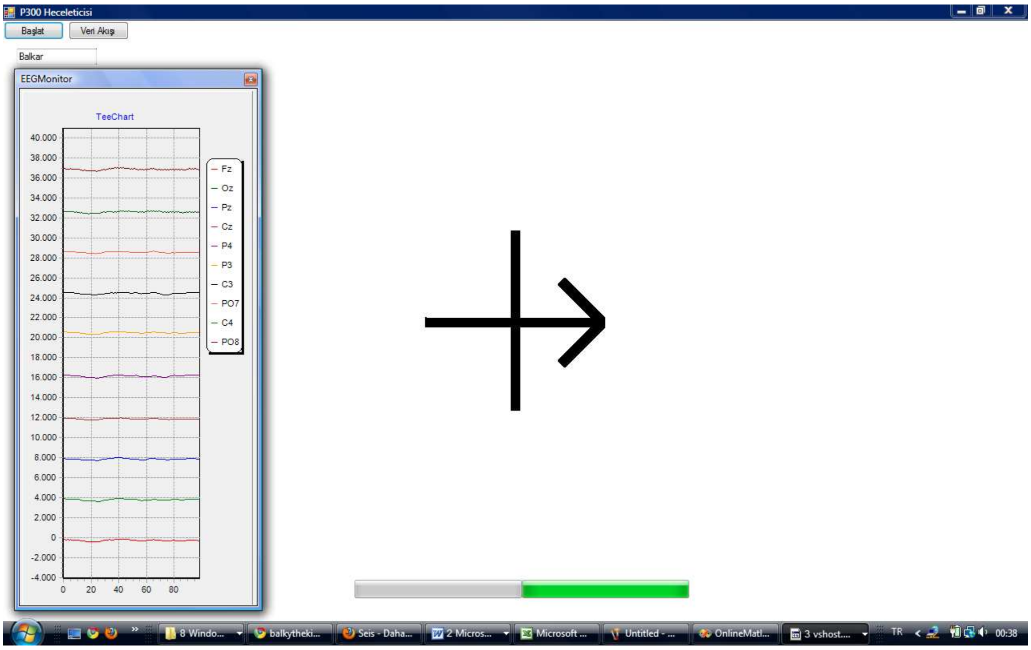


Figure 5-6: The user interface screen of cue-based application. The cross with the arrow informs the user about the task and timing. Slide-bar in the bottom is the feedback indicating the classifier output.

In the training screen, the user is informed about the type of the required task and the time to start and finish the imagination. It is known that feedback is effective on the subject training and system performance [52]. Therefore, there is also a slider bar which is an optional item and can be used to inform the subject about the classification output. By this way, the subject directly sees the result of the prediction and adjusts himself for a better imagination. This process constitutes the subject training.

In Figure 5-7, the process of the interface for one trial is given. This process has been commonly used in most of the cue-based BCI applications [39]. Some modifications are made in timing and feedback adjustments according to this study.

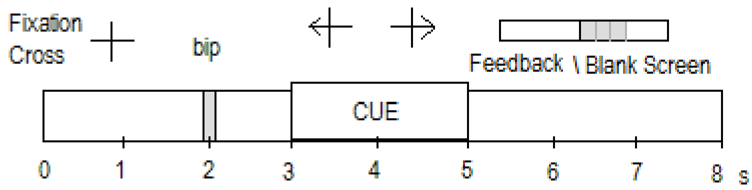


Figure 5-7: Process of one trial (Modified from [39])

Each trial lasts in 8 seconds. In the beginning of the trial, a fixation cross is displayed on the screen which informs that the trial starts and the subject should concentrate. 2 seconds later, the subject is warned by an audio tone to prepare himself/herself for the cue. After 1 second, the cue is displayed for 2 seconds and the subject imagines the required movement during this period. At the end of this step, the cue disappears and the classification process starts. The result is given to the screen in following 1-1.5 seconds with a slider bar indicating the direction of the predicted imagination. The storage rate of the slider bar indicates the accuracy rate of the classification result. By this way, one trial is completed and before the new trial starts there is 3-second relaxing period including the feedback display. The new one starts by the display of the fixation cross. Here, the tasks of movement imagination are given in a randomized order to prevent the adaptation of the subject [40]. The detailed explanation of the process will be given with the experiments in Chapter 6.

This system provides output only once after the end of the imagination duration indicating the predicted side. For training purpose, it is useful; however it is a poor system to be a real life application since it is not exactly real-time and not continuous. Therefore, another system is constructed with a game interface based on continuous left and right control. The reason of selecting a game application is to increase the motivation of the subject and hence the strength of the intention.

5.3.2 Continuous Response Game Application

Drawback of the previous system is the single discrete output for the whole 2-second imagination duration. The response only indicates whether the imagined task is correct or not. However, for an application it is necessary to provide continuous output.

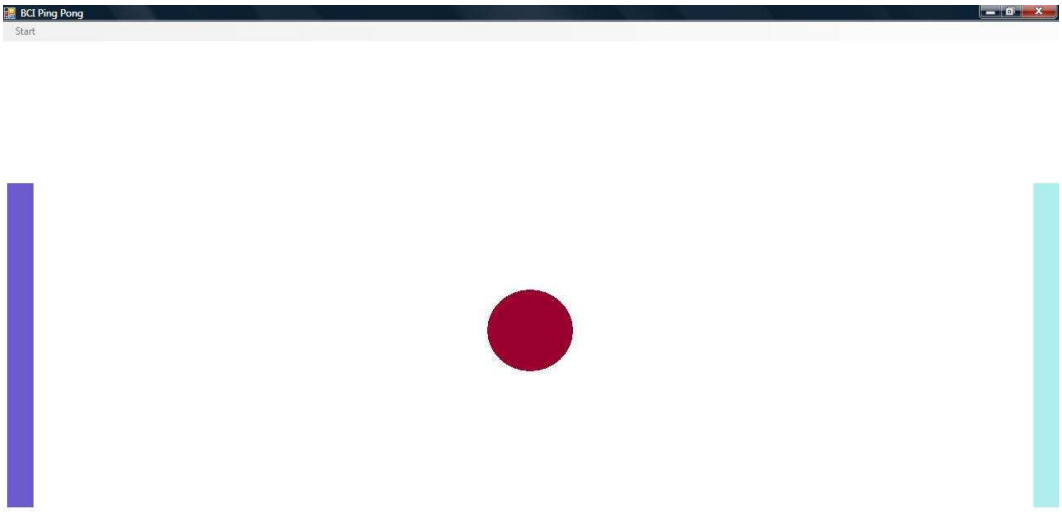


Figure 5-8: Application interface for the Ping-Pong like game

A ping-pong like game is constructed which is again based on left and right movement control. In the interface seen in Figure 5-8, there are two colored rackets in the left and right hand side of the screen and there is a ball placed in the middle of the screen. The cue is given by the racket such that the color of the racket in the side to be imagined is changed until the end of the imagination. The imagination duration varies according to the intended use. When the screen is used for training purposes; the duration is shorter, at about 5 seconds and during online game it depends on the preference of the subject. Between the trials there is a break duration of 2 to 4 seconds.

When any of the rackets is colored, the ball starts to move. The aim of the game is to hit the colored racket by the ball in the required time. When the time is up, the color of the racket turns to normal. If the ball reaches to the racket the trial is said to be successful, otherwise it is a fail.

5.3.3 Wheelchair Application

At first sight, a game application is not a crucial system for disabled people. However, the purpose of this study is to construct the basis for any other useful application that can be easily adapted to the designed BCI system. In this chapter, it is aimed to show how this system can be adapted to a wheelchair control.

Having left and right hand imagination tasks, the wheelchair can be controlled in two dimensions. However, it is not meaningful to apply left and right control since there is no other control to use in forward movement. Therefore, it is rational to control the wheelchair in backward and forward movement by encoding left and right comments.

In this application, the interface of the game application is used to inform the subject about the task with the start and the end of the trial. The decision is made by the developed algorithms after each 50 ms and it is transmitted to the wheelchair to perform the predicted action. Besides it is displayed on the screen with the ball movements. The output command signal does not have a smooth characteristic since it is provided in each 50 ms. A rapid change in the prediction may not cause any problem in the game application. However, in the wheelchair control, frequent change will result in unstable movement of the device and potential harm to the motors. Therefore, the command output of the processing algorithm should be smoothed by post processing methods. For this purpose, a 10th order weighted moving average filter is applied before the motor control.

CHAPTER 6

RESULTS AND DISCUSSION

The methodologies described in chapter 4 are applied in three motor imagery BCI datasets; first of which is a public dataset provided by BCI Competition organizers [2]. The second and third datasets are composed in the experiments conducted in Hacettepe University Biophysics Department and METU Electrical and Electronics Engineering Brain Research Laboratories. The results and the explanation of each dataset are presented in the following sections after providing a common evaluation criterion for the performance of the algorithms on these datasets.

6.1 Performance Evaluation

There are several methods to evaluate the success of the BCI systems. Most of them depend on the confusion matrix which is accepted as a common methodology in BCI performance evaluation [41]. For offline studies, most popular performance measures are the single-trial prediction accuracy, kappa value and the error rate most of which employ the confusion matrix in their calculation. These terms are discussed in the following subsections.

6.1.1 Confusion Matrix

The measure of the classification performance can be best described by a confusion matrix: it shows how the classifier prediction is related with the true class labels. For instance, consider the following table where there are two classes and four classification cases.

Table 6-1: The confusion matrix for a 2-class example

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="2">True Labels</td></tr>
<tr><td>Class 1</td><td>Class 2</td></tr>
<tr><td rowspan="2">Predicted labels</td><td>Class 1</td><td>A</td><td>B</td></tr>
<tr><td>Class 2</td><td>C</td><td>D</td></tr>
</table>

In the table, A refers to number of labels predicted correctly as Class 1 and D refers to number of labels predicted correctly as Class 2. On the other hand, C is the number of labels predicted as Class 2, whereas they actually belong to Class 1. Similarly, B is the number of labels predicted as Class 1 whereas they actually belong to Class 2.

6.1.2 Overall Accuracy and Error Rate

The classification accuracy (ACC) can be defined as the ratio of the correct prediction over the total number of instance predictions. Mathematically relating to the confusion matrix, it has the form:

$$ACC = \frac{A+D}{A+B+C+D} \tag{6.1}$$

The error rate is just the complement of the classification accuracy and can be formulated as:

$$(ERR = 1\text{-}ACC) \tag{6.2}$$

These two concepts are the most widely used evaluation criteria in BCI research due to their ease of calculation and interpretation. However, most of the time, they do not reflect the real success of an algorithm. For instance, consider the case that, a classifier using equal number of observations for each class assigns the same class label to all of the instances in the dataset. This already gives (100/N)% prediction accuracy to the classifier (N is the number of classes). Another disadvantage occurs in the case of unequal number of observations from the classes in which less frequent classes have smaller weight on the accuracy [41].

6.1.3 Kappa Statistics

In order to obtain more realistic success measurement, there is an alternative calculation known as Kappa coefficient proposed by Cohen in 1960 [42]. The expression for kappa (κ) coefficient is as follows:

$$\kappa = \frac{(ACC - p_e)}{(1 - p_e)} \tag{6.3}$$

where ACC and p_e represents the overall accuracy and the chance agreement. The formulation for the chance agreement is given in equation 6.4.

$$p_e = \frac{(A+C)*(A+B)+(B+D)*(C+D)}{N^2} \tag{6.4}$$

The kappa coefficient is mainly used in multi-class problems but it is also applicable in the two-class case where it is more indicative about the classification success as compared to error rate and overall accuracy.

6.2 BCI Competition IV: Dataset IIb

BCI Competition IV is the final BCI competition organized in 2008 and provides several datasets for known BCI paradigms. Among these, the dataset IIb is prepared for continuous motor imagery classification for left and right hand movement imagination [2]. This dataset is selected in order to provide a rational comparison between the investigated methods and the winning algorithms of the competition on a standard basis. Although one can reach the details related to this dataset, for completeness of the context, it is summarized in the following subsection.

6.2.1 Explanation of the Dataset

6.2.1.1 Experimental Setup

Dataset IIb consists of EEG data from 9 different subjects. All subjects were sitting in an armchair, looking to a screen placed approximately 1m away at eye level. For each subject there are 5 sessions: first two sessions contain training data without feedback (screening) and the last three sessions were recorded with feedback. Each session was completed in six runs of 10 trials each for two classes. As a result, there are 120 trials in one session. Each session consists of several runs and each run consists of trials illustrated in Figure 6-1.

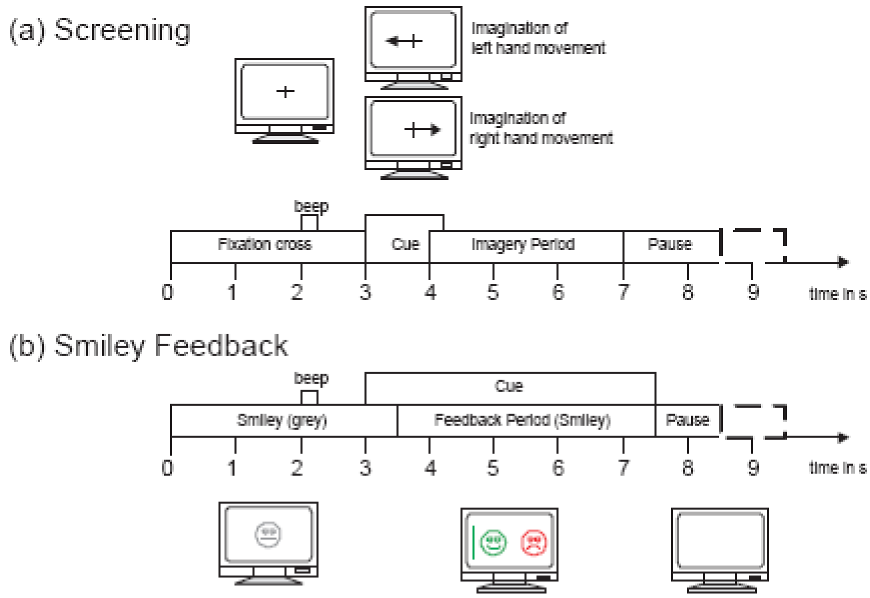


Figure 6-1: Events and timing in the trials during the experiment [2].

Each trial starts with a fixation cross and an additional short acoustic warning tone. 3 seconds later, an arrow is displayed for 1.25 seconds as a cue pointing to the side of the requested class. After that there is a period of 4 seconds in which the subjects have to imagine the corresponding hand movement. Trials are separated by a break of at least 1.5 seconds and together with a randomized time in order to avoid subject adaptation [2].

Three online feedback sessions were recorded with smiley feedback. Each of them consists of four runs of twenty trials for each type of motor imagery. At the beginning of each trial, the feedback (a gray smiley) is centered on the screen. At second 2, a short beep tone is given as a warning. The cue is presented from second 3 to 7.5. During the feedback period, the smiley changes to green color indicating that the predicted direction is correct, otherwise it becomes red. At second 7.5 the trial ends with blank screen and a random duration of 1.0 to 2.0 seconds is added for rest [2].

6.2.1.2 Data Collection

The data collection is based on two-class motor imagery paradigm consisting of left hand (Class 1) and right hand (Class 2) classes according to the cue-based screen interface given in Figure 6-1.

Three bipolar EEG channels were recorded at electrode locations C3, Cz, and C4 (see Figure 5-1) with a sampling rate of 250 Hz. The data is originally band-pass filtered between 0.5 Hz and 100 Hz, and a 50 Hz Notch filter is used. The electrode location Fz is used as EEG ground [2].

6.2.1.3 Data Structure

All datasets are stored in the General Data Format (GDF). The start of each trial is labeled in a header file with the recorded signals. In this file, cue onset for left and right imagination is provided with the class label for the training dataset whereas for evaluation dataset only onset time information is available. Also, the trials with artifact are indicated and some of them are identified to be rejected.

6.2.1.4 Evaluation

Continuous classification output is required for each sample in the dataset including all trials and the classification accuracy is evaluated regarding the kappa coefficient. The largest average kappa value for all subjects indicates the most successful algorithm. Furthermore, all algorithms should be causal.

6.2.2 Results

In this part, the steps of the study will be given in detail for all subjects. First of all, general description of the training analysis will be given which consists of preprocessing, feature extraction, feature selection and classifier training parts. This general process is the same for all subjects and the only difference is the subject-specific parameters. The output of the processes including these parameters will be given for each subject and classification results will be explained. Finally, obtained results will be discussed and compared with the competition results.

6.2.2.1 Analysis Procedure

Data Extraction and Preprocessing

As mentioned in the dataset description, there is 5-session data for each subject three of which are spared for training part and the other two parts are used in the testing part as evaluation. This corresponds to 400 trials for training and 320 trials for testing. In each trial, there is a 3-second imagination duration after 1-second of cue display. In the analysis, a 2-second period is used in the processes. The following figure shows the interval selection starting from 0.5 second after the cue onset which is also preferred by the winner algorithm of the competition [43].

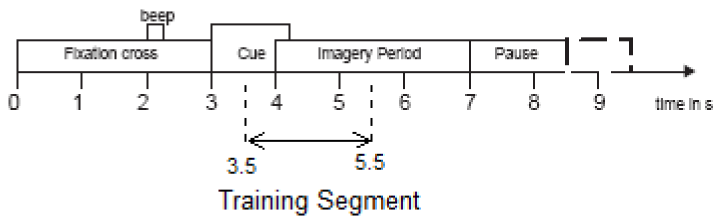


Figure 6-2: The part of the trial used for signal analysis and training (Adapted from [2])

First of all, signals in this interval are filtered with 0.5-30 Hz band-pass filter with 250 Hz sampling rate. By this way, irrelevant frequencies and the higher frequency noise components are eliminated. The next step is the downsampling of the signal to 125 Hz since 250 Hz is more than enough for motor imagery study and this operation reduces the computational effort for next steps. As a result, 2-

seconds of imagery data are extracted and preprocessed resulting in trials of 250 (2x125) samples each.

Feature Selection and Extraction

As explained in chapter 4, the motor imagery patterns are characterized by both temporal and spectral attributes beside the spatial features. For left-right hand discrimination, the selection of spatial information is straight-forward, knowing the fact that the channels in the left side of the scalp carry the information for right hand imagination and vice versa. Since there are 3 bipolar channels in the dataset, C3 and C4 are selected for processing and Cz is not included in the analysis.

Subject-specific frequency components are investigated with Distinction Sensitive Learning Vector Quantization (DSLVQ) method which outputs the most discriminative features for a subject according to the classes. First of all, extracted imaginary time domain signals are transformed to Fourier domain with 1 Hz resolution and the power of each frequency component is calculated for each channel (C3 and C4). The power values between 1 and 30 Hz are selected and concatenated for two channels for each trial. Then concatenated power values are normalized in order to provide normalization of each channel among all frequency components and normalization between the channels. The processed data obtained from all training trials are inserted into the DSLVQ algorithm with the corresponding class labels. Inside the algorithm, each frequency feature coming from each channel is weighted among all features iteratively. Resulting weights indicate the significance of each spectral feature of each channel for discrimination of the two classes. The DSLVQ outputs of the subjects for C3 and C4 channels are provided in the plots on the following pages.

Beside the DSLVQ method, a search method for the frequency features is constructed in order to validate and fine-tune the DSLVQ results. In this search, each frequency is treated as a single feature in the classification. Using only one frequency component, the classification model is trained and tested with randomly split trials as train and test parts. This classification is performed 50 times with random distributions and the average accuracies are compared among all frequencies. However, it should be noted here that, this method does not directly show the effect of the frequency on classification since it evaluates only the features corresponding to one frequency component. That is, the set of several frequencies are more discriminative as compared to the case that they are treated separately. Nevertheless, the accuracy for a single frequency component gives priory information about the effect of that specific frequency on the overall accuracy. This is a longer process than the DSLVQ since it has more computations. However, in offline analysis, it provides a way for the checksum of DSLVQ results. Therefore in the results, the average accuracy plots for the frequency components in 1-30 Hz range are also provided for each subject.

Combining the results of the DSLVQ and frequency search algorithms provides proper feature selection for the classification process. Before the selection, features are extracted with Short Time Fourier Transform (STFT). In this analysis, the time-frequency spectrum of the 2-second imagery data is computed by using window size of 0.4 s and 50% overlapping. For each channel, the data is transformed to the Fourier domain, using a 0.4-second window and sliding each window by 0.2 s. As a result, for each frequency value, 9 time-dependent power data is obtained for each channel. Among all frequency values, the most informative ones are determined by DSLVQ and the search method. The power values with respect to time for these frequencies are combined from channels C3 and C4 to form the feature set. In the end of this feature extraction and selection process, there are 72 features coming from 2 channels, 4 frequency components and 9 time values for each trial. These combined features are then normalized and fed to the SVM classification algorithm.

The results of the explained steps are given for all subjects with the necessary plots. The same methods are applied for each subject resulting in subject specific parameters and different classification models. The main procedure will be explained for Subject 4 who elicits the best performance among all subjects. For the other subjects, slight differences for the parameters will be mentioned and at the end overall accuracies for all subjects will be given with the extracted subject specific parameters.

6.2.2.2 Results for Subject 4

In Figure 6-3, the weight coefficients obtained for 1-30 Hz frequency components of channels C3 and C4 are given for Subject 4. DSLVQ method is applied to spectral components in 1 Hz steps. The weights found for both channels are given in the same plot to observe the common active frequencies.

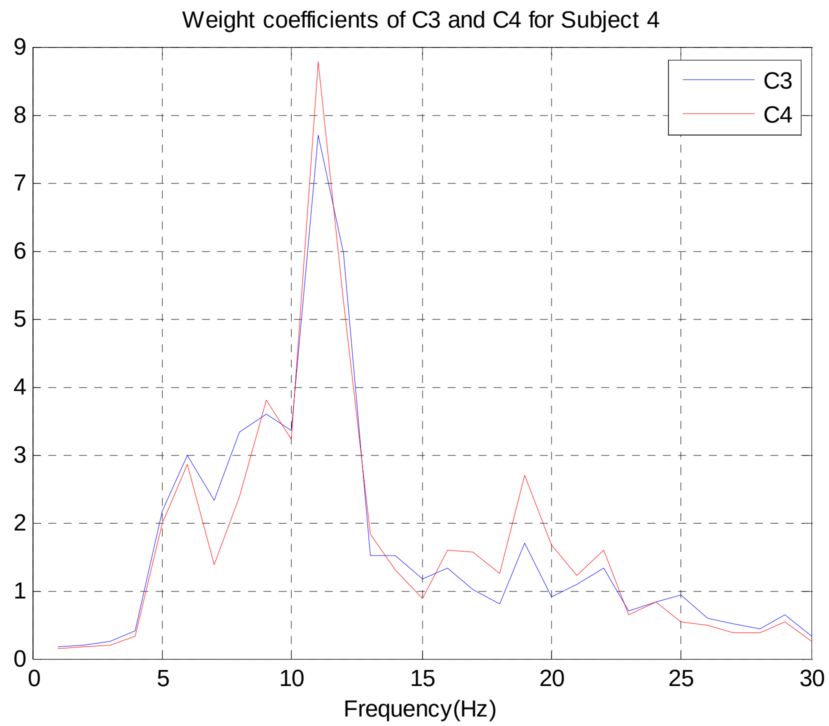


Figure 6-3: DLSVQ coefficients for the frequencies 1-30 Hz for C3 and C4 (Subject 4)

The frequency components with higher weights indicate higher importance in the separation of the classes. The spectral discriminative features are consistent for two channels as seen in the figure above. 10, 11 and 12 Hz features are the most significant ones for both channels. Then 8 and 9 Hz components follow them. The weights for 5 and 6 Hz components seem to be high also. But these are not taken into account since they are not in the range of mu and beta band. Thus, they are not relevant for discrimination of imagery left and right hand movements.

On the other hand, frequency search method is computed with 1 Hz steps over 50 trials. The average accuracy for each frequency component calculated for Subject 4 is shown in Figure 6-4.

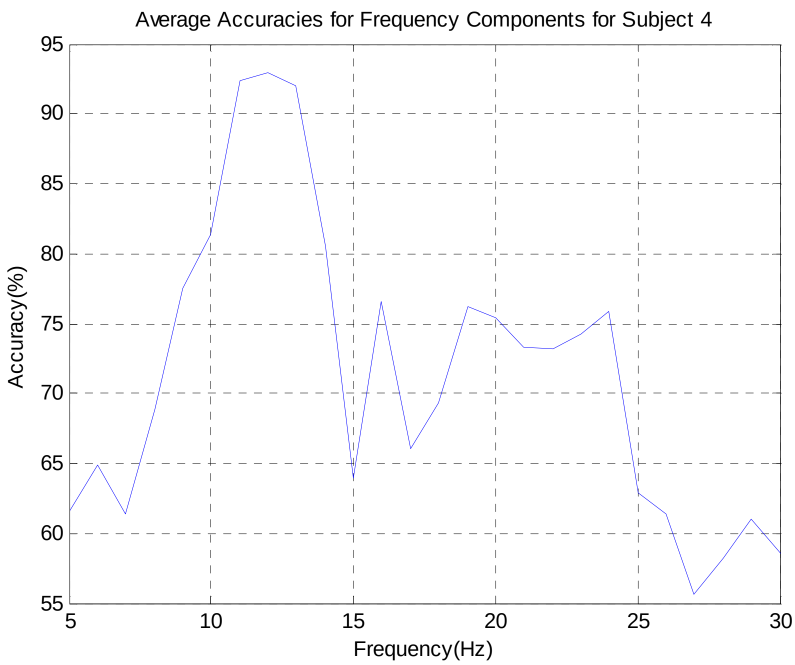


Figure 6-4: Relevant components found by frequency search method via classification. (Subject 4)

Result of this search indicates that the frequencies around 11, 12 and 13 Hz are the leading ones whereas 10 and 14 Hz come next. This result is consistent with the DSLVQ for 10, 11 and 12 Hz. Combining the best frequencies for DSLVQ and the frequency search algorithm, 10, 11, 12, 13 and 14 Hz components are selected as the features to be used in the classification for Subject 4.

STFT is computed for each 2-second imagery data with sliding the Fourier transform window by 0.2 s. By this way, the time-frequency spectrum is calculated. In Figure 6-5 and Figure 6-6, average power spectrum plots are given for left and right hand imagination trials observed in the contralateral channels. Spectrums in the figures are calculated with 0.08 s window starting from 1 second before the cue onset (2 seconds before the imagination) to the end of the 3-second imagination duration. Temporal resolution used in these plots is higher than the resolution used in the algorithm to provide a clear visualization of the power change in the plots. For frequencies between 1 - 30 Hz and time steps of 0.04 s, the power changes can be observed in detail. In both figures, the decrease in the power can easily be observed in approximately 10th sample corresponding to 0.4 s after the cue onset which is termed as event-related desynchronization (ERD).

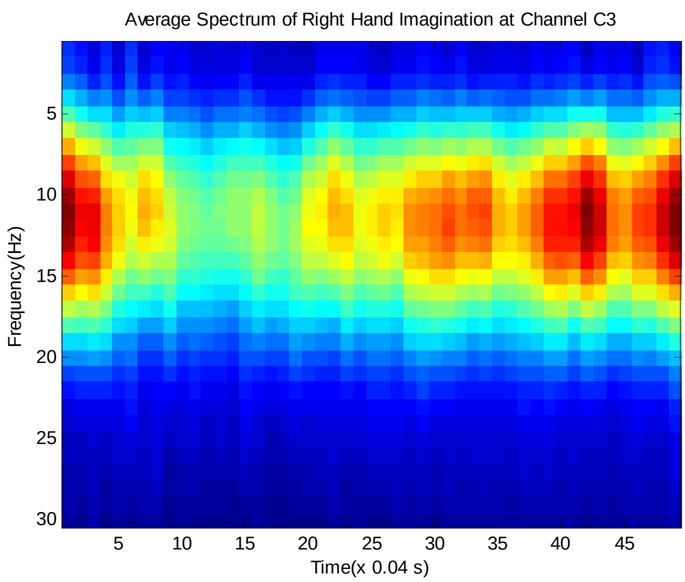


Figure 6-5: Average power spectrum on channel C3 for the right hand movement imagination task

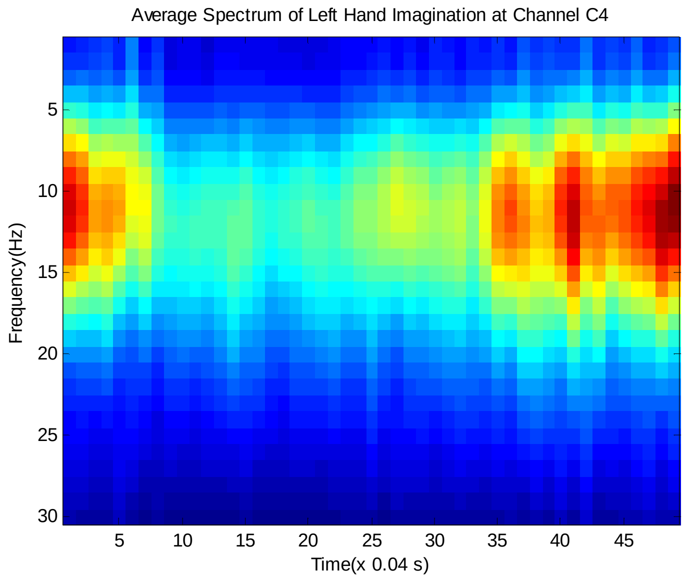


Figure 6-6: Average power spectrum on channel C4 for the left hand movement imagination task.

Among all frequency values, the most informative frequencies determined by DSLVQ and search method are 10, 11, 12, 13 and 14 Hz. The power values with respect to time for these frequencies are combined from channel C3 and C4 to form the feature set. For each trial, feature vector is normalized and fed to the classification algorithm as one observation. All normalized observations are inserted into linear SVM algorithm [58] and the classification model is constructed.

The training dataset composed of 400 trials is used in construction of a classification model. The training algorithm performs cross-validation such that the dataset is randomly split in the ratio of 0.7 for training and 0.3 for testing. In both sub-dataset, there is equal number of trials from both classes to prevent misleading the classifier. The randomly split data is trained and tested 100 times in the algorithm and the cross validation accuracies for all iterations are compared. Classification model giving the largest cross validation accuracy becomes the final model to be used in the testing part. The contribution of this algorithm is the optimization of the trial selection since there might be unsuccessful trials in the training set and this method helps to eliminate them and therefore construct the most probably successful model. The training model selected according to this method has a 5-fold cross-validation accuracy of 95.62%.

After construction of the training model, the evaluation dataset is applied the same procedure for preprocessing and feature extraction. It is filtered with band-pass (5-30 Hz) filter and downsampled to 125 Hz. Then the time-frequency features of 2-second data are extracted by STFT. The frequencies determined in training are used in feature selection and resulting feature set is classified by the constructed SVM model. First of all, testing is performed using the same time interval with the training interval (see Figure 6-2) and the prediction accuracy is found to be 96.88% (310 true prediction / 320 trials) which corresponds to 93.76% kappa value. However, the competition requires continuous output; thus the evaluation interval is extracted as given in Figure 6-7 which brings computational load. For this reason, the classification is performed on each 10th sample of the dataset and the inter-values are padded with the latest output. This corresponds to 10/125 = 0.08 s resolution of response. Figure 6-7, shows the timing of the evaluation and output part.

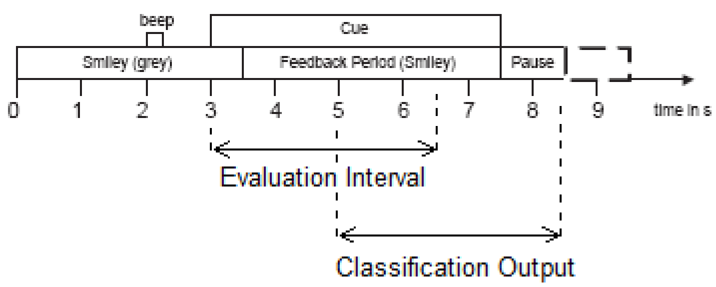


Figure 6-7: The part of the trials used for evaluation of the algorithms and the duration of continuous classification output (Adapted from [2])

The classification model is constructed on 2-second data and the prediction algorithm is required to be casual, thus in order to have a prediction in a time instant, processing should start 2 seconds prior to the required response instant. Therefore, the algorithm is started 2 seconds before the trial starts and at each 10th sample, past 2-second data is classified for 11 seconds to see the whole trial duration. The average accuracy and kappa values are obtained starting 1s later than the beginning of the imagination to the 1s after the imagination ends. In Figure 6-8, the interval between second 5 and 8.5 that contributes to the average kappa can be seen.

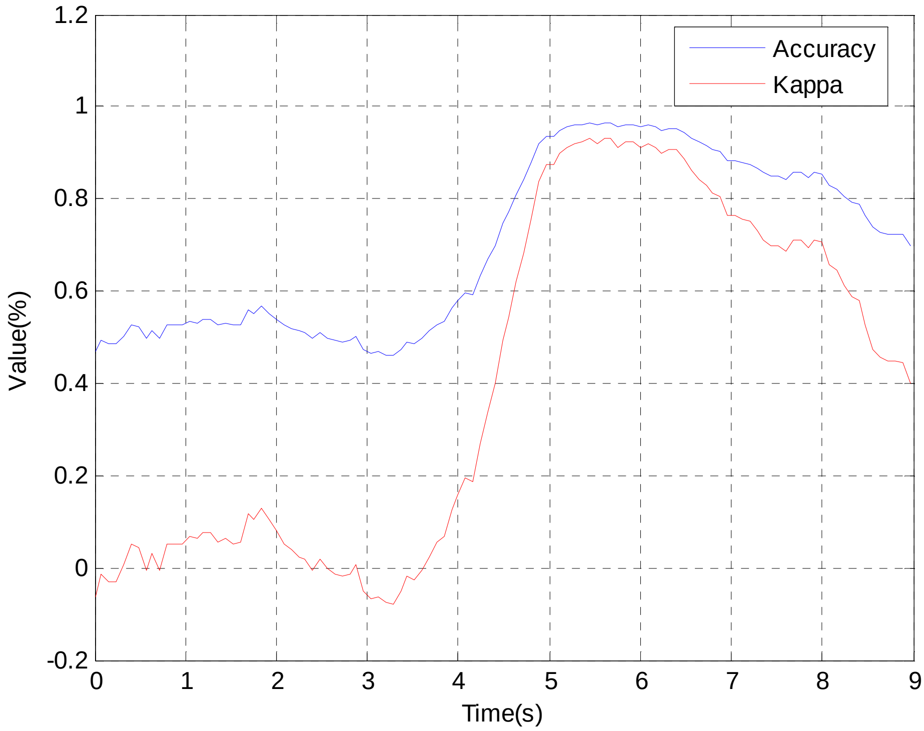


Figure 6-8: Accuracy and the kappa values of predictions at different time instances for subject 4. Between 5 - 8.5 seconds, maximum accuracy = 96.875% (310/320), average kappa = 0.8330, average accuracy = 0.9165

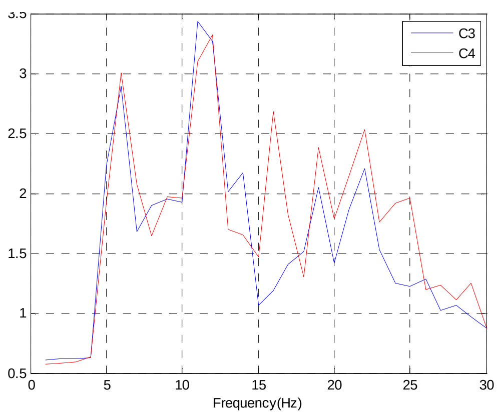
The imagination starts from second 4 and continues until second 7.5. Giving the classification output as soon as possible is important in terms of feedback.

Classifying the 2-second past data will be misleading if the output starts simultaneously with the imagination since there is no imagery data in the processed data. These initial predictions are not expected to be true. Therefore, the start of the classification is shifted 1 second after the imagination start. Equal amount of shift is also applied at the end of the trial which means that the output of the algorithm comes with 1 s delay. As a measure of the classification in this interval, an average kappa value of 83.30% and an average accuracy of 91.65% are observed for subject 4.

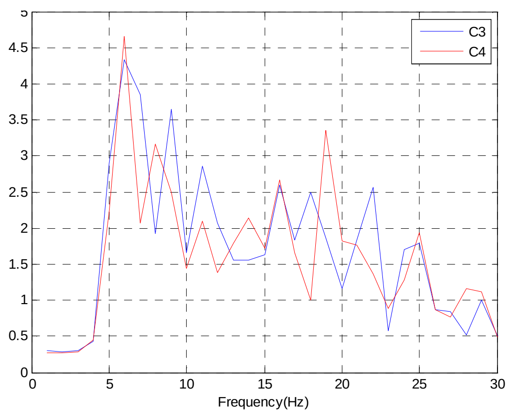
6.2.2.3 Results for Other Subjects

DSLVQ Outputs

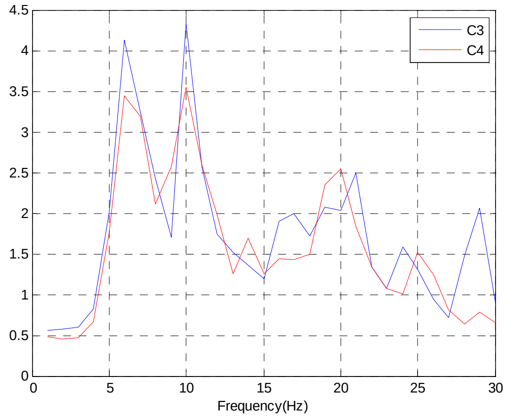
Below, one can find the weight coefficients found by DSLVQ for each subject. Selected frequency parameters are shown in Table 6-2.



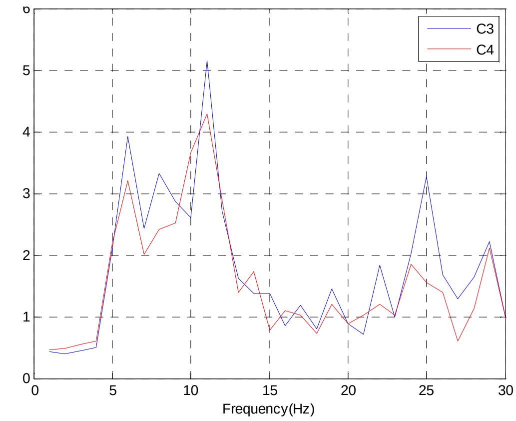
(a) Subject 1



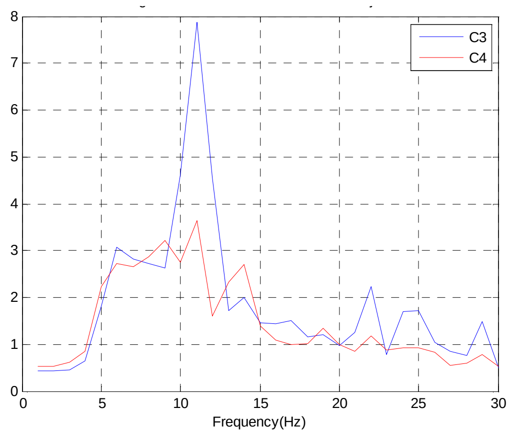
(b) Subject 2



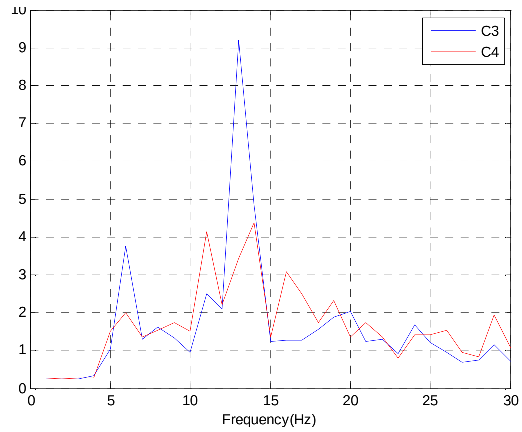
(c) Subject 3



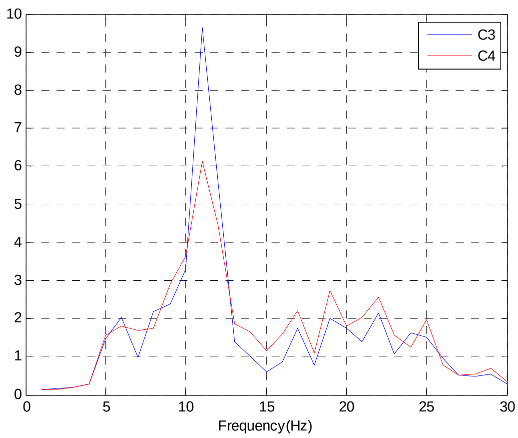
(d) Subject 5



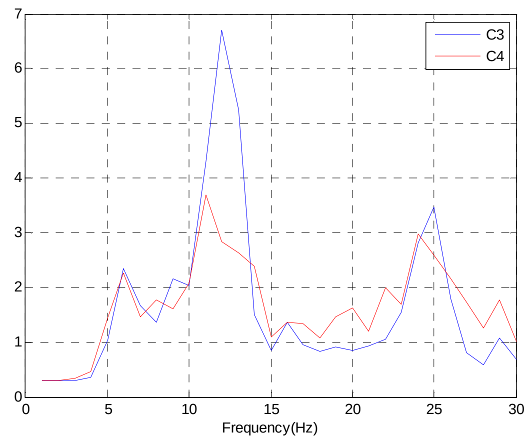
(e) Subject 6



(f) Subject 7



(g) Subject 8

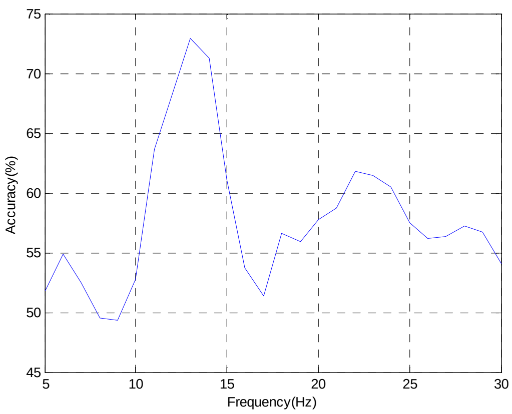


(h) Subject 9

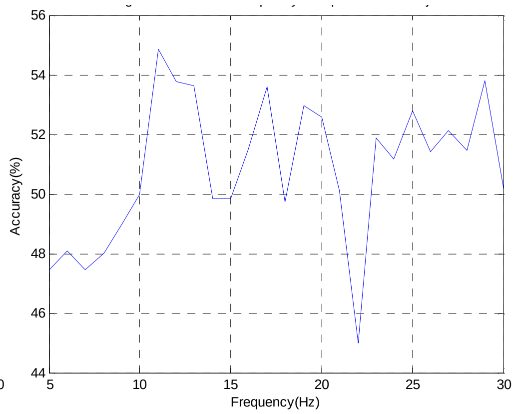
Figure 6-9: DLSVQ coefficients for the frequencies 1-30 Hz and channels C3 and C4 for all subjects (excluding Subject 4).

Average Accuracy Plots with the Frequency Search Method

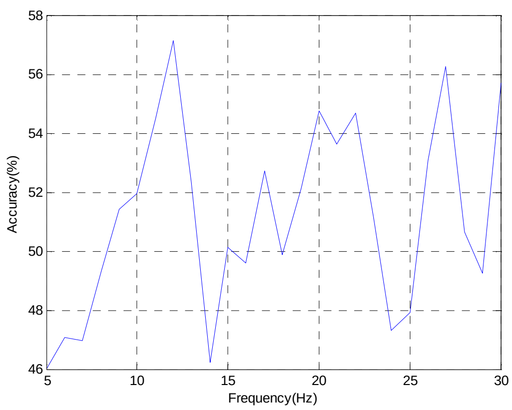
For all subjects (excluding subject 4), the preclassification results performed by the frequency search method are provided in Figure 6-10.



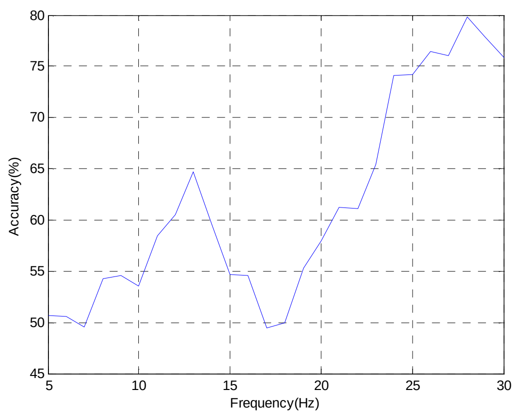
(a) Subject 1



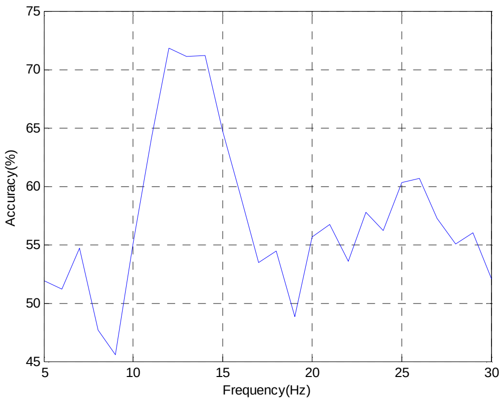
(b) Subject 2



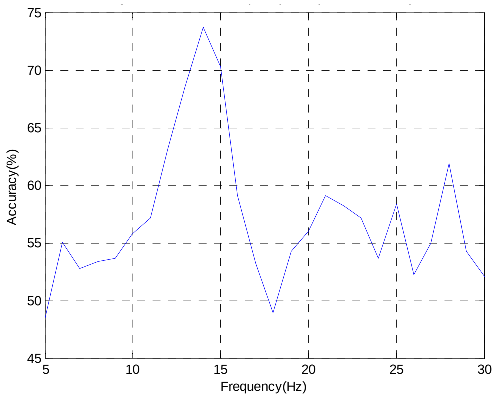
(c) Subject 3



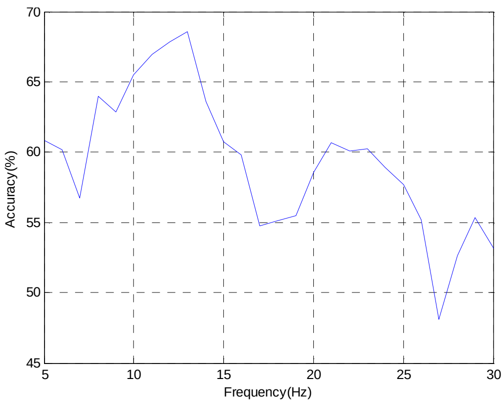
(d) Subject 5



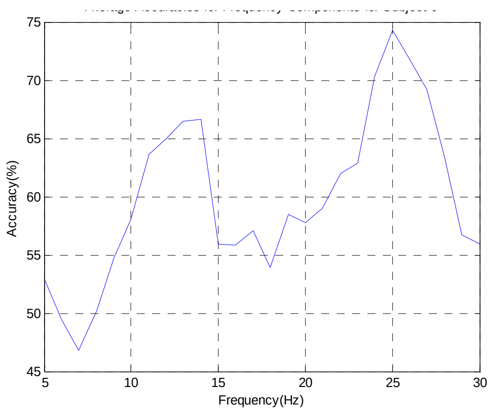
(e) Subject 6



(f) Subject 7



(g) Subject 8



(h) Subject 9

Figure 6-10: Relevant frequency components found by the frequency search method employing pre-classification.

In Figure 6-10, one can observe the similarities and the differences between the features extracted by two methods. For subject 2, DSLVQ shows some inconsistency between channels C3 and C4. The significant frequencies for C3 are 9, 11, 16, 18 and 22 Hz whereas for C4 they are 8, 11, 14, 16 and 19 Hz components. At the same time, frequency search method indicates that 11, 12, 13, 17, 19 and 29 Hz components have higher significance. In such inconsistent cases, the output of the search method is emphasized, resulting in 11, 12, 13 and 16 Hz for Subject 2.

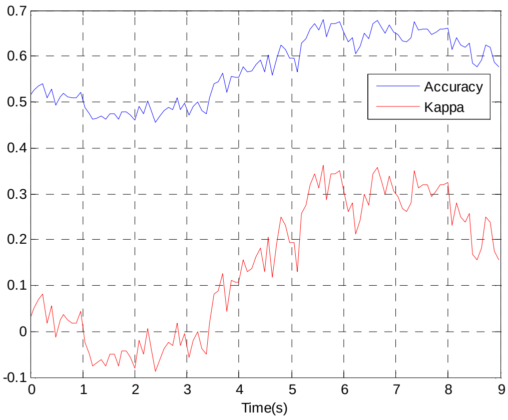
The consistency of the DSLVQ results with the frequency search is observed to be highly dependent on the quality of the dataset. For the subjects that have high accuracy and kappa values, the frequencies determined by DSLVQ are close to the frequencies obtained by iterative search. These two methods give both common and complementary frequency features such that when they are combined, the prediction accuracy increases according to the accuracies achieved separately by these methods.

Table 6-2: Common frequency features for channels C3 and C4 selected with the DSLVQ and frequency search methods for all subjects

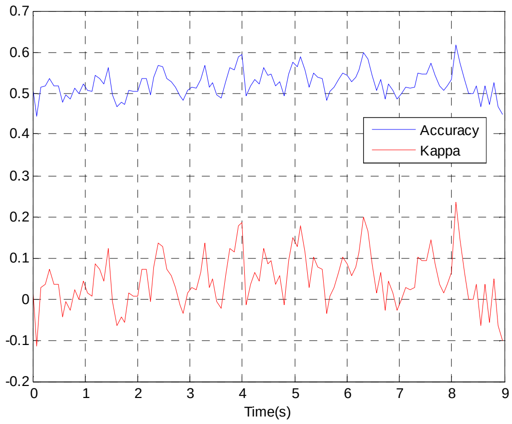
Subject	DSLVQ Output (Hz)	Frequency Search Output (Hz)
1	11,12,16,19,21	11,12,13,14
2	8,11,14,16,19	11,12,13,17,19,29
3	9,10,11,12,19,20,21	10,11,12,13,20,21,22,27
4	8,10,11,12	10,11,12,13,14
5	10,11,12,24,25,26,29	26,27,28,29,30
6	7,8,9,10,11,12	11,12,13,14,15
7	11,12,13,14	12,13,14,15,16,28
8	9,10,11,12	8,9,10,11,12,13, 14
9	11,12,13,24,25	11,12,13,14,24,25,26,27

Average Accuracy and Kappa Values

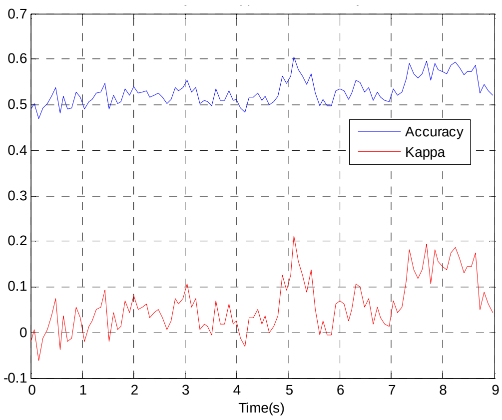
The average accuracy and the kappa coefficients of the classification for all subjects are shown in Figure 6-11.



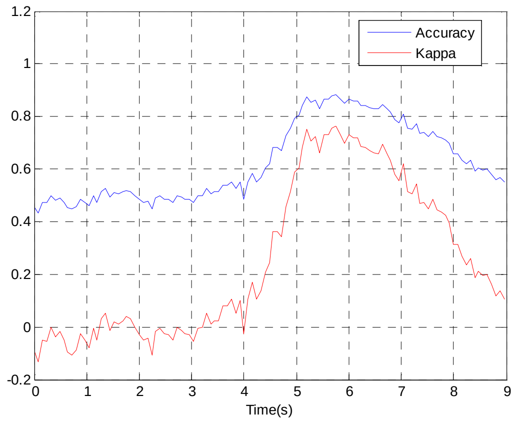
(a) Subject 1



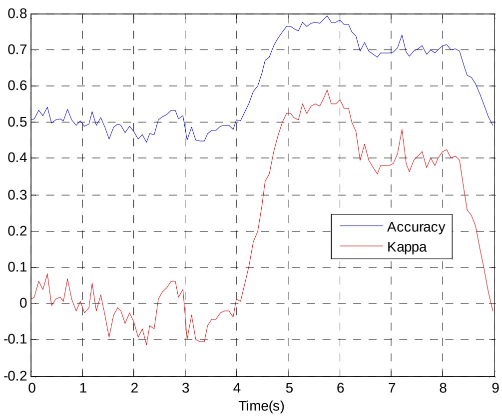
(b) Subject 2



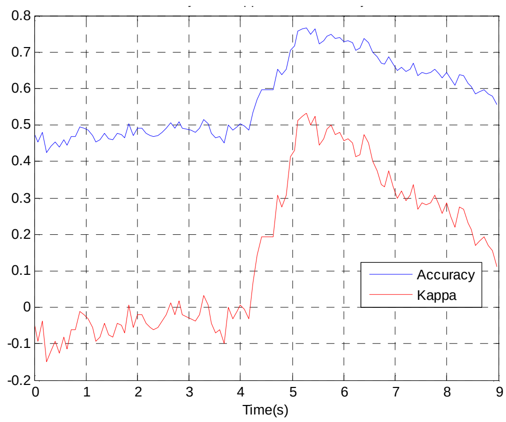
(c) Subject 3



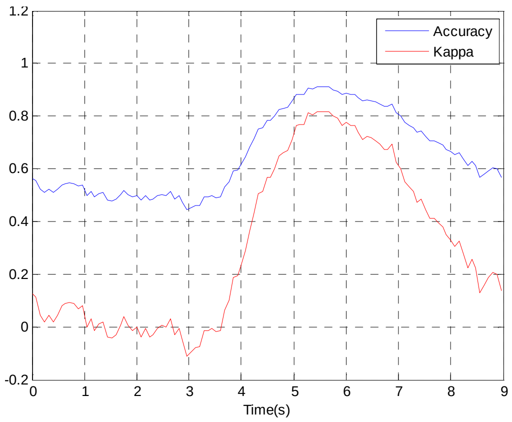
(d) Subject 5



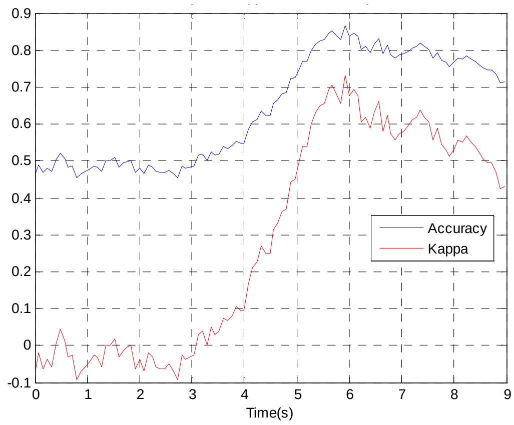
(e) Subject 6



(f) Subject 7



(g) Subject 8



(h) Subject 9

Figure 6-11: Accuracy and the kappa values of the predictions at different time instances for all subjects (excluding subject 4). Only the interval between 5-8.5 seconds should be considered for evaluation.

The features selected by the methods and their overall performance for all subjects are summarized in Table 6-3.

Table 6-3: Summary of the selected features and the resulting classification performances of the methods for all subjects

Subject	DSLVQ Output (Hz)	Frequency Search Output (Hz)	Combined Frequencies (Hz)	Test Accuracy (%)	Average Accuracy (%)	Average Kappa (%)
1	11,12,16,19,21	11,12,13,14	11,12,13,14	68.13	64.00	29.41
2	8,11,14,16,19	11,12,13,17,19,29	11,12,13,16	55.36	53.39	6.79
3	9,10,11,12,19,20,21	10,11,12,13,20,21,22,27	10,11,12,20,21,22	53.44	54.67	9.34
4	8,10,11,12	10,11,12,13,14	10,11,12,13,14	96.88	91.65	83.30
5	10,11,12,24,25,26,29	26,27,28,29,30	26,27,28,29,30	86.75	80.45	60.91
6	7,8,9,10,11,12	11,12,13,14,15	11,12,13,14,15	78.75	73.09	46.17
7	11,12,13,14	12,13,14,15,16,28	11,12,13,14,15,16	73.75	69.60	39.20
8	9,10,11,12	8,9,10,11,12,13,14	8,9,10,11,12,13	90.94	82.59	65.19
9	11,12,13,24,25	11,12,13,14,24,25,26,27	24,25,26,27	83.75	80.09	60.17

The average accuracy for 9 subjects is 72.17% and kappa is 0.45 (45%) corresponding to 4th rank in the competition. The winner group achieved 0.60 of kappa value [44].

6.3 METU Brain Research Laboratory - BCI Experiments

6.3.1 Experimental Environment

Measurement environment is crucial on the signal quality such that electronic device, sound or movement around the acquisition system can easily distort the signal. Mainly, the external noise should be eliminated by instrumentation in the EEG system during acquisition, though it is not possible to discard this noise totally. In order to prevent such kinds of external artifacts, there are special EEG rooms shielded by Faraday cage. However, in this study it is aimed to develop a portable and practical application regardless the environment conditions. Therefore, the data acquisition is mostly performed in the laboratory environment.

In this study, the data is acquired by 10-channel EEG developed for BCI studies in METU Brain Research Laboratory. The details of EEG acquisition hardware are given in chapter 5. There is no electrical shielding in the laboratory environment where the measurements are performed.

6.3.2 The Dataset

The two class data is collected from 2 different subjects. Subject K is a 26 year-old female and is trained for left and right hand imagery task for nearly one month with different sessions both in METU Brain Research Laboratory and Hacettepe University Biophysics Department. Also she is experienced in BCI experiments. Subject M is a 27-year old male who is experienced in BCI systems but not in MI applications.

The subjects are supposed to give two kinds of data one of which is composed of only imagination data whereas in the other, they are allowed to perform limited movement beside the imagination. The movement in this kind should be slight not to distort the EEG record. For pure imagination data, the subjects are asked to concentrate on movement such that they should both try for moving the hand and at the same time stop themselves just before the movement as if it is a contention with the motor system of the body.

In these experiments, concentration of the subject is crucial, so that the duration of the experiment should be adjusted well not to be too long. Regarding this fact, the sessions of training data collection are composed of approximately 5-10-minute parts. Thereby, the subject is able to have breaks to have rest whenever s/he becomes bored or tired.

External noise is eliminated by the active filters in the EEG instrumentation, but internal distortions are directly added to the signal. The most effective internal distortions are the movements of the limbs close to the EEG cap. Thus, the subject should stay stable as much as possible during the imagination. Also it is observed that the eye blinks cause artifacts in the EEG signals. In some of the EEG applications, eye blink effects are recorded by Electrooculogram (EOG) and subtracted from the EEG records. Due to the practicality and speed considerations, eye blink artifact removal is not implemented in this study. In order to decrease the effects of the eye blinks, the subject is asked to try not to blink the eyes during the 2-second imagination part.

6.3.3 Two-Class Cue-Based Experiments

First stage of the experiments is the offline analysis with the interface given in Figure 5-6. The process of the offline experiment that the system is trained can be itemized as below:

- The subject sits in a relaxing chair.
- EEG cap is placed on the head and a conductive gel is applied to the subject's scalp.
- The subject is asked to follow the directions given by the interface on the screen.
- The interface begins with a 3-second empty screen that lets the subject to prepare him / herself.
- The trial begins with a cross sign in the middle of the screen and the subject is asked to focus on the screen with this sign.
- 2 seconds later, a beep tone is given and the subject is asked to become ready for the upcoming task.
- 1 second after the audio stimuli, the task is displayed as an arrow showing the direction of the hand movement imagination.
- In the 2-second imagination duration, the subject is supposed to concentrate on the movement imagination.
- When the imagination duration is finished, the arrow disappears and 3-second of empty screen follows for rest.
- New trial begins and the overall process is repeated when the cross sign appears on the screen.

For the online analysis of the system, the whole procedure of the experiment is the same except the feedback part. In online testing, the classification output follows the imagination part instead of an empty screen. About 1-1.5 seconds after the arrow disappears, the output of the classification is given with a slider bar pointing to the predicted direction by the amount of the prediction value.

The analysis procedure for the offline and online applications will be explained step by step in the following subsections.

6.3.4 Experiments for Subject K

6.3.4.1 Dataset 1- Offline Analysis Results

First of all, EEG channels to be used in the analysis should be selected. Since the purpose is to provide the fastest classification response, the minimum number of channels containing the most discriminative information should be used in the analysis. C3 and C4 are the commonly preferred EEG channels in left and right hand MI BCI applications. However, in our preliminary experiments on the channels, P3 and P4 performed better than C3 and C4. Thus, the algorithms of offline and online analyses are applied on the signals coming from P3 and P4 channels.

The signals are collected with the sampling rate of 100 Hz by the EEG acquisition system explained in chapter 5. Next step is the digital filtering in which the signal outside the alpha and the beta band are eliminated using a 5-25 Hz equiripple FIR band-pass filter.

In one trial, there is a 2-second of imagination part and this interval is considered in further processes for all trials. 200 samples corresponding to the imagination period is extracted for each trial and stored in a matrix each row of which corresponds to one trial.

As given in the methodology and analysis procedure for the BCI dataset, after the selection of channels P3 and P4 for spatial information, temporal and spectral features are extracted by time-frequency analysis. Discriminative frequency components are investigated by DSLVQ method. Application procedure of DSLVQ is the same as in BCI dataset case giving the weight coefficients obtained for 1-30 Hz with 1 Hz steps. The weight coefficients obtained by DSLVQ method for channels P3 and P4 are provided in Figure 6-12.

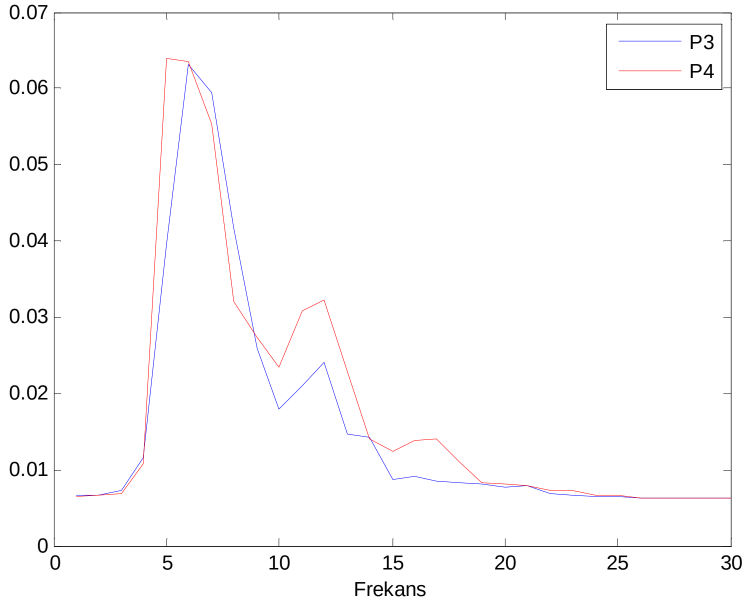


Figure 6-12: DSLVQ weight coefficients of frequency features for P3 and P4 for subject K

Using the fact that higher weights indicate higher importance, the activity in the brain seems to be focused around alpha band in Figure 6-12 such that 7, 8, 9 and 12 Hz frequencies are found to be most significant ones for channel P3 and 7, 8, 11 and 12 Hz frequencies are the most discriminative ones for P4. The weights for 5 and 6 Hz components are high again but they are not taken into account since they are irrelevant for MI activity. It can be concluded that the common important frequency components for P3 and P4 are 7, 8 and 12 Hz components. Therefore, only these frequency values are considered as feature items for time-frequency analysis of subject K.

STFT is used for time-frequency analysis of the 2 seconds with window size of 0.5 s and 50% overlapping. For each channel, 0.5-second window is transformed to Fourier domain, sliding by 0.25 s. As a result, for each frequency value there are 7 time-dependent power data for each channel. Power distribution for the determined frequencies 7, 8 and 12 Hz are combined from channel P3 and P4 as fetaure set. In the end, there are 42 features coming from 2 channels, 3 frequency components and 7 time values for each trial.

In Figure 6-13, average power spectrum plot is given for left hand imagination trials observed in P4 for Subject K. Spectrum is calculated with 0.5 s window of 0.1 s time resolution for 1-30 Hz interval. Figure 6-14 shows the power spectrum for right hand imagination obtained by averaging the trials recorded from P3. In both figure, the decrease in the power can easily be observed in between 0.4-1.2 s.

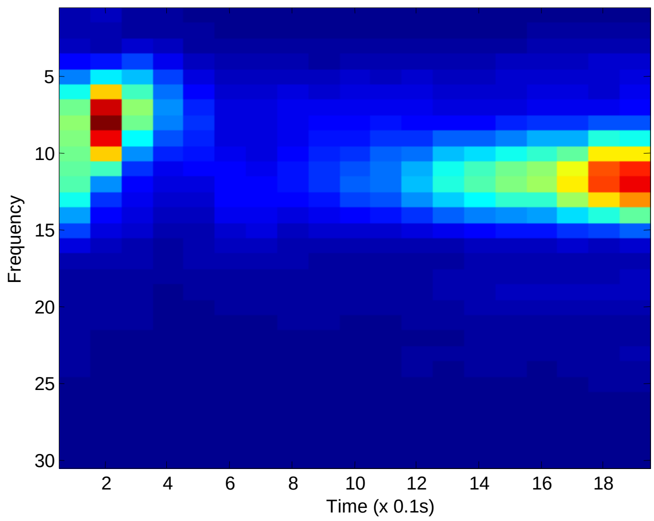


Figure 6-13: Averaged spectral power for channel P4 and left hand imagination task

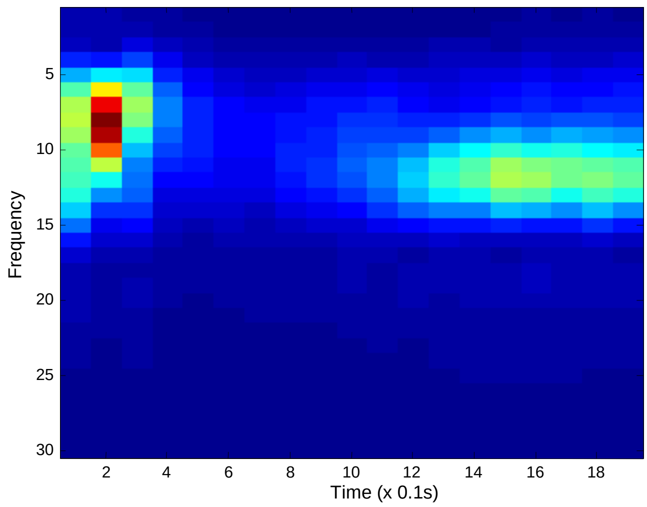


Figure 6-14: Averaged spectral power for channel P3 and right hand imagination task

For offline analysis, 2 different types of data are recorded from subject K one of which is totally imagery data whereas the other one consists of slight movements beside the imagination. In order to see the difference between imagination and realization of the movement, the subject is allowed to move the hands slightly in one part of the records. This part consists of 4 sessions, 60 trials for left and 60 trials for right hand movement imagination tasks. In the other record which is totally imagery, there are 103 trials for left and again 103 trials for right hand movement imagination.

Two kinds of data are transformed to the feature space with time-frequency operations explained above resulting in 42 features for each trial. Two classification algorithms should be developed separately for these data. In this point, there are two feature matrices; one of which is a 120x42 matrix and the other is 206x42 matrix. Support vector machines (SVM) with linear kernel is used in order to train the models. LIBSVM Toolbox is the tool used for the SVM classifier [58]. Resulting models are stored to be tested on new data in online analysis.

When the data are trained with SVM classifier, cross-validation is used to understand the accuracy of the training model. For this reason, 10-fold cross-validation is performed by using the Libsvm toolbox. The resulting accuracies for two types of activity are given in Table 6-4.

Table 6-4: Cross Validation Accuracies for Offline Training for Subject K

Type of Activity	**Cross Validation**
Real Movement	74.38%
Movement Imagination	87.43%

Being higher than 70%, the cross validation accuracies give some insight to the success of the training model. It seems that the training dataset is consistent and the constructed model is settled enough to be tested in online session.

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6.3.4.2 Dataset 1- Online Analysis Results

After the classification algorithm is trained for two types of data in offline analysis, the subject performs an online session in which the classification is applied on the data just after the imagination process. Online analysis consists of two sessions as in offline analysis. In the first session, imaginations with slight movements are tested with 33 trials of randomly ordered tasks. In the second session, pure imagination of the hand movements is tested with 41 trials.

In online analysis, whole analysis is done during the experiment and reflected to the subject as a feedback simultaneously. The experiment starts at the same time with the interface. For each trial, as soon as 2-second imagination duration finishes, the analysis process starts with filtering by 5-25 Hz pass-band filter. The frequencies determined in offline analysis are used in time-frequency spectrum calculation for both channels. The spectrums for both channels are concatenated for the selected frequencies and normalized before classification. The procedure of the process is same as the offline process in order to transform the data into the valid format. The classification is performed with the model trained in the offline session. The classification result is given to the screen as an arrow in the predicted direction in about 1-1.5 seconds.

In online session, for slight movement, 32 trials are predicted successfully over 33 trials, only the third trial, which is actually a left hand movement imagination, is labeled as right hand imagination by the classification algorithm. For pure imagination, 40 trials are predicted with true labels over 41 trials which is a slightly higher accuracy than the real movement. In this case, misclassified trial is originally again a left hand task. Table 6-5 shows the accuracy values in percentage for this online session of subject K.

Table 6-5: Accuracy Values for Online Classification for Subject K

Type of Activity	**Accuracy**
Real Movement	96.97% (32/33)
Movement Imagination	97.56% (40/41)

6.3.4.3 Dataset 1 – Further Analysis

As mentioned before, the patterns of the motor activity in the brain are not only caused by movement. There are other situations in which similar patterns are observed. It is shown that the motor system can also be activated by imagining or observing movements [23].

In order to test the effect of the visual cue, an online experiment without showing the arrows on the screen is performed for subject K. During the experiments, it is observed that beside imagination, visually observing the movement enhances the patterns in the brain. The classification model that is trained with the cue based data is used for prediction. When the classification results are compared, it is seen that visualization provides more successful classification. For left / right hand discrimination in the cue-based application, the accuracy exceeds 90% if the cue is given as directed arrows whereas it decreases to 60%'s when the subject is informed by only audio stimuli. This fact shows that the patterns that the classifier catches in P3 and P4 channel data might not be MI-related. Furthermore, it has been mentioned in 3.1.2 that the area P channels lie on is related with visual stimulus [21]. This fact strengthens the idea that the caught patterns might be a response to the visual stimuli. However, the purpose is to detect the MI patterns rather than a response to a stimulus. Therefore, it is reasonable to reduce the significance of the channels P3-P4 and give weight to C3-C4 and F3-F4 channels in the classification.

For this purpose, further investigations in the classification are performed with combinations of C3-C4 and P3-P4 channel pairs. Furthermore, in order to decrease the effect of stimulus, Common Average Referencing (CAR) method is used which moves the ear reference close to the channel Cz for the case of given electrode layout (see section 5.1.1). Using the same train and test dataset (dataset 1), the accuracies for different channel selections are computed in offline analysis for both cases, with ear reference and CAR. Besides linear SVM; RBF SVM, Multilayer Perceptron and Naive Bayesian classifiers are applied on the data in order to provide complete investigation. The classification results for C3-C4, P3-P4 and C3-C4-P3-P4 channel combinations are given in Table 6-6, Table 6-7 and Table 6-8 respectively.

In the detailed analysis, beside STFT method, Morlet transform and CSFP methods are used in feature extraction stage. Using the determined frequencies, STFT algorithm is run for 0.24 s (24 samples) of window size with 0.04 s (4 samples) sliding. For Morlet transform, the center frequency of the band in which the discriminative frequencies lie is determined and a morlet wavelet is formed with this center frequency in order to convolve with the signal. In CSFP method, spectral feature selection is not performed. Instead, the signal is decomposed into 4-Hz bands around 6, 10, 14, 18 and 22 Hz for each channel. Then the CSFP algorithm linearly weights all feature combinations (2 channels x 6 spectral features) and the best ones are selected for the classification.

Using C3 and C4, best results are obtained with STFT method (Ear reference) and SVM classification in the imagination case where the accuracy is 87.80% and corresponding kappa is 0.756. For this case, the application of CAR decreases the success significantly.

Table 6-6: The accuracy (%) and Kappa values obtained for C3-C4 channel pair on dataset 1 for Subject K

C3, C4		STFT				Morlet Tr				CSFP			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Linear SVM	87.80	0.7560	60.98	0.2153	85.37	0.7092	68.29	0.3571	78.05	0.5633	68.30	0.3647
	Radial SVM	87.80	0.7560	60.98	0.2153	82.93	0.6604	68.29	0.3571	78.05	0.5633	68.30	0.3647
	MLP	82.93	0.6586	65.85	0.315	70.73	0.4157	51.22	0.0238	58.54	0.1633	43.90	-0.116
	Bayesian	78.05	0.5610	63.42	0.2652	85.37	0.7092	73.17	0.4573	73.17	0.4663	63.41	0.267
Realization	Linear SVM	78.79	0.5714	66.67	0.3265	63.64	0.2667	78.79	0.5746	48.48	0	51.52	0.0571
	Radial SVM	78.79	0.5714	57.58	0.1476	66.67	0.329	78.79	0.5746	48.48	0	51.52	0.0571
	MLP	72.73	0.4530	66.67	0.329	63.64	0.2694	60.61	0.2186	54.55	0.0884	63.64	0.2721
	Bayesian	72.73	0.4469	54.55	0.0816	69.70	0.3889	72.73	0.453	36.36	-0.281	48.48	-0.0408

Table 6-7: The accuracy (%) and Kappa values obtained for P3-P4 channel pair on dataset 1 for Subject K

P3 , P4		STFT				Morlet Tr				CSFP			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Linear SVM	90.24	0.8043	90.24	0.8038	95.12	0.9021	95.12	0.9021	80.49	0.6105	82.93	0.6571
	Radial SVM	90.24	0.8043	90.24	0.8038	95.12	0.9021	95.12	0.9021	80.49	0.6105	82.93	0.6571
	MLP	92.68	0.8537	99.01	0.9803	95.12	0.9021	97.56	0.9512	80.49	0.6086	70.73	0.4115
	Bayesian	90.24	0.8048	85.37	0.7071	92.68	0.8534	92.68	0.853	75.61	0.5131	78.05	0.5591
Realization	Linear SVM	69.70	0.3889	75.76	0.5093	87.88	0.7591	84.85	0.6961	81.82	0.6387	78.79	0.573
	Radial SVM	69.70	0.3889	75.76	0.5093	87.88	0.7591	84.85	0.6961	81.82	0.6387	78.79	0.573
	MLP	78.79	0.5698	75.76	0.5147	42.42	-0.1633	78.79	0.5746	75.76	0.5147	60.61	0.2157
	Bayesian	63.64	0.2612	63.64	0.2639	78.79	0.5746	66.67	0.324	63.64	0.2639	60.61	0.1981

Using P3 and P4, Morlet transform performs quite better than STFT in average. The maximum accuracies are achieved by applying CAR and classifying with Multilayer Perceptron. CAR is not effective in most cases but for MLP it increases the success above 95%. However, this high accuracy is not trustable since the source of this success is the stimulation for P3-P4 channel pair. Imagination case is again observed to be more successful than realization part.

When the C3-C4 and P3-P4 channels are combined, the accuracy becomes higher which indicates that both stimulated and motor imaginary patterns are used in the classification. Morlet Transform performs slightly better than STFT in this case.

For all cases, it is seen that the results of RBF SVM and linear SVM are totally same. The reason can be low dimensionality of the data or the low variance value set for RBF SVM causes the classifier to behave as if it is linear.

According to the results, C3-C4 channel pair does not perform as well as P3-P4 pair. This fact shows that stimulations are more dominant than MI patterns in this record.

Table 6-8: The accuracy (%) and Kappa values obtained for C3-C4-P3-P4 channel combination on dataset 1 for Subject K

C3 , C4 , P3 , P4		STFT				Morlet Tr				CSFP			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Linear SVM	95.12	0.9021	90.24	0.8038	97.56	0.9511	90.24	0.8038	82.93	0.6604	82.93	0.6563
	Radial SVM	95.12	0.9021	90.24	0.8038	97.56	0.9511	90.24	0.8038	82.93	0.6604	82.93	0.6563
	MLP	92.68	0.8537	90.24	0.8043	97.56	0.9512	87.80	0.7557	78.05	0.5602	85.37	0.7071
	Bayesian	87.80	0.7574	87.80	0.7557	87.80	0.7574	92.68	0.853	80.49	0.6114	78.05	0.5581
Realization	Linear SVM	81.82	0.636	84.85	0.695	87.88	0.7574	81.82	0.6347	69.70	0.3911	87.88	0.7582
	Radial SVM	81.82	0.636	84.85	0.695	87.88	0.7574	81.82	0.6347	69.70	0.3911	87.88	0.7582
	MLP	81.82	0.6333	63.64	0.2667	72.73	0.459	75.76	0.5147	78.79	0.573	84.85	0.6984
	Bayesian	60.61	0.1981	60.61	0.2041	78.79	0.5714	69.70	0.3866	42.42	-0.1764	84.85	0.695

6.3.4.4 Dataset 2

Subject-specific patterns vary according to the time such that characteristics of the brain activity might change after a while [63]. Therefore, it is necessary to work on different datasets of a subject collected in different times. For this purpose, a new dataset is collected from subject K 4 months after the collection of dataset 1. The classification results for the same procedure (using channel combinations and CAR) are provided for the dataset 2 for Subject K in order to validate the results given in Table 6-6, Table 6-7 and Table 6-8.

Dataset 2 is composed of only imagination data obtained with the same interface and procedure with Dataset 1. The classification results are provided for all cases in Table 6-9, Table 6-10, Table 6-11 and Table 6-12.

Table 6-9: The accuracy (%) and Kappa values obtained for C3-C4 channel pair on dataset 2 for Subject K. *Cz is used for only CSFP analysis

C3, C4 ,Cz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	71.14	0.4258	73.82	0.4773	74.50	0.4908	72.48	0.4505	67.79	0.3565	65.78	0.3198
	RBF SVM	71.14	0.4258	73.82	0.4773	74.50	0.4908	72.48	0.4505	67.79	0.3565	65.78	0.3198
	MLP	67.11	0.3443	73.15	0.4637	55.70	0.1137	67.79	0.3561	66.44	0.3282	61.75	0.2381
	Bayesian	61.75	0.2364	65.10	0.3032	71.81	0.4363	70.47	0.4104	66.44	0.33	61.75	0.2381

Table 6-10: The accuracy (%) and Kappa values obtained for C3-C4-F3-F4 channel combination on dataset 2 for Subject K. *Cz and Fz are used for only CSFP analysis

C3, C4, F3, F4, (Cz, Fz)*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	69.80	0.3998	65.77	0.3176	75.17	0.5052	48.99	0	66.44	0.3304	59.73	0.2021
	RBF SVM	69.80	0.3998	65.77	0.3176	75.17	0.5052	48.99	0	66.44	0.3304	59.73	0.2021
	MLP	67.11	0.3457	72.48	0.4505	68.46	0.3707	50	0	63.76	0.2784	59.73	0.2012
	Bayesian	62.41	0.25	61.07	0.2212	71.14	0.4243	65.77	0.3157	66.44	0.3315	61.42	0.2545

Table 6-11: The accuracy (%) and Kappa values obtained for C3-C4-F3-F4-P3-P4 channel combination on dataset 2 for Subject K. *Cz, Fz and Pz are used for only CSFP analysis

C3, C4, F3, F4, P3, P4 (Cz, Fz, Pz)*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	79.87	0.5989	79.87	0.5989	81.88	0.6387	83.22	0.6656	76.51	0.5314	75.17	0.506
	RBF SVM	79.87	0.5989	79.87	0.5989	81.88	0.6387	83.22	0.6656	76.51	0.5314	75.17	0.506
	MLP	79.87	0.5985	70.47	0.4098	81.21	0.6248	77.85	0.5577	64.43	0.2896	69.80	0.3982
	Bayesian	73.83	0.4776	71.81	0.4366	78.52	0.5717	73.83	0.4781	74.50	0.4917	74.50	0.4919

Table 6-12: The accuracy (%) and Kappa values obtained for P3-P4 channel pair on dataset 2 for Subject K. *Pz is used for only in CSFP analysis

P3, P4 ,Pz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	83.22	0.6656	83.22	0.6653	80.54	0.6117	79.19	0.5863	75.17	0.5052	80.54	0.6119
	RBF SVM	83.22	0.6656	83.22	0.6653	80.54	0.6117	79.19	0.5863	75.17	0.5052	80.54	0.6119
	MLP	81.21	0.625	83.89	0.6779	81.21	0.6246	78.52	0.5719	71.14	0.4262	75.84	0.5176
	Bayesian	75.17	0.5046	76.51	0.5319	78.52	0.5721	76.51	0.5334	75.17	0.5046	75.17	0.5046

In Dataset 2, the general accuracy decreases for all cases due to two possible reasons. One reason is the difference between recording times of two datasets since the MI patterns might change in time. The other possible reason is the fact that the subject is aware of the dominance of the stimulation in this record and she is required to be more careful about this fact.

Considering the C3-C4 channel pair mainly, it is seen that Morlet performs quite better than STFT while CSFP is not as good as them. The maximum accuracy achieved is 75.17% in C3-C4-F3-F4 combination regardless the P3-P4 pair results. The accuracy achieved by C3-C4 pair, 74.50% is also close to this accuracy which means that F3-F4 pair does not provide a significant contribution on the classification. On the other hand, using channels C3 and C4, 87.80% accuracy was achieved with the Dataset 1 for Subject K showing that there is a significant change in the MI patterns of Subject K in 4-month duration.

6.3.5 Informed Cue Dataset

It is observed that stimulations are dominant in the discrimination especially for P3-P4 channels. In our case, the stimulus is the arrow showing up on the screen. At the same time, the subject starts to imagine the movement thus the imagination and stimulation happen at the same time resulting in suppression of the motor imagery patterns by the evoked patterns. In order to prevent this situation and observe the effect of the cue on the classification patterns, a new dataset is collected in which the cue is given prior to the imagination and there is no cue during the imagination.

In this part, the dataset will be described and the results will be given with the use of STFT and Morlet wavelet transform.

6.3.5.1 Experiment Procedure

This dataset is collected from Subject K since she has more experience in motor imagery tasks and by this way the results can be compared. It consists of 156 trials in total with 78 left and 78 right hand movement imagination trials. There is not any visual cue displayed in the beginning and during the imagination. The flow of the trials is similar to the previous trial format (see Figure 5-7). The cue is again an arrow showing the hand side to be imagined to move. The only difference is the timing of the cue. It is presented 3 seconds prior to the start of the imagination and it is only displayed for 1 second. After two seconds the cue disappears, the imagination starts and during 5-second imagination the subject does not see anything on the screen.

For this dataset, 3 pairs of channels F3-F4, C3-C4 and P3-P4 are analyzed separately and then combined for the offline analysis. For each case, two types of analysis are used in terms of feature extraction which are STFT and Morlet wavelet transform. The frequency search, training and testing are performed for these features separately.

In this dataset, both frequency search method and DSLVQ are performed. According to the search method, the beta band frequencies give higher accuracy. However, DSLVQ gives the discriminative frequencies among the alpha band. Since the search method gives the importance of a single frequency feature by directly classifying, they are robust and reliable. The result of the search show that the left/right movement information lies in the beta band and DSLVQ is not reliable for the beta band. Therefore only the search outputs are used in the classification.

According to the frequency search, beta band is more informative meaning that the spectral region of interest is higher for this dataset. Thus, temporal resolution should be increased for the time frequency analysis. For the computation of STFT features, the window width is selected as 0.2 s (20 samples) and it is shifted by

0.02 s (2 samples). For morlet transformation, the spectral resolution is same with the sampling frequency therefore it is high enough for the processes.

Until now, the interval that the imagination starts is investigated in order to detect the state change of the brain from idle to imagination. In such a state change, the patterns are more significant than a continuous imagination case. By this analysis, it is also aimed to understand the imagination intention in case of continuous imagination. Therefore last 4s of the duration is chosen to be processed for the offline analysis over 5 s imagination duration. In other words, the duration in which the imagination is stationary is taken into account and there is not any pattern reflecting the transition between idle and imagination. The results can be seen in Table 6-13.

Table 6-13: 5-fold cross validation and average prediction accuracy results with the features exracted by the methods (Subject K)

Channel Combination	Frequencies	General CV (%)	Avg. CV (%)	Avg. Test Accuracy (%)
F3 , F4				
DSLVQ	7, 8, 9, 10	-	-	-
STFT	17, 23, 24	57.86	54.51	54.62
Morlet	10, 15, 22	64.78	60.93	64.17
C3 , C4				
DSLVQ	7, 8, 9, 10	-	-	-
STFT	23, 28	62.89	57.95	59.09
Morlet	13, 21, 22	61.01	61.13	63.09
(F3 + C3)/2 , (F4 + C4)/2				
DSLVQ	7, 8, 9, 10	-	-	-
STFT	11, 22, 23	52.20	53.83	54.78
Morlet	21, 22	56.61	60.76	60.02
P3 , P4				
DSLVQ	12, 13, 16, 23	-	-	-
STFT	23, 24, 28, 29	52.83	53.18	55.50
Morlet	19, 27, 28, 29	58.49	59.65	59.56
F3 , F4 , C3 , C4				
STFT	23, 28	59.12	56.44	54.56
Morlet	10, 13, 22	66.04	62.07	63.09
F3 , F4 , C3 , C4 , P3 , P4				
STFT	23, 28	57.86	53.18	56.61
Morlet	10, 21, 22	52.20	54.75	55.78

For the Morlet transformation results, channel pairs C3-C4 and F3-F4 perform bettter than P3-P4 since the effect of evoked patterns is decreased by the new interface. When they are all inserted into analysis, the accuracy is observed to decrease. The reason can be explained with the large number of features. With Morlet transformation, feature vector corresponding to each frequency and channel has a length of whole processed duration which is 4 s (400 samples). Therefore, combining 3 frequencies and 6 channels results in a feature vector of 3x6x400 = 7200 elements which might lead to curse of dimensionality.

The inconsistency between the frequencies found by DSLVQ and iteratively searched ones might arise due to the properties of the acquisition system. As stated before, our EEG system performs a filtering operation between 0.1 – 40 Hz, however after 13 Hz the gain starts to decrease significantly when it is compared with the 0.1- 12 Hz interval [6]. Due to this characteristic of the analog filter, the alpha band is amplified better than beta band. This fact causes a decrease in the amplitude of the beta band signals which are already weaker than alpha band signals. Therefore it becomes harder to detect the patterns in beta band. Since DSLVQ analyzes according to the total power of each frequency component, the high power signals are more dominant whereas the low power signals seem to be less effective even they carry more discriminative information. Therefore, beta band is suppressed by the alpha band during DSLVQ analysis and alpha band seems more effective while beta band is actually more informative as found by the frequency search.

6.4 Experiments Conducted at Hacettepe University Biophysics Department

The probable defects of our acquisition system might have important effects on the analysis results; therefore it is necessary to compare the system with an external reference. For this purpose, another dataset is recorded in Hacettepe University Biophysics Department with a SynAmps EEG system in a shielded room.

In this experiment, interface for Ping-Pong like game is used since it is less stimulative when it is compared with the cue-based experiment. For this dataset, three methods are used: STFT, Morlet Transform and CSFP. Using this dataset, it is aimed to observe the effect of the acquisition system on the accuracy and provide comparison of the methods with a reliable dataset.

The dataset is collected from Subject K and she has performed two types of experiment one of which is only imagination and the other one is slight movements. She is required to perform or imagine the hand movements by an action such as softly clenching a ball.

The cross validation and overall accuracies are computed for four different classification algorithms: Linear SVM, Radial Basis SVM, Multilayer Perceptron and Naive Bayesian Classifier. The results for different channel combinations are given in Table 6-14, Table 6-15 and Table 6-16.

Table 6-14: The accuracy (%) and Kappa values obtained for C3-C4 channel pair on Hacettepe dataset for Subject K. *Cz is used for only CSFP analysis

C3 , C4, Cz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	60.22	0.2018	69.89	0.3986	61.29	0.2236	67.74	0.3557	58.06	0.1583	61.29	0.2225
	RBF SVM	60.22	0.2018	69.89	0.3986	61.29	0.2236	67.74	0.3557	58.06	0.1583	61.29	0.2225
	MLP	50.54	0.0097	59.14	0.1831	61.29	0.2236	66.67	0.3337	46.2366	-0.0749	59.14	0.1808
	Bayesian	62.37	0.2464	67.74	0.3551	61.29	0.225	62.37	0.2484	53.76	0.0737	55.91	0.1167
Realization	Lin. SVM	61.34	0.2277	66.39	0.3283	63.03	0.2602	61.34	0.2268	68.07	0.3604	60.52	0.2104
	RBF SVM	61.34	0.2277	66.39	0.3283	63.03	0.2602	61.34	0.2268	68.07	0.3604	60.52	0.2104
	MLP	62.18	0.2433	59.66	0.1932	50	0	56.30	0.1267	63.87	0.2755	57.14	0.1424
	Bayesian	57.14	0.1419	57.14	0.1444	61.34	0.2273	59.66	0.1921	67.23	0.3435	59.66	0.1937

Table 6-15: The accuracy (%) and Kappa values obtained for C3-C4, F3-F4 channel combination on Hacettepe dataset for Subject K. *Cz and Fz are used for only CSFP analysis

C3 , C4, F3 , F4, Cz , Fz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	69.89	0.3961	53.76	0.0737	64.52	0.2871	60.22	61.29	0.2271	0.0224	56.99	0.1337
	RBF SVM	69.89	0.3961	53.76	0.0737	64.52	0.2871	60.22	61.29	51.61	0.0224	56.99	0.1337
	MLP	56.99	0.1405	62.37	0.2484	56.99	0.1393	61.29	0.2271	63.44	0.2681	55.91	0.1159
	Bayesian	54.84	0.0963	51.61	0.0319	63.44	0.2681	63.44	0.2687	63.44	0.2684	52.69	0.0515
Realization	Lin. SVM	59.66	0.1939	67.23	0.3453	57.98	0.1591	60.50	0.2108	63.87	0.2765	63.87	0.2765
	RBF SVM	59.66	0.1939	67.23	0.3453	57.98	0.1591	60.50	0.2108	63.87	0.2765	63.87	0.2765
	MLP	70.59	0.4113	63.03	0.2607	56.30	0.1262	56.30	0.1262	57.98	0.1596	57.98	0.1596
	Bayesian	51.26	0.0243	67.23	0.3448	58.82	0.1763	59.66	0.1923	60.50	0.2084	60.50	0.2084

Table 6-16: The accuracy (%) and Kappa values obtained for C3-C4, F3-F4, P3-P4 channel combination on Hacettepe dataset for Subject K. *Cz, Fz and Pz are used for only CSFP analysis

C3 , C4, F3 , F4, P3 , P4, Cz , Fz , Pz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	76.34	0.5259	72.04	0.4392	73.12	0.4607	75.27	0.5041	73.12	0.4609	70.97	0.4183
	RBF SVM	76.34	0.5259	72.04	0.4392	73.12	0.4607	75.27	0.5041	73.12	0.4609	70.97	0.4183
	MLP	66.67	0.3325	73.12	0.4624	70,97	0.4189	74.19	0.4829	65.59	0.3111	59.14	0.1816
	Bayesian	60.22	0.204	64.52	0.2897	67.74	0.3542	73.12	0.4614	63.44	0.2667	65.59	0.3092
Realization	Lin. SVM	71.43	0.4285	75.63	0.512	75.63	0.5132	70.59	0.4116	68.07	0.3602	73.1	0.4611
	RBF SVM	71.43	0.4285	75.63	0.512	75.63	0.5132	70.59	0.4116	68.07	0.3602	73.1	0.4611
	MLP	70.59	0.4115	66.39	0.3271	69.75	0.3947	73.95	0.4793	58.82	0.1758	63.87	0.2761
	Bayesian	61.34	0.2266	71.43	0.4279	68.07	0.3618	73.11	0.462	69.75	0.3937	70.59	0.4106

The dominancy of the P3-P4 channel pair is again observable but it is less in this experiment. Without P3 and P4 the maximum overall accuracy is 70.59% while 75.63% is obtained by using C3-C4, F3-F4 and P3-P4 pairs. Even the optimum conditions are provided for data acquisition, the system couldn’t discriminate better than the dataset 1 analysis. This result might depend on the time varying MI patterns or lack of subject concentration.

6.4.1 Experiments for Subject M

Subject M is a 27-year old male and has experience in BCI studies and data collection but has not performed motor imagery tasks. He is applied the same recording and analysis procedure for both cue-based and ping-pong like experiment. The offline classification results for cue-based experiment can be seen in Table 6-17 and Table 6-18.

Table 6-17: The accuracy (%) and Kappa values obtained for C3-C4 channel pair on dataset for Subject M. *Cz is used for only CSFP analysis

C3 , C4, Cz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	85.89	0.7179	78.21	0.5641	82.05	0.641	71.79	0.4359	87.18	0.7436	83.33	0.6667
	RBF SVM	84.62	0.6923	78.21	0.5641	82.05	0.641	71.79	0.4359	87.18	0.7436	83.33	0.6667
	MLP	74.36	0.4872	73.08	0.4615	74.36	0.4872	75.64	0.5128	92.31	84.62	74.36	0.4872
	Bayesian	79.49	0.5897	82.05	0.641	76.92	0.5385	76.92	0.5385	87.18	0.7436	79.49	0.5897

Table 6-18: The accuracy (%) and Kappa values obtained for P3-P4 channel pair on dataset for Subject M. * Pz is used for only CSFP analysis

P3 , P4, Pz*		STFT				Morlet Tr				CSFP*			
		Ear Ref.		CAR		Ear Ref.		CAR		Ear Ref.		CAR	
		Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*	Acc	*K*
Imagination	Lin. SVM	82.05	0.641	93.59	0.8718	76.92	0.5385	87.18	0.7436	74.36	0.4872	85.11	0.7001
	RBF SVM	82.05	0.641	93.59	0.8718	76.92	0.5385	87.18	0.7436	74.36	0.4872	82.05	0.641
	MLP	76.92	0.5385	91.03	0.8205	76.92	0.5385	87.18	0.7436	67.95	0.359	78.21	0.5641
	Bayesian	76.92	0.5385	79.48	0.5897	73.08	0.4615	79.49	0.5897	75.64	0.5128	80.85	0.6123

It is seen that P3-P4 channel pair is less dominant for Subject M. There still exists the effect of evoked patterns in these channels but it does not suppress the MI patterns in C3-C4 channels. Therefore Subject M is more suitable for an online application than Subject K.

For online application, the algorithms to be used in the analysis should be chosen. For this purpose, the results obtained from the experiments are averaged for each combination of classifier and feature extraction method for subject K and M. The resulting average accuracy values show that Linear SVM classification with STFT feature extraction method performs the highest accuracy (see Table 6-19).

Table 6-19: Average accuracies for combination of classification and feature extraction methods

Accuracy (%)	STFT	Morlet	CSFP
Lin SVM	76.26	75.80	72.77
RBF SVM	75.95	75.19	72.77
Multilayer	68.74	65.52	65.88
Naive Bayes	70.42	73.85	70.14

6.5 Online Ping-Pong Game

A training dataset is collected from Subject M by using the Ping-pong like game interface. By offline analysis, the subject specific parameters are investigated with both DSLVQ and search methods.

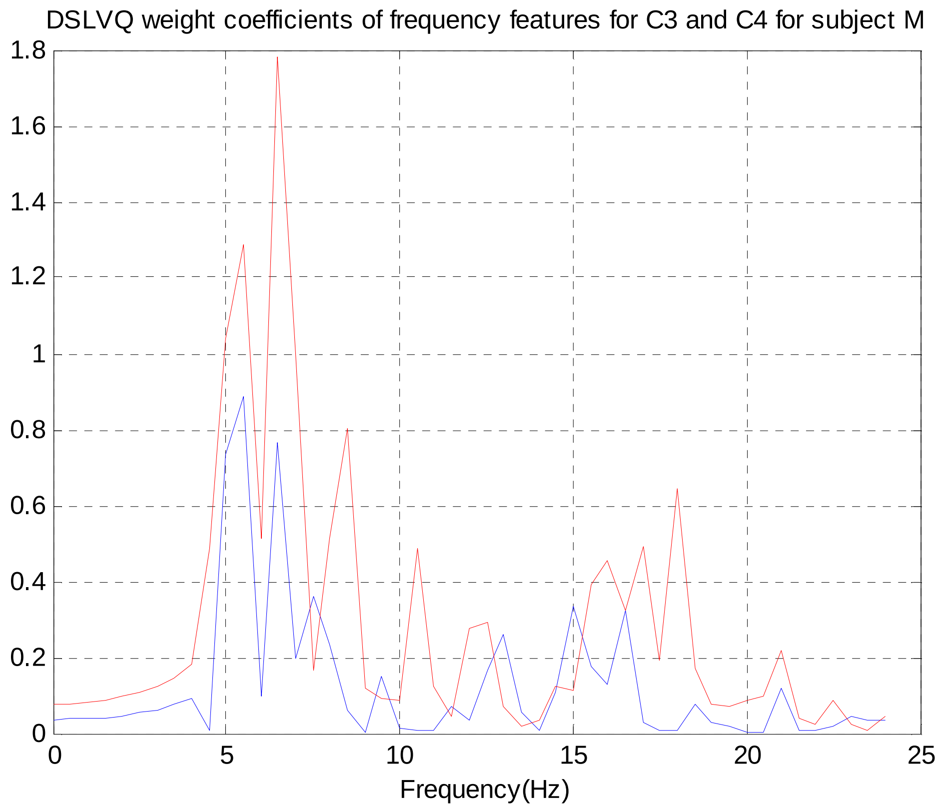

Figure 6-15: DSLVQ weights of frequency features for C3–C4 channel pair for Subject M

The activation in beta band can be observed by DSLVQ method despite the supression effect of both acquisition system and DSLVQ. There is also alpha band activity which seems a little bit more effective on discrimination. However, in order to see more realistic weights, the output of the search algorithm should be considered.

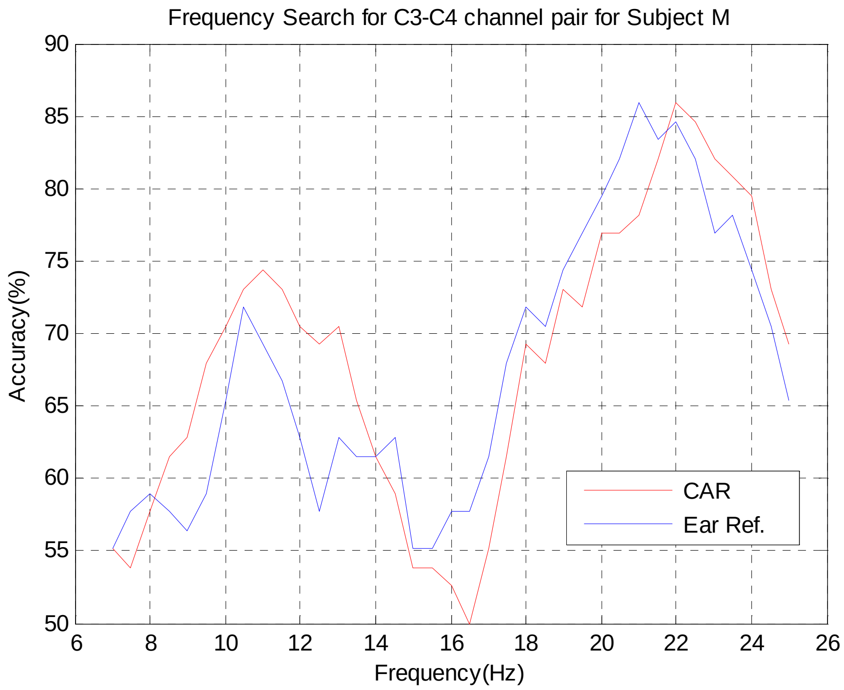

Figure 6-16: Frequency Search Results using C3-C4 channels in CAR and Ear Ref. case for Subject M

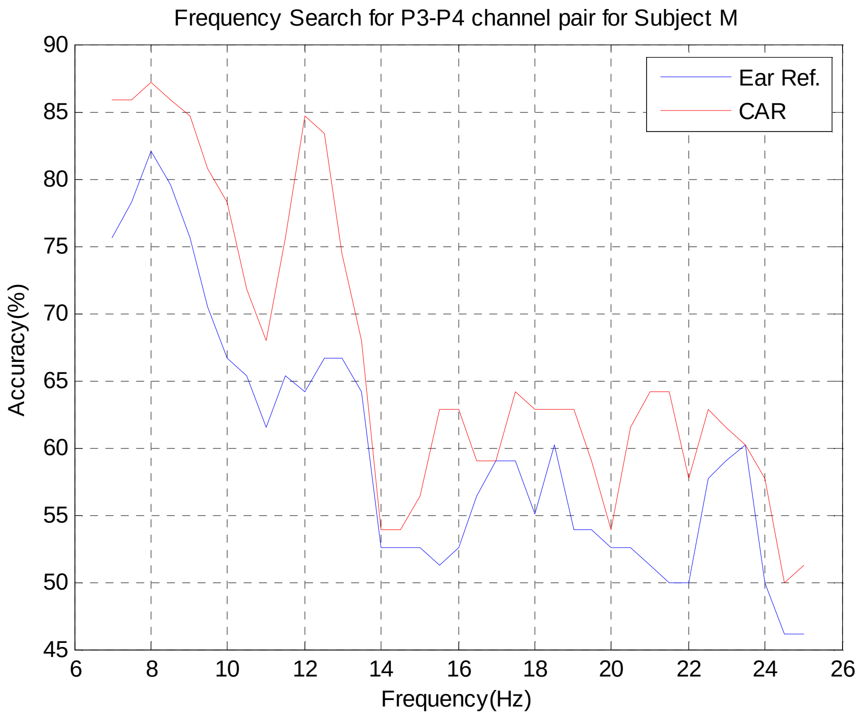

Figure 6-17: Frequency Search Results using P3-P4 channels in CAR and Ear Ref. case for Subject M

For C3-C4 channels, beta band is more informative whereas for P3-P4 pair the case is reverse. It can be concluded that evoked patterns are observed generally in the alpha band which explains the reason that MI patterns cannot be caught for subject K.

For the online analysis, the classifier model is trained with STFT of first two seconds of imagination period. On the other hand, CAR seems to be more contributive for evoked patterns rather than MI patterns. Therefore, it is not used in the online analysis.

In the online experiment, the game is started by an external mechanism. Then there are 10-second trials with 2-second break in between. When the trial starts, one of the rackets is colored randomly in one second. The subject is supposed to move the ball toward the colored racket to hit at most in 10 seconds. If the ball hits the racket before the trial ends, it is counted as a success and the trial is ended even the time is not over. Otherwise, the trial ends up with fail.

The classifier produces output in each 50 ms using the last 2-second data which is nearly a continuous classification. The success of the system is evaluated by hit rate which is defined as the ratio of the trials when the target is hit to the total number of trials. Current hit rate is displayed on the screen after each trial. In the following figure, the experiment carried by Subject M can be seen.

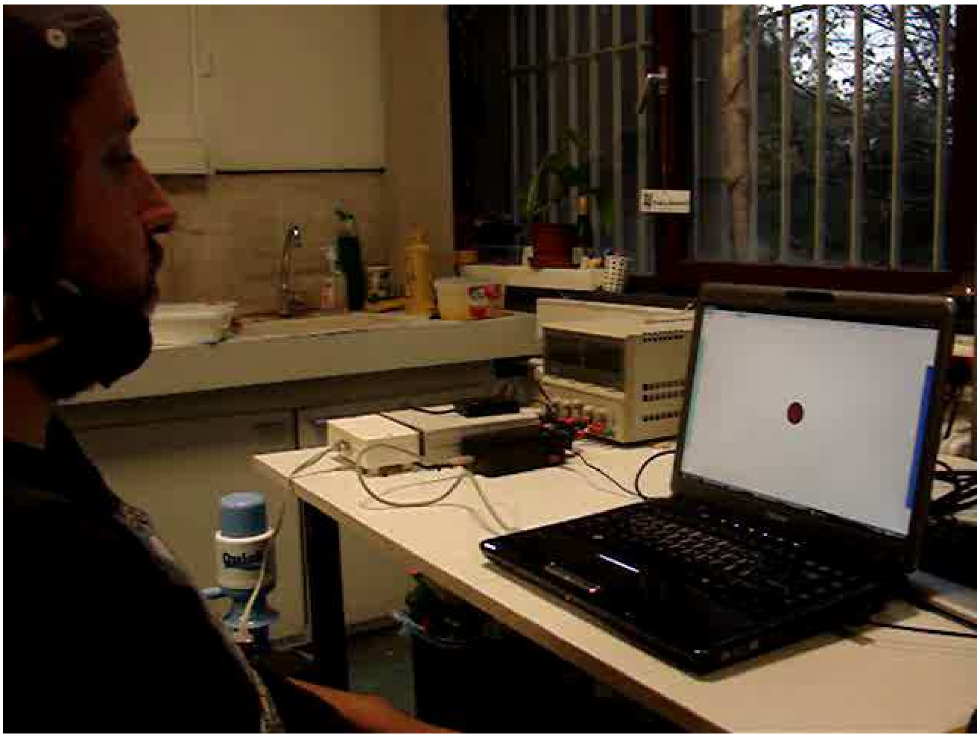

Figure 6-18: Picture of the online game experiment carried by Subject M. He tries to move the red ball to the blue racket.

Subject M has played the online game four times performing average hit rate of 85%. In this result, first trials of the experiment are not taken into account since the subject gets adapted to the system in this duration.

At the end of online experiment, the subject M reported that it takes time to get adapted to the system even it is trained for him. Also he claimed that predictions are more consistent whenever he calms down.

6.6 Wheelchair Experiments

In this partial study, a prototype wheelchair system is constructed in order to investigate the applicability of the developed online BCI system on an external electronic device.

The control of the wheelchair is provided for backward and forward movement by using left and right hand imagination commands.

Figure 6-19: Pictures from the wheelchair experiments

The experiments with the wheelchair have been performed by Subject M as a continuous control. All instrumentation is placed on the wheelchair at the back and side parts in a way not to disturb the subject.The subject is prepared for the EEG data acquisition and sits on the wheelchair. A PC is provided in front of the subject for both the system to operate on and the subject to follow the instructions.

The system is initiated by the subject with an external switch which is always accessible to be used in also emergency cases for shutting down. After the system starts, the same interface with the game application is used for the directives to be given to the subject. Furthermore, two feedbacks are given simultaneously with the wheelchair and the game screen. When the wheelchair moves forward, the ball on the screen slides through the right racket and similarly backward motion of the wheelchair is accompanied by the ball movement through the left racket. The speed of the control is kept in the minimum level in order to prevent distortions in the EEG record due to the sudden movements. Since the control is kept in the lowest speed, the trial duration is extended to 15 s and the wheelchair performs movement in each 50 ms in this duration.

The subject has performed 3 online sessions. The wheelchair system is evaluated by hit rate as in the game application since the same predicted output is used for the game and wheelchair. However, the hit rate of the wheelchair is averaged as 55% which is a 30% decrease according to the experiment that only game application was performed.

The decrease in the success of the wheelchair might be due to the insufficient smoothing of the moving average (MA) filter. When the wheelchair movements are compared with the ball movements on the screen, it is verified that filter provides smoothing such that wrong predictions are eliminated for a short duration. However; in the case of command change, the wheelchair stops and tries to move in the reverse direction in 50 ms which causes some vibration on the system resulting in signal distortions. In order to prevent these sudden movements of the wheelchair, a better post processing method should be investigated.

CHAPTER 7

CONCLUSION

In the scope of this thesis, a movement imagination based BCI system design is performed and realized with 2 online applications, namely the ping-pong like game application and the power wheelchair device control. The study includes the implementation of several signal processing and classification algorithms as well as the design of a hardware for the integration of the wheelchair with an existing EEG system [6].

7.1 Summary of the Thesis

To summarize the work done on the signal processing and classification part of this thesis:

- Short Time Fourier Transform (STFT) is implemented to extract the temporal and spectral patterns of the MI tasks.
- Morlet Transform is investigated as an alternative method to the STFT.
- Informative spectral features are selected with the Distinction Sensitive Learning Vector Quantization (DSLVQ) method.
- A frequency search method is realized to validate the results of the DSLVQ and the results of these two feature selection methods are combined in the analyses.

- Common Spectral Frequency Patterns (CSFP) algorithm is implemented for the automatic selection of the spectral and spatial features simultaneously.
- For the classification, Support Vector Machines (SVM) [58] is employed with the linear and radial basis kernel options. Multilayer Perceptron (MLP) and Naïve Bayesian classifiers are used as alternative classification tools [69].

These methods are investigated on several MI BCI datasets and the results are evaluated to form the basic framework of the developed BCI system.

The study also includes the following hardware and software work:

- A power wheelchair drive hardware is designed and implemented such that the wheelchair can be operated by an external controller mechanism.
- Two online BCI applications are developed and integrated with the existing EEG system
- Several hardware modifications are performed on the EEG system to enable its communication with external electronic devices in a master-slave mode.

7.2 Investigated Datasets and Discussions

To evaluate the performance of the algorithms on a reliable basis, the BCI Competition IV - dataset IIb is investigated. For this purpose, STFT method is used to extract features, and then DSLVQ and frequency search methods are combined for feature selection. The winning algorithms of the competition are compared with the aforementioned methods on this dataset regarding the kappa values as the evaluation criteria of the competition. According to the obtained results, the methodologies presented in this thesis have the 4th rank among the participants of the competition with the average kappa value of 0.45 for all subjects.

Furthermore, the most successful result obtained in this dataset belongs to Subject 4 with an average kappa value of 0.83 and the worst accuracy is obtained in Subject 3 with the kappa value of 0.09. When the results of 9 subjects are compared (see Table 6-2), it is seen that the variability of the success is too high among the subjects. This result can be considered as a good example for the significance of the subject dependency of BCI systems. In other words, it cannot be guaranteed that an algorithm will work well for all subjects.

In addition to the BCI Competition dataset, several MI experiments are conducted at METU Brain Research Laboratory. To realize the experiments, the original cue based MI paradigm is implemented to run with an EEG system. 2 subjects participated in these experiments.

For the subject K, 4 datasets are collected in each of which the electrodes P3 and P4 showed higher relevance to the discrimination of the left and right hand imagination tasks. For dataset 1, accuracies up to 97.56% are achieved in the online classification. This is expected to be a suspicious result, since these channels are not related to the motor imagination activities by the literature. Therefore, the reason of this result is questioned and the existence of visual stimulation effects is suspected. In order to investigate the relevance of these channels with the motor activity, another experiment is conducted for subject K without using the visual arrow cue. Instead, an audible cue is given by the supervisor. In this experiment, it is observed that the classifier success decreased dramatically for electrodes P3 and P4. This result confirmed the suspicions on the origin of the information from these electrodes and it is concluded that the classifier does not discriminate the imagery patterns. Instead it classifies the evoking effect of the visual cue on the brain.

However, it is also interesting that the stimulation effects are highly informative for the discrimination and more dominant than the MI patterns in these datasets. For instance, the accuracy in these results is as high as 95% for both imagination and realization. This might be due to the fact that the displayed cues function as visual stimuli and the brain shows different responses to left and right arrow cues. Then it can be concluded from Figure 6-13 and Figure 6-14 that the decrease in the power of P channel pair, which is similar to the ERD occurrences in C channel pair but more significant, is actually the sign of visual stimulus. This is reasoned to the closeness of channels P3 and P4 to area 7 (see Figure 3-2) which is the visual stimulus processing center of the brain. This effect might be caused by the asymmetric shapes of the arrows used in the display of the cues resulting in asymmetric and strong responses in the parietal regions of the brain.

On the other hand, our major goal in this study is to detect the motor imagery patterns. Therefore, for the further experiments, the C3-C4 and F3-F4 channel pairs are mainly considered.

As a next step, the same dataset for subject K is analyzed in detail using channel combinations and different methods in order to compare the channel effect on the discrimination. By using C3-C4 channels, the maximum prediction accuracy of 87.8% is achieved. If the P3 and P4 channels are taken into account with C3 and C4 channels, the accuracy increases up to 97.6% again. This means that the visual evoked response is again dominant when the channels C3-C4 and P3-P4 are considered together. At this point, Common Average Referencing (CAR) method is used instead of ear referencing in order to see the effect on MI and evoked patterns. It is observed that CAR weakens the MI patterns such that the discrimination in C channel pair decreases by an amount of 20% whereas it slightly enhances the evoked patterns. Unlike the common sense that CAR enhances MI patterns, the opposite situation has been observed in this study. The reason might be using small number of electrodes in computing the CAR point. Furthermore, the locations of these electrodes are not distributed uniformly on the scalp. Instead, they are concentrated on the sensorimotor areas of the brain (see section 5.1.1 for electrode locations).

After 4 months, dataset 2 is collected from subject K with the same procedure as dataset 1. Following the same analysis steps, the dominance of P3-P4 channel pair is again observed. The most significant result obtained from this dataset is the decrease in the general accuracy for all methods which is an indication of time dependency of the MI patterns for a subject.

After observation of the evoked potential effects, a new interface is designed such that the cue stimulation is reduced as much as possible. To achieve this, cue display is ended 2 seconds prior to the imagination. In other words, in the beginning of the imagination interval, the subject already knows what to do but does not see any visual cue. The dataset collected for subject K by this interface is analyzed with only SVM method using both Morlet Transform and the STFT as feature extraction algorithms. It is observed that all channels have similar effect on the success and none of them is dominant. Furthermore, the overall accuracy in this case has decreased as compared to the previous datasets of subject K. This decrease can be related with the early cue onset which might cause the preparation of the subject before the required imagination time. Probably as the most of the MI patterns are observed just before and at the beginning of the imagination; the most informative interval is missed before the required imagination interval. In other words, the state change of the brain from idle to imagination might not be observed since the subject already knows the next task and prepares herself involuntarily.

For the informed cue dataset, the DSLVQ and frequency search method give inconsistent outputs such that the frequencies found by search method are in beta band whereas DSLVQ indicates that alpha band is informative. However, the results show that beta band carries more relevant information. DSLVQ is an energy-based method and it evaluates each spectral component lying in the power of each trial. Therefore the bands having higher energy are determined to be more effective even if the case might be reverse. This might be the reason for improper feature selection of DSLVQ. Also, it might depend on the hardware deficiency in our EEG system such that the frequencies higher than 13 Hz are not acquired as well as the lower band due to the analog filters employed in the system.

Finally, a separate dataset is collected in Hacettepe University Biophysics Department with a commercial EEG system called SCAN NuAmps Express [78]. The experiments are conducted in an electrically shielded environment. Furthermore, the interface is changed to the ping-pong game application since the cue onset is less stimulating for this case. Beside the Morlet Transfom and STFT methods, CSFP method is also constructed for automatic selection of frequency and channel components for this dataset. For the classification part, three other methods, Multilayer Perceptron, Radial Basis SVM and Naive Bayesian classifiers are applied on the data besides the linear SVM. In this experiment, the parameters are optimized as much as possible in terms of environmental conditions, training of the subject and application of several methods in a comparative basis. The results on this dataset show that the dominance of the P3-P4 pair is weakened but not eliminated for subject K. The maximum prediction accuracy obtained for subject K is 69.9% excluding the channel pair P3-P4 from the analyses. It is also seen that the channels F3 and F4 do not have any significant contribution on the overall accuracy, and hence they are discarded in the final design of the BCI system to reduce the number of EEG channels.

Some of the analyses applied to subject K are performed for subject M in order to compare the performance of the algorithms on different subjects. For this purpose, a dataset is collected from subject M with the same procedure as dataset 1 (cue-based application). It is observed that MI patterns are strong enough to provide 92.3% discrimination with C3-C4 channels where channels P3 and P4 show a prediction accuracy of 93.6% which means these channels do not dominate the

C3-C4 information for subject M. This result once more emphasizes the subject dependency in MI BCI patterns.

Regarding the superior analysis results obtained from subject M, the ping-pong like game experiment is carried out with continuous (50 ms period) and real-time prediction output. In this online analysis, linear SVM classification with STFT method is used since these are found to be the best couple among all method combinations (see Table 6-19). The performance is evaluated as average hit rate of 85% which corresponds to the rational count of the racket-hit by ball in 10-second intervals. After the experiments, the subject M reported that correct control of the game is performed easily when he can retain his calmness.

When the feature selection outputs (see Figure 6-15, Figure 6-16, Figure 6-17) of the methods are investigated for this dataset, it is seen that the beta band activity of the subject M is higher than the beta band activity of the subject K which seems to be reason for better classification results.

In order to provide the basis for a potential hardware application, several experiments are conducted with subject M on the developed wheelchair system. Finally, the subject M is able to operate the wheelchair using the timing prepared for the game application. Smoothing operation with weighted moving average filtering is applied to the outputs of the classification model as a post-processing step to reduce the rapid change of the predictions and hence smooth the movement of the wheelchair. In this application, the performance is again assessed by the hit rate followed from the screen. Hit rate has decreased to 55% due to the disturbance and vibration exposed on the EEG system as a result of the wheelchair movements. One may find the videos of these preliminary experiments in the BCI sections of the webpage:
http://www.eee.metu.edu.tr/~biomed/brl/

7.3 Future Studies

- It is a well known fact that MI based BCI systems are too much subject dependent such that the brain signal patterns considered in these systems may not be observed clearly for all subjects. Therefore the algorithms should be tested on different subjects in order to have a meaningful measure of performance. One of the future tasks of this study is to perform deeper analysis of the algorithms on numerous subjects.

- In the training phase of the classification model, one specific time interval has been used in this study. Considering the fact that MI patterns are more observable in the duration of transition (rest to imagery or imagery to rest), the training data are selected from the beginning of the imagination. Then the continuous prediction is provided during whole imagination time by using this classification model. However, a generalization can be performed by training the model from all instances distributed over the trial duration. This procedure might give better results since the continuous imagination patterns are also considered in the classification model. The second task to be completed after this study is to consider various time intervals to train the classification algorithms.

- The movements of the wheelchair should be smoothed both for the EEG signal quality, hence the system success and for practical use. For this purpose, it is aimed to improve the post processing method by applying Kalman filtering.

- Since the aforementioned applications are developed regarding the needs of the disabled people, a cue- based MI BCI system can be a solution in a limited extent. In order to provide flexibility and freedom, the MI BCI should be developed in a self-paced manner such that the only controller of the system is the subject without dependency on the computer directives. The final future objective of the study is to design a self paced MI BCI system that can be accurately operated by the disabled people.

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