

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE
ENGINEERING AND TECHNOLOGY

**DEVELOPMENT OF CLASSIFICATION METHODS FOR
ELECTROENCEPHALOGRAM BASED BRAIN COMPUTER INTERFACES**

Ph.D. THESIS

Zafer IŞCAN

Department of Electronics & Communication Engineering

Electronics Engineering Programme

MARCH 2012

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**Zafer İŞCAN
(504052207)**

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Thesis Advisor: Prof. Dr. Zümray DOKUR

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İÇİN SINIFLAMA YÖNTEMLERİNİN GELİŞTİRİLMESİ**

DOKTORA TEZİ

**Zafer İŞCAN
(504052207)**

Elektronik ve Haberleşme Mühendisliği Anabilim Dalı

Elektronik Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Zümray DOKUR

MART 2012

Zafer İŞCAN, a **Ph.D.** student of ITU **Graduate School of Science Engineering and Technology** student ID 504052207, successfully defended the **dissertation** entitled “DEVELOPMENT OF CLASSIFICATION METHODS FOR ELECTROENCEPHALOGRAM BASED BRAIN COMPUTER INTERFACES”, which he prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Prof. Dr. Zümray DOKUR**
İstanbul Technical University

Jury Members : **Prof. Dr. Ahmet ADEMOĞLU**
İstanbul Şehir University

Prof. Dr. Tülay YILDIRIM
Yıldız Technical University

Prof. Dr. Mehmet KORÜREK
İstanbul Technical University

Prof. Dr. Serhat ŞEKER
İstanbul Technical University

Date of Submission : 30 December 2011

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To my mother and father,

FOREWORD

After a very long study period, I have finished my Ph.D. thesis. Although this thesis has been written by me, there are a lot of people who contributed to it in a direct or indirect way. I would like to express my gratitude to them.

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I hope this thesis can be useful for future researchers.

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ABBREVIATIONS

App	: Appendix
ALS	: Amyotrophic Lateral Sclerosis
AP	: Action Potential
AR	: Autoregressive
ASSR	: Auditory Steady State Response
AUC	: Area under ROC curve
BCI	: Brain Computer Interface
BP	: Band-pass
CAR	: Common Average Reference
CCA	: Canonical Correlation Analysis
CNS	: Central Nervous System
CT	: Computerized Tomography
DFT	: Discrete Fourier Transform
ECG	: Electrocardiogram
EEG	: Electroencephalogram
EMG	: Electromyogram
ECoG	: Electrocorticogram
EOG	: Electrooculogram
fCMC	: Functional Corticomuscular Coupling
fMRI	: Functional Magnetic Resonance Imaging
fte	: Test Feature Value
fthr	: Threshold Feature Value
GUI	: Graphical User Interface
HMM	: Hidden Markov Model
Hz	: Hertz
ITR	: Information Transfer Rate
ITW	: Improved T-Weight Method
K-NN	: K-Nearest Neighbor
LCD	: Liquid Crystal Display
LDA	: Linear Discriminant Analysis
LVQ	: Learning Vector Quantization
MCTW	: Multi-class T-Weight
MEG	: Magnetoencephalogram
MLP	: Multi-layer Perceptron
MLSP	: Machine Learning for Signal Processing
MRI	: Magnetic Resonance Imaging
N/A	: Not available
NIRS	: Near Infrared Spectroscopy
NMC	: Nearest Mean Classifier
No	: Number
P300	: Positive Wave, 300 milliseconds
PCA	: Principal Component Analysis

PCG	: Phonocardiogram
PET	: Positron Emission Tomography
PSD	: Power Spectral Density
RBF	: Radial Basis Function
REM	: Rapid Eye Movement
ROC	: Receiver Operating Characteristic
SCP	: Slow Cortical Potential
SNR	: Signal to Noise Ratio
SSVEP	: Steady State Visual Evoked Potential
SVM	: Support Vector Machines
vEOG	: Vertical Electrooculogram

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DEVELOPMENT OF CLASSIFICATION METHODS FOR ELECTROENCEPHALOGRAM BASED BRAIN COMPUTER INTERFACES

SUMMARY

Brain Computer Interfaces (BCIs) transform the electrical signals acquired from brain to various commands and use them for different purposes. In this thesis, it was aimed to develop appropriate classification methods for electroencephalogram (EEG) based BCIs. Focus was given to P300 (positive 300) and SSVEP (steady state visual evoked potential) based systems.

First of all, existing methods and datasets in literature related to the topic were analysed in order to gain experience in EEG signal classification. By using the combination of time and frequency based features on an epilepsy dataset, it was shown that classification with high accuracy can be achieved.

It was demonstrated that a previously proposed classification method (T-Weight) that was applied to a P300 based problem in literature can become more successful in classification by proper preprocessing. The method was adapted to the competition data of IEEE MLSP 2010 Workshop and generated the second best performance among 35 participant groups. By addition of a threshold determination function to this method, a classifier structure (Improved T-Weight Method) that is successful for problems with two classes was developed. This method was applied to a frequently used slow cortical potential (SCP) based competition dataset in literature and generated better results than the methods used in the competition. In order to increase the general applicability of the method, MCTW (Multi-Class T-Weight) method which can work for multi-class problems was proposed. The method was tested on an SSVEP based BCI experiment with four classes on 20 subjects and compared with different classifiers. Obtained results show that MCTW method generates successful results. Proposed methods have potential to be used in classification problems in different fields. In another SSVEP based BCI experiment with nine classes, nine subjects achieved a very high classification accuracy (99.75%).

For P300 and SCP based datasets, samples with specific lengths (e.g. 1s, 2s, 3s) are taken as features from time domain for classification. In SSVEP datasets, power spectral density (PSD) features which take the advantage of the frequency characteristics of the signals and canonical correlation analysis (CCA) that uses the correlation values are used. CCA features generated better results than the PSD features.

Finally, a novel stimuli presentation scheme different from the experiment designs in literature for BCI was proposed. In the proposed SSVEP based method, subjects form the characters that they want to write by drawing lines between different points. This design was called "Character Plotter". It was tested on online experiments with visual feedback and it was suggested that Character Plotter can be used as a new approach for BCIs. Details about the SSVEP based experiment designs were explained in the thesis.

ELEKTROENSEFALOGRAF TABANLI BEYİN BİLGİSAYAR ARAYÜZLERİ İÇİN SINIFLAMA YÖNTEMLERİNİN GELİŞTİRİLMESİ

ÖZET

Günümüzde beyin aktivitesinin ölçümü için çok sayıda yöntem mevcuttur. Elektroensefalografi yöntemiyle elde edilen elektroensefalogram (EEG), kafa yüzeyinden elektrotlar aracılığıyla algılanan beyin elektriksel aktivitesidir. EEG ölçümü, girişimsel olmayan bir yöntem olması bakımından güvenlidir ve beyin bilgisayar arayüzleri (BCI) gibi gerçek zaman uygulamaları için yeterli zaman çözünürlüğüne sahiptir.

Beyin bilgisayar arayüzleri, beyinden alınan elektriksel işaretlerin çeşitli komutlara dönüştürülerek farklı amaçlar doğrultusunda kullanılmasını sağlamaktadır. Genel bir BCI sisteminin bileşenleri, işaret toplama, işaret işleme ve kontrol edilen cihaz olarak gruplanabilir. Bu bileşenler donanım veya yazılım tabanlıdır.

Tezde, EEG tabanlı BCI için uygun sınıflama yöntemlerinin geliştirilmesi amaçlanmıştır. Yüksek başarılı BCI gerçekleştirmek için, sınıflamada kullanılan algoritmalar kadar, uyaran sunumu ve deneysel tasarım da önemlidir. Dolayısıyla tezde yeni sınıflama yöntemlerinin yanında, deneysel tasarım üzerine de odaklanılmıştır.

EEG tabanlı BCI'lar, EEG içerisinde gömülü farklı işaretleri kullanmaktadırlar. Örneğin, olaya ilişkin gerilimler, görsel ya da işitsel harici uyaranlar nedeniyle EEG üzerinde oluşan gerilim sapmalarıdır. Görsel uyarılmış potansiyel tabanlı BCI'lar, P300 (pozitif 300) ve SSVEP (durağan hal görsel uyarılmış potansiyel) tabanlı olmak üzere sınıflandırılabilirler. Tezde P300 ve SSVEP tabanlı sistemler üzerine odaklanılmıştır. Ayrıca SCP (yavaş kortikal gerilimler) tabanlı bir sistem üzerinde de bir sınıflama yapılmıştır.

P300, seyrek beklenen uyaran geldiğinde yaklaşık 300 ms sonra EEG üzerinde oluşan pozitif sapmadır. Oluşan bu sapmanın genliği EEG'ye nazaran çok küçük olduğundan, işaretin gürültüye oranını artırmak için çok sayıda uyaran cevabının ortalaması alınmalıdır.

SSVEP, sabit frekanstaki bir ışık kaynağına bakıldığında, EEG üzerinde ilgili frekansın harmoniklerinde oluşan genlik artışıdır. SSVEP tabanlı BCI'lar, gürbüzlükleri ve P300 gibi çok sayıda denemenin ortalamasının alınmasına ihtiyaç duymamaları nedeniyle tercih edilmektedirler.

SCP'ler, EEG üzerinde oluşan pozitif veya negatif kaymalardır. SCP tabanlı BCI'larda denekler, geribildirim yoluyla EEG işaretlerini pozitif veya negatif yönde kaydırabilmektedirler.

Tezde ilk olarak, EEG işareti sınıflamasında deneyim kazanmak için literatürde yer alan mevcut yöntemler ve konuya ilişkin veri kümeleri incelenmiştir. Bir epilepsi veri kümesi üzerinde zaman ve frekans tabanlı öznelikler bir arada kullanarak yüksek başarılı bir sınıflama yapılabileceği gösterilmiştir.

Literatürde önceden önerilen ve P300 tabanlı bir probleme uygulanan bir sınıflama yönteminin (“T-Weight”), uygun önışleme adımları sayesinde sınıflamada daha başarılı hale getirilebileceği gösterilmiştir. Yöntem, IEEE MLSP 2010 Çalıştay kapsamında EEG sınıflamasına yönelik “Mind Reading” konulu yarışma verisine (P300 tabanlı) uyarlanmış ve katılan 35 grup arasında en iyi ikinci başarıyı veren yöntem olmuştur. Yarışmada amaç, uygun yöntem kullanarak verilen EEG verisini P300’lü veya P300’süz olmak üzere iki kategoriye ayırmaktır. Denek, bir LCD ekran üzerinde uydu görüntülerine bakarken EEG verisi kaydedilmiştir. Denek, görüntülerin merkezine odaklanmakta ve beklediği hedefi gördüğünde aralık tuşuna (“space bar”) basmaktadır. Beklenen hedefin görüldüğü durumlarda, deneğin EEG’si üzerinde P300 işaretinin oluşması beklenmektedir.

T-Weight yöntemine eşik bulma fonksiyonu dahil edilerek, iki sınıflı problemler için genel bir sınıflayıcı (“Improved T-Weight” (ITW) yöntemi) geliştirilmiştir. Bu yöntem, literatürde yaygın olarak kullanılan SCP tabanlı bir yarışma veri kümesi (BCI Competition 2003, datasets I-a, I-b) üzerinde denenmiş ve yarışmadaki yöntemlerden daha başarılı sonuçlar elde edilmiştir. Bu yarışmadaki amaç, bir imlecin ekran üzerinde yukarı ve aşağı doğru hareket ettirilmesidir. Bu sırada deneğin kortikal gerilimleri kaydedilmektedir. Deney, bir sağlıklı ve bir yapay solunum yapan ALS hastası üzerinde gerçekleştirilmiştir.

ITW yönteminin genel uygulanabilirliğini artırmak için, çok sınıflı problemlerde çalışabilen “Multi-Class T-Weight” (MCTW) yöntemi önerilmiştir. Bu yöntem, SSVEP tabanlı dört ve beş sınıflı hazırlanan ilk BCI tasarımında 20 denek üzerinde denenmiş ve farklı sınıflayıcılarla karşılaştırılmıştır. Bu BCI deneyinde amaç, deneğin ekran üzerinde her biri ayrı frekansta titreşen dört adet daireden ve bunların ortasında yer alan bir adet noktadan hangisine odaklandığını belirleyebilmektir. Deneyde, her bir daireye ve noktaya sırayla 30s boyunca bakılırken kayıt alınmıştır. Elde edilen veriler, MCTW yönteminin başarılı sonuçlar verdiğini ortaya koymuştur.

Geliştirilen ITW ve MCTW yöntemlerinin farklı alanlardaki sınıflama problemlerinde kullanıma potansiyeli bulunmaktadır.

Tasarlanan SSVEP tabanlı, dokuz sınıflı ikinci BCI deneyinde, katılan dokuz denek çok yüksek sınıflama başarımlarına (%99,75) ulaşmıştır. Bu BCI deneyinde de amaç, deneğin ekran üzerinde her biri ayrı frekansta titreşen dokuz adet daireden hangisine odaklandığını belirleyebilmektir. Kullanılan monitörün 120 Hz’lik yenileme oranı, SSVEP yanıtlarının güçlü olduğu 5-20 Hz frekans bandından dokuz adet frekans seçilebilmesini sağlamıştır. Ayrıca daireler ekran üzerinde, komşu dairelerin frekansları birbirinden mümkün olduğu kadar uzak olacak şekilde yerleştirilmiştir. Bu yerleşim, sınıflamada daha iyi ayırım yapılmasını sağlamaktadır. Deneyde deneklerden, kendilerine rastgele sırada gösterilen 9 adet daireye 3s boyunca odaklanmaları istenmiştir. Bu 3s’lik süreden sonra, odaklanılacak yeni dairenin işaret edildiği 1s’lik süre vardır. Bu şekilde tüm dairelere bakıldıktan sonra, aynı prosedür on defa tekrarlanmakta ve bir denek deney süresince toplam 90 adet daireye bakmaktadır.

Son olarak, literatürde kullanılan deney tasarımlarından farklı olarak, BCI için yeni bir uyaran sunum şekli önerilmiştir. Önerilen SSVEP tabanlı üçüncü tasarımda, kullanım kolaylığı, işlem süresi ve başarımdan ödün vermeden, az sayıda uyaran ile mümkün olduğunca fazla karakter oluşturmak hedeflenmiştir. Denekler yazmak istedikleri karakterleri, ekranda farklı frekanslarda titreşen altı adet daire (karakter daireleri) arasında çizgiler çizerek, adım adım oluşturmaktadır. Ayrıca, karakter

çizimini kontrol eden üç adet farklı frekanslarda titreşen daire (kontrol daireleri) kullanılmaktadır. Kontrol daireleri, geri alma (“undo”), kaldırma (“raise”) ve tamamlama (“OK”) işlevlerini gerçekleştirmek için kullanılmaktadır. Bu tasarıma, Karakter Çizici (Character Plotter) adı verilmiştir. Tasarım, uyarıların sunumunda dokuz daireli ikinci tasarımı baz almaktadır.

Önerilen sistemde altı adet daire arasında 13 adet çizgi çizilebilmektedir. Tezde gerçekleştirilen tasarımın 64 karakterlik bir alfabesi bulunmaktadır. Ancak bu alfabe, değişik uygulamalar için genişletilebilir. Teorik olarak 8192 adet (2^{13}) sembolün iletilmesi mümkündür. Bu sayı, literatürde önerilen BCI tasarımlarının kapasitesinden daha yüksektir.

Önerilen tasarımın altyapısını oluşturan dokuz farklı frekanslı SSVEP tabanlı arayüzün çevrimdışı (“offline”) başarımı incelenmiş ve geribildirimli çevrimiçi (“online”) deneylerde kullanılabilecek kadar yüksek olduğu görülmüştür. Ardından, geribildirimli çevrimiçi deney gerçekleştirilmiştir. Çevrimdışı başarımı %95’in üzerinde olan 15 denekten İngilizce (“it is OK”) ve Türkçe (“Hava çok güzel”) olarak belirlenmiş iki cümleyi Karakter Çizici ile yazmaları istenmiştir. Deneklerin hepsi istenilen görevi hatasız veya çok küçük hatalarla yerine getirebilmiştir.

Karakter Çizici’de uyarı sunumundan sonra, sınıflamanın yapılması için gereken süreden kaynaklanan kısa bir gecikme oluşmaktadır. Bu gecikme, sınıflama algoritmasının donanım içerisinde gerçekleştirilmesiyle en aza indirgenerek daha hızlı sınıflama mümkün olabilir.

Literatürdeki BCI tasarımlarının çoğunda, yanlış sınıflamadan kaynaklanan bir sonucun geri alınması zahmetli olmakta, karakteri oluşturmaya en baştan başlanmaktadır. Karakter Çizici’de ise, karakter adım adım oluşturulduğundan, yapılan bir hatada en başa dönmek yerine son çizilen çizgi silinmektedir.

“Karakter Çizici,” insanların doğal yazım şekliyle uyumlu bir yapıya sahip olduğundan, deneklerin sisteme uyumu çok kısa bir süre içerisinde gerçekleşmektedir. BCI tasarımlarının en önemli sorunlarından birinin, uyum için gerekli eğitim zamanı olduğu göz önüne alındığında, bu özelliğin ne kadar önemli olduğu aşîkârdır. Karakter Çizici’nin tasarımına ait ayrıntılar ve geribildirimli çevrimiçi deneyin akış şeması tez içerisinde belirtilmiştir.

Tasarlanan SSVEP tabanlı BCI’larda, EEG kaydı elektriksel ve akustik olarak gürültülü bir ortamda yapılmasına rağmen, elde edilen sınıflama başarımları yeterince yüksek bulunmuştur. Gürültüyü azaltmak için, aktif elektrotlu bir sistem tercih edilmiştir. EEG kuvvetlendiricisi olarak 16 kanallı V-Amp16 sistemi kullanılmıştır. 16 adet elektrot, SSVEP yanıtlarının ortaya çıktığı beyin oksipital ve paryetal bölgelerine yerleştirilmiştir. Ölçümler hem tek kanal hem de 16 kanal için yapılmıştır. 16 kanaldan elde edilen başarımlar, tek kanaldan elde edilen başarımlardan daha yüksek çıkmıştır.

Tez içerisinde önerilen sınıflayıcıların haricinde, kıyaslama için literatürde EEG tabanlı BCI uygulamalarında yaygın olarak tercih edilen SVM (“Support vector machines”), LDA (“Linear discriminant analysis”) ve NMC (“Nearest mean classifier”) sınıflayıcıları kullanılmıştır.

P300 ve SCP tabanlı veri kümeleri için belirli uzunluktaki (ör: 1s, 2s, 3s) örnekler zaman uzayından alınarak sınıflamada kullanılmak üzere öznitelik çıkartma işlemlerine tabi tutulmuştur. SSVEP veri kümelerinde, SSVEP cevaplarının frekans karakteristiklerini göz önüne alan güç spektral yoğunluğu (PSD) ve korelasyon

değerlerini baz alan kanonik korelasyon analizi (CCA) öznitelikleri kullanılmıştır. Diverjans analizi ve t-testinden elde edilen değerler, SSVEP tabanlı sistemlerde CCA özniteliklerinin, PSD özniteliklerinden daha iyi sonuçlar verdiğini göstermiştir.

Tezde elde edilen deneyimler ışığında, BCI'ların deneğe özgü bir şekilde tasarlanması gereği kavranmıştır. Sistem kullanıcının karakteristiklerine uyarlanmalıdır. Uyarlanma prosesi, en iyi özniteliklerin, kanalların, uyaran süresinin, uyaran frekanslarının ve sınıflayıcının seçimini kapsamaktadır.

Gelecekte, EEG tabanlı BCI yöntemleri için sınıflama yöntemlerinin geliştirilmesi konusu önemini koruyacaktır. Farklı işaretlerin birleşiminin (ör: P300 ve SSVEP), daha yüksek sınıflama başarımlarına ulaşmada yardımcı olacağı düşünülmektedir.

1. INTRODUCTION

Functions of biological structures (e.g. organs) are evaluated by measurement of related biological signals. These signals can be classified as electrical based (e.g. electroencephalogram (ECG), electromyogram (EMG), electroencephalogram (EEG)) and non-electrical based (e.g. phonocardiogram (PCG), blood pressure) signals. Both type of signals provide some information about underlying malfunctions or temporary disorders in the body and they help doctors in diagnosis of various diseases. For example, ECG is used in diagnosis of cardiac arhythmias whereas EEG is used in diagnosis of epilepsy.

Brain is the most complex organ which commands the whole body and it contains information about the functioning of all biological system. Therefore, biological signals acquired from brain by using different methods (e.g. functional magnetic resonance imaging (fMRI), electrocorticography, electroencephalography) are difficult to interpret. This makes brain signals a popular research area among scientists. Recently, many thesis have been published in this field.

Unfortunately, with current technology, it is not possible to measure the response of each single neuron in the brain to the external or internal stimuli. Moreover, knowledge about the functional connections of different brain parts is very limited.

Methods in measuring the neural activity of the brain use different approaches. For instance, fMRI uses blood oxygenation of cells. Electroencephalography benefits from the electrical activity of the brain whereas magnetoencephalography utilizes the magnetic field results from the electrical currents inside the brain. All the measurement methods have some advantages or disadvantages in terms of spatial / temporal resolution, practical usage, cost, invasiveness, subject's health, etc.

Electroencephalography is a safe and non-invasive method. EEG provided by this method has a very good time resolution which makes it preferable in real-time applications (e.g. BCIs). However, EEG has a poor spatial resolution. Recorded EEG from the scalp is a filtered,

attenuated and aggregated form of original electrical sources located inside the brain. It is hard to extract useful information from this complex and nonstationary signal in its ‘natural’ course. Therefore, some ‘tricks’ are used in order to understand the content of EEG. For this purpose, expected responses to some standard stimuli are recorded. Afterwards, these responses can be used for the diagnosis of diseases or controlling BCIs.

A BCI is a system in which subject’s brain signals are transformed into messages or control signals for interaction with the outer world. Wolpaw et al. (2002) defines the BCI as: “A BCI is a communication system in which messages or commands that an individual sends to the external world do not pass through the brain’s normal output pathways of peripheral nerves and muscles.” In Fig. 1.1, blocks of a general BCI system can be seen.

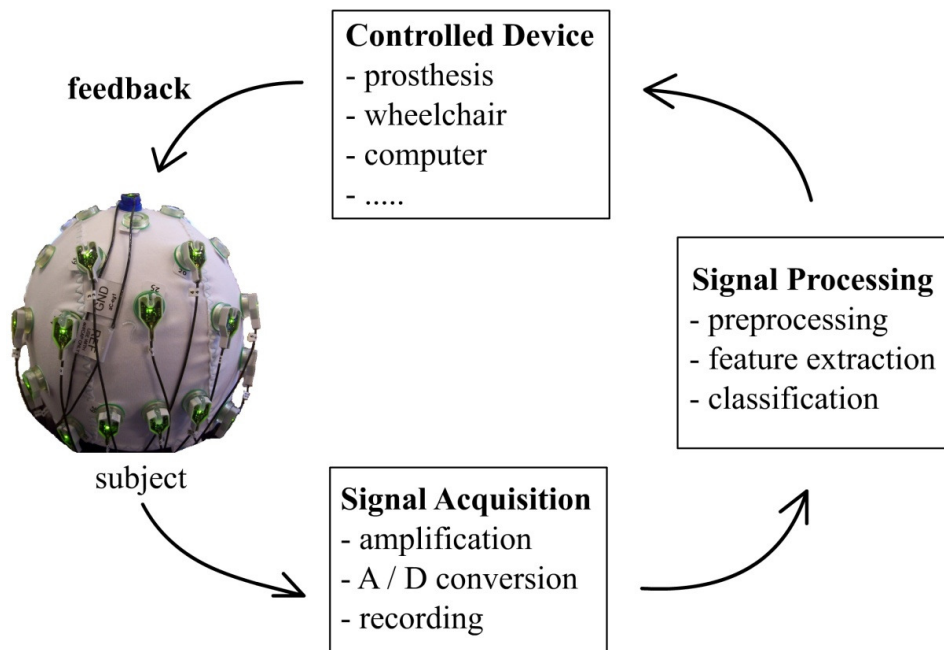


Figure 1.1 : A general BCI system.

Blocks of the system can be grouped as signal acquisition (amplification, analog to digital (A/D) conversion, recording), signal processing (preprocessing, feature extraction, classification) and controlled device (e.g: prosthesis, wheelchair, computer). Subject receives feedback from the controlled device. These blocks are composed of hardware (e.g. electrodes, amplifier, filter, trigger, connectors) and software (programme, algorithm, visual interface) parts. Hardware part is critical to obtain a reliable (i.e. noise-free) EEG. Next,

recorded EEG must be handled in software part carefully to be able to classify the responses in a quick and accurate way. The thesis focuses on development in software part.

BCIs have a great potential to help severely disabled people by providing functional increase and independency. Recently, there is an intensive research in this area (Felton, 2007). Furthermore, BCIs have a potential to be used in entertainment (e.g. games) sector (Chumerin et al., 2011). Research and development (R & D) in this area needs cooperation of different science fields including neurobiology, psychology, engineering, mathematics and computer science (Wolpaw et al., 2002).

BCIs can be classified as invasive and non-invasive BCIs. Invasive BCIs benefit from the activity recorded by brain implanted electrodes (Birbaumer, 2006). Brain signals that are used in invasive BCIs include (Birbaumer, 2006):

- Action potentials from nerve cells or nerve fibers,
- Synaptic and extracellular field potentials,
- Electrocorticogram (ECoG).

Most of the research on invasive BCI was carried out on monkeys (Sanei and Chambers, 2007). Although the invasive BCIs can benefit from higher resolution, bandwidth and amplitudes, their usage on human subjects are risky and limited to extreme cases. Therefore, noninvasive BCIs are used commonly in the human experiments. These BCIs use the activity (e.g. EEG) recorded by electrodes outside the body boundaries (Birbaumer, 2006).

EEG based BCIs use different kinds of signals embedded into EEG. For instance, event related potentials (ERPs) are the transient voltage deviations on EEG generated by external visual or auditory stimuli (Garcia Molina, 2004). The advantages of using visual ERP based BCI is the easy adaptation of users and less need for training (Andrews et al., 2008). Visual ERP based BCIs can be classified into P300 based and SSVEP based BCIs (Andrews et al., 2008).

P300 speller is based on the oddball paradigm which states that: “Rare expected stimuli produce a positive deflection in the EEG after about 300 ms.” This P300 component is present in nearly every human (Rakotomamonjy and Guigue, 2008). In Fig. 1.2, P300 signal can be seen (Wolpaw et al., 2002).

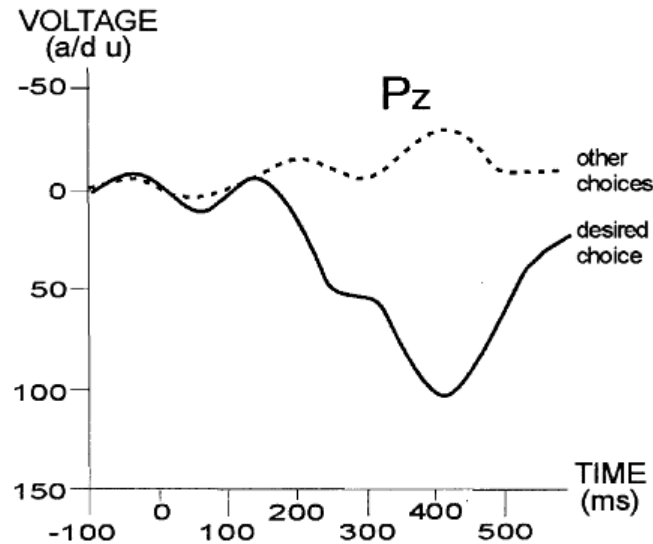


Figure 1.2 : P300 signal (Wolpaw et al., 2002).

In Fig. 1.2, P300 signal occurs only in the responses generated by the desired choice and the BCI uses this difference in order to determine the subject's intent (Garcia Molina, 2004). Unfortunately, the difference related to a single P300 response is very small. Therefore, such BCIs need averaging of many responses.

P300 wave attracted the highest interest among all EP (evoked potentials). Its amplitude and latency are affected from the attention, difficulty of the task and frequency of the stimulus. However, it is not affected from the physical properties and the modality of the stimulus (Bayraktaroğlu, 2009). Citi et al. (2009) exploited a modulation in amplitude of P300 caused by target-to-target interval differences and they showed that this modulation can improve the classification accuracy.

SSVEP is a resonance phenomenon that occurs mainly in the visual cortex (Friman et al., 2007). When a subject looks at a light source flickering at constant frequency, there is an increase in the amplitude of the subject's EEG at flickering frequencies and their harmonics which can be observed mainly over the occipital and parietal lobes of brain (Friman et al., 2007). In Fig. 1.3, frequency spectrum of EEG data recorded from O2 channel can be seen for the flickering frequency = 4.6 Hz. It can be noticed that there is an obvious peak on 4.6 Hz and its 2nd harmonic (i.e. 9.2 Hz). Sometimes, the amplitude of the second harmonic may be greater than the amplitude of the fundamental frequency as in this case (Tong and Thankor, 2009). Therefore, second harmonic should also be considered when classifying SSVEPs.

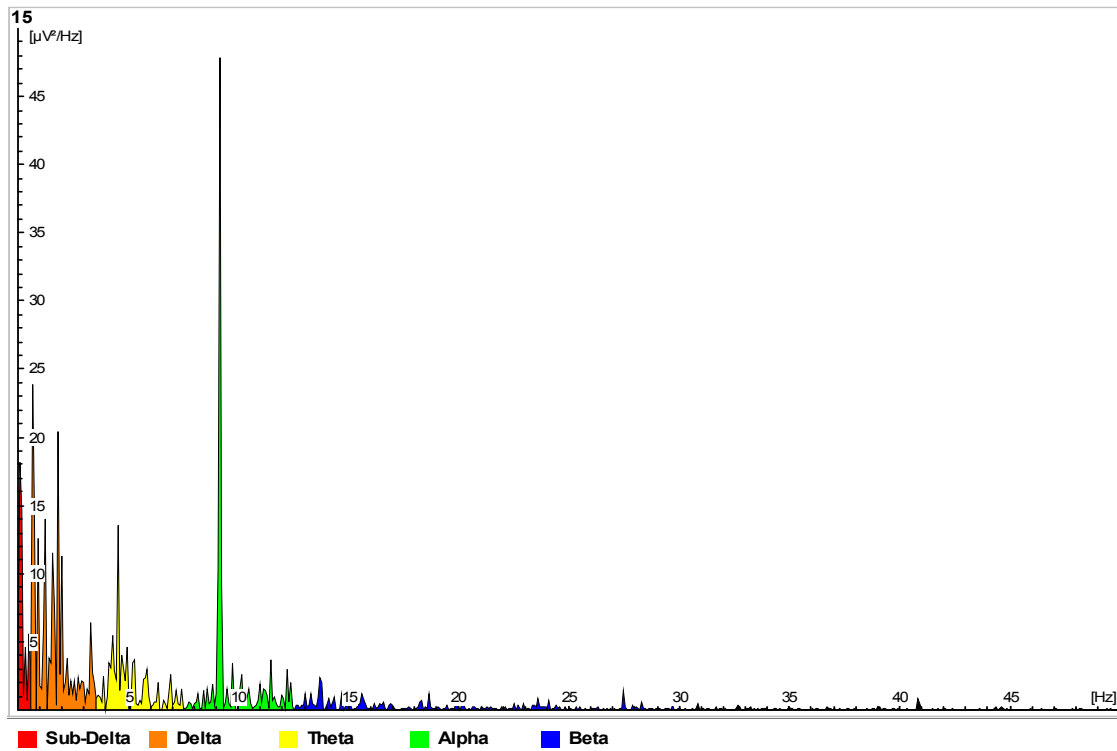


Figure 1.3 : Frequency spectrum of EEG for stimulus frequency = 4.6 Hz.

In Fig. 1.3, It is important to note that the SSVEP response related to the stimulation is embedded into EEG and must be acquired accurately to be able to perform any classification task.

SSVEPs are widely used in development of brain-computer interfaces (BCIs) (Wu et al., 2008). Relative independency from higher level cognitive tasks brings robustness to the SSVEP based BCIs (Friman et al., 2007). Since the single trial accuracy of SSVEP designs are very high, they do not need averaging of many trials. This is one of the advantages of SSVEPs over P300 signals. Furthermore, SSVEPs can provide maximum information with a few number of electrodes (Wang et al., 2008).

According to the BCI literature, methods using SSVEPs provide faster and more accurate communication opportunity (Gao et al., 2003).

Channel locations, time window length and number of harmonics are critical parameters in SSVEP-based BCI systems (Bin et al., 2009). Besides, stimulator selection should be considered. Wu et al. (2008), evaluated the spectrum differences of light-emitting diode (LED), diode, the cathode ray tube (CRT) of a desktop monitor and the liquid crystal display

(LCD) of a laptop screen. They showed that fundamental frequency amplitude of the LED flicker was significantly larger than that of the CRT and LCD flickers. They did not find a significant difference between the amplitude of the fundamental frequency of CRT and LCD. However, they mentioned that the CRT was more tiring than the other stimulators.

Selection of the stimulation frequencies is important for the classification performance and limited because of the limited bandwidth of EEG (Srihari Mukesh et al., 2006). Since for each selection (target) there should be one frequency in traditional approaches, it is very desirable to increase the number of choices using a few number of stimulation frequencies. To overcome this problem, different approaches were suggested. Srihari Mukesh et al. (2006) used a suitable combination of frequencies to increase the number of commands. Yamaguchi et al. (2010) proposed a RC (row/column) Speller which combines the responses of row and columns in a character matrix to make classification. They used three different frequencies for a nine-class classification task. For a 3s record length, they reached classification accuracies between 70% - 85% on 2 subjects. In another approach proposed by Yan et al. (2009), each target is composed of two flickers (modulated at specific frequencies) placed on right and left visual fields. Based on this method, a BCI system with nine targets was achieved using only three different frequencies. Reported accuracies on 8 subjects vary from 40% to 96.3%.

Although most of the SSVEP based BCI systems use the amplitude at stimulus frequency, phase information can also be useful. Lopez-Gordo et al. (2010) showed that the phase shifts of different stimuli can be recovered from SSVEP responses. They mentioned the joint use of phase and amplitude for increased classification accuracy. Afterwards, with the integration of phase information, Jia et al. (2011) achieved to design an SSVEP based BCI system with 15 targets by using three stimulus frequencies. They evaluated the performance of the system on 10 subjects. By using the first three harmonics of the stimulation frequencies, their system generated an average accuracy around 85% for 2s record length.

There are also operant conditioning based BCIs. This type of BCIs provide control through operant conditioning feedback. However, although subjects can learn to modulate their brain activity, it is well known that the learning process can take a very long time (e.g. several weeks) (Garcia Molina, 2004).

BCIs functioning under operant conditioning can be classified into SCP shifts, oscillatory sensorimotor activity and other hemispheric specialized mental activities (Garcia Molina, 2004).

SCPs are defined as the “changes in cortical polarization of the EEG lasting from 300 ms to several seconds” and SCP amplitudes vary from several micro volts (μV) to more than 100 μV depending on different brain conditions (Birbaumer, 1999). Negative SCP shifts are generally associated with the tasks involving cortical activation whereas positive SCP shifts are related to reduced activation (Garcia Molina, 2004). When the subjects learn to generate positive and negative shifts through feedback, they become able to achieve binary control (Garcia Molina, 2004). Therefore, SCPs can be used as control signals in BCIs. However, a successful SCP self-regulation training must take both the psychological factors and technical aspects into consideration (Hinterberger et al., 2003).

Sensory stimulation, motor behavior and mental imagery can change the functional connectivity within the cortex and give rise to amplitude suppression (event-related desynchronization (ERD)) or amplitude enhancement (event-related synchronization (ERS)) of mu (μ) and central beta (β) rhythms (Garcia Molina, 2004). These changes can be used in BCIs. However, Vuckovic et al. (2011) reported that motor imagination can cause pain in spinal cord injured patients suffering from central neuropathic pain. Besides, ERD related to motor imagery is weak in the motor cortex corresponding to the painful region. Therefore, they concluded that motor imagery type BCI is not convenient for this type of patients.

Apart from only-EEG based BCIs, there are also combined signal approaches. Chang and Seo (2009) proposed a mouse control system using EEG and EMG combination. Similarly, Leeb et al. (2010) showed that the fuse of EEG and EMG outperformed individual EEG and EMG performances.

A BCI system must be designed carefully such that it must be comfortable and should not contain risks for the health of the user (Krepki, 2004).

Main drawback of BCI systems is the low information transfer rate (ITR). ITR is the amount of information communicated per unit time and it shows both speed and accuracy in a single value. Formulation of ITR in terms of bits/trial (B) is given below (Wolpaw et al., 2002).

$$B = \log_2 N + P \log_2 P + (1 - P) \log_2 \frac{1 - P}{N - 1} \quad (1.1)$$

In (1.1), N is the number of possible choices (classes). P is the probability that the desired choice will actually be selected (classification accuracy). The equation is valid if each choice has the same probability of being the one that the user desires and if P is always the same. Besides, each of the undesired choices should have the same probability of selection (i.e. $(1-P)/(N-1)$). Bit rate provides an objective measure for comparing different BCIs (Wolpaw et al., 2002).

BCIs can also be classified as synchronous (cue-based) and asynchronous (self-paced) BCIs. In synchronous BCIs, EEG is analysed in predefined time intervals and the subjects need to follow the timetable of the system. In the synchronous BCIs, an external stimulus from the system is always necessary and the system always makes a decision among different predefined choices (Leeb et al., 2007). Even the most of the proposed BCI systems are synchronous, real-world applications require the identification of brain patterns asynchronously without any timing constraints. In that case, the user should control the timing of the task instead of the computer (Leeb et al., 2007). Asynchronous BCIs continuously analyses the brain activity and they detect not only the intentional-control states but also the pause periods, where the user is in an idling (non-control) state. Therefore, asynchronous BCIs are more complicated than the synchronous ones (Leeb et al., 2007).

Successful BCI operation depends on the adaptation of both the subject and the system (Garcia Molina, 2004). Adaptations can be summarized as follows:

- Initial adaptation of the system to the user's signal characteristics,
- Continuous adaptation of the recognition parameters as more training data become available,
- Adaptation of brain to produce EEG patterns that best control the BCI using feedback (Garcia Molina, 2004).

Besides, there are some important factors that should be considered as follows (Krepki, 2004):

- Non-invasiveness is preferable for attractive BCIs. Invasive techniques can be appropriate for only severely disabled patients.

- Electrodes should be quickly and easily mountable and removable. The need for electrolyte gel makes the procedure more difficult and time-consuming.
- Real-time operation is important for acquiring bio-feedback in accordance with the user's actions.
- BCI systems based on features dependent to other communication paths provide its user with an appealing feeling of control, but not with an additional communication channel. Therefore, system should rely on independent brain features.
- System must require no or only minimal user training. In many of the current BCI systems, users suffer from excessive training.
- It must be inexpensive enough to be desirable for the user.
- It must remove external noise and be able to detect subject generated artifacts (Garcia Molina, 2004).
- It must have high classification accuracy.

In general, there is a trade-off between the classification accuracy and the speed of the system.

In conclusion, a BCI system must be user-friendly and it must provide high accuracy in classification. Therefore there is a need for original stimuli and interface designs.

1.1 Purpose of Thesis

The main objective of this study is development of appropriate classification methods for EEG based BCIs. There exist many BCI systems developed by different research groups. Most of these systems are developed for a specific task (e.g., prosthesis control, communication, game control). However, all these tasks can be considered as a classification problem. Therefore, any improvement in classification speed or accuracy will be very important for BCIs. Although the structure of the algorithms used in classification are very important for obtaining high performance, experimental design including stimuli presentation and subject tasks is more critical. Briefly, in order to obtain satisfactory results, both the classification algorithm and the computer interface part need to be designed wisely. Therefore, in the thesis, main emphasis is given to development of convenient classification algorithms and experimental designs for BCIs.

1.2 Main Contributions

In the thesis, main contributions are summarized as below:

- By using the combination of time and frequency based features, higher classification accuracies were obtained in a classification problem on an epilepsy dataset.
- Accuracy of an existing classification method (T-Weight Method) is increased by proper pre-processing methods.
- Automatic threshold determination function is integrated into the architecture of T-Weight method. The new method is called “Improved T-Weight Method (ITW)”. Thanks to threshold integration, T-Weight Method becomes appropriate to be used in any two-class classification problem.
- By generating multiple feature sets and threshold integration, Multi-Class T-Weight (MCTW) Method is proposed for multi-class problems.
- An original SSVEP based BCI design called “Character Plotter” is proposed and its performance is evaluated on offline and online classification tasks. Proposed design converges a more natural way of writing than the other proposed designs in literature and it has the capability of defining 2^{13} symbols / characters.

1.3 Content of The Study

In Chapter 2, some basic information about EEG is given. In Chapter 3, existing classification methods in BCI field are given with the proposed ones. Chapter 4 is devoted to BCIs. Here, BCI designs in literature and proposed BCI designs are explained. In Chapter 5, classification results on different datasets are shown by comparing the performances of the proposed methods with the other methods in literature. Conclusions and recommendations are given in the last Chapter.

The thesis structure is mainly composed of the following three blocks:

- Feature Extraction
- Classifiers
- BCI Design

In Fig. 1.4, general structure of the thesis is summarised.

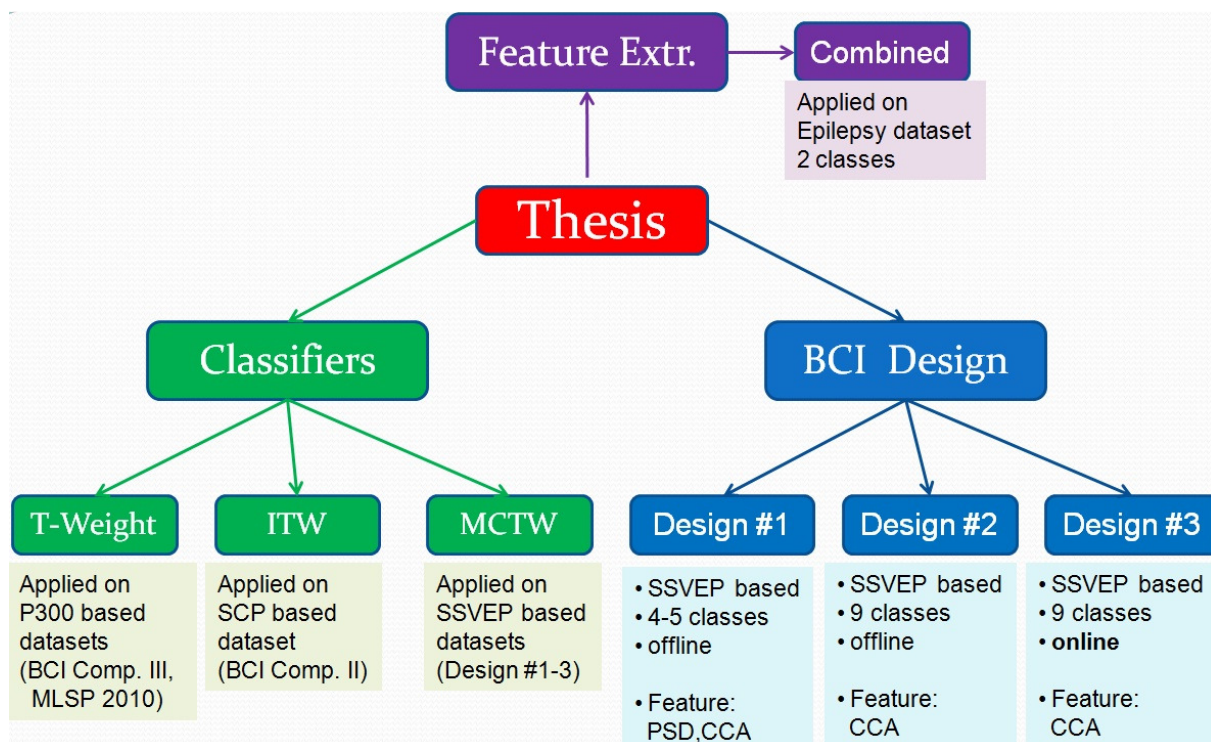


Figure 1.4 : General structure of the thesis.

Details about these blocks are given in the next Chapters.

2. ELECTROENCEPHALOGRAM (EEG)

Brain electrical activity research began in 19th century. In 1875, British neurophysiologist Richard Caton recorded the electrical activity of the brains of rabbits and monkeys directly from the brain tissue (Caton, 1875). However, first human EEG was recorded by Hans Berger in 1924. He characterised the wave patterns including alpha (α) and beta (β) waves and coined the term “electroencephalogram” (Haas, 2003).

EEG signals are the projection of neural activities that are attenuated by leptomeninges, cerebrospinal fluid, dura matter, bone, galea, and the scalp (Sanei and Chambers, 2007).

2.1 Origin of EEG Signals

The neural activity of the human brain begins to appear between the 17th and 23rd weeks of prenatal development (Sanei and Chambers, 2007). The activities in the central nervous system (CNS) are induced by the synaptic currents between the junctions (synapses) of axons and dendrites or the junctions among dendrites of cells (Sanei and Chambers, 2007). The current in the brain is generated mostly by pumping the positive ions of sodium (Na^+), potassium (K^+), calcium, (Ca^{++}) and the negative ion of chlorine (Cl^-), through the neuron membranes in the direction governed by the membrane potential (Sanei and Chambers, 2007). Normally, membrane potential of the cell body is between -60 mV and -70 mV in resting condition. However, due to the variations in synaptic activities, this potential changes (Sanei and Chambers, 2007). Action potential (AP) is the temporary change in the membrane potential which is usually initiated in the cell body and normally travels in one direction (Sanei and Chambers, 2007). The membrane potential goes positive for a while and then becomes more negative than the resting potential. Finally, it returns to the normal value. Duration of AP is generally between 5-10 ms and the conduction velocity changes between 1 and 100 m/s (Sanei and Chambers, 2007). APs are initiated by many different types of stimuli including chemical, light, electricity, pressure, touch, and stretching. However, the nerves inside the CNS are generally stimulated by chemical activity at synapses (Sanei and

Chambers, 2007). Moreover, the nerves require ~ 2 ms before a new stimulus is presented (Sanei and Chambers, 2007).

Because of the attenuation caused by skull and the noise generated by the system itself or by the external sources, only large populations of active neurons can generate enough potential to be recordable using the scalp electrodes (Sanei and Chambers, 2007).

2.2 EEG Rhythms

Based on the mental state, different EEG rhythms occur on the scalp. These rhythms are called according to the frequency sub-bands of EEG. These sub-bands are delta (δ), theta (θ), alpha (α), beta (β) and gamma (γ). However, there is no strict boundary for these sub-bands. In Table 2.1, intervals for sub-bands are given from different references.

Table 2.1 : EEG sub-bands in different references.

Reference	delta (δ)	theta (θ)	alpha (α)	beta (β)	gamma (γ)
Garcia Molina (2004)	2 – 4	4 – 8	8 – 13	13 – 30	> 30
Allison (2003)	0.5 – 4	4 – 8	8 – 13	13 – 40	-
Dastidar (2007)	0 – 4	4 – 8	8 – 13	13 – 30	30 – 60
Krepki (2004)	0.5 – 3.5	3.5 – 8	8 – 13	13 – 25	25 – 40
Calderon (2007)	0.5 – 4	4 – 8	8 – 13	13 – 25	25 – 70

The delta rhythm appears during deep sleep, anesthesia, and various meditative states involving willful and conscious focus of attention in the absence of other sensory stimuli (Garcia Molina, 2004).

The theta rhythm is the result of interactions between cortical and hippocampal neuronal groups and appears in emotional stress periods and rapid-eye-movement (REM) sleep (Garcia Molina, 2004). It is associated with very relaxed or deep meditative states (Allison, 2003).

The alpha rhythm can be observed in resting condition and disappears by perceiving a sensory signal or during mental efforts (Garcia Molina, 2004). Alpha rhythm increases over the occipital lobe and becomes evident when the eyes are closed (Allison, 2003). In Fig 2.1, an EEG record from 16 channels is given for a subject who participated in the thesis experiment.

The beta rhythm reflects the intense activity of the nervous system and occurs mainly in the parietal and frontal regions (Garcia Molina, 2004). It usually consists of irregular waves that have very small amplitudes (Allison, 2003).

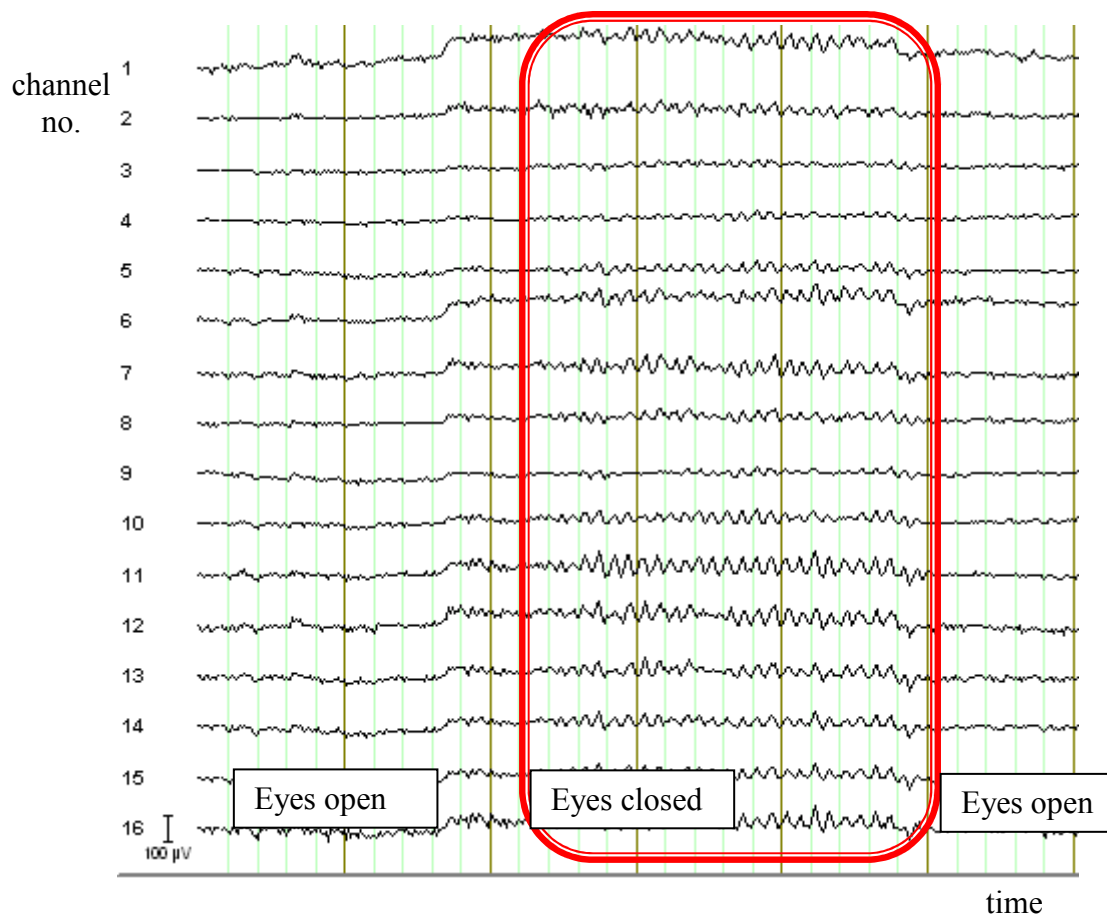


Figure 2.1 : Appearance of alpha (α) rhythm when the eyes are closed.

The gamma oscillations are believed to be associated with attention, perception and cognition (Garcia Molina, 2004).

2.3 Measurement of EEG Signals

First of all, subject whose EEG will be collected should be informed about the recording procedure and the experiment in a detailed manner. Ethical principles mentioned in Helsinki Declaration (Url-2) must be obeyed.

EEG can be measured by either macroelectrodes or microelectrodes. A macroelectrode is flat or cone-shaped metal disk that has a width of 5 - 10 mm and typically made of gold (Au), tin (Sn), silver (Ag), or silver chloride (AgCl) (Allison, 2003). In order to acquire a clean signal from the scalp, the area where the electrode contacts the skin is abraded (Allison, 2003). This painless operation removes the dead cells that have poor electrical conduction from the scalp

and thereby prevents noise (Allison, 2003). Afterwards, a conductive gel is used to reduce the impedance between the electrode and the skin. The impedance must be lower than a value (e.g. 5 k Ω) for all the electrodes in order to get noise-free and consistent EEG. Electrodes are placed on the scalp according to international 10 – 20 system (Jasper, 1958). In Fig. 2.2 this system can be seen (Url – 5).

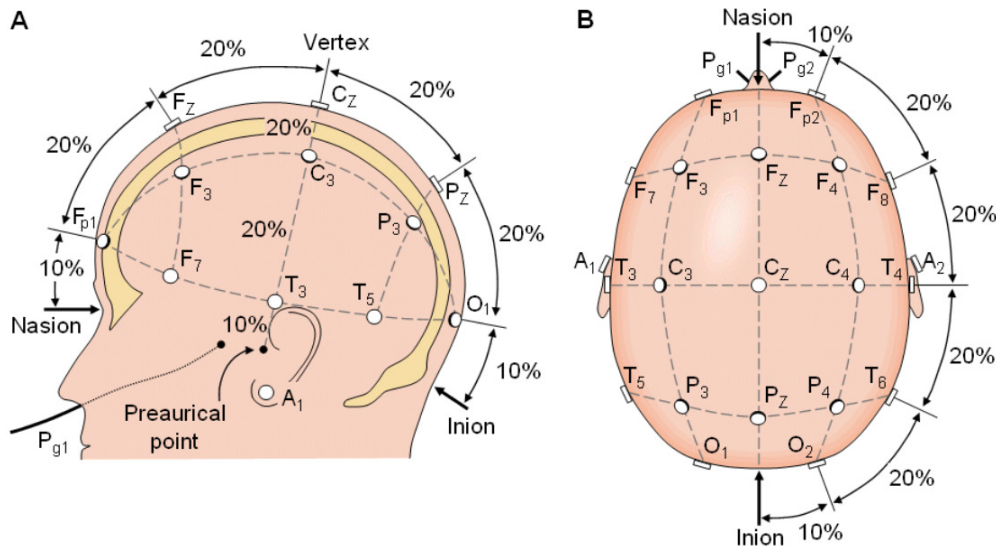


Figure 2.2 : Electrodes in the international 10-20 system seen from (A) left and (B) above the head. A: Ear lobe, C: central, Pg: nasopharyngeal, P: parietal, F: frontal, Fp:frontal polar, O: occipital (Url – 5).

In Fig. 2.2, even numbers indicate the electrodes located on the right side of the head whereas odd numbers indicate the ones on the left side and capital letters are used to reference each cortical zone (Garcia Molina, 2004). As it can be noticed from the figure, “10-20” name is coming from the percentage ratio of distances.

In order to increase the spatial resolution, in general more electrodes are placed on the scalp. In this case, extended 10 – 20 systems are used to name the electrode positions. Due to ease of use, electrode caps with predetermined electrode positions are used. These caps are manufactured in different sizes to be able to fit different heads. On the other hand, people also have different head shapes. Therefore, for each subject each electrode location should be carefully determined. Such a procedure will be time consuming and difficult for subjects. Because of these reasons, many researchers prefer using caps with fixed electrode positions. Common electrode numbers in these caps are 16, 32, 64, 128 and 256. According to the theoretical calculations, the distance of the EEG electrodes can be reduced down to 20 mm,

which corresponds to the 256 electrode system (for closer distances, signal to noise ratio (SNR) slightly decreases and mechanical size of electrodes can bring difficulties) (Malmivuo et al., 1997). Using excessive number of electrodes is not feasible for practical BCIs since the time for subject preparation and data for signal processing are increased (Allison, 2003).

When measuring EEG, monopolar or bipolar measurements are used. In monopolar montage, voltage difference between each electrode and a common reference is measured. The common reference is generally placed at a “neutral” site (e.g. mastoid, earlobe) where the electrical activity is presumed to be unaffected by brain activity (Allison, 2003). The reference signal can also be the average of two or more electrodes (Allison, 2003). When the average of all electrodes are determined as reference, it is called common average reference (CAR). In bipolar montage, voltage difference between each non-overlapping electrode pair is measured (Allison, 2003).

The disadvantage of using scalp recordings is the low quality of the signals due to attenuation on their way to the electrodes (Sanei and Chambers, 2007).

Microelectrodes can be used to record a single neuron or more neurons activity. Microelectrodes used in BCIs must perform continuous recording and are typically made of tungsten wires insulated with varnish (Allison, 2003).

Relative comparisons of neurological recording methods in terms of spatial resolution, bandwidth, and signal levels can be summarized in Fig. 2.3 (Denison et al., 2007).

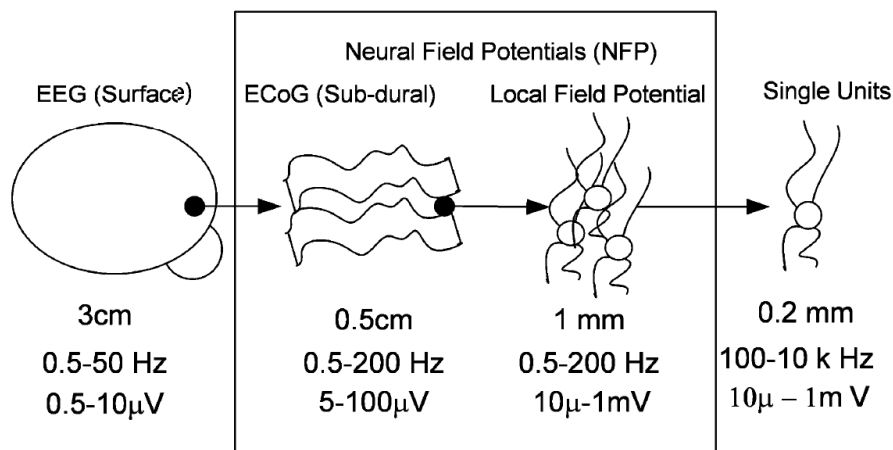


Figure 2.3 : Spatial resolution, bandwidth, and signal levels for different recording methods (Denison et al., 2007).

In Fig. 2.3, it is clear that, signal amplitude, bandwidth and spatial resolution decreases on the way from a single neuron to the surface.

While recording EEG, effects of bioelectric or electromagnetic sources interfering with the desired signal should be carefully considered. Electromagnetic interferences can be avoided by using a shielded cabin during EEG recordings. However, for practical BCI applications, shielded cabins can not be used. In general, electromagnetic interferences are well localized in frequency domain and located beyond the EEG band (Garcia Molina, 2004). Eye blink and eye movement artifacts generate low-frequency signals that can have greater amplitudes (up to 100 μ Vs) than EEG signals of interest (Garcia Molina, 2004). Eye movement artifacts are resulted from the reorientation of the retinocorneal dipole and they are recognized by their quasi square shape and amplitude in regular EEG range (Overton and Shagass, 1969). In order to detect the electrical activity related to eye movements, electrooculogram (EOG) of the subject is recorded from one or two electrodes near the eyes (Allison, 2003). Muscular movement artifacts also interfere with EEG. Although they can be caused by activity in different muscle groups, neck and facial muscles' activities have more influence on EEG (Garcia Molina, 2004). Muscle artifacts have wide frequency bandwidth. In Fig. 2.4, interferences of different electromagnetic and bioelectric sources are illustrated (Yazicioglu et al., 2007).

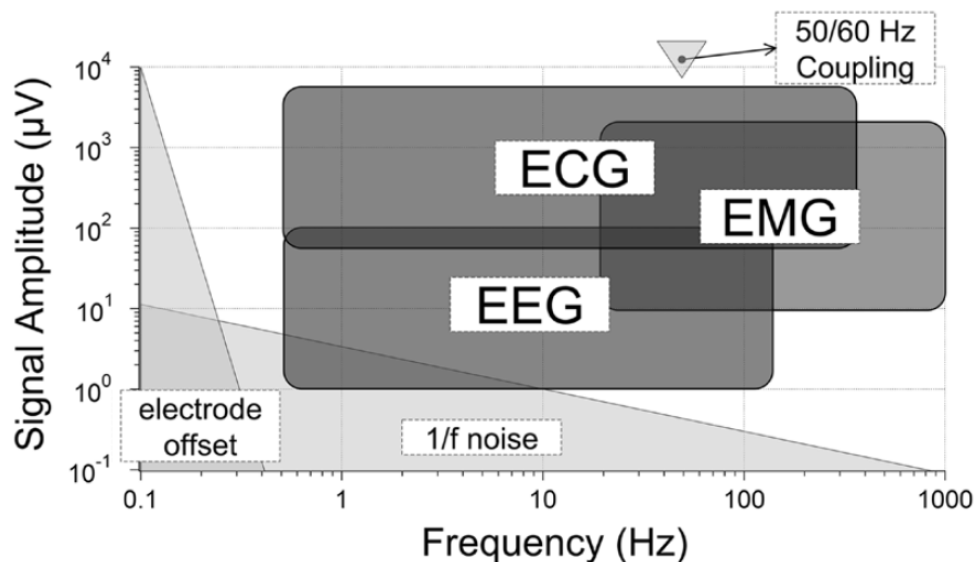


Figure 2.4 : Interferences of different electromagnetic and bioelectric sources (Yazicioglu et al., 2007).

When EEG is recorded inside a magnetic resonance imaging (MRI) system, additional interferences related to static magnetic field, switching magnetic field gradients and cardiac pulses arise (Sijbers et al., 2000).

There are several methods for removing each of these artifacts. However, there is a risk of losing the significant information embedded in EEG when removing artifacts. Therefore, artifact reduction should be carried out seriously.

2.4 Applications of EEG Signals

2.4.1 Epilepsy

Epilepsy is the main application area of EEG. In order to detect the epileptic seizures, several methods are used. Although functional MRI (fMRI), computerized tomography (CT), magnetic resonance spectroscopy and positron emission tomography (PET) can be used in diagnosis, only electroencephalography or magnetoencephalography can directly measure the brain activity thanks to their good time resolution (Russell, 2007). However, EEG and magnetoencephalogram (MEG) have low spatial resolution. Therefore, they are not good enough to determine cortical regions related to seizures (Russell, 2007).

There are several studies on seizure detection and prediction from EEG analysis in literature. Adeli et al. (2007) proposed a wavelet-chaos methodology for analysis of EEGs and EEG subbands to detect seizure and epilepsy. They used three different groups of EEG signals: healthy (normal) subjects, epileptic subjects during a seizure-free interval (interictal) and epileptic subjects during a seizure (ictal). They concluded that for the beta and gamma subbands, the correlation dimension differentiates between the three groups. On the other hand, largest Lyapunov exponent differentiates for the alpha subband. Ghosh-Dastidar and Adeli (2007) used improved spiking neural networks for seizure detection. They also applied their method on three groups mentioned above and obtained classification accuracy of 92.5%. Same researchers presented a principal component analysis (PCA)-enhanced cosine radial basis function (RBF) neural network for epilepsy and seizure detection. PCA rearranged the input space along the principal components of the data and improved the classification accuracy of the cosine radial basis function (RBF) neural network. The accuracy was 99.3% for two-class (normal, interictal) case (Ghosh-Dastidar and Adeli, 2008).

In the beginning of the thesis period, classification of epilepsy signals was considered. For this purpose, time and frequency methods were analysed. Combination of time and frequency based features for discriminating healthy and an epileptic EEG records was proposed (İşcan et al., 2011b). As time domain features, cross-correlations of the EEG time series are selected (Chandaka, et al., 2009) due to their high performance in classification. As frequency domain features, spectral power ratios of the main EEG bands (theta, delta, alpha, beta and gamma) were calculated after application of discrete Fourier transform (DFT) to the EEG series. Calculating power spectrum for different EEG frequency bands is a popular method in literature (Nguyen-Ky et al., 2009). Dataset was acquired from Andrzejak et al. (2001) paper. Only 2 sets (set A and E) are considered. Set A was formed with the segments taken from healthy surface EEG recordings that were carried out on five healthy volunteers (eyes open) using a standardized electrode placement scheme. Set E was formed with the segments taken from five patients and contains seizure activity. More information about the dataset can be found in the Andrzejak et al. (2001) paper.

Results obtained with different classifiers showed that the combination of features generally yields the highest accuracy as compared to the individual cross correlation and power spectrum features. Details about the classification results can be seen in İşcan et al. (2011b) paper.

2.4.2 Other application areas

Besides epilepsy, EEG has many application areas. Yang (2008), evaluated the effect of fatigue on functional corticomuscular coupling (fCMC) and showed that it weakens strength of fCMC between EEG and EMG.

Nodine (2008) wanted to develop a drowsiness detection system to overcome accidents by finding the parameters related to driver drowsiness.

Parsons (2007) presented a method to enhance the subcortical target localization in stereotactic neurosurgery for the placement of chronic implant stimulation electrode for deep brain stimulation therapy.

Since the EEG data acquired from many channels form a huge size of data, it became a research field of data mining (Wang, 2007, Kammerdiner, 2008, Dastidar, 2007).

Sleep analysis is another popular area of EEG. Kassebaum (2008), showed that a frequency-domain based state-space analysis of EEG is effective for identifying sleep stages.

Walshaw (2008) used EEG with other techniques in order to understand the differences between bipolar disorder and attention-deficit hyperactivity disorder.

EEG is also used as a control signal in BCIs. In the next Chapter, BCIs are analysed in a detailed manner.

All these studies in literature show the great potential of EEG in various research fields.

3. CLASSIFICATION METHODS

This Chapter is composed of feature extraction methods and classifiers. First of all, feature extraction methods used in literature for EEG based BCIs are summarized. Afterwards, two methods used in the thesis are explained. These methods are power spectral density (PSD) and canonical correlation analysis (CCA). Second, classifiers used in EEG based BCI systems are summarized. Here, a brief information about the well-known classifiers (e.g. support vector machines (SVM), linear discriminant analysis (LDA)) which were used in the thesis is given. Afterwards, proposed methods in the thesis were explained in a detailed manner. The efficiency of the developed algorithms are demonstrated on widely used datasets in the literature by comparing them with successful classification methods in BCI field (See Chapter 5).

3.1 Feature Extraction Methods in EEG Based BCI Systems

Feature extraction is a critical signal processing step in classification. In order to extract the hidden information from EEG, features should be selected in a proper way. Feature extraction method should be chosen according to the “nature” of the expected response in EEG. For instance, in P300 based BCIs, the critical information related to the expected response is located in time domain whereas in SSVEP based BCIs it is located in frequency domain. Therefore, the feature extraction methods should take the advantage of the proper domains.

Some of the features used in BCI design are amplitude of EEG, band power, power spectral density (PSD) values, autoregressive (AR) and adaptive autoregressive (AAR) parameters, time-frequency features and inverse model-based features (Lotte et al., 2007).

In the thesis, samples with specific lengths (e.g. 1s, 2s, 3s) are taken as features from time domain for P300 and SCP based classification tasks. On the other hand, for SSVEP designs, PSD features which take the advantage of the frequency

characteristics of the signals and CCA that uses the correlation values are used. A brief information about these methods are given in the following sections.

3.1.1 Power spectral density (PSD)

Power spectral density is generally used for characterizing random processes. It can be calculated with the help of Fourier transform (Howard, R. M., 2002). In the thesis, Discrete Fourier Transforms (DFTs) of filtered EEG segments are calculated using (3.1).

$$X(k) = x(n) \cdot e^{-\frac{j2\pi kn}{N}} \quad k=0, 1, \dots, N-1 \quad (3.1)$$

In (3.1), $x(n)$ represents the discrete samples of EEG data. N is the length of the EEG data.

After calculation of DFT ($X(k)$) of EEG samples, power spectrum of EEG (equation (3.2)) is calculated.

$$P(k) = |X(k)|^2 \quad k=0, 1, \dots, N-1 \quad (3.2)$$

In one of the proposed experimental designs (see section 4.2) where PSD method is used, there are four circles located in the up, down, right and left direction on a computer screen. Each circle has a particular stimulus frequency (4.60, 6.43, 8.03, 10.70 Hz). In Fig. 3.1, PSD of the upper, lower, right and left circles are presented for a segment length of 3s for subject #10 (see section 5.3.1.1). Peaks around the stimulation frequencies and their harmonics can be seen. Other peaks can result from the interactions of different frequency components and ongoing brain activity.

Maximum PSD amplitudes around the neighborhood of fundamental stimulation frequencies (first harmonics) and their second harmonics are taken as features. These harmonics are located in the strongest SSVEP response range (Friman et al., 2007). As a result, there are two features for each stimulation frequency. Neighborhood was determined as the frequency resolution (the difference between successive points in the frequency axis). In literature, third harmonic frequencies were also found to be useful (Müller-Putz and Pfurtscheller, 2008) in the classification. However, performance obtained with only two harmonics generated better results in thesis study.

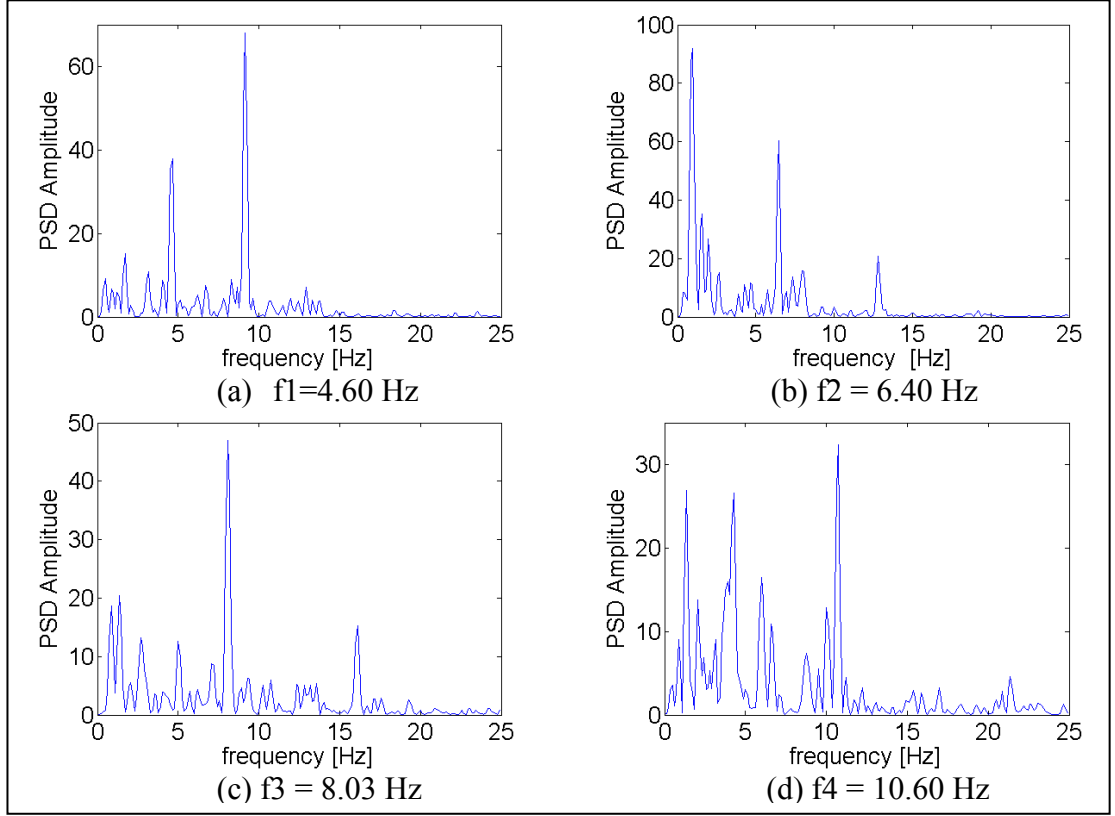


Figure 3.1 : PSD of upper (a), lower (b), right (c) and left (d) circle responses (segment length: 3s, subject #10).

3.1.2 Canonical correlation analysis (CCA)

CCA is a multivariable statistical method developed by H. Hotelling (Yan et al., 2009). This method is used when there are two sets of data which may have some correlation and it tries to find a pair of linear combinations of these sets, such that the correlation between the two canonical variables is maximized (Bin et al., 2009).

Let X and Y be the datasets. CCA tries to maximize the correlation between

$x = X^T W_x$ and $y = Y^T W_y$ by finding weight vectors W_x and W_y . The maximum of ρ with respect to W_x and W_y is the maximum canonical correlation and it can be calculated by the following equation (Bin et al., 2009).

$$\max_{W_x, W_y} \rho(x, y) = \frac{E[x^T y]}{\sqrt{E[x^T x]E[y^T y]}} = \frac{E[W_x^T X Y^T W_y]}{\sqrt{E[W_x^T X X^T W_x]E[W_y^T Y Y^T W_y]}} \quad (3.3)$$

In (3.3), E denotes the expected value operation.

In order to implement CCA, artificial EEG segments (sine and cosine functions) which have the same lengths with the original EEG data are created. The frequencies of the sine and cosine functions are defined as the first and second harmonics of the stimulation frequencies. Afterwards, correlation values are calculated by CCA between the acquired biological EEG segments and the artificial ones. As a result, correlation values are used as the features for classification. An illustration for usage of CCA is given in Fig. 3.2.

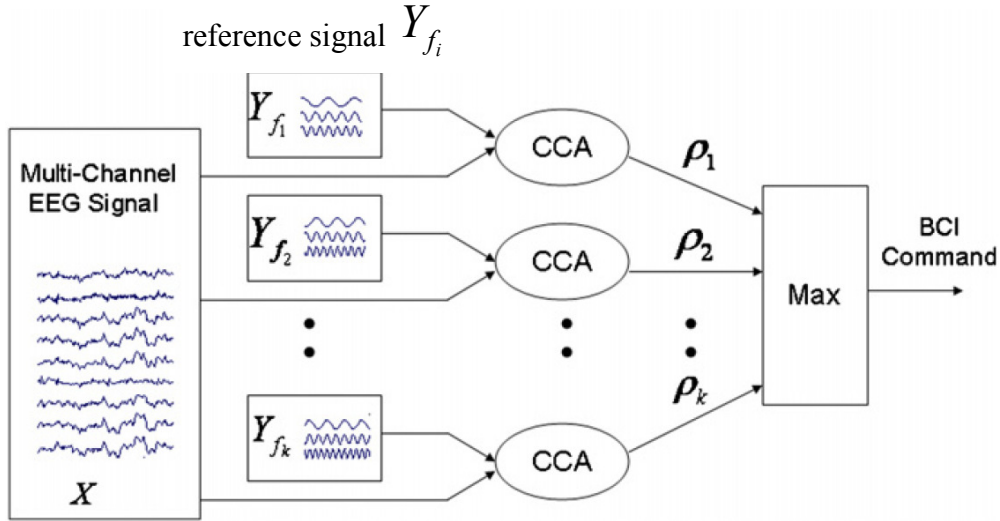


Figure 3.2 : Use of CCA in EEG classification (Bin et al., 2009).

In Fig. 3.2, X is the multi-channel EEG signal whereas Y_{f_i} ($i=1,2,\dots,k$) is the artificial reference signal (sine or cosine) in f_i hertz. ρ_i ($i=1,2,\dots,k$) is the correlation value. Classical correlation analysis is dependent on the coordinate system in which the variables are described. However, CCA finds the coordinate system that is optimal for correlation analysis (Yan et al., 2009).

3.2 Feature Evaluation by Divergence Analysis

In order to evaluate the performance of the extracted features by PSD and CCA quantitatively, divergence analysis (Cohen, 1986) is used. The divergence is a class separability measure and gives information about the distribution of class vectors in the feature space. Calculations for obtaining divergence value (D) are shown below (Dokur and Ölmez, 2009):

$$D = \text{tr}((W)^{-1}B) \quad (3.4)$$

$$W = \sum_{j=1}^C W_j ; \quad W_j = \sum_n (\underline{K}_j^n - \underline{\hat{\mu}}_j) \cdot (\underline{K}_j^n - \underline{\hat{\mu}}_j)^T ; \quad j=1, 2, \dots, C$$

$$B = \sum_{j=1}^C (\underline{\hat{\mu}} - \underline{\hat{\mu}}_j) \cdot (\underline{\hat{\mu}} - \underline{\hat{\mu}}_j)^T ; \quad \underline{\hat{\mu}} = \sum_{j=1}^C \underline{\hat{\mu}}_j$$

In (3.4), D is the divergence value and $\text{tr}(\cdot)$ is the trace operation. W_j is the within class scatter matrix of the j th class whereas B is the between-class scatter matrix. $\underline{K}_j^n$ is the n th feature vector of the j th class, $\underline{\hat{\mu}}_j$ is the mean vector of the feature vectors of the j th class, C is the number of classes. Divergence value decreases for indiscriminately scattered class vectors. If the between-class scattering is high and within-class scattering is low, divergence value increases. Therefore, divergence value is an indicator of good discrimination in feature vectors from different classes.

3.3 Classifiers Used in EEG Based BCI Systems

Many classification methods have been used so far in classification of EEG. Lotte et al., (2007) reviewed the classification algorithms used in EEG based BCIs. Selection of the most appropriate classifier depends on the features and their properties (Lotte et al., 2007). Lotte et al. (2007) underlined the two main problems in BCI field (the curse-of-dimensionality, bias–variance tradeoff) and they divided the classification algorithms into 5 categories in their survey:

- Linear classifiers (e.g. LDA, SVM),
- Neural networks (e.g. multi-layer perceptron (MLP), Gaussian classifier, learning vector quantization (LVQ), radial basis function (RBF) neural network)
- Nonlinear Bayesian classifiers (e.g. Bayes quadratic, hidden Markov model (HMM)),
- Nearest neighbor classifiers (e.g. k-nearest neighbor (K-NN), Mahalanobis distance based classifiers),
- Combinations of classifiers (e.g. boosting, voting, stacking).

They observed different classifier performances between synchronous and asynchronous BCI. They concluded that SVMs are particularly efficient for

synchronous BCI due to their regularization property and immunity to the curse-of-dimensionality.

In many BCI systems, classification is performed by using a single classifier. (Senthilmurugan et al., 2011). On the other hand, combinations of classifiers and dynamic classifiers were found to be very efficient in synchronous experiments (Lotte et al., 2007).

Müller et al. (2003) presented some specific examples related to the application of linear and non-linear methods to EEG data. Afterwards, they summarized the advantages and disadvantages of these methods. Simplicity generally gave the best result so they recommended the use of linear methods. On the other hand, they stated that nonlinear methods can generate better results in some particular applications (e.g. complex or large datasets).

Apart from linear classifiers, neural networks (NNs) are also very popular in BCI systems (Senthilmurugan et al., 2011).

Senthilmurugan et al. (2011) used fuzzy inference system and they reached a performance similar to SVM.

Cinar and Sahin (2011) compared the Fuzzy Functions Support Vector Classifier, Improved Fuzzy Functions Support Vector Classifier and Particle Swarm Optimization with Radial Basis Function Networks (PSO-RBFN) in EEG classification. They concluded that PSO-RBFN could compete with the other methods and be an alternative technique in the classification of EEG signals for real-time applications due to its simple implementation.

Based on the experience in literature, SVM, LDA and nearest mean classifier (NMC) are selected to be used in the classification during thesis study. Besides, MCTW method which was developed during thesis studies is explained. The method is an extension of T-Weight Method (Liu et al., 2005). By the integration of a threshold, T-Weight method is improved and the obtained classifier is called Improved T-Weight Method (ITW). Afterwards, multi-class version of ITW method is proposed and it is called Multi-Class T-Weight (MCTW) method. In the following sub-sections, basic information about these classifiers is given.

3.3.1 Support vector machine (SVM)

Support vector machines and their variants, generally called as kernel-based methods, have been applied to many pattern classification and function approximation problems (Abe, 2010).

SVMs use nonlinear mapping in order to represent patterns in dimensions higher than the original feature space's dimension. Thanks to mapping, data samples from two different classes become separable by a hyper-plane (Duda et al., 2001).

SVMs try to find the optimal hyperplanes between classes. For two-class problems, the hyperplane can be defined as (3.5) (Abe, 2010).

$$D(\mathbf{x}) = \mathbf{w}^T \mathbf{x} + b = c \quad -1 < c < 1 \quad (3.5)$$

In (3.5), $\mathbf{x}$ represents the training inputs belonging to class 1 or class 2. b is the bias term. The distance between the training data sample nearest to the hyperplane and separating hyperplane is called the margin (Abe, 2010). In Fig. 3.3, margin and the optimal hyperplane are illustrated for a two-class classification problem on two-dimensional (2D) feature space.

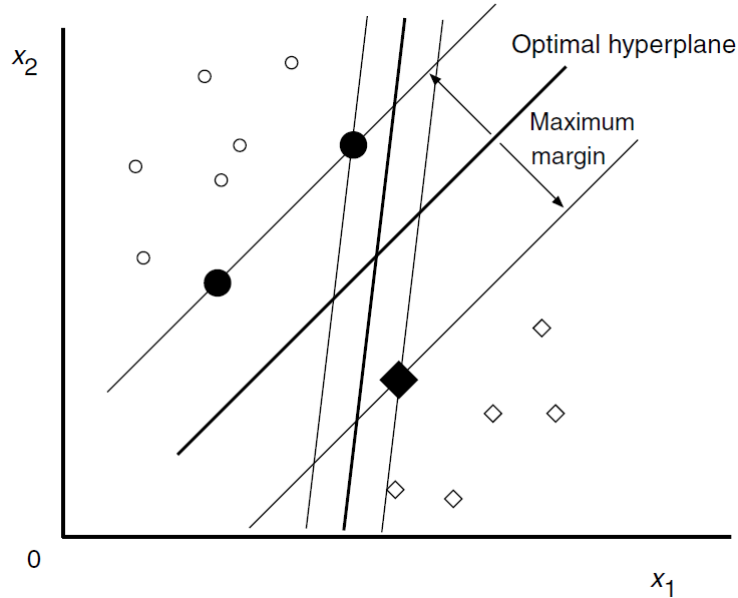


Figure 3.3 : Maximum margin and the optimal hyperplane are illustrated for a two-class classification problem (Abe, 2010).

In Fig. 3.3, circles and the squares denote different classes. x_1 and x_2 represent features.

Finding the optimal hyperplane requires the solution of the following minimization problem for $\mathbf{W}$ and b (Abe, 2010).

$$Q(\mathbf{w}, b) = \frac{1}{2} \|\mathbf{w}\|^2 \quad (3.6)$$

$$y_i(w^T x_i + b) \geq 1 \quad \text{for } i = 1, \dots, M \quad (3.7)$$

$y_i = 1$ for class 1 and $y_i = -1$ for class 2. M denotes the number of training inputs. Equation (3.6) should be minimized subject to (3.7) (Abe, 2010).

SVMs generally generate better performances as compared with the LDA classifier (Senthilmurugan et al., 2011). In EEG based BCI systems, kernel based methods like SVM are considered as the state-of-the-art methods (Zhong et al., 2008).

3.3.2 Linear discriminant analysis (LDA)

Reducing the dimensionality of the feature space is critical to get rid of the “curse of dimensionality” (Duda, 2001). In Fisher’s LDA, samples from different classes are projected from a high dimensional space to lower dimensional space. Achieving a proper projection orientation results in well-separated projected samples (Duda, 2001). In Fig. 3.4, two different projections from two-dimensional (2D) space to 1 dimensional (1D) space are illustrated.

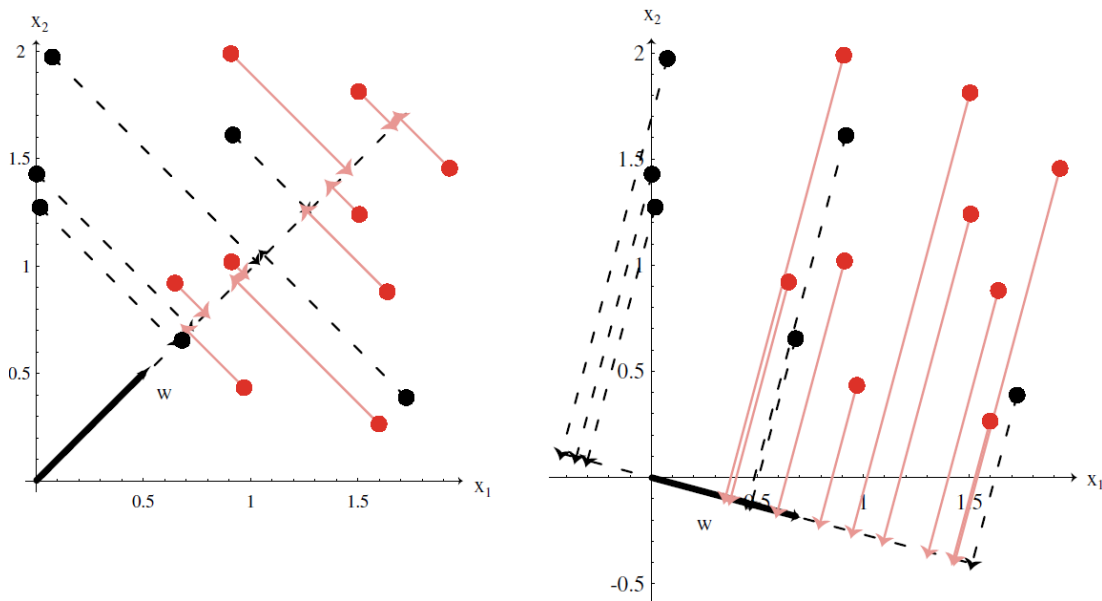


Figure 3.4 : Two different projections from 2D to 1D space (Duda, 2001).

In Fig. 3.4, It is clear that the projection placed on the right is better for class separation. In Fisher's LDA, the idea is obtaining a linear function that is capable of maximizing the ratio of between-class scatter to within-class scatter (Duda et al., 2001). In order to achieve this, LDA takes the sample covariances into account with the class means (Stoeckel et al., 2001). In (3.8), criterion that should be maximized is given (Duda et al., 2001).

$$J(w) = \frac{|\tilde{m}_1 - \tilde{m}_2|^2}{\tilde{s}_1^2 + \tilde{s}_2^2} \quad (3.8)$$

In (3.8), $|\tilde{m}_1 - \tilde{m}_2|$ is the distance between the projected means. $\tilde{s}_1^2 + \tilde{s}_2^2$ is the total within-class scatter of the projected samples (Duda et al., 2001).

Its simple structure and the low computational complexity makes the LDA a suitable classifier for the online BCI systems. Therefore, LDA has been widely used in different BCI systems like motor imagery based BCI and asynchronous BCI (Senthilmurugan et al., 2011).

3.3.3 Nearest mean classifier (NMC)

NMC performs a classification by measuring the Euclidean distances between each feature vector and each of class mean vectors (Duda et al., 2001). Therefore, the feature vector's class is determined by the nearest mean vector's class. NMC is a special case of LDA when the sample covariance matrix is equal to identity matrix (Stoeckel et al., 2001).

Decision regions for a NMC is given in Fig. 3.5 for a two dimensional classification task.

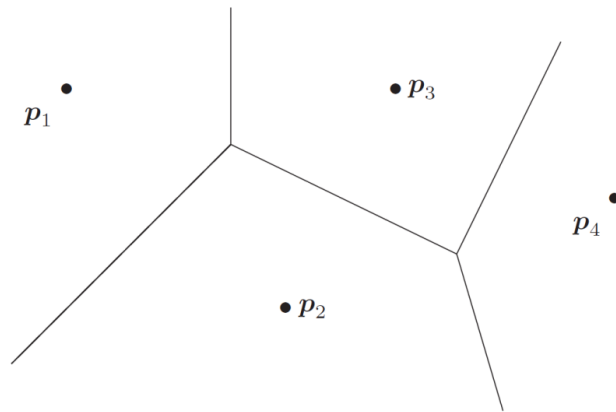


Figure 3.5 : Decision regions for NMC (Webb and Copsey, 2011).

In Fig. 3.5, $p1 - p4$ are the means of four different classes (Webb and Copsey, 2011).

3.3.4 T-Weight method

T-weight method is based on multiplication of features in the feature vector with the optimum weights $(\alpha, \beta, \dots, \gamma)$ and taking the weighted sum as the f value as the following equation (Liu et al., 2005).

$$\begin{aligned} f_{\mathbf{x},i} &= \alpha x_{i,1} + \beta x_{i,2} + \dots + \gamma x_{i,N} & i &= 1, 2, \dots, n_1 \\ f_{\mathbf{y},j} &= \alpha y_{j,1} + \beta y_{j,2} + \dots + \gamma y_{j,N} & j &= 1, 2, \dots, n_2 \end{aligned} \quad (3.9)$$

In (3.9), $f_{\mathbf{x},i}$ and $f_{\mathbf{y},j}$ denote the feature values (f) obtained by multiplication of weights $(\alpha, \beta, \dots, \gamma)$ with the features of target ($\mathbf{x}$) and non-target ($\mathbf{y}$) feature vectors. n_1 and n_2 denote the number of target and non-target feature vectors respectively. N is the dimension of the feature vector for the given problem. As a result, T-Weight performs a 2-class classification task. The weights $(\alpha, \beta, \dots, \gamma)$ and the features $x_{i,k}$ and $y_{j,k}$ ($k=1, 2, \dots, N$) should be written as vectors rather than scalars for multiple channel case. The method is trying to maximize the difference between the f values that belong to target ($\mathbf{x}$) and non-target ($\mathbf{y}$) training feature vectors (Liu et al., 2005). The mean values for $x_{i,k}$ and $y_{j,k}$ over all i and j are denoted as $\mu_{\mathbf{x},k}$ and $\mu_{\mathbf{y},k}$ whereas the variances are denoted as $\sigma_{\mathbf{x},k}^2$ and $\sigma_{\mathbf{y},k}^2$ respectively. In order to evaluate the separability between $f_{\mathbf{x},i}$ and $f_{\mathbf{y},j}$, two sample t -statistics is used as a criterion as the following equation (Bostanov, 2004).

$$t = C \frac{\overline{f_{\mathbf{x},i}} - \overline{f_{\mathbf{y},j}}}{\sqrt{(n_1 - 1)S_{\mathbf{x}}^2 + (n_2 - 1)S_{\mathbf{y}}^2}} \quad C = \sqrt{\frac{(n_1 + n_2 - 2)n_1 n_2}{(n_1 + n_2)}} \quad (3.10)$$

In (3.10), $\overline{f_{\mathbf{x},i}}$ and $\overline{f_{\mathbf{y},j}}$ denote the mean values of $f_{\mathbf{x},i}$ and $f_{\mathbf{y},j}$. $S_{\mathbf{x}}^2$ and $S_{\mathbf{y}}^2$ are the variances of $f_{\mathbf{x},i}$ and $f_{\mathbf{y},j}$. Assuming that the signals are uncorrelated, (3.10) can be written as follows (Liu et al., 2005).

$$t = C \frac{\alpha \Delta \mu_1 + \beta \Delta \mu_2 + \dots + \gamma \Delta \mu_N}{\sqrt{\alpha^2 \Delta \sigma_1^2 + \beta^2 \Delta \sigma_2^2 + \dots + \gamma^2 \Delta \sigma_N^2}} \quad (3.11)$$

$$\Delta \mu_k = \mu_{\mathbf{x},k} - \mu_{\mathbf{y},k} \quad \Delta \sigma_k^2 = (n_1 - 1) \sigma_{\mathbf{x},k}^2 + (n_2 - 1) \sigma_{\mathbf{y},k}^2 \quad k = 1, 2, \dots, N$$

Since the t value should be maximum with the optimum weights, the weights ($\alpha, \beta, \dots, \gamma$) are calculated by taking the partial derivative of t with respect to the weights and making it equal to zero as (3.12) (Liu et al., 2005).

$$\frac{\partial t}{\partial \alpha} = 0, \quad \frac{\partial t}{\partial \beta} = 0, \quad \dots \quad \frac{\partial t}{\partial \gamma} = 0 \quad (3.12)$$

According to Liu et al. (2005), weights can be set as follows.

$$\alpha = \frac{\Delta \mu_1}{\Delta \sigma_1^2}, \quad \beta = \frac{\Delta \mu_2}{\Delta \sigma_2^2}, \quad \dots \quad \gamma = \frac{\Delta \mu_N}{\Delta \sigma_N^2} \quad (3.13)$$

3.3.5 Improved T-Weight method (ITW)

T-Weight Method is improved by integration of a threshold determination step into the original algorithm. The new method is called Improved T-Weight (ITW) Method and the performance of the ITW Method is evaluated on classification of SCPs for a BCI task (İşcan and Dokur, 2011). Two different datasets from BCI Competition 2003 (Blankertz et al., 2004) are used for classification. It is shown that ITW Method outperforms all the other submissions in the Competition in terms of classification error (İşcan and Dokur, 2011) (See section 5.2).

The original T-Weight method only finds the f values (f) related to target and non-target feature vectors by calculating the optimum (most discriminative) weights (see (3.13)). According to the Method (Liu et al., 2005), f values for the target vectors should be higher than those for non-targets. This information can be used in classification if the number of the feature vectors from each class is known. However, in most of the classification problems, the number of the feature vectors from each class is not known in advance for the test set. In order to overcome this problem in T-Weight Method, Improved T-Weight Method (ITW) is proposed. With the integration of a threshold determination step into original T-Weight Method, ITW method can be used in 2-class problems without any restriction (İşcan and Dokur, 2011).

In the ITW method, after calculating f values (see (3.9)) for training vectors, the vectors are sorted according to their f values. In Figs. 3.6 and 3.7, ITW method is explained using the datasets (dataset I-a,b) in section 5.2.1 (İşcan and Dokur, 2011).

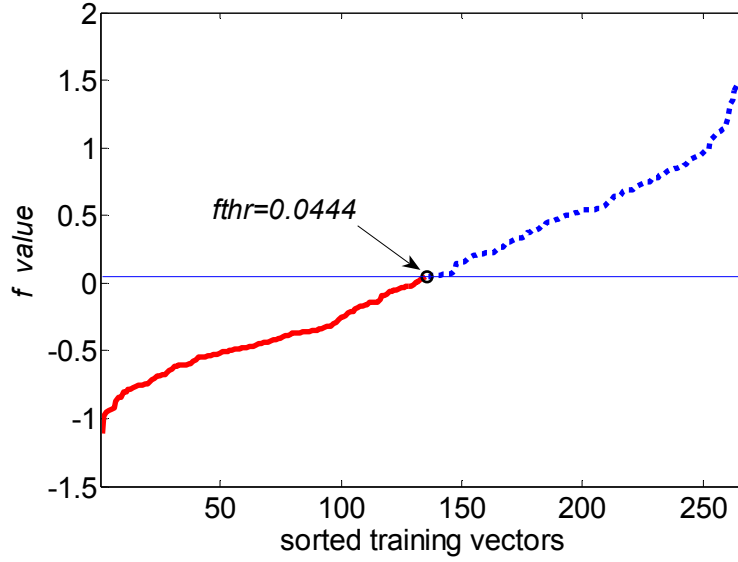


Figure 3.6 : Sorted training feature vectors according to f values and selection of threshold for dataset I-a (268 feature vectors in the training set).

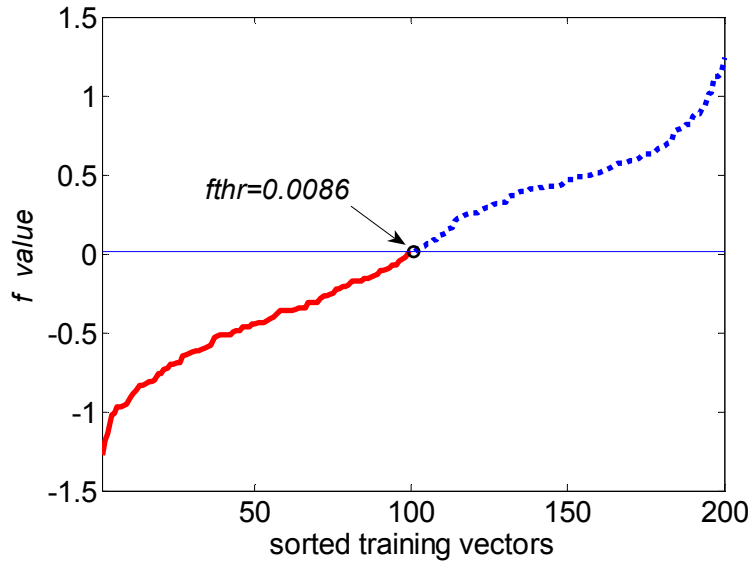


Figure 3.7 : Sorted training feature vectors according to f values and selection of threshold for dataset I-b (200 feature vectors in the training set).

Since the numbers of the target ($\mathbf{x}$) and non-target ($\mathbf{y}$) feature vectors in the training set are known (n_1 and n_2 respectively), a threshold ($fthr$) for discriminating between target and non-target feature vectors can be determined. It should be remembered that f values for the target vectors should be higher than those for non-targets.

Therefore, in the sorted training feature vectors, feature vectors with smaller f values are more likely to be non-targets whereas feature vectors with higher f values are more likely to be targets. In Figs. 3.6 and 3.7, sorted f values and the $fthr$ for discrimination are illustrated for datasets I (a-b) respectively (İşcan and Dokur, 2011).

There are n_2 non-target (indicated with red lines in Figs. 3.6 and 3.7) and n_1 target (indicated with blue dotted lines in Figs. 3.6 and 3.7) feature vectors in the training set. Therefore, a threshold ($fthr$) for discrimination can be determined as in (3.14) (İşcan and Dokur, 2011).

$$fthr = \frac{f(n_2) + f(n_2 + 1)}{2} \quad (3.14)$$

In Fig. 3.6, there are 268 sorted training vectors. For 135 (n_2) non-target and 133 (n_1) target feature vectors, threshold $fthr = 0.0444$.

In Fig. 3.7, there are 200 sorted training vectors. For 100 non-target and 100 target feature vectors, threshold $fthr = 0.0086$.

In Figs. 3.6 and 3.7, thresholds ($fthr$) are marked with a circle. f values for the test set (fte) are calculated by applying the T-Weights obtained from training set to the test set. It should be noted that PCA coefficients obtained from training set must be applied to the test set before applying the T-weights. Hereafter, binary classification is performed by comparing fte and $fthr$, as (3.15) (İşcan and Dokur, 2011).

$$class = \begin{cases} 1 & fte \geq fthr \\ 0 & fte < fthr \end{cases} \quad (3.15)$$

According to (3.15), if f value of a test vector (fte) is greater than or equal to $fthr$, test vector is classified as a target (class=1). Otherwise, the vector is classified as non-target (class=0) (İşcan and Dokur, 2011).

3.3.6 Multi-Class T-Weight (MCTW) method

In this sub-section, Multi-Class T-Weight Method (MCTW) is presented as a novel classification method for BCI systems. Proposed method is an extension of ITW Method. By creating multiple feature vector sets, Improved T-Weight method becomes appropriate for multi-class problems. Proposed method is applied on the

frequency and correlation based features obtained from EEG data of 20 Subjects in an SSVEP based offline BCI classification task.

In order to explain the algorithm of MCTW Method, pseudo-code is given in Fig. 3.8.

```

labeling of feature vector sets (including training & test vectors)
for each labeled training vector set
    for multi-channel case apply PCA
    calculate T-weights (see (3.13))
    calculate  $f$  values for training vectors (see (3.9))
    sort training vectors according to  $f$  values
    calculate threshold  $fthr(set)$  for discrimination } threshold
end                                                         determination
for each labeled test vector set
    for each test vector
        for multi-channel case apply PCA coefficients
        apply T-weights
        calculate  $f$  value ( $fte(vector, set)$ ) (see (3.9))
    end
end

```

Figure 3.8 : Pseudo-code for Multi-class T-Weight Method (MCTW).

First of all, for each subject, different feature vector sets are generated. This is due to labeling of each feature vector set by using one vs. all method. In this labeling, for each feature vector set, one class is selected as target and all the other classes are becoming non-targets. Therefore, number of the different feature vector sets is equal to total class number.

For each training vector set, T-Weights are calculated. If there is more than one channel, PCA should be applied to remove correlations between the channels before calculating T-Weights (light gray lines in Fig. 3.8 must be omitted if there is only one channel).

In the ITW method, classification is done by determining threshold values from training sets. f values for the test set (fte) are calculated by applying the T-Weights obtained from training set to the test set and classification is performed by comparing fte and $fthr$ (see (3.15)). Such a comparison is enough for a 2-class classification task. However in multi-class case, binary comparison is not sufficient for a proper classification. Pseudo-code for classification using threshold in MCTW method is given in Fig. 3.9.

```

for each test vector
  for each set
    if  $fte(\text{vector}, \text{set}) > fthr(\text{set})$ 
       $\text{class}(\text{vector}, \text{set}) = 1$ 
    else
       $\text{class}(\text{vector}, \text{set}) = 0$ 
    end
  end
  if  $\sum_{\text{set}} \text{class}(\text{vector}, \text{set}) > 1$ 
     $\text{maxset} = \text{find}(\max / fte(\text{vector}, \text{set}) - fthr(\text{set}) / )$ 
    for each set
       $\text{class}(\text{vector}, \text{set}) = 0$ 
    end
     $\text{class}(\text{vector}, \text{maxset}) = 1$ 
  end
  if  $\sum_{\text{set}} \text{class}(\text{vector}, \text{set}) < 1$ 
     $\text{minset} = \text{find}(\min / fte(\text{vector}, \text{set}) - fthr(\text{set}) / )$ 
     $\text{class}(\text{vector}, \text{minset}) = 1$ 
  end
end

```

Figure 3.9 : Pseudo-code for classification using threshold in MCTW method.

First of all, binary classification is performed by comparing fte and $fthr$ like ITW method. However, if there are more than two classes, there is a risk that a test vector is classified into more than one class or not classified into any of the classes. In this case, two queries should be done. If a test vector is classified into more than one class, the class of the test vector is determined by checking the distances between fte and $fthr$ values for each set. The set number that gives the maximum distance is assigned as the test vector's class. If a test vector is not classified into any of the classes, the test vector's class is the set number that generates the minimum distance between fte and $fthr$ values. After setting the classes according to the queries, the algorithm guarantees that each test vector is assigned to a single class.

4. BRAIN COMPUTER INTERFACES AND EXPERIMENTAL DESIGN

In this section, current BCI designs in the literature are summarized briefly. Afterwards, proposed experimental designs are described in a detailed manner.

4.1 Previous Experimental Designs

Although the signal processing algorithms are very important for BCI performance, effective stimulation design directly correlates with the classification speed and accuracy. In literature, many BCI stimulation methods have been developed based on different EEG signals. Here, some examples of P300 and SSVEP based BCI designs are evaluated. Moreover, designs using different signals are mentioned.

4.1.1 P300 based designs

In P300 based BCI designs, common method is dividing the monitor into a grid structure (rows and columns) where each cell contains a special character. In Fig. 4.1, an example for such a design is presented (Blankertz et al., 2006a).

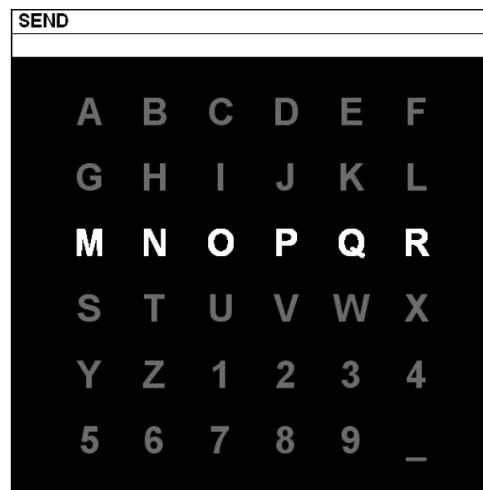


Figure 4.1 : P300 speller design (Blankertz et al., 2006a).

In Fig. 4.1, each row or column is intensified randomly. When the character that the subject concentrates on is intensified, P300 signal should occur in EEG. In this

design, data was acquired using BCI2000's (a general-purpose system for BCI research) P3 Speller Paradigm (Schalk et al., 2004).

The character matrix shown in Fig. 4.1 can be extended for different applications. Allison and Pineda (2003) analyzed the effect of matrix size on P300 signal and showed that there is an increase in the difference between attended and ignored P300 amplitude in larger matrices. They thought that this is due to the reduced target probability and increased nontarget probability of larger matrices. Besides, they recommended taking three factors into consideration when choosing the matrix size: User factors, early components, and novel preprocessing and pattern recognition approaches.

Sirvent et al. (2010) proposed a P300 based BCI for internet browsing. They used BCI2000 platform for sampling and signal processing (Schalk et al., 2004).

There is also a commercial product developed for patients (Url-6).

The problem with P300 based designs is the low signal to noise ratio (SNR) of P300. Therefore, in order to increase the signal to noise ratio (SNR), averaging of many trials is needed.

4.1.2 SSVEP based designs

In SSVEP based designs, each character/character block or command has its own particular flickering frequency. In order to speed up the classification time, characters or commands can be grouped. Cecotti (2010) proposed such an SSVEP based BCI speller. In Fig. 4.2, sequence for character selection in his design can be seen.

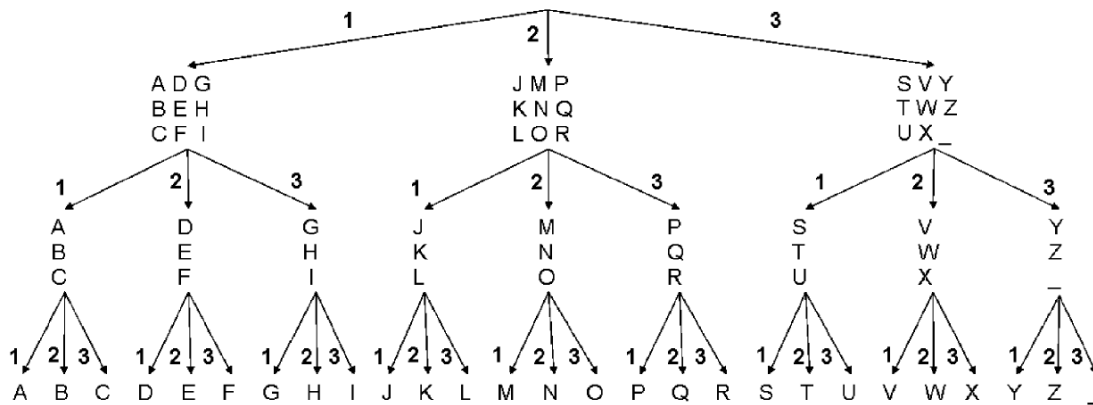


Figure 4.2 : Sequence tree for character selection (Cecotti, 2010).

In Fig. 4.2, each of three options has its particular stimulation frequency. Besides there are two more stimulation frequencies related to “previous” and “delete” action.

One of the advantages of SSVEP based designs over P300 based ones is the analogue control capability. In P300 based system, the target response (P300) used for classification occurs in specific time points. However, in SSVEP based systems, the response continuously exists in EEG. Therefore, analogue control becomes possible. Wilson and Palaniappan (2011) presented an online BCI in which the control of a mouse pointer is directly proportional to the user’s intent. They stated that analogue control allows subjects to move the pointer faster to the target location compared to traditional discrete control. In Fig. 4.3, a screenshot from their design can be seen.

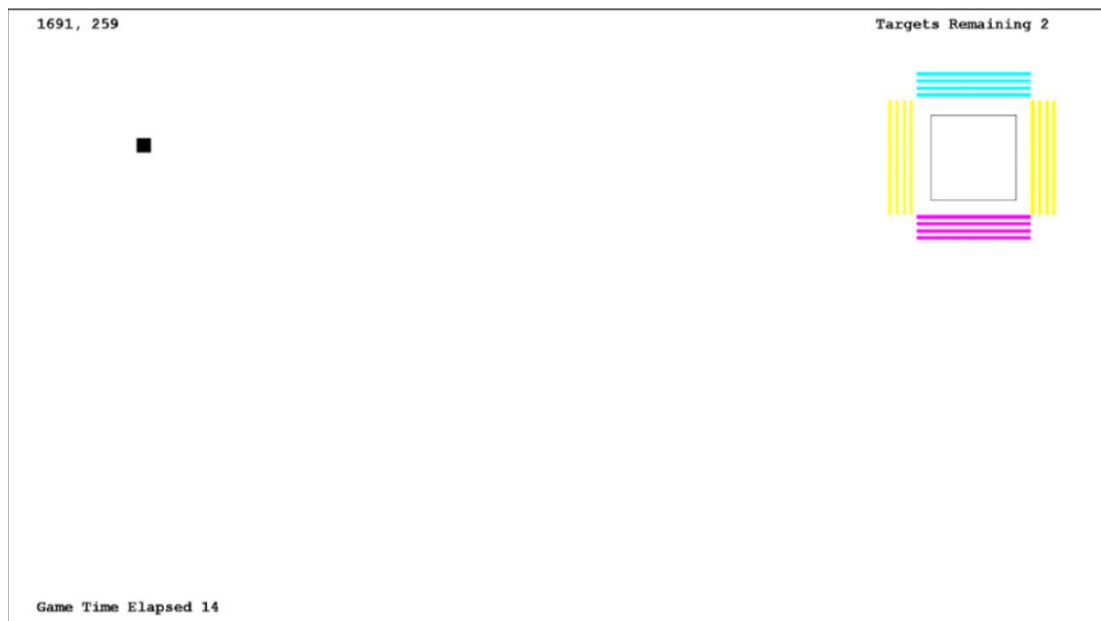


Figure 4.3 : Analogue mouse pointer control (Wilson and Palaniappan, 2011).

In Fig. 4.3, the pointer is located in the upper-right region. Top, left, right and bottom lines around the pointer have different flickering frequencies (8.57, 10, 12 and 15 Hz). Subjects are trying to reach the black dots when they appear by looking at the proper lines.

Dasgupta et al. (2010) presented an SSVEP based BCI for controlling a robot remotely in real-time using video feedback from the robot’s eye view over the internet. For the navigation of the robot, selection of the commands was accomplished by focusing gaze on one of the four flickering checkerboards around the video feedback window.

4.1.3 Other BCI designs

Beyond SSVEP and P300 based designs, there are some different designs that should be mentioned. Blankertz et al. (2006b) presented a novel typewriter application “Hex-o-Spell” which is controlled by two mental states (e.g. imagined right hand and imagined right foot movement). Selection of a symbol is done with the arrow in the center of the circle. The arrow turns clockwise by imagining a right hand movement and it stops and starts extending by imagining right foot movement (See Fig. 4.4).

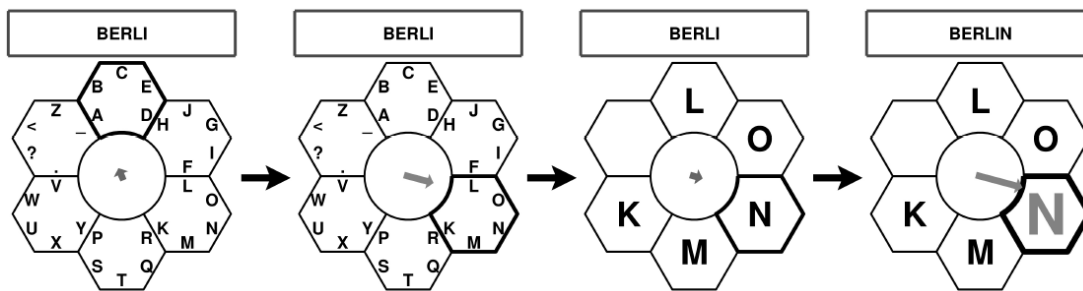


Figure 4.4 : Mental Typewriter. States control the turning and growing of the gray arrow (Blankertz et al., 2006b).

Gandhi et al. (2010) were inspired by “Hex-o-Spell” and proposed a graphical user interface (GUI) which is faster than “Hex-o-Spell” design in terms of information transfer rate (ITR). Their aim was to provide effective control of a wheelchair or a robot where the maximum number of tasks is six.

Combination of different signals was also performed by several researchers. Li et al. (2010) combined the mu/beta rhythm and P300 potential for controlling the cursor in 2D. In their design, horizontal movements were accomplished by motor imagery whereas the vertical movements were performed with P300 signal. Panicker et al. (2011) proposed an asynchronous P300 BCI with SSVEP based control state detection. In the offline and online experiments performed on ten subjects, they showed that fast and accurate control state detection is possible without degrading the performance.

McFarland et al. (2010) showed that humans can learn to use EEG for 3D control. They used specific frequency bands at specific scalp electrodes as features and concluded that with further development, complex movements of robotic arms or neuroprostheses can be controlled with EEG based BCIs.

Kim et al. (2011) investigated the feasibility of using auditory steady-state responses (ASSRs) elicited by selective attention to a specific sound source and implemented the first online ASSR-based BCI system that demonstrated the possibility of materializing a totally vision-free BCI system. In their design, they used two pure tone burst trains with different beat frequencies (37 and 43 Hz) generated simultaneously from two speakers located at left and right positions (See Fig. 4.5).

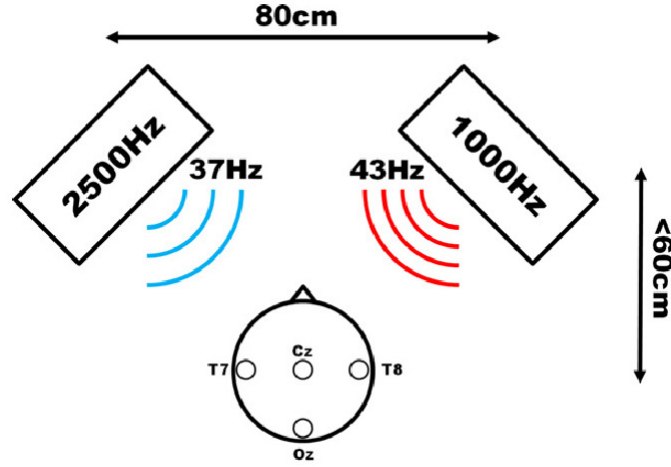


Figure 4.5 : ASSR-based BCI system (Kim et al., 2011).

There are also some BCI designs which use techniques other than EEG. Eklund et al. (2010) presented a BCI example using real-time fMRI with five degrees of freedom. Even their system was slow and not very accurate, they showed that the communication through real-time fMRI could be feasible. Besides, there are also near infrared spectroscopy (NIRS) based BCIs designed for rehabilitation (Yanagisawa et al., 2010) or gameplay (Oum et al., 2010). Since the thesis is focused on EEG based designs, other kind of designs are not explained in detail.

4.2 Proposed Experimental Design #1

The goal of the experiment is determining the circle on which the subject focuses. In the stimulation interface, there are four red circles, each flickering at a different constant frequency (İşcan et al., 2011a). The frequencies can be adjusted independently. In Table 4.1, frequencies of the four circles are given (İşcan et al., 2011a).

Table 4.1 : Flickering frequencies of the red circles.

Circle	Frequency (Hz)
up	4.60
down	6.43
right	8.03
left	10.70

The diameter of each circle is 6 cm and there is a black fixation point (diameter=4 mm) in the middle of the window. Circles are placed around this point (up, down, right and left). These circles can represent different commands (e.g. for prosthesis control) or directions (e.g. for cursor control) depending on the application. In Fig. 4.6, interface which was presented to the subjects on a notebook LCD is given (İşcan et al., 2011a).

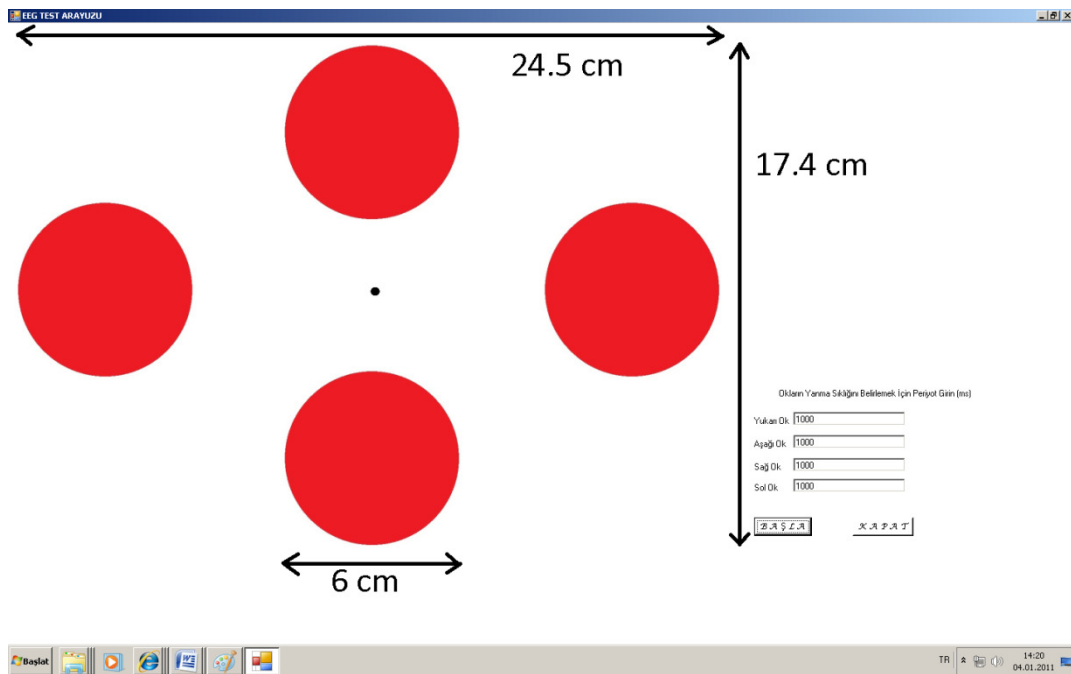


Figure 4.6 : SSVEP stimulation interface with four red circles flickering at different frequencies.

Stimulation frequencies were determined according to the fact that the SSVEP response arises when a person focuses his or her visual attention to a flickering light source above 4 Hz and the strongest response is obtained between 5 – 20 Hz (Friman et al., 2007). Frequencies in Table 4.1 are the exact stimulation frequencies (delays were taken into account). Resolution of the notebook LCD which was used for stimulus presentation is 1366 x 768 pixels. The stimulation program was designed in Microsoft Visual C# (İşcan et al., 2011a).

EEG recordings were acquired in a laboratory that is exposed to electrical and acoustical noises. Use of shielded cabin was not preferred since a practical BCI system is expected to work in real-life conditions. On the other hand, in order to increase the performance of a scalp EEG based BCI, it is crucial to get reliable EEG, free of noise and artifacts (Choi and Lee, 2007). Therefore, active electrode system (ActiCap) (Url-3) that has integrated noise reduction circuit was used. Instrumentation units with the subject are depicted in Fig. 4.7 (İşcan et al., 2011a).

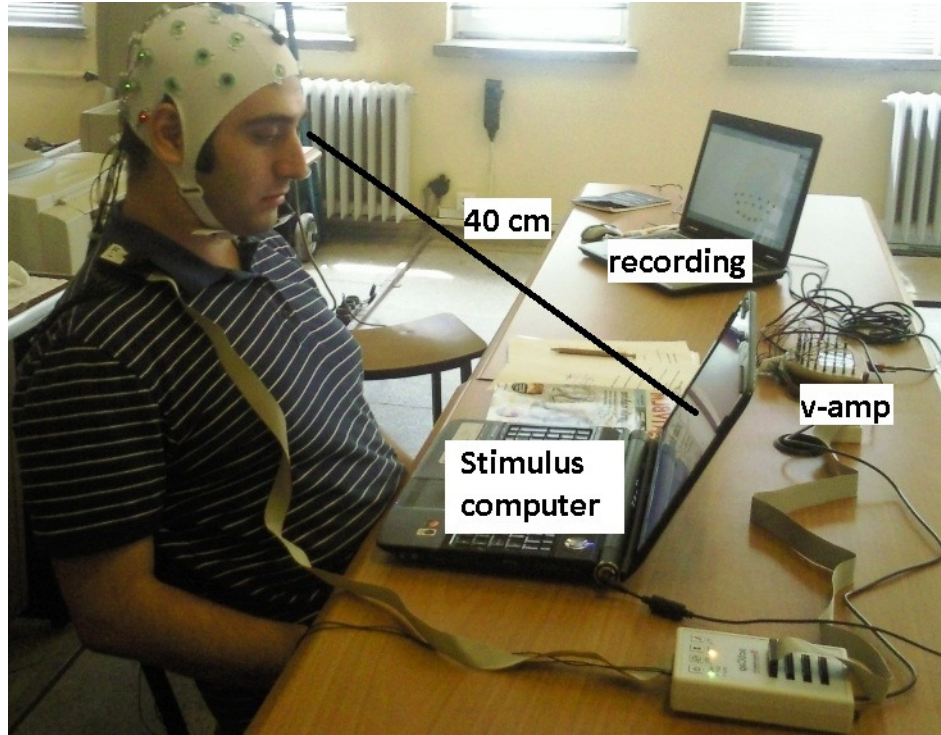


Figure 4.7 : Instrumentation units.

The red circles which are used as visual stimuli are presented to the subject by the help of stimulus computer shown in Fig. 4.7. Scalp EEG signals acquired from the 16 active electrodes are sent to the V-Amp16 (Url-3) amplifier by connectors. V-Amp16 amplifies and performs analog to digital conversion. Recording parameters are given in Table 4.2 (İşcan et al., 2011a). Converted signal is transferred to the recording computer via USB connection.

Table 4.2 : Recording parameters of EEG amplifier.

Parameter	value
channels	16
ADC resolution	24 bits
sampling frequency	500 Hz

The distance between the subject and the stimulus computer's LCD monitor is determined as 40 cm. The positions of the 16 electrodes on the scalp according to the international 10 – 20 system (Jasper, 1958) can be seen in Fig. 4.8.

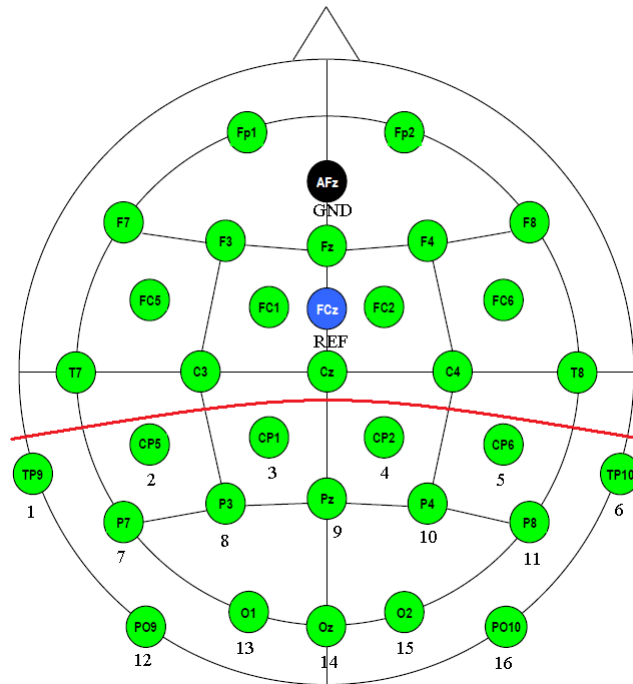


Figure 4.8 : Positions of the electrodes (Acticap manual (Url-3)).

Labels of the 16 electrodes are TP9, CP5, CP1, CP2, CP6, TP10, P7, P3, PZ, P4, P8, PO9, O1, OZ, O2 and PO10. Reference electrode (REF) is attached to the FCZ and ground electrode (GND) is attached to AFZ position. It is known that the SSVEP response is widely distributed over the occipital and parietal lobes (Friman et al., 2007). Therefore, 16 electrodes are placed densely on this area (see Fig. 4.9).

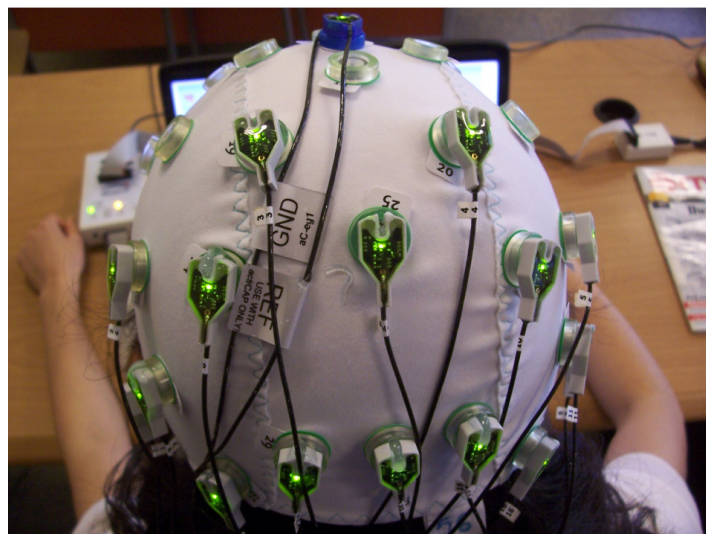


Figure 4.9 : Electrode placement on the scalp.

Similar electrode placement approach was used in (Trejo et al., 2006). Electrode-skin impedances were kept below 20 k Ω for all electrodes in every subject. EEG recordings were done for ten different conditions. In this thesis, only five of them are analyzed. Remaining five conditions are related to “covert attention” and subject of another study. Subjects rested as much as they wanted between each recording condition. For each condition, the length of the EEG record is 30 seconds. In Table 4.3, five different recording conditions used in this study are presented (İşcan et al., 2011a).

Table 4.3 : Five recording conditions for each subject.

#	Eyes focused on	Recording length
1	upper circle	30s
2	lower circle	30s
3	right circle	30s
4	left circle	30s
5	fixation point	30s

In Table 4.3, each condition is taken as a different class. Hence, there are five different classes. First four (#1-4) conditions are used for 4-class classification (İşcan et al., 2011a). Details about the dataset and classification results on this experiment can be seen in section 5.3.1.

4.3 Proposed Experimental Design #2

In this design, there are 9 equally sized circles (stimuli) on a 19" CRT monitor (Samsung SyncMaster 957 MB). Each of the circles has an individual flickering frequency ($f1$ - $f9$). These frequencies are selected from the highest SSVEP response range. Besides, none of the frequencies is the harmonic of the others in this range. In Table 4.4, selected frequencies are given.

Table 4.4 : Individual frequencies for the stimuli (f : frequency, refresh rate:120 Hz).

f	$f1$	$f2$	$f3$	$f4$	$f5$	$f6$	$f7$	$f8$	$f9$
	120/7	120/15	120/10	120/11	120/19	120/13	120/8	120/17	120/9
Hz	17.14	8	12	10.90	6.31	9.23	15	7.05	13.33

In Table 4.4, the frequencies are calculated by taking the monitor refresh rate (120 Hz) and frame repetitions into account. White circles are shown on the screen in every 7, 8, 9, 10, 11, 13, 15, 17 and 19 frames depending on the stimulus position.

High monitor refresh rate helps to choose many frequencies (i.e. increase the number of classes).

In Fig. 4.10, the placement of the circles on the monitor screen can be seen in the original aspect ratio. Circles are positioned in a way that the frequencies of neighboring circles are as far as possible. This kind of placement helps better discrimination of circles during classification.

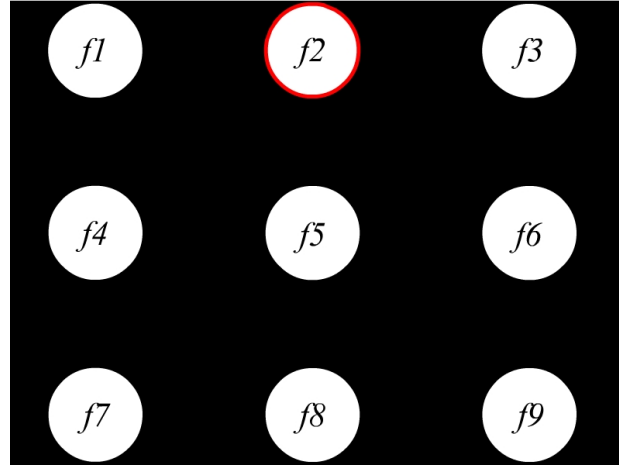


Figure 4.10 : Placement of the circles on the monitor screen.

In Table 4.5, dimensions of the circles and the screen are summarized.

Table 4.5 : Dimensions of the circles and the screen.

screen size	800 × 600 pixels
diameter of the circles	120 pixels
distance from neighbor circles (horizontal)	160 pixels
distance from neighbor circles (vertical)	115 pixels

The stimulus program was designed in Matlab (Url-4) with the help of Psychophysics Toolbox 3 (Kleiner et al., 2007). This toolbox was used for accurate timing of the flickering stimuli (Chumerin et al., 2011). The recording parameters are same as the previous SSVEP experiment (See Table 4.2) and 16 electrodes are placed on the same sites (See Fig. 4.8). Electrode-skin impedances were kept below 15 k Ω for all electrodes in every subject.

4.3.1 Experiment setup

EEG recordings were acquired in a room that is exposed to electrical and acoustical noises. Active electrodes (ActiCap) (Url-3) and V-Amp16 (Url-3) system were used. Instrumentation units with the subject are depicted in Fig. 4.11.



Figure 4.11 : Instrumentation units with the subject for experimental design #2.

The distance between the subject and the monitor is 40 cm. Connections between instruments can be better understood in Fig. 4.12. Personal computer (PC) is responsible for presenting the stimulus to the monitor and recording the EEG data of the subject. Besides, in order to save the critical time points during recording, trigger commands are sent from the parallel port to the V-Amp16 system.

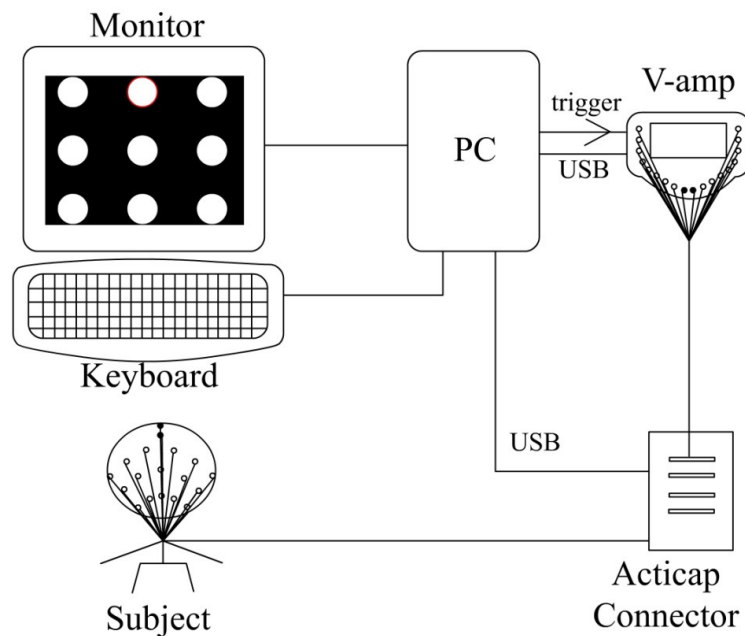


Figure 4.12 : Connections between instruments.

4.3.2 Experiment task

Subjects must focus on the circle which is pointed out by a red circle for 3s. After 3s, there is a duration of 1s in which the new target circle is pointed out for the subject to focus on. In the stimulation program, there are 10 continuous trials. In each trial, subject focuses on each of the circles once in a random order (Matlab program is used to generate uniformly distributed pseudorandom numbers). There is a fixed duration (4s) between each trial. Before the recording stage, stimuli are presented to subject in one trial. This initial stage is required to make the subject understand the given task. Timing of the experiment task is summarized in Table 4.6.

Table 4.6 : Timing of the experiment.

welcome message	blank screen	task is reminded	target circle pointed out	stimuli presented
4s	1s	3s	1s	3s
repeat 8 times				
repeat 9 times				

The overall duration of the experiment is 404s. During the experiment subject focuses on 90 circles totally. In Fig. 4.13, obtained EEG (10s) from a subject can be seen.

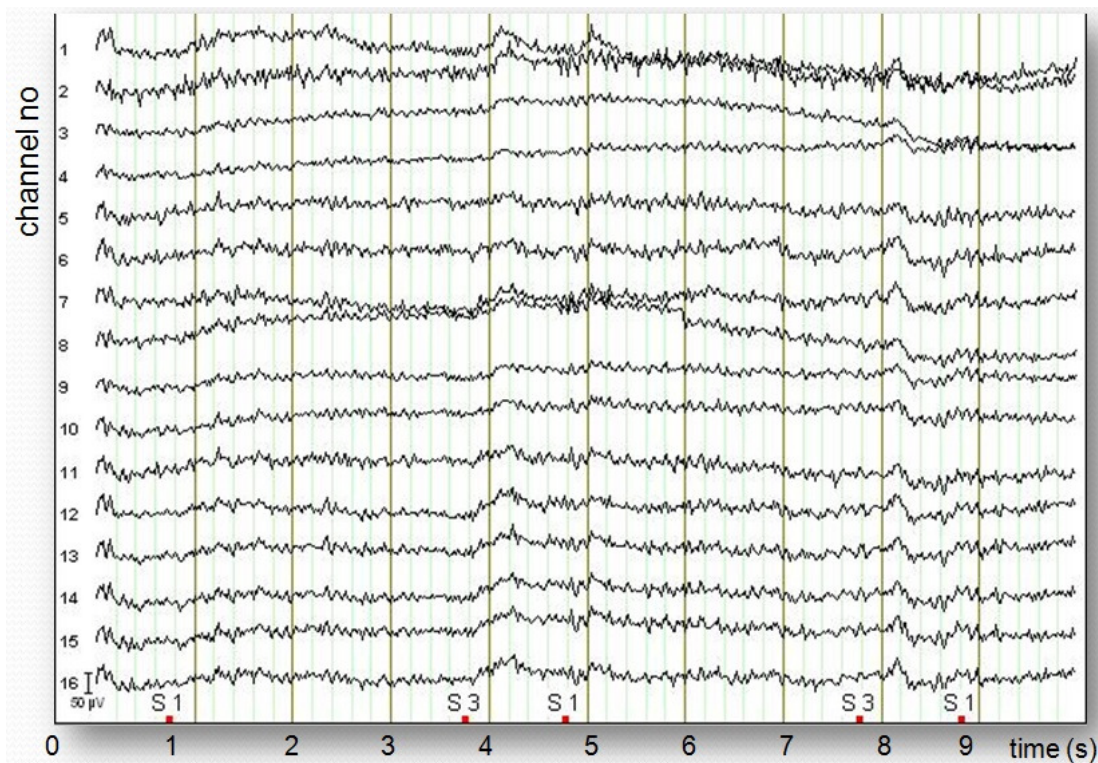


Figure 4.13 : EEG data from 16 channels with stimuli markers (S1, S3) (10s).

In Fig. 4.13, EEG data for 16 channels can be seen. In this figure, S1 and S3 are the markers that show the beginning (S1) and the end (S3) of the stimuli. Vertical lines show the segments of 1s.

In section 5.3.2, dataset, preprocessing and classification results for this design are given.

4.4 Proposed Experimental Design #3 (Character Plotter)

Representation of symbols has been an important field of study. The main problem is transmitting maximum information with minimum number of stimulus. This is mostly due to the limited number of the available choices. Assigning a stimulus to each symbol is not desirable for practical reasons. Therefore finding a suitable way to represent symbols is critical. In Fig. 4.14, the Braille signs developed for Turkish alphabet are given.

A	B	C	Ç	D	E	F	G
Ğ	H	I	İ	J	K	L	M
N	O	Ö	P	Q	R	S	Ş
T	U	Ü	V	X	W	Y	Z

0	1	2	3	4	5	6	7	8	9

Figure 4.14 : Braille signs (Url-7).

In Braille Alphabet, since there are 6 dots, 64 different characters/symbols can be defined. Increasing the number of dots will increase the learning time of the alphabet. On the other hand, decreasing the number of dots will decrease the number of symbols. Therefore, according to the application, optimum choice of dots (i.e. stimuli) is required. When the communication channel is very limited, characters are represented with sequential stimuli. In Fig. 4.15, such a case (international Morse code) is depicted.

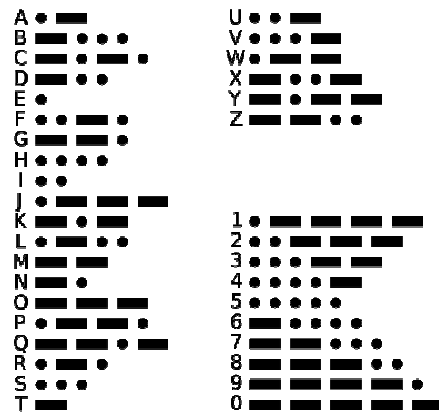


Figure 4.15 : International Morse code (Url-8).

In the previous sections, it is stated that P300 based designs suffer from required repetitions and it is not possible to achieve analogue control with them. On the other hand, SSVEP based designs do not require repetitions and analogue control is possible. However, since the available stimulation frequency band is limited, number of stimulators is limited.

In this section, a novel SSVEP based BCI design called “Character Plotter” is proposed and described in detail. Main idea behind developing this type of design is trying to converge to a ‘natural’ writing scheme as far as possible even though the writing and the BCI themselves are not ‘natural’ ways of communication. It is thought that Character Plotter can be an initial basis for future BCI designs.

In Character Plotter, each character is generated by plotting lines between six circles (character circles) on the screen and by using additional control circles. In Fig. 4.16, visual interface of the proposed system is depicted.

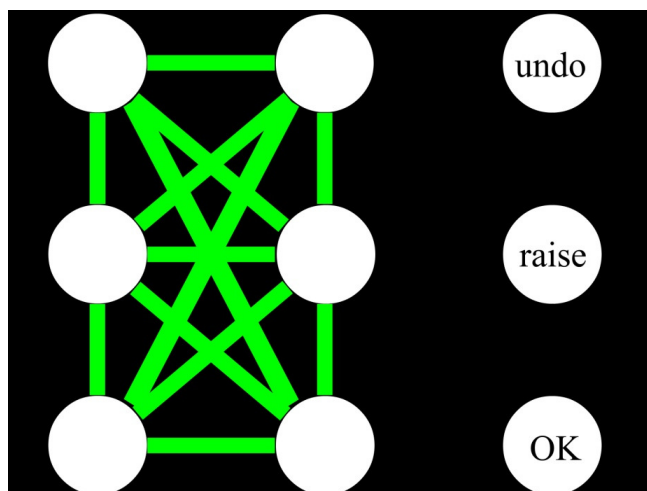


Figure 4.16 : Visual interface of Character Plotter.

The interface is composed of character circles (leftmost 6 circles), control circles (rightmost 3 circles) and the lines which can be plotted between the character circles. In Fig. 4.16, 13 different lines can be plotted between 6 character circles. Therefore the system is able to define 2^{13} different symbols / characters.

Character Plotter is based on the proposed experimental design #2. Therefore, offline experiment setup and the offline experiment task are the same as in section 4.3.1.

In Fig. 4.17, a photo taken from an online experiment can be seen.

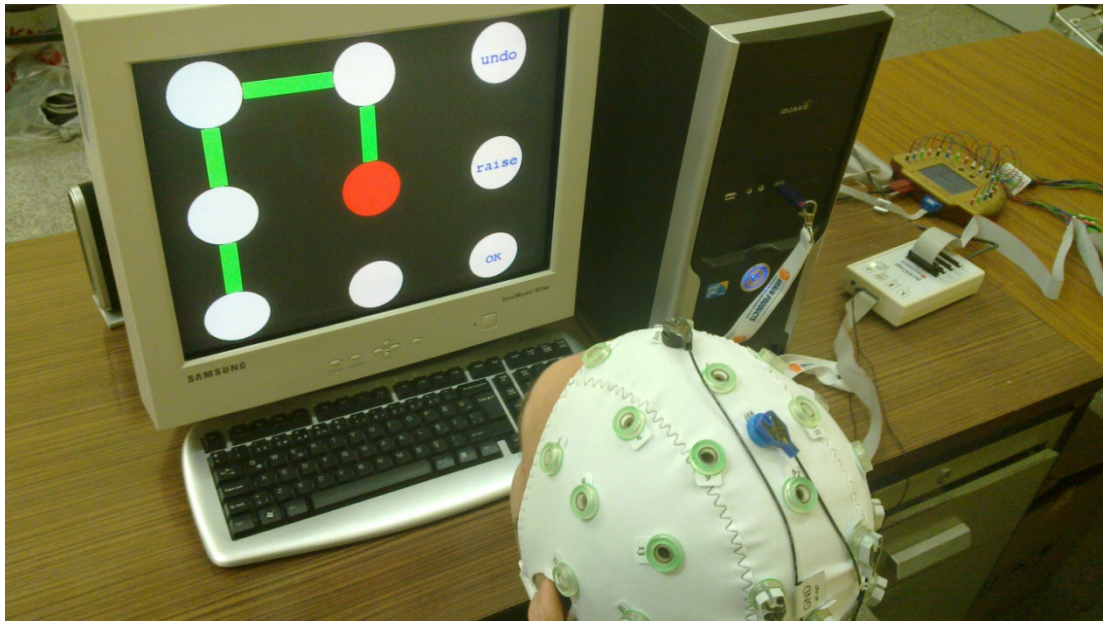


Figure 4.17 : Online experiment for Character Plotter.

The functions of the control circles are given below:

- undo: Remove the previous selection.
- raise: Go to the next choice without plotting a line.
- OK: Display the character. (If OK is pressed after displaying the character, display a null character (space bar)).

4.4.1 Online algorithm

In Fig. 4.18, flowchart of the online algorithm is illustrated. In order to choose a single circle, stimuli are presented for 2s, 3s, 4s or 5s depending on the offline classification accuracy (must be greater than 95%) of the subject. Afterwards, all of the 90 responses in the offline experiment are used to train the classifiers. In the

online experiment, trained classifiers are used for detecting the circle which the subject focuses on.

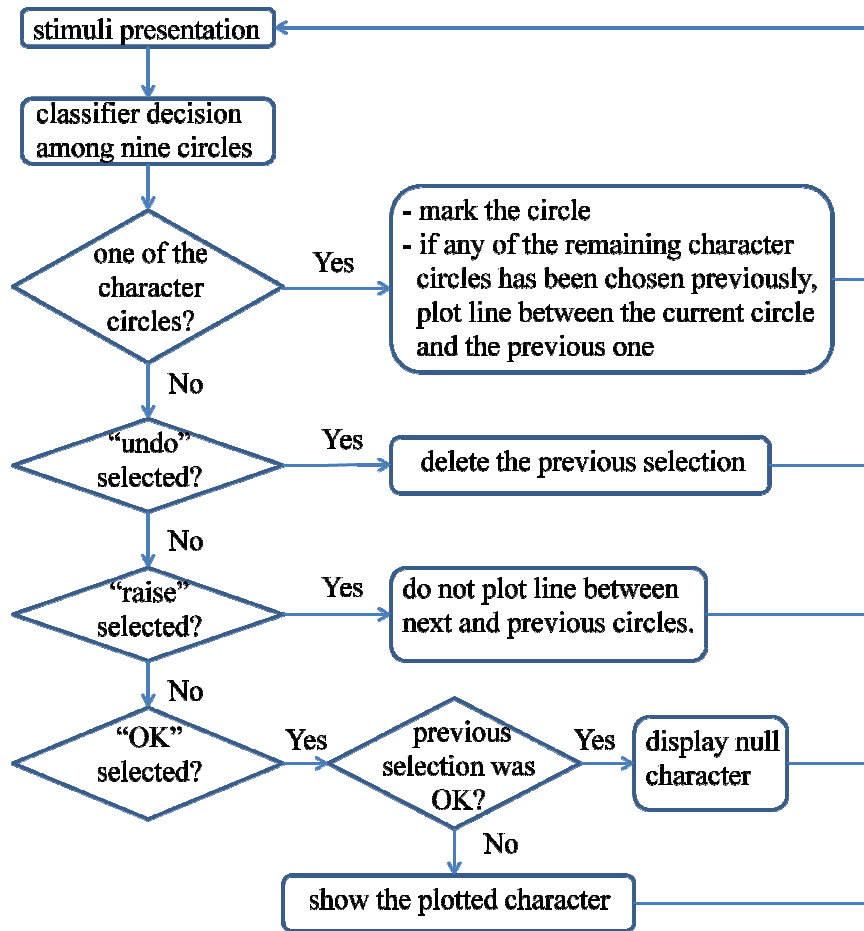


Figure 4.18 : Flowchart of the character plotter algorithm.

Depending on the classifier decision, several options occur:

- If the classifier selects one of the character circles, related circle is marked with red color. If any of the remaining character circles has been selected previously, a green line is plotted between these circles.
- If the classifier selects “undo” circle, previous selection is deleted.
- If the classifier selects “raise” circle, no line will be plotted between the next and the previous circles.
- If the classifier selects “OK” circle, plotted character will appear on the screen and the process will go on for the new character.

Sequential “OK” selections generate blank character (space bar). There is a break of 1s after each decision. Subjects should focus on the next character in this time.

4.4.2 Character set

In order to use the system, first of all, subjects must be familiar with the character set generated for Character Plotter. In Fig. A.1, (see Appendix A), designed characters can be seen. More characters can be added when it is necessary.

4.4.3 Experiment task

The subjects are asked to write the following English and Turkish sentences.

- 1) “it is OK”
- 2) “Hava çok güzel” (in English: “The weather is very beautiful”)

In order to see the performance of the proposed system, a simple (sentence #1) and a moderate (sentence #2) sentence are determined. All subjects who reached a classification accuracy greater than 95% in the offline design, achieved to write these sentences after a very short training session. Results are given in section 5.3.3.

5. DATASETS AND CLASSIFICATION RESULTS

In this Chapter, performance of the proposed algorithms and experimental designs are evaluated on different datasets. These datasets are categorized as P300-based, SCP-based and SSVEP-based datasets. For P300 and SCP-based BCI data, well-known datasets in literature were used. SSVEP data were collected by the author in the laboratory.

5.1 P300-Based Datasets

In the thesis two P300-based datasets are used for classification. The first dataset is the dataset II of BCI Competition III (Url-1). The second dataset was obtained from the “Mind Reading” Competition (Hild II et al. (2010)) of IEEE Machine Learning and Signal Processing Workshop. Details about these datasets are given below.

5.1.1 Dataset #1 – BCI Competition III (2004)

T-Weight method described in the section 3.3.4 was applied to the dataset II of BCI Competition III by Liu et al. (2005).

5.1.1.1 Dataset

Recording information on the dataset is given in Table 5.1.

Table 5.1 : BCI Competition III – Dataset II properties.

channels	64
sampling rate (Hz)	240
band-pass (BP) filter (Hz)	0.1 - 60

BP filter is applied in order to filter redundant frequencies. The electrode placement for the dataset is given in Fig. 5.1 (Url-1).

In the experiment, two subjects (Subjects A and B) were presented with a 6×6 matrix in which there are some characters (Fig. 5.2).

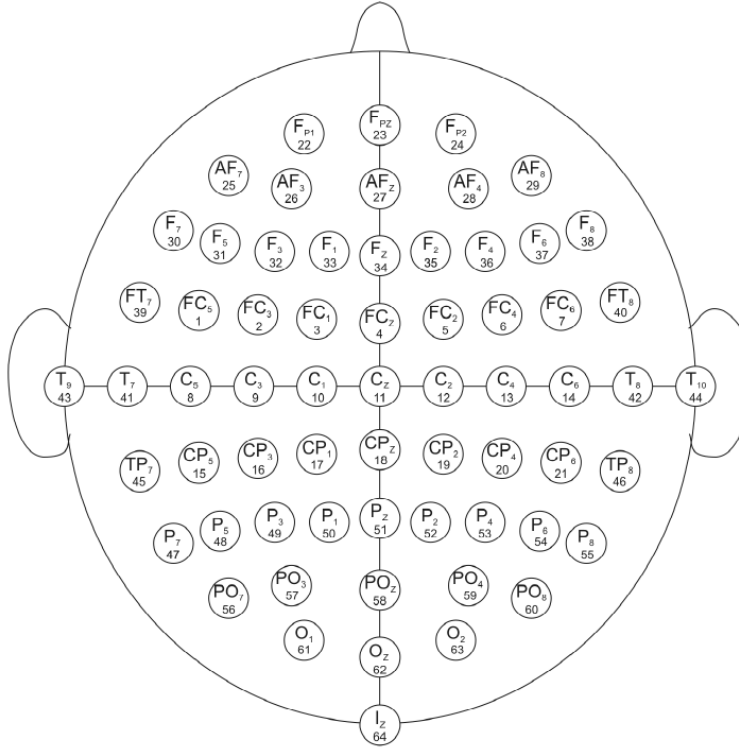


Figure 5.1 : The electrode placement (64 Channels) (Url-1).

	1	2	3	4	5	6
7 →	A	B	C	D	E	F
8 →	G	H	I	J	K	L
9 →	M	N	O	P	Q	R
10 →	S	T	U	V	W	X
11 →	Y	Z	1	2	3	4
12 →	5	6	7	8	9	_

Figure 5.2 : 6 × 6 matrix presented to the subjects (Url-1).

In the beginning of the recording session, there is a blank matrix. Afterwards, rows and columns of the matrix are intensified in a random manner. When the row or column related to the expected character is shown, P300 signal should appear on EEG of the subject. Therefore, it is known in advance that there will be one P300

response in every six intensified rows or columns. In order to increase SNR, all rows and columns are scanned 15 times for each character.

There are 85 characters in the training set and 100 characters in the test set for both subjects. Details about the Competition and the dataset can be found in Blankertz et al. (2006a).

5.1.1.2 Preprocessing

In the proposed method by Liu et al. (2005), multi-channel EEG data is filtered with a low-pass (4 Hz) filter and then the average of 15 repetitions is calculated in order to enhance the SNR. Liu et al. (2005) used a window length of 700 ms (168 samples) after each row or column intensification. In this case, for each character, a segment matrix (168 samples x 64 channels) is obtained. To be able to use T-Weight method, Liu et al. (2005) performed PCA and removed the correlations between different channels.

Liu et al. (2005) paper was replicated and some changes (e.g. filter characteristics) were integrated into the method. The modified method is called “İscan’s method”. Obtained results are compared with both the original paper (Liu et al. (2005)) and the competition winner’s (Rakotomamonjy and Guigue, (2008)) results (İscan, 2011).

In Figs. 5.3 and 5.4, high cut-off frequency dependency of the classification performance in terms of overall accuracy is given for Subject A and B respectively (İscan, 2011).

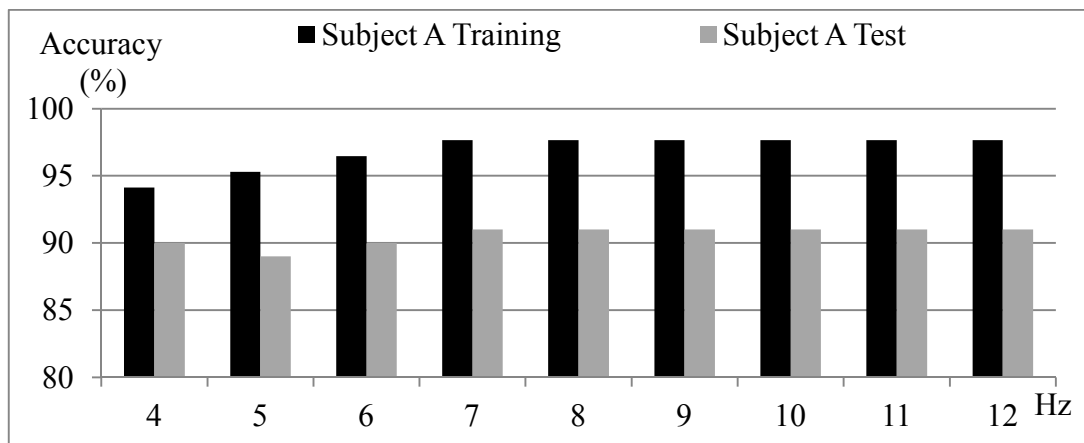


Figure 5.3 : High cut-off frequency vs. accuracy (Subject A).

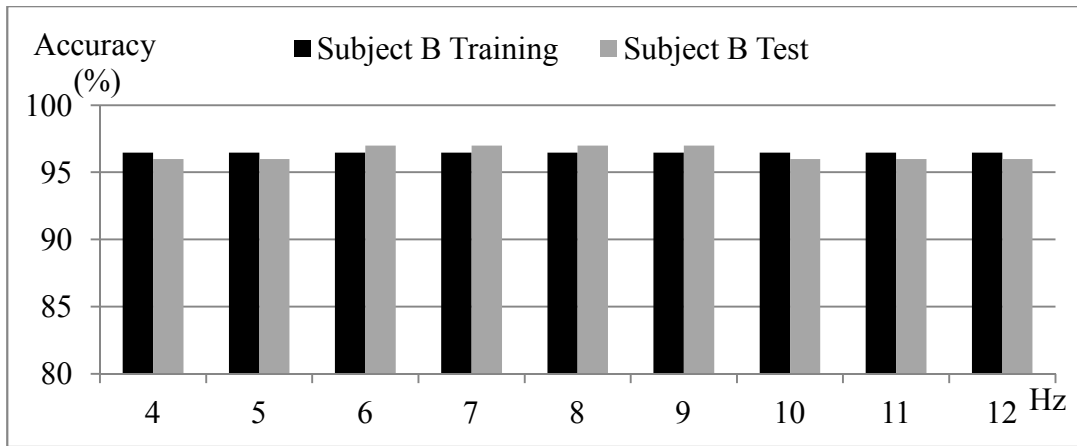


Figure 5.4 : High cut-off frequency vs. accuracy (Subject B).

It can be noticed that, 4 Hz suggested by Liu et al. (2005), as the high cut-off frequency does not generate the best performance. When the obtained performances for Subject A and Subject B are evaluated together, 8 Hz used by Rakotomamonjy and Guigue (2008) (winners of the BCI Competition III) seems more plausible for the high cut-off frequency. In EEG literature, it is known that the P300 responses are generally limited up to 8 Hz (Andrews et al., 2008). Therefore, successive performance analysis is done for 2nd degree Butterworth BP filter (0.5-8 Hz).

5.1.1.3 Results

In Figs. 5.5 and 5.6, repeat number vs. classification accuracy is given when the classifier is trained with Subjects A and B respectively.

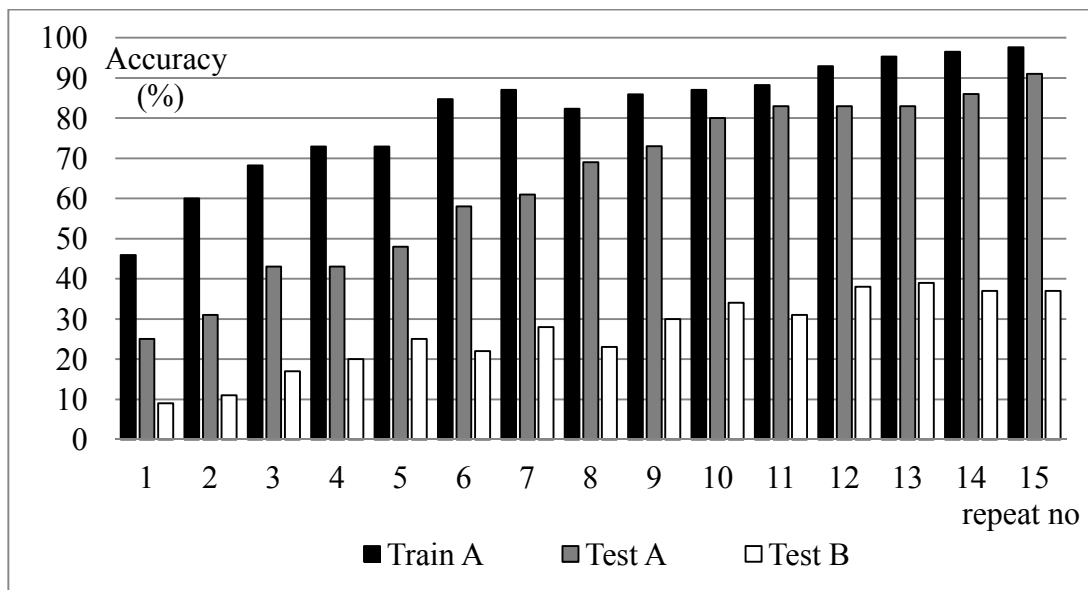


Figure 5.5 : Repeat no. vs. accuracy - trained with Subject A.

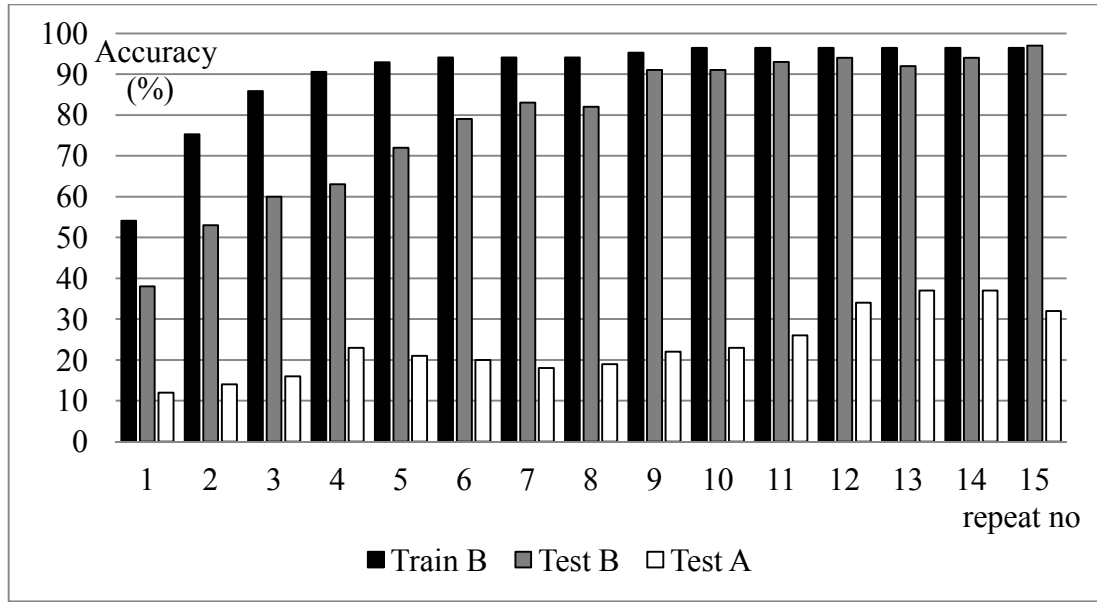


Figure 5.6 : Repeat no. vs. accuracy - trained with Subject B.

In these figures, it is easy to see the effect of averaging on classification accuracy for different repetitions in the methods trained for Subject A and B respectively (İşcan, 2011).

The analysis for different repetition numbers helped comparison of the method with the Competition winners' method (Rakotomamonjy and Guigue, 2008). In Tables 5.2 and 5.3, classification accuracies for different numbers of repetition sequences are demonstrated for different methods respectively (İşcan, 2011).

Table 5.2 : Repeat no. vs. accuracy (%) (Rakotomamonjy and Guigue, 2008).

repeat	1	2	3	4	5	10	13	15
subject A	16	32	52	60	72	83	94	97
subject B	35	53	62	68	75	91	96	96
mean	25.5	42.5	57.0	64.0	73.5	87.0	95.0	96.5

Table 5.3 : Repeat no. vs. accuracy (%) (İşcan, 2011).

repeat	1	2	3	4	5	10	13	15
subject A	25	31	43	43	48	80	83	91
subject B	38	53	60	63	72	91	92	97
mean	31.5	42.0	51.5	53	60	85.5	87.5	94

By looking at Table 5.2 and Table 5.3, it can be concluded that for single trial (no repetition) case, İşcan (2011) method performed better than Rakotomamonjy and Guigue (2008) method for both Subjects. Besides, for Subject B, İşcan (2011)

method generated slightly better performance (97%) when the number of sequences was 15.

5.1.2 Dataset #2 - MLSP 2010 Competition

By using the classification experience obtained from BCI Competition III, T-Weight method proposed by Liu et al. (2005) was used in the “Mind Reading” Competition (Hild II et al. (2010)) of IEEE Machine Learning and Signal Processing Workshop with some modifications explained here (İşcan, 2010).

The aim in the Competition is to classify the given EEG data into one of the categories (P300 or without P300) by using an appropriate method. Here, a brief explanation about the competition datasets and adaptation of T-weight method for these datasets will be given. More information can be learned from the Hild II et al. (2010) paper.

5.1.2.1 Dataset

EEG data was recorded when a subject was looking at some satellite images on an LCD monitor. In Table 5.4, some information about training setup is given (Hild II et al., 2010).

Table 5.4 : Experiment setup used for training (Hild II et al., 2010).

number of channels	64
number of samples	176378×64
sampling frequency (Hz)	256
total blocks	75
number of images in each block	37
total number of images	$75 \times 37 = 2775$

In Fig. 5.7, 75 blocks each composed of 37 images are illustrated.

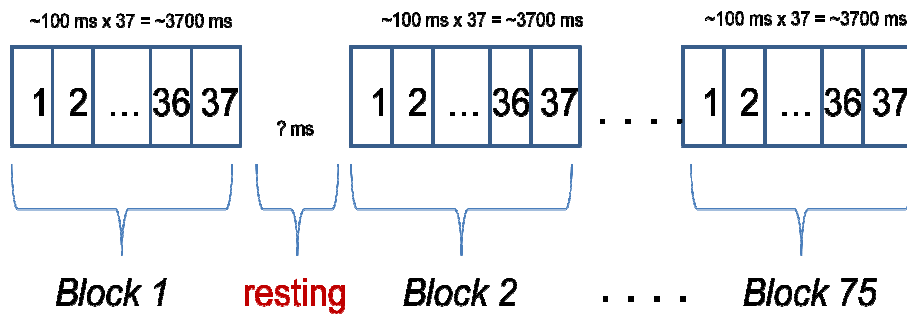


Figure 5.7 : Presented image blocks during training.

In the training setup, time interval between consecutive images are 100 ms. Subject is focusing on the center of the image and presses space bar button when he sees the expected target. When the subject sees a target in any of the satellite images, P300 signal is expected to occur on the subject's EEG. In Table 5.5, some information about test setup is summarized (Hild II et al., 2010).

Table 5.5 : Experiment setup used for test (Hild II et al., 2010).

number of channels	64
number of samples	1603334×64
sampling frequency (Hz)	256
total blocks	890
number of images in each block	N/A
total number of images	9891

In the test setup, 4 different image durations (~50, 100, 150 and 200 ms) are used. All the images in the same block have the same durations (Hild II et al., 2010). Every block contains 22, 10, 7 and 5 satellite images when the image duration is 50, 100, 150 and 200 ms respectively. Information about the number of images in each block was not available (N/A). In Fig. 5.8, 890 image blocks composed of four different types are illustrated.

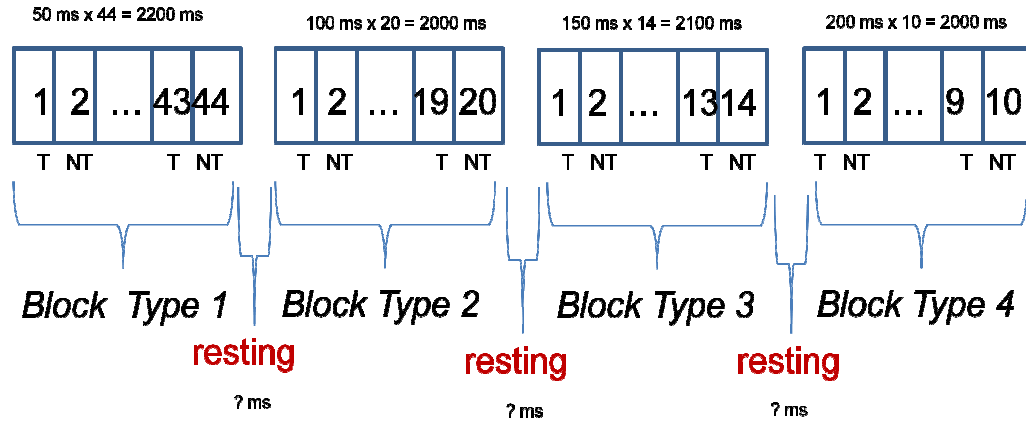


Figure 5.8 : Presented image blocks during test.

5.1.2.2 Preprocessing

First of all, target (with P300) and non-target (without P300) responses ($162 \text{ samples} \times 64 \text{ channels}$) beginning from the presentation of each image were acquired from the training set. Afterwards, these responses were pre-processed. Pre-processing steps included trend removing, BP filtering (0.5 – 8 Hz) and PCA. Then, T-weight method was applied to the pre-processed responses and sample weights (162×64)

were calculated (İşcan, 2010). In Fig. 5.9, processing blocks applied to the training and the test datasets are given.

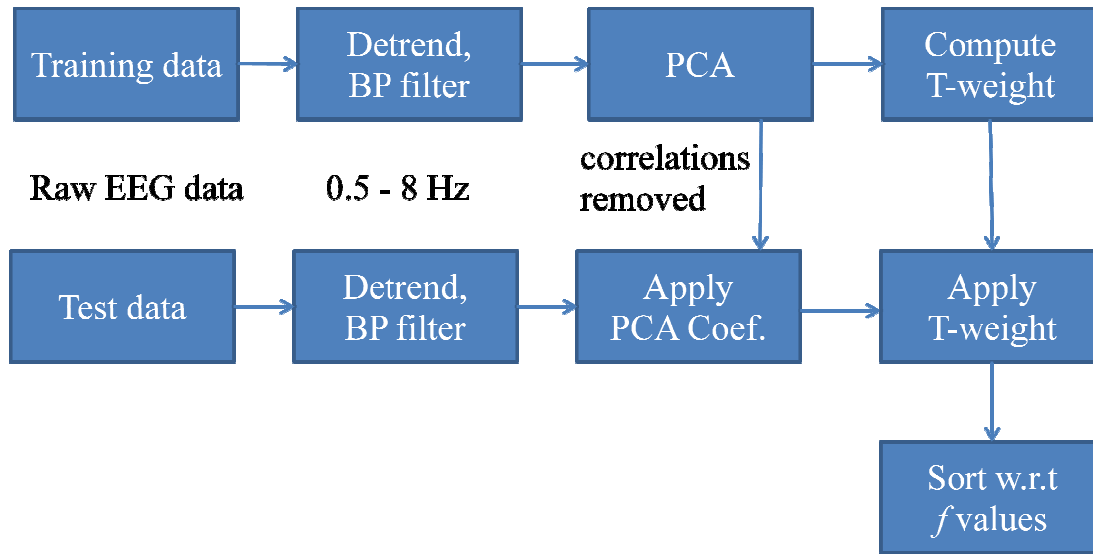


Figure 5.9 : Processing blocks applied to the training and test datasets.

In the detrend block, best straight-line fit linear trend is subtracted from the data. In this way, a systematic increase or decrease in the data can be removed. Weights (162×64) obtained from T-weight method and PCA coefficients (64×64) were saved to be used for test dataset. According to the method, f values related to the target (with P300) responses should be higher than the ones for non-target (without P300) responses.

5.1.2.3 Results

Proposed Matlab code was tested on the test dataset by MLSP 2010 organizers (Hild II et al., 2010). Ranking was done according to the area under receiver operating characteristic (ROC) curve. In Table 5.6, top three teams and their results in terms of area under ROC curve (AUC) are given (Hild II et al., 2010).

Table 5.6 : Top 3 teams in MLSP 2010 Competition (Hild II et al., 2010).

Rank	Name(s)	Affiliation(s)	AUC
1	Jose M. Leiva Suzanne M. M. Martens	Univ. Carlos III de Madrid Max Plank Ins. Biol. Cyb.	0.8229
2	Zafer İşcan	Istanbul Technical Univ.	0.8217
3	Benjamin Labbe Xilan Tian Alain Rakotomamonjy	INSA de Rouen INSA de Rouen Université de Rouen	0.8188

In the Competition, there were 35 teams from 14 countries. Others' results can be seen in the competition paper (Hild II et al., 2010). According to the results, T-weight method is found to be very successful in classifying this P300-based EEG dataset.

5.2 SCP-Based Dataset

5.2.1 Dataset #3 - BCI Competition 2003 – (datasets I-a, I-b)

5.2.1.1 Dataset

Two EEG datasets (datasets I-a, I-b) used in the study are acquired from BCI Competition 2003 (Blankertz et al., 2004).

In dataset I-a, a healthy subject was asked to move a cursor up and down on a computer screen while his cortical potentials were being recorded (Blankertz et al., 2004). The subject received visual feedback of his SCPs during recording. Cortical positivity leads to a downward movement of the cursor on the screen whereas the cortical negativity leads to an upward movement. Duration of each trial is 6s. The task was visually presented after 0.5s until the end of the trial to indicate negativity or positivity. Between 2 - 5.5s visual feedback was presented. In training and testing datasets provided by the Competition, only this 3.5s interval (896 samples) including feedback was provided. In Table 5.7, some of the recording parameters and details about the dataset I-a are given. Further details can be found in the Competition's web site (Blankertz et al., 2004).

Table 5.7 : Recording parameters and details of dataset I-a.

parameter	value
sampling rate	256 S/s
channels	6
recording length	3.5s (896 samples)
EEG samples in each trial	$6 \times 896 = 5376$ samples
training trials for class 0	135
training trials for class 1	133
total training trials	268
test trials	293

In dataset I-b, an artificially respiration ALS patient was asked to do the same task as healthy subject in dataset I-a while his cortical potentials were being recorded (Blankertz et al., 2004). The subject received auditory and visual feedback of his

SCPs. Here, each trial lasted 8s. The task was visually and auditorily presented after 0.5s until the 7.5s of every trial to indicate negativity or positivity (Blankertz et al., 2004). In addition, “up” or “down” task was vocalised at 0.5s between 2 - 6.5s. In training and testing dataset provided by the Competition, only this 4.5s (1152 samples) interval including feedback was provided (Blankertz et al., 2004). There is an additional vertical EOG (vEOG) channel as it could provide useful information (Blankertz et al., 2004).

In Table 5.8, some of the recording parameters and details about the dataset I-b are given (Blankertz et al., 2004).

Table 5.8 : Recording parameters and details of dataset I-b.

parameter	value
sampling rate	256 S/s
channels	7
recording length	4.5s (1152 samples)
EEG samples in each trial	$7 \times 1152 = 8064$ samples
training trials for class 0	100
training trials for class 1	100
total training trials	200
test trials	180

In Fig. 5.10, recording setup for both datasets are illustrated (İşcan and Dokur, 2011).

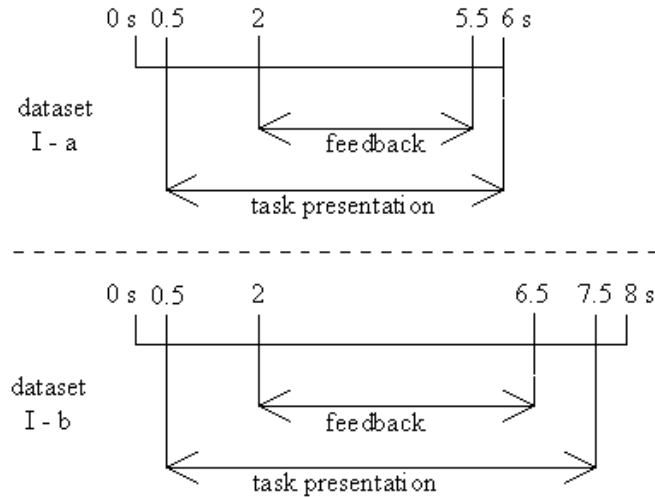


Figure 5.10 : Recording setup for dataset I-a and I-b.

Methods used for preprocessing and the proposed ITW Method are explained in the following sub-sections.

5.2.1.2 Preprocessing

Before applying Improved T-Weight Method, first of all, best straight-line fit linear trends in the multi-channel data related to the feedback period obtained from datasets I (a-b) were removed (İşcan and Dokur, 2011). Afterwards, 4th degree Butterworth BP filter (0.5 – 20 Hz) was applied to the data. 20 Hz boundary was decided using trial and error method. In Figs. 5.11 (a - c), effects of trend removing and filtering operations can be seen. In order to remove the correlations between the EEG channels, PCA was applied to training sets. PCA coefficients obtained from training sets were applied to test sets (İşcan and Dokur, 2011).

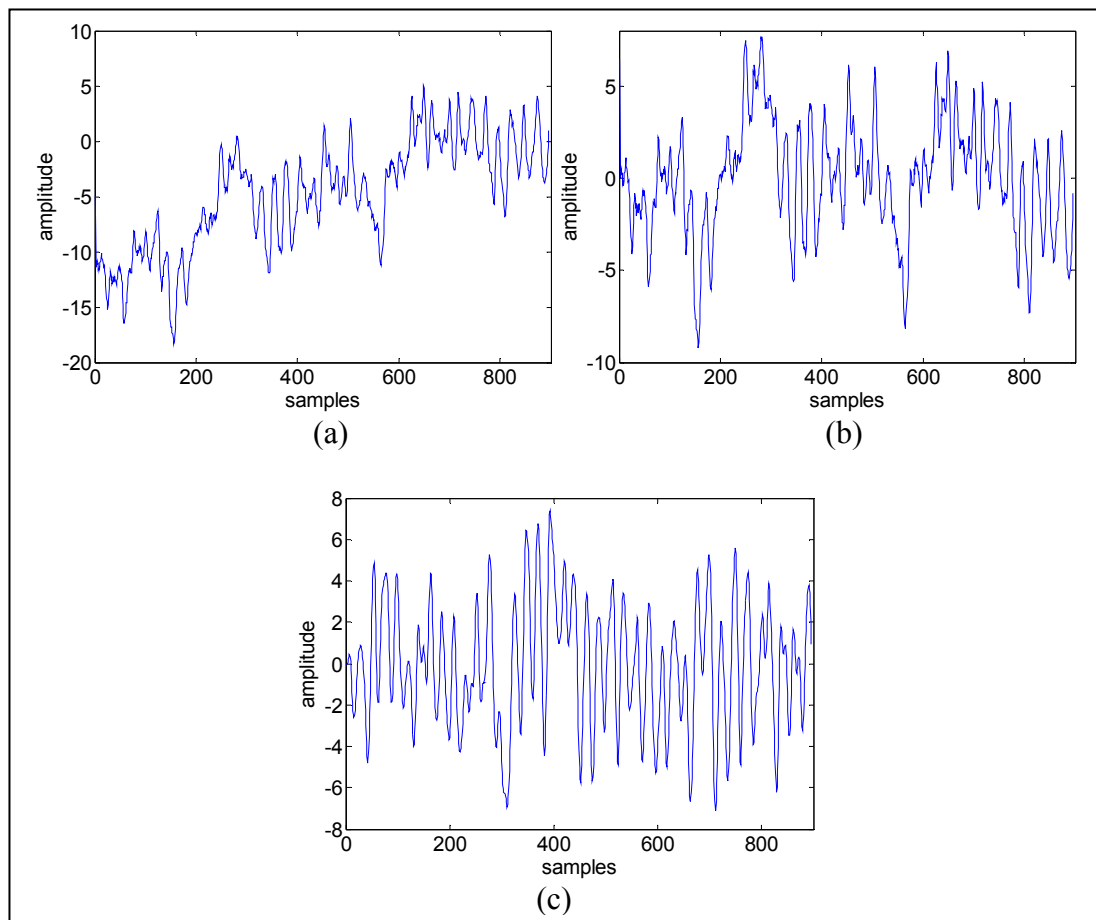


Figure 5.11 : Effects of trend removing and filtering on a segment length of 3.5s (896 samples) in dataset I-a. (a) raw data, (b) trend is removed, (c) BP filtered version of (b).

5.2.1.3 Results

In Table 5.9, classification accuracy of ITW for the training and test sets are presented for two datasets (İşcan and Dokur, 2011).

Table 5.9 : Classification accuracies for training and test sets.

classification accuracy (%)	training	test
dataset I-a	90.2	90.1
dataset I-b	92.0	56.6

The performance of classification was the correct response rate defined by the number of correctly classified trials divided by the total number of trials. Since there are two classes, classification accuracy of 50% is by chance for each dataset.

In Tables 5.10 and 5.11, classification performances in terms of classification error obtained by ITW Method are compared with the Competition participants' results (Url-1) for dataset I-a and dataset I-b respectively. Eight highest performances are given (İşcan and Dokur, 2011).

Table 5.10 : Classification performances for dataset I-a (Url-1).

#	contributor	error (%)	institution	co-contributor(s)
	Z. İşcan	9.8	Istanbul Tech. Uni.	Z. Dokur
1	B. Mensh	11.3	MIT	J. Werfel, S. Seung
2	G. Dornhege	11.6	Fraunhofer FIRST (IDA)	B. Blankertz, K-R. Müller
3	Kai-Min Chung	11.9	National Taiwan Uni.	T-K. Huang, C-J. Lin
4	Tzu-Kuo Huang	15.0	National Taiwan Uni.	K-M. Chung, C-J. Lin
5	D. Pinto	15.7	Univ. of Florida	
6	J. Mbwana	17.1	Yale Uni.	M. Laubach
7	V. Bostanov	17.4	Uni. of Tübingen	
8	U. Hoffmann	17.8		

Table 5.11 : Classification performances for dataset I-b (Url-1).

#	contributor	error (%)	institution	co-contributor(s)
	Z. İşcan	43.3	Istanbul Tech. Uni.	Z. Dokur
1	V. Bostanov	45.6	Univ. of Tübingen	
2	Tzu-Kuo Huang	46.7	National Taiwan Univ.	K-M. Chung, C-J. Lin
3	J. Mbwana	46.7	Yale Univ.	M. Laubach
4	Kai-Min Chung	47.8	National Taiwan Uni.	T-K. Huang, C-J. Lin
5	X. Sun	48.3	Fraunhofer FIRST (IDA)	Q. Cheng, B. Blankertz
6	A. Saffari	53.3	Sahand Uni. of Tech.	T. Emami, S. Ashkboos
7	F. Torre	54.4	Uni. of Lille, GRAppA	F. Torre
8	B. Mensh	56.1	MIT	

In Table 5.10, ITW method achieved an error rate of 9.8% for dataset I-a. According to the results of other participants, ITW method generated the best result for this dataset (İşcan and Dokur, 2011).

In Table 5.11, ITW method achieved an error of 43.3% for dataset I-b which is close to chance level (50%). Although this error rate is very high, it is the best result among all participants. According to Blankertz et al. (2004), obtained results close to chance level might indicate that test set for dataset I-b may not contain task-related information and it shows the difficulties in training a locked-in patient who is not able to give information about his consciousness level.

For dataset I-a, the competition winner B. Mensh and his colleagues used LDA on the dc potentials of the first two channels and high beta power as additional dimensions for classification (Blankertz et al., 2004). G. Dornhege and his colleagues used regularized linear discriminant classifiers and K.-M. Chung and his friends applied an SVM on the dataset after downsampling to 25 Hz.

For dataset I-b, the winner V. Bostanov applied a step-wise LDA on wavelet transformed data (Blankertz et al., 2004).

The popular classifiers among the participants were SVM, LDA, and neural networks (NNs) (Url-1). Although the ranking of the results given in Tables 5.10 and 5.11 may not provide a completely objective assessment of different methods for several reasons (Blankertz et al., 2004) (e.g. chance effect), they provide quantitative comparison between different approaches.

5.3 SSVEP Based Datasets

5.3.1 Dataset #4 – SSVEP based experimental design #1

5.3.1.1 Dataset

10 healthy males (mean age: 25.2, varies between 21 and 30) and 10 healthy females (mean age: 24.6, varies between 21 and 29) voluntarily participated in the experiment after giving their written consent. All of the subjects were students at Istanbul Technical University. None of the participants had neurological disease background. The participants were informed about the recording procedure and the ethical issues in the Declaration of Helsinki (Url-2) before the experiment.

5.3.1.2 Preprocessing

In the proposed experimental design #1 (see section 4.2), recorded EEG data (30s) of each subject is segmented into 30 and 10 pieces respectively. Therefore, the segment lengths are selected as 1s and 3s. Selection of two different segment lengths was preferred to show the dependency of classification accuracy on the segment length. After performing trend removing, 4th order BP Butterworth filter (0.53 – 40 Hz) is applied for filtering. The Butterworth filter has a flat frequency response in the passband. In Fig. 5.12, preprocessing steps are illustrated.

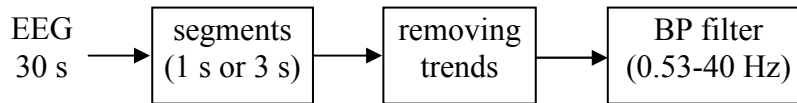


Figure 5.12 : Preprocessing steps.

5.3.1.3 Results

PSD and CCA (see sections 3.1.1,3.1.2) based features (eight features) are used in classification. In Table 5.12, divergence values for the features are given

Table 5.12 : Divergence values for PSD and CCA features.

	PSD		CCA		channel
	1s	3s	1s	3s	
4 - class	0.1560	0.4852	0.3954	1.1336	1 ch. OZ
	0.3325	0.9776	0.3841	1.5690	16 channels
5 - class	0.1188	0.3776	0.2767	0.8339	1 ch. OZ
	0.2650	0.7495	0.2540	1.0973	16 channels

In Table 5.12, the divergence values of CCA features are higher than the divergence of PSD features for all conditions except 5-class and 16-channels case when the segment length is 1s. Best discrimination between features are obtained in CCA features for 4-class, 16 channels and 3s. condition.

The features are normalized between 0 and 1 before classification. In Table 5.13, the numbers of the total feature vectors for two different segment lengths (1s, 3s) and classes (4, 5) are given.

Table 5.13 : Numbers of the total feature vectors.

	4-class	5-class
1s (500 samples)	120	150
3s (1500 samples)	40	50

The performance of the MCTW method is compared with different classifiers from PR Tools 4.0 (Duin et al., 2004) using Matlab (Url-4). Classifiers which generated the best results Fisher's LDA, SVM and NMC are presented here. In the study, polynomial kernel is used for SVM and the regularization parameter is selected as 1.

In Table 5.14 and Table 5.15, classification performances of the PSD and CCA based features can be seen respectively.

Table 5.14 : Performances for PSD features (mean accuracies (%)).

		Nearest Mean		Fisher's LDA		SVM		MCTW		channel
		1s	3s	1s	3s	1s	3s	1s	3s	
4 - class	length									1 ch. OZ
	male	51.4	78.0	49.4	74.0	47.3	74.0	50.0	78.2	
	female	64.6	89.2	64.0	88.0	60.7	86.7	64.8	89.0	
	mean	58.0	83.6	56.7	81.0	54.0	80.3	57.4	83.6	16 channels
	male	48.0	68.5	31.3	62.7	55.9	68.0	49.3	68.0	
	female	59.8	84.0	39.2	81.5	70.5	85.0	61.9	87.2	
5 - class	length									1 ch. OZ
	male	44.2	67.2	42.3	64.0	41.5	62.4	43.2	68.2	
	female	56.6	79.8	56.8	81.8	49.4	76.4	57.0	81.6	
	mean	50.4	73.5	49.6	72.9	45.5	69.4	50.1	74.9	16 channels
	male	44.4	58.2	36.6	57.8	47.1	62.4	44.1	61.2	
	female	52.0	73.6	40.8	71.4	60.0	76.2	54.2	76.4	
5 - class	length									1 ch. OZ
	male	44.2	67.2	42.3	64.0	41.5	62.4	43.2	68.2	
	female	56.6	79.8	56.8	81.8	49.4	76.4	57.0	81.6	
	mean	50.4	73.5	49.6	72.9	45.5	69.4	50.1	74.9	16 channels
	male	44.4	58.2	36.6	57.8	47.1	62.4	44.1	61.2	
	female	52.0	73.6	40.8	71.4	60.0	76.2	54.2	76.4	
5 - class	length									1 ch. OZ
	male	44.2	67.2	42.3	64.0	41.5	62.4	43.2	68.2	
	female	56.6	79.8	56.8	81.8	49.4	76.4	57.0	81.6	
	mean	50.4	73.5	49.6	72.9	45.5	69.4	50.1	74.9	16 channels
	male	44.4	58.2	36.6	57.8	47.1	62.4	44.1	61.2	
	female	52.0	73.6	40.8	71.4	60.0	76.2	54.2	76.4	

Table 5.15 : Performances for CCA features (mean accuracies (%)).

		Nearest Mean		Fisher's LDA		SVM		MCTW		channel
		1s	3s	1s	3s	1s	3s	1s	3s	
4 - class	length									1 ch. OZ
	male	57.4	79.5	56.5	76.5	52.5	76.0	56.9	78.5	
	female	74.9	91.2	74.2	92.2	73.5	90.2	75.3	90.5	
	mean	66.1	85.3	65.3	84.3	63.0	83.1	66.1	84.5	16 channels
	male	65.9	90.7	63.8	91.2	59.6	89.5	64.9	91.2	
	female	72.7	95.2	71.5	93.5	69.9	94.5	74.1	94.5	
5 - class	length									1 ch. OZ
	male	48.0	68.2	45.5	66.0	43.6	62.6	47.0	68.8	
	female	64.6	82.8	64.3	83.4	57.8	79.8	65.0	83.4	
	mean	56.3	75.5	54.9	74.7	50.7	71.2	56.0	76.1	16 channels
	male	56.0	84.2	52.5	80.4	45.9	75.0	58.6	83.2	
	female	62.0	87.4	60.0	83.8	51.8	80.2	66.1	86.6	
5 - class	length									1 ch. OZ
	male	48.0	68.2	45.5	66.0	43.6	62.6	47.0	68.8	
	female	64.6	82.8	64.3	83.4	57.8	79.8	65.0	83.4	
	mean	56.3	75.5	54.9	74.7	50.7	71.2	56.0	76.1	16 channels
	male	56.0	84.2	52.5	80.4	45.9	75.0	58.6	83.2	
	female	62.0	87.4	60.0	83.8	51.8	80.2	66.1	86.6	

Classification results are given for 4-class (Table 4.3: conditions #1, 2, 3, 4) and 5-class (Table 4.3: conditions #1, 2, 3, 4, 5) cases when the recording segment lengths

are 1s and 3s. Performances are given according to the mean overall accuracy after performing leave-one out classification. Best performances are shown in bold characters. It can be observed that the performances obtained for CCA features are higher than the ones for PSD.

To be able to evaluate the significance of this result, statistical t-test was performed for the results of each classifier between Table 5.14 and Table 5.15. In Table 5.16, p values obtained from t-test are given. Significant results ($p < 0.05$) are emphasized with bold characters.

Table 5.16 : t-test results (p values) for CCA and PSD performances.

	Nearest Mean		Fisher's LDA		SVM		MCTW		channel
	1s	3s	1s	3s	1s	3s	1s	3s	
length	0.126	0.672	0.113	0.468	0.099	0.598	0.122	0.839	1 ch. OZ
	0.000	0.000	0.000	0.002	0.389	0.001	0.004	0.001	16 channels
5 - class	0.240	0.664	0.315	0.740	0.206	0.726	0.251	0.797	1 ch. OZ
	0.002	0.000	0.000	0.007	0.942	0.032	0.002	0.000	16 channels

According to the t-test, CCA outperformed the PSD based features significantly ($p < 0.05$) for 16 channels and 3s. cases.

According to the results, it is obvious that the classification accuracies become better as the segment length increases. Since the frequency resolution is directly proportional with the segment length, this is an expected result that is consistent with the previous studies mentioned in literature. In order to achieve a good localization in frequency domain, segment size should be chosen larger.

Mean classification accuracies obtained for female subjects are found to be higher than those for male subjects for all classifiers. The differences are significant ($p < 0.05$) when only OZ channel is used. In this case, female performances are better than male ones. However, inclusion of all 16 channels removes the significance of differences between genders although female performances are still higher than male ones. Similar results were found in (Allison et al., 2010) where the authors claim that performances tend to be better in both young and female subjects. Therefore, they conclude that SSVEP BCIs may be better suited to younger and/or female subjects although they could not attain statistical significance.

5.3.2 Dataset #5 - SSVEP based experimental design #2

5.3.2.1 Dataset

6 healthy males (mean age: 28, varies between 22 and 31) and 3 healthy females (mean age: 25.3, varies between 23 and 28) voluntarily participated in the experiment (see section 4.3) after giving their written consent. All of the subjects were students at Istanbul Technical University. None of the participants had neurological disease background and 6 of the subjects had BCI experience before. The participants were informed about the recording procedure and the ethical issues in the Declaration of Helsinki (Url-2) before the experiment.

5.3.2.2 Preprocessing

Filtering and trend removal steps are the same as in section 5.3.1.2.

5.3.2.3 Results

PSD values of the responses obtained from subject #9 are given in Fig. B.1 (see Appendix B). It can be seen that the stimuli frequencies are clearly noticable on the frequency spectrum. However, in this design CCA method (see section 3.1.2) was used to extract features due to its higher performance in classification. For each stimulus frequency and its second harmonic, two different artificial signals (sine, cosine) are generated. Therefore, two canonical correlation values (ρ) are calculated for each frequency and its second harmonic. When the maximum of the two correlation values is used, there are 18 features in the feature vector. Otherwise, all the 36 features are used in classification. In the results, accuracies are given for 18 features.

The features are normalized between 0 and 1 before classification. In classification step, there are totally 90 feature vectors (one vector for each focused circle). Three different recording lengths (1s, 2s, 3s) from the onset of stimulus are used to understand the performance dependance on the focus duration. FieldTrip Toolbox (Oostenveld et al. 2011) was used for extraction of recorded segments from the whole EEG data. In Figs. C.1-C.3 (see Appendix C), distributions of each CCA feature are given for subject #6 for a segment length of 3s. In the figure, feature vectors are sorted according to classes. Therefore, consecutive 10 feature vectors are from the same class. Dashed lines show the interval (particular class) where the CCA

feature values are expected to be higher than the ones in other classes. It can be seen that, for the fundamental frequencies (feature #1-9), CCA values in the related class are easily distinguishable from the others. However, for the second harmonics, (feature #10-18), the distinction is not very clear for some of the features (e.g. feature #12, 13, 15) on the figures.

SVM, LDA and NMC classifiers from PR Tools 4.0 (Duin et al., 2004) (see section 4.4.4.2) and proposed MCTW classifier (see section 3.3.6) are used for classification. In Table 5.17, classification performances are given according to the mean overall accuracy after performing leave-one out classification for three different recording lengths.

Table 5.17 : Classification performance of 9 subjects.

segment	1s				2s				3s			
classifier	SVM	LDA	NMC	MCTW	SVM	LDA	NMC	MCTW	SVM	LDA	NMC	MCTW
accuracy(%)	75.30	76.42	79.01	80.86	97.16	97.40	97.65	98.39	99.50	99.75	99.75	99.13
bits/trial	1.62	1.67	1.79	1.89	2.89	2.91	2.93	3.00	3.10	3.13	3.13	3.07
bits/min	48.67	50.23	53.96	56.74	57.96	58.36	58.77	60.05	46.64	47.05	47.05	46.07

In Table 5.17, it can be seen that 9 classes are classified with an overall accuracy greater than 97% for a segment length $\geq 2s$. Individual classification performances of the subjects (S1-S9) for MCTW classifier are given in Fig. 5.13.

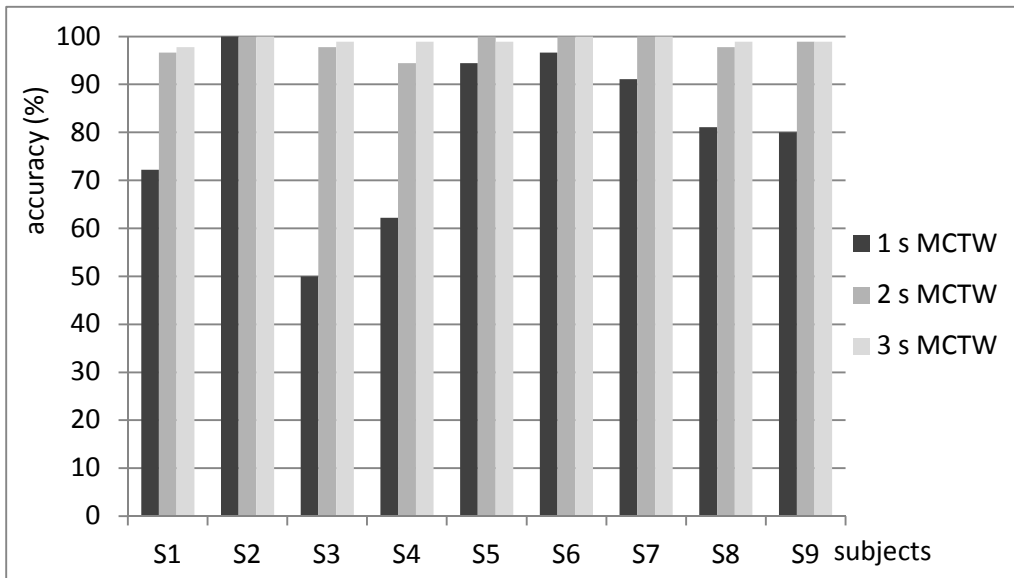


Figure 5.13 : Individual performances of the subjects (S1-S9) for MCTW.

According to the results given in Fig. 5.13, some subjects can achieve very high classification accuracies for even 1s. However, in order to make the BCI work

successfully for every subject, segment length ≥ 2 s must be chosen. S7, S8 and S9 are females.

In Table 5.17, ITR values in terms of bits/trial and bits/min are also given (see (1.1)). Trial/min is 30, 20 and 15 when the recording length is 1s, 2s and 3s respectively. Pause (1s) between the successive stimuli was taken into account. Even the bits/trial value increases with the segment length, trial/min decreases. Therefore, bits/min value was found higher in 2s case. By decreasing the pause duration, obtained ITRs can be increased further. In Table 5.18, proposed design is compared with other SSVEP based designs in terms of ITR values.

Table 5.18 : Comparison of proposed design #2 with others in terms of ITR.

Reference	Accuracy (%)	# of subjects	ITR (bits/min)
This design	98.39	9	60.05
Bin et al. (2009)	95.3	12	58 ± 9.6
Volosyak et al. (2011)	93.83	27	49.93

In Table 5.18, it is evident that the proposed design #2 can compete with the latest designs in literature in terms of ITR value.

5.3.3 Dataset #6 – SSVEP based experimental design #3 (Character Plotter)

5.3.3.1 Dataset

8 healthy males (mean age: 28, varies between 24 and 32) and 8 healthy females (mean age: 26.8, varies between 22 and 41) voluntarily participated in the experiment after giving their written consent. None of the participants had neurological disease background and 9 of the subjects had BCI experience before. The participants were informed about the recording procedure and the ethical issues in the Declaration of Helsinki (Url-2) before the experiment.

5.3.3.2 Preprocessing

The preprocessing steps are the same as in section 5.3.1.2.

5.3.3.3 Results

CCA method was used in feature extraction (see section 3.1.2). The first part of the experiment is determining the adequate classification accuracy for the subjects. In

order to do that, experimental design #2 is used. Results are given in Table 5.19 for 18 features.

Table 5.19 : Mean classification performance of 16 subjects.

segment	1s				2s				3s			
classifier	SVM	LDA	NMC	MCTW	SVM	LDA	NMC	MCTW	SVM	LDA	NMC	MCTW
accuracy	65.22	66.48	70.40	71.89	89.96	90.52	90.96	91.43	94.92	95.68	95.66	95.65
bits/trial	1.19	1.24	1.40	1.46	2.39	2.43	2.46	2.49	2.72	2.78	2.78	2.78
bits/min	35.83	37.32	42.16	44.09	47.96	48.66	49.21	49.81	40.91	41.75	41.73	41.71

In Table 5.19, it can be seen that 9 classes can be classified with an overall accuracy greater than 89% for a stimuli length ≥ 2 s. The accuracies and the ITR values are lower than the ones presented in Table 5.17. This is mainly due to the results of the subject #6, the only one who could not reach an accuracy greater than 95% for any given stimuli length less than 7s. Therefore S6 is excluded from the online experiment. Further analysis on S6 in different sessions showed that the accuracy increases with the increasing stimuli length. Individual classification performances of the subjects (S1-S16) for MCTW are given in Fig. 5.14.

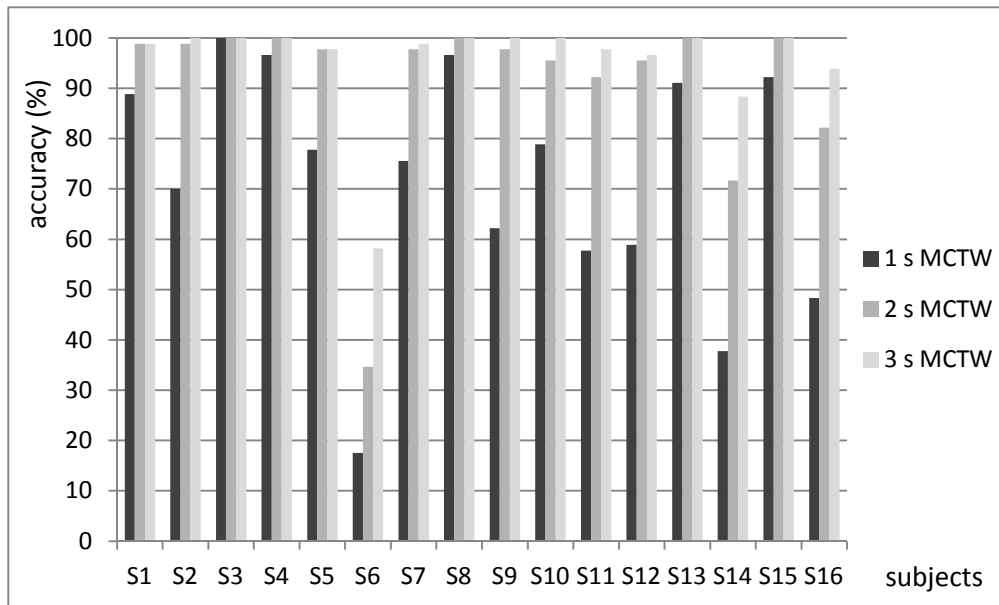


Figure 5.14 : Individual performances of the subjects (S1-S16) for MCTW.

The results are given for single sessions except S6 (average of 5 sessions), S14 (average of two sessions) and S16 (average of two sessions). In the online experiment, subjects were told to write two different sentences with the system. 36 CCA features were used in classification. However, obtained results showed that

using 18 features instead of 36 generates better performances. Moreover, using less features increases the classification speed.

Stimuli length was determined according to the offline classification performances of the subjects. Some subjects were not able to reach an accuracy of 95% for 2s. Therefore longer stimuli length was used for them. For all subjects except S11, S12, S14 and S16, stimuli length is 2s. For S11 and S12, stimuli length is 3s whereas for S14 it is 4s. Stimuli length is 5s for S16.

In Table 5.20, generated sentences by each subject are given. All subjects who participated in the online experiment were able to write the English sentence: “iT is oK”. For the Turkish sentence which is longer (more difficult), simple mistakes were done by several participants. It should be noted that the subjects could familiarize themselves with the alphabet and the visual interface in a very short period. This is due to the similarity of the proposed system to the natural writing method. In the online classification, SVM is used as the classifier.

Table 5.20 : Sentences written by different subjects.

Subject	Sentence #1	Sentence #2
S1	iT is oK	HAVA oK GüzEL
S2	iT is oK	haVa oK GüzEL
S3	iT is oK	hAVA oK GüzEL
S4	iT is oK	HAVA oK GüzEL
S5	iT is oK	haVa oK GüzeL
S6	N/A	N/A
S7	iT is oK	HAVA oK G üzEL
S8	iT is oK	HAVA oK GüzEL
S9	iT is oK	HAVA oK GüzEL
S10	iT is oK	HAVA oK GüzEL
S11	iT is oK	haVa oK GüzEL
S12	iT is oK	HAVA oK Güz?L
S13	iT is oK	HAVA oK GüzeL
S14	iT is oK	hAVA oK GüzEL
S15	iT is oK	HAVA oK GüzEL
S16	iT is oK	?HAVA oK GüzE L

Although subjects wrote more or less the same sentences, classification time for each of them is different. In Table 5.21, some information about the online classification speed of each subject is given for the two sentences. Total circles represent the number of the circles that the subject uses for writing the whole sentence. Here, performance evaluation using duration may not be a good idea since the stimuli lengths change for several subjects. Therefore, circles per character

(circles/character) is a more objective measure for evaluating the subject's performance.

Table 5.21 : Online classification performances of subjects.

Subject	Stimuli length	Sentence #1			Sentence #2		
		Total circles	Duration (s)	Circles/ character	Total circles	Duration (s)	Circles/ character
S1	2s	34	113.85	4.25	88	301.95	6.28
S2	2s	33	110.37	4.12	86	292.81	6.14
S3	2s	35	117.41	4.37	103	352.82	7.35
S4	2s	33	110.53	4.12	89	304.05	6.35
S5	2s	52	175.96	6.50	92	315.26	6.57
S6		N/A					
S7	2s	39	130.78	4.87	97	331.52	6.92
S8	2s	35	117.27	4.37	106	362.87	7.57
S9	2s	61	206.88	7.62	96	328.02	6.85
S10	2s	33	110.50	4.12	111	380.25	7.92
S11	3s	34	147.10	4.25	84	369.98	6.00
S12	3s	40	173.82	5.00	110	486.24	7.85
S13	2s	47	158.46	5.87	101	344.95	7.21
S14	4s	35	185.90	4.37	89	480.79	6.35
S15	2s	40	134.54	5.00	98	334.66	7.00
S16	5s	44	278.26	5.50	112	718.99	8.00

In Table 5.21, circles per character value changes between 4.12 (in English sentence) and 8.00 (in Turkish sentence). Average circle / character value is higher for Turkish sentence. This is an expected result because the characters of the English sentence are easier (need less lines) than the Turkish one.

By decreasing the pause length (1s) and enhancing the classification speed, overall speed of the BCI system can increase.

6. CONCLUSIONS AND RECOMMENDATIONS

This thesis presented new classification methods (ITW, MCTW) and an original stimuli presentation scheme for development of effective BCIs.

In the thesis, an improvement in a previously proposed T-Weight method (Liu et al., 2010) is shown. By slight changes in the pre-processing steps, classification performance is increased. Performance of the modified method is evaluated on the BCI Competition III: dataset II and compared with other successful submissions. Moreover, proposed modified method was adapted to MLSP 2010 Competition dataset and generated very high performance (İşcan, 2010).

To be able to use the T-Weight method as a general classifier, threshold determination step is added into the T-Weight method. Obtained classifier is called ITW. Proposed algorithm is evaluated on a SCP based BCI task. Results obtained by ITW method were compared with the other participants' results for two different datasets of BCI Competition 2003. ITW method generated the best results among the others for both datasets. The simple structure and the high classification performance of the method are promising for the future usage of ITW method in different research fields.

By creating feature sets for every class vs. others, the ITW method is extended to multi-class classification problems. The new algorithm which uses multiple thresholds is called MCTW method. Proposed classifier generates similar performances as compared with the well-known classifiers.

Finally, a novel SSVEP based BCI approach for writing characters is proposed. The proposed design using feedback is called "Character Plotter". Its simple interface allows writing letters and numbers. In the thesis, only 64 different characters were defined (See Appendix A). However, with the extension of the character set, many different symbols can be transmitted. Theoretically, the system is able to define 2^{13} different symbols. This is higher than the number of available characters in the other proposed BCI designs in literature. Character set can be generated according to the

application (e.g., communication for disabled people, game, military). Experimental results approved the feasibility of the design. Proposed design needs a short adaptation period and converges a natural way of writing. Therefore it can be a basis for future BCI designs.

In Character Plotter, there is a delay between 300-400 ms resulting from the classification algorithm. This delay can be minimized if the classification algorithm is embedded into hardware. Therefore, a future step for improving the BCI performance can be implementing the algorithm in hardware. Besides, by associating less lines with the frequently used characters, the overall classification speed can be increased.

In most of the proposed online BCI designs in literature, undo/delete operation due to a misclassification requires much more time than the undo operation in Character Plotter. In Character Plotter, since the character is being plotted step by step with single lines, undo operation removes only the last line. Therefore there is no need to start plotting the character from the beginning. This is one of the advantages of the proposed design over the others in literature.

During the classification task in Character Plotter, it was observed that the subjects are more likely to make a wrong classification just after a misclassified circle. This was explained by the loss of concentration after misclassification.

In the proposed SSVEP based designs, even the EEG was recorded in a laboratory that is exposed to electrical and acoustical noises, obtained classification accuracies were very high. In order to minimize the noise, use of active electrodes were preferred. These electrodes were placed on the occipital and parietal regions of the scalp since the SSVEP response is widely distributed over these regions (Friman et al., 2007).

In the proposed designs, V-Amp16 system was used as the EEG amplifier. The system has 16 electrodes. Measurements were performed for both single channel and 16 channels. Obtained results with 16 channels were higher than the ones with single channel.

Some subjects reported that looking at CRT monitor was tiring. This was an expected effect as reported in Wu et al. (2008) paper. In order to minimize this effect, LCD monitor instead of CRT can be used in future studies.

Main drawback of the proposed designs are the dependency on the gaze control. Subjects who can control their gaze can accomplish the given tasks by using eye-trackers. In this case EEG is not needed. Therefore, it is desirable to reach high classification accuracies with BCIs when the subject is not able to control gaze. In this case, EEG electrodes should be placed not only on the visual cortex but also on the brain sites where the covert attention is reflected.

Obtained experience from P300 and SSVEP based classification tasks shows that, SSVEP responses are less sensitive to subjects as compared to P300 responses. Amplitude and latency of the P300 responses differ in every subject. However, in SSVEP responses, even the amplitudes may be different for each subject, there is no latency in the frequency domain. Besides, SSVEP based classification does not need averaging of several trials which is time consuming and tiring for the subjects.

In SSVEP based designs it was observed that CCA features generated better performances as compared to the PSD features. This result was verified by using divergence analysis and statistical t-test. The distributions of CCA features in Appendix C for one subject show that the between-class scatter is high and within-class scatter is low. Even the distribution of the CCA features differ for each subject, the general behaviour of the scattering is preserved.

BCIs should be subject-specific which means that the system must adapt itself to the user characteristics. The adaptation process includes the selection of the optimum features, channels, stimuli length, stimuli frequencies and classifier.

In order to increase the classification accuracy in SSVEP based BCIs, frequencies for which the subject is more sensitive can be predetermined and used as stimuli frequencies.

High variation was observed in the classification accuracies of the subjects for a fixed stimuli length. Some subjects reached an accuracy of 95% for even 1s whereas some others could not reach the same accuracy for a stimuli length of 3s. Therefore, optimum stimuli length can be predetermined for each subject in order to increase the classification performance.

In the future, development of classification methods for EEG based BCIs will preserve its importance. Combination of different signals (e.g. P300 and SSVEP) can help for better classification accuracies.

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APPENDICES

APPENDIX A: Character set for Character Plotter

APPENDIX B: PSD of SSVEP responses

APPENDIX C: Distributions of CCA features

APPENDIX A: Character set for Character Plotter

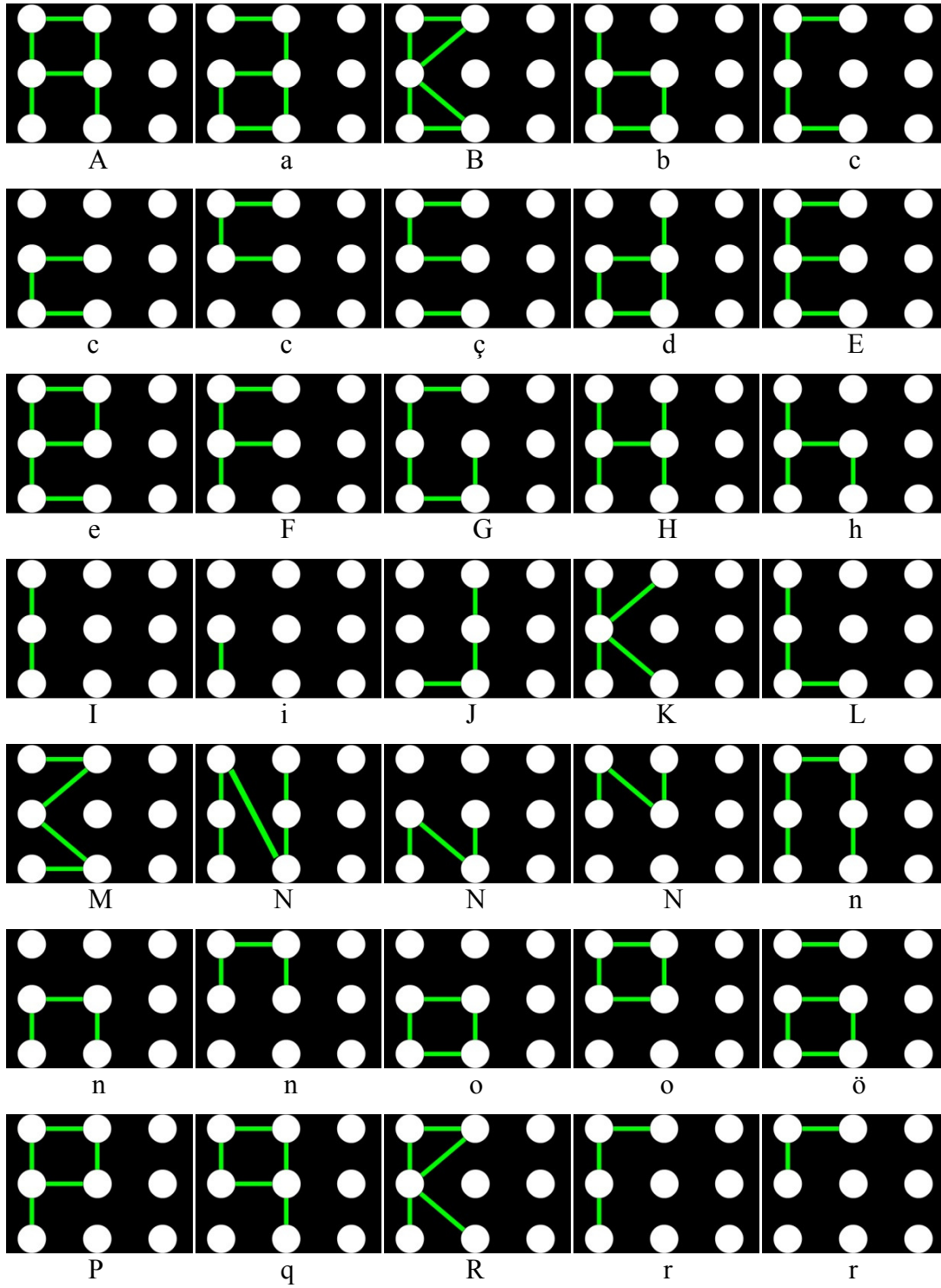


Figure A.1: Character set for Character Plotter.

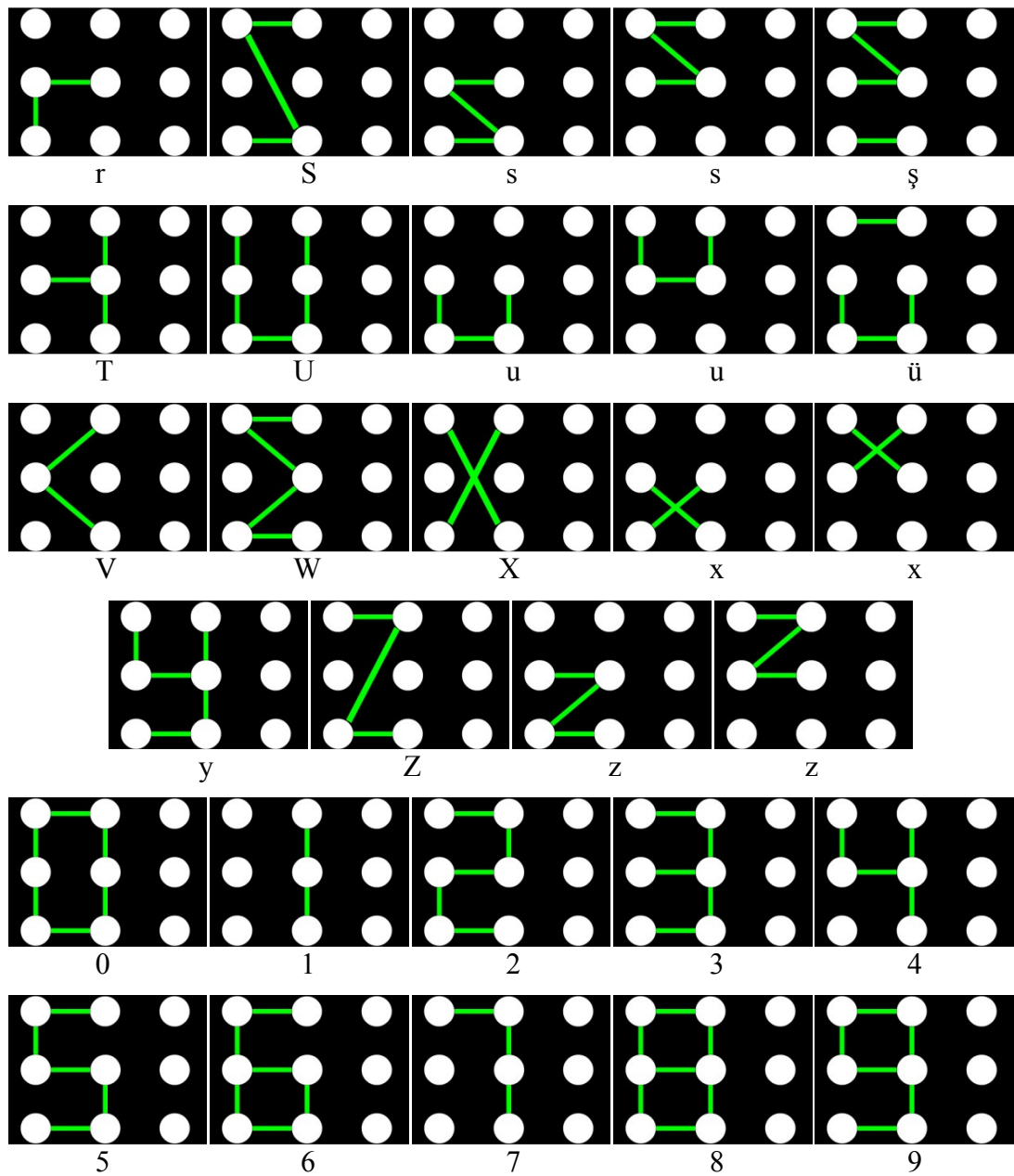


Figure A.1 (continued): Character set for Character Plotter.

APPENDIX B: PSD of SSVEP responses

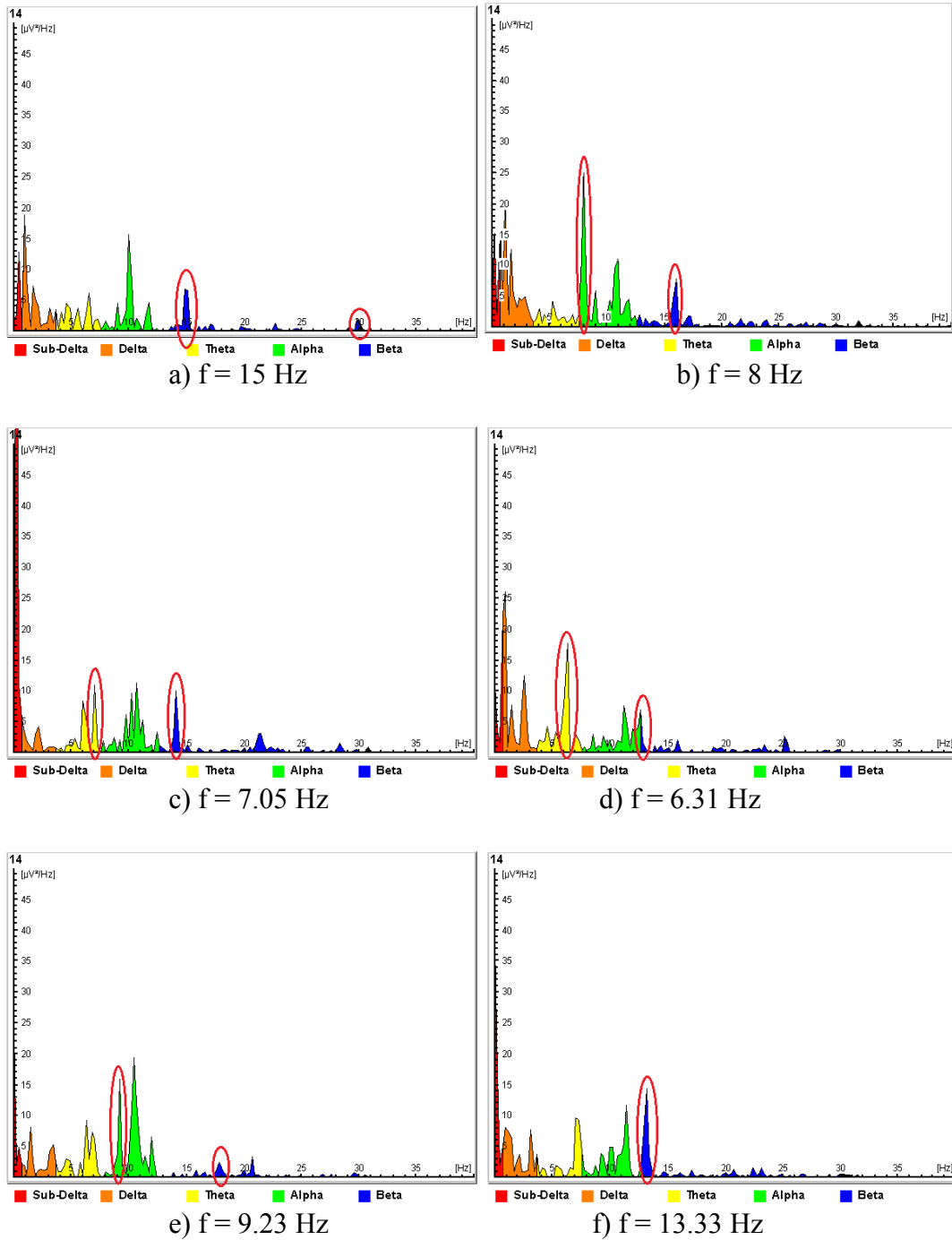


Figure B.1 : PSD of SSVEP responses of Subject #9 in experimental design #2 for nine different stimulation frequencies (a-i). Results belong to the first nine responses of ninety responses.

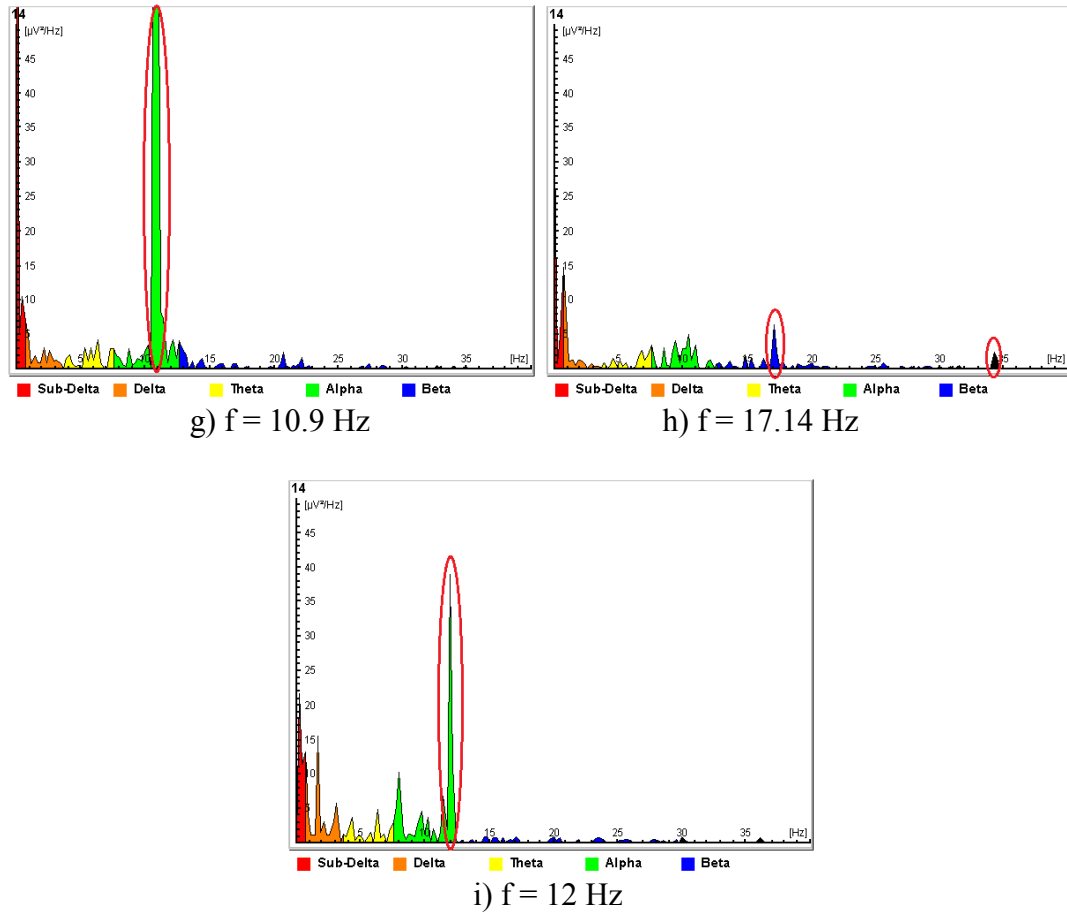


Figure B.1 (continued): PSD of SSVEP responses of Subject #9 in experimental design #2 for nine different stimulation frequencies (a-i). Results belong to the first nine responses of ninety responses.

APPENDIX C: Distributions of CCA features

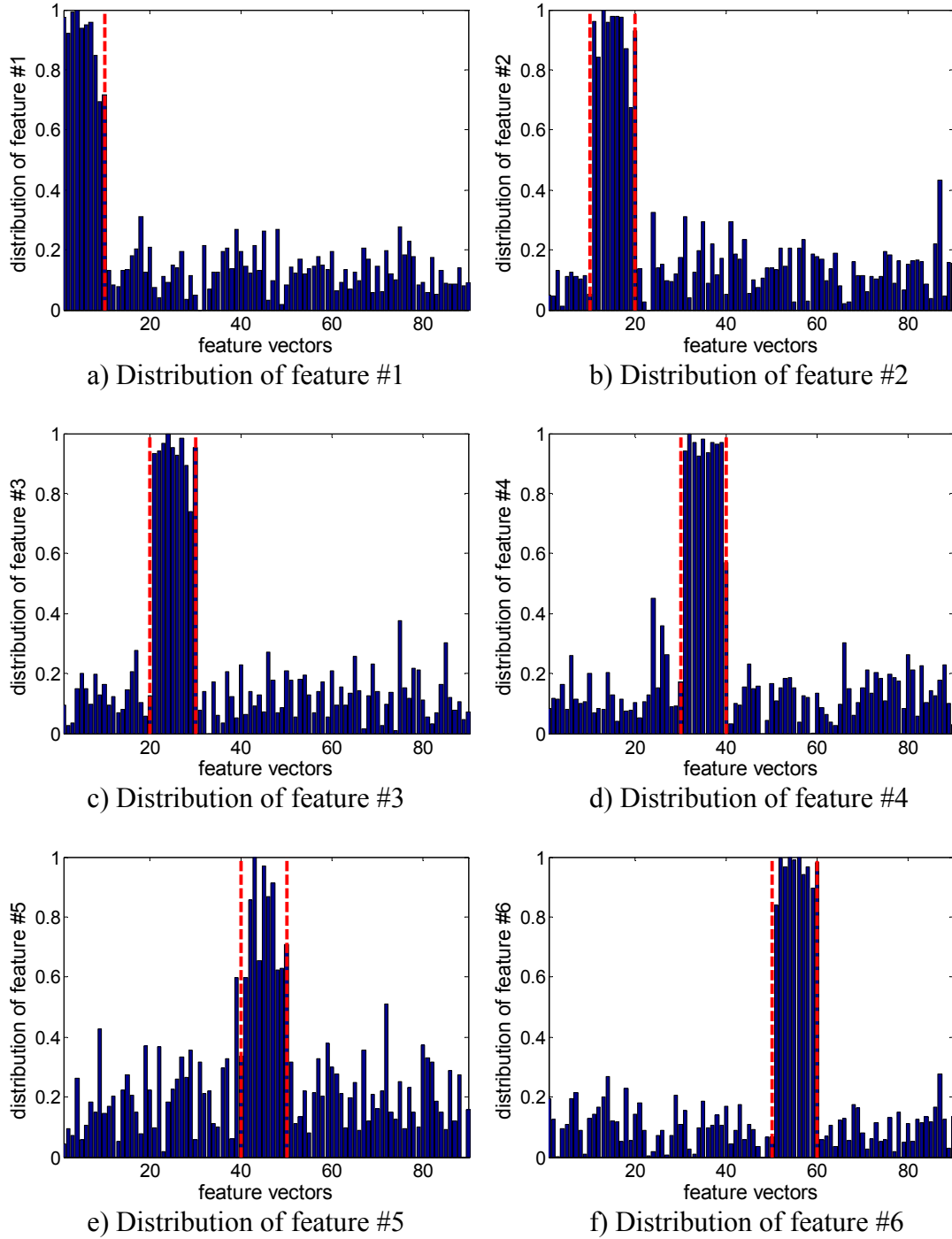


Figure C.1 : Distributions of CCA features (#1-6) obtained from subject #6 in experimental design #2 for 3s (a-f). Consecutive ten feature vectors are from the same class.

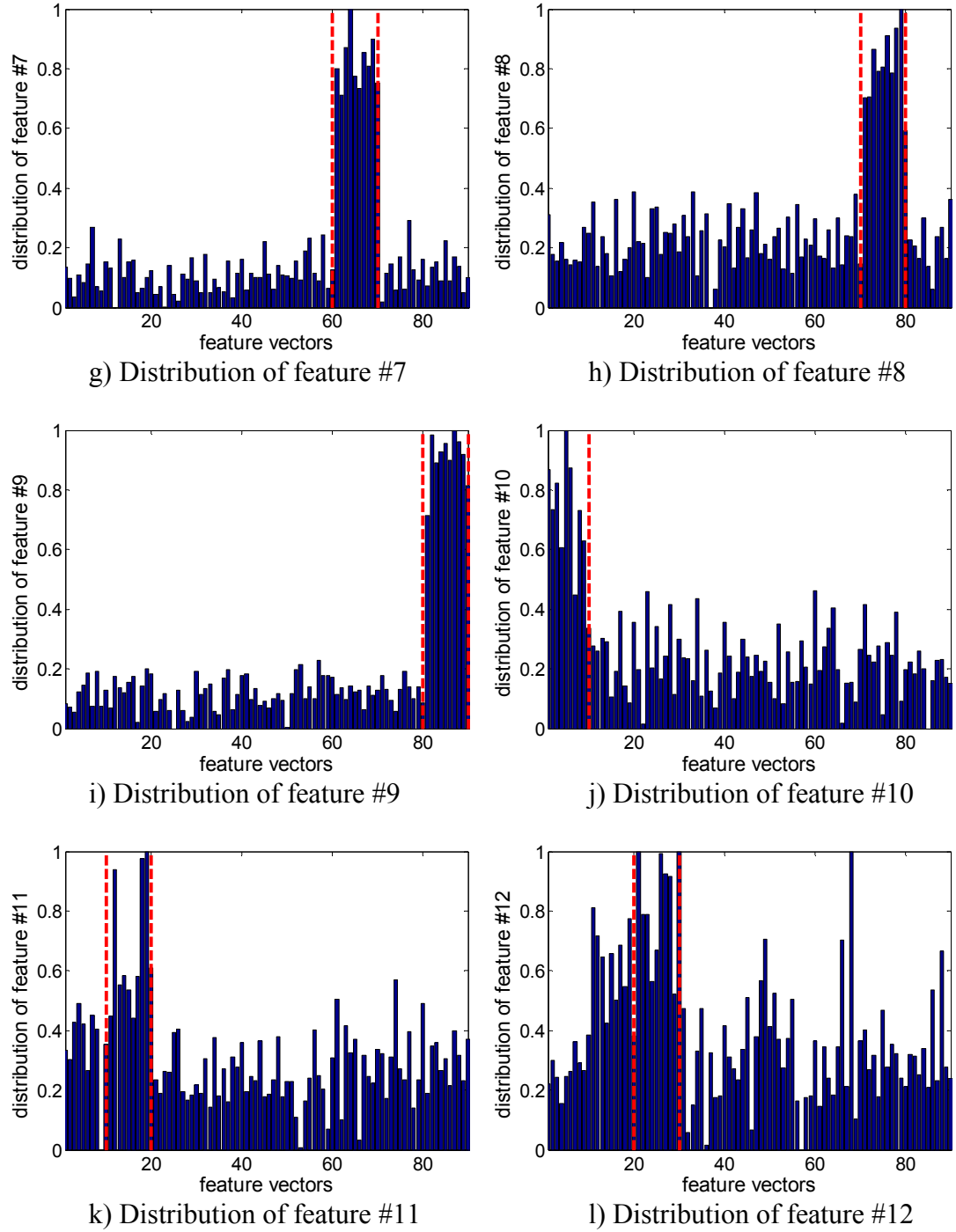
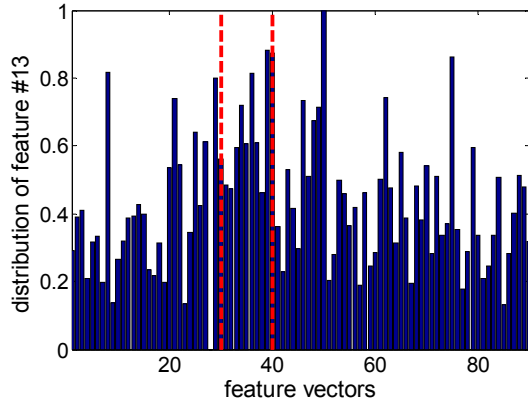
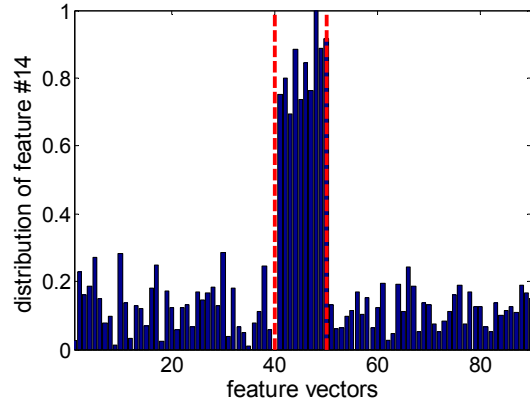


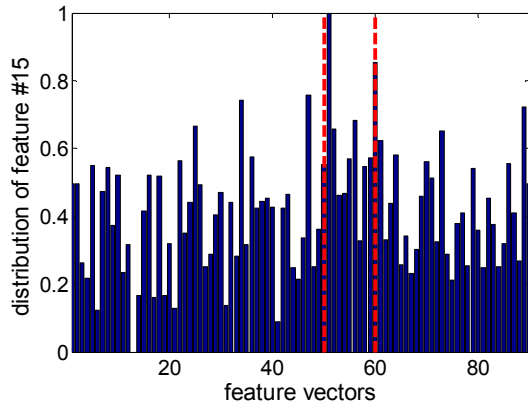
Figure C.2 : Distributions of CCA features (#7-12) obtained from subject #6 in experimental design #2 for 3s (g-l). Consecutive ten feature vectors are from the same class.



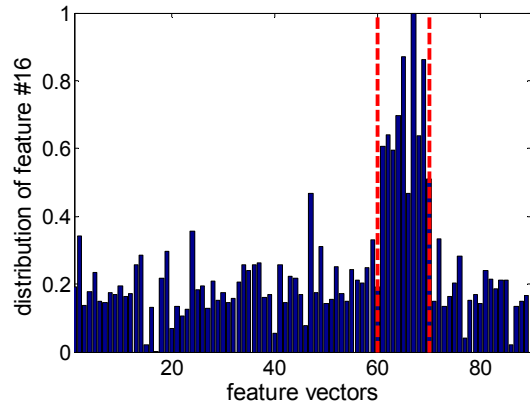
m) Distribution of feature #13



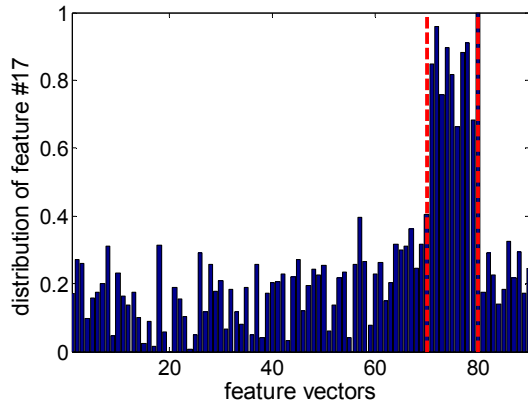
n) Distribution of feature #14



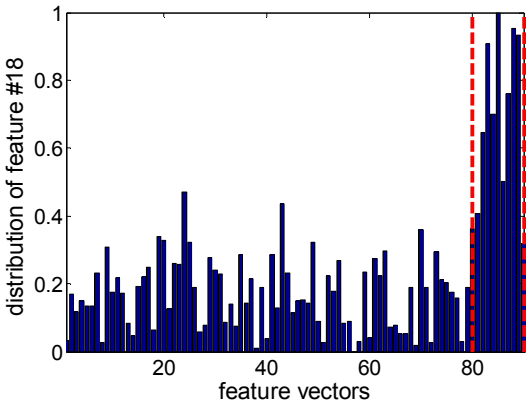
o) Distribution of feature #15



p) Distribution of feature #16



q) Distribution of feature #17



r) Distribution of feature #18

Figure C.3 : Distributions of CCA features (#13-18) obtained from subject #6 in experimental design #2 for 3s (m-r). Consecutive ten feature vectors are from the same class.

CURRICULUM VITAE



Name Surname: Zafer İŞCAN

Place and Date of Birth: Üsküdar, 05 March, 1981

E-Mail: zaferiscan@yahoo.com

B.Sc.: Istanbul Technical University – Electronics & Communication Eng. (2002)

M.Sc.: Istanbul Technical University – Biomedical Eng. (2005)

Erasmus Student: Ecole Polytechnique Federale de Lausanne (Mar. – Sep. 2007)

Professional Experience and Rewards:

- Istanbul Technical University - Research and Teaching Assistant (2005 – 2012)
- TSD Projects s.r.l (Milan, ITALY) – Intern - (Oct. 2004- Mar. 2005)
European Union - Leonardo da Vinci Vocational Training Programme
- Istanbul Technical University – European Union Center – Student Assistant (Part-time) (Oct. 2003 – Sep. 2004)
- Birim - Public Relations Research & Consultancy Ltd - Data Entry Staff (Part-time) (Aug. – Nov. 2003)
- IEEE International Workshop on Machine Learning for Signal Processing (MLSP 2010), Kittila, Finland - "Mind Reading" Competition: 2nd prize.

List of Publications:

Journal Papers

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Master Thesis: Segmentation of Ultrasound Images by Using Artificial Neural Networks (Nov. 2005) (in Turkish)

Undergraduate Project: Modelling and Control of Motion Control Systems (May. 2002) (in Turkish)

PUBLICATIONS/PRESENTATIONS ON THE THESIS

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