EEG BASED BRAIN-COMPUTER COMMUNICATION SYSTEM

A DISSERTATION

Submitted in partial fulfillment of the requirements for the award of the degree of

01

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ELECTRICAL ENGINEERING

(With Specialization in Measurement & Instrumentation)

By

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CANDIDATE'S DECLARATION

I hereby declare that the work presented in this dissertation entitled "EEG Based Brain-Computer Communication System" submitted in partial fulfillment of the requirement for the award of the degree of Master of Technology with specialization in Measurement and Instrumentation in the Department of Electrical Engineering, Indian Institute of Technology Roorkee, is an authentic record of my own work carried out from July 2005 to June 2006 under the guidance of Ms. Ambalika Sharma, Assistant Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee.

I have not submitted the matter embodied in this report for the award of any other degree or diploma.

Date: 29 June 2006 Place: Roorkee

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CERTIFICATE

This is to certify that the above statement made by the candidate is true to the best of my knowledge and belief.

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Assistant Professor, Department of Electrical Engineering, Indian Institute of Technology Roorkee, Roorkee – 247667. I express my foremost and deepest gratitude to **Ms. Ambalika Sharma**, Assistant Professor, Department of Electrical Engineering, Indian Institute of Technology, Roorkee for her valuable guidance, support and motivation throughout this work. I have deep sense of admiration for her innate goodness and inexhaustible enthusiasm. The valuable hours of discussion and suggestions that I had with her have undoubtedly helped in supplementing my thoughts in the right direction for attaining the desired objective. I consider myself extremely fortunate for having got the opportunity to learn and work under her able supervision over the entire period of my association with her.

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Abstract

There exists a significant population who, due to disease or injury, is totally paralyzed but have normal or near-normal brain function. In such cases, called Locked-in-Syndrome, the individual is aware of his or her surroundings, but has no way of communicating with the outside world. In cases where the person has even a slight degree of voluntary movement (e.g., eyebrow motion), it is possible to use that movement as a switch for controlling a computer. Likewise, when the person has good eye control, he or she can be fitted with an eye-tracking device to control cursor movement on a computer screen. In many cases, however, the individual may have no reliable voluntary motion to attach a switch to, and eye-movement may not be precise enough to use with an eye-tracking device. In such cases, the only possible method of communication would be to use electrical signals produced by the brain as a switching device for computer interaction i.e. Brain Computer Interface (BCI).

A Brain Computer Interface (BCI) is a real-time communication system designed to allow users to voluntarily send messages or commands without sending them through the brain's normal output pathways. BCI users send information by engaging in discrete mental tasks that produce distinct EEG signatures. These tasks, called cognemes, form the basis of a BCI language. In P300 BCIs, users view a display containing several stimuli, one of which is the target. Stimuli are flashed sequentially, and

ii

users count target flashes, thereby conveying one of two cognemes (/flash attended/ or /flash ignored/). Only attended flashes produce robust P300s, enabling target identification via the EEG.

The aim of this dissertation is to develop a Brain Computer communication system, which predicts the correct character in each of the provided character selection epochs using the P300 event related potential. The P300 is a late positive wave that occurs between 250 and 800 milliseconds after the onset of a meaningful stimulus. Because of its robustness, the evoked electrical potential called P300 has been used in EEG-based computer interface. In these experiments, a user focused on one out of 36 different characters. The objective in this dissertation is to predict the correct character in each of the provided character selection epochs. Detection and classification of P300 evoked potentials namely was carried out by averaging, peak picking and classification algorithms.

The algorithm developed in the present study have been tested on the data sets obtained from Wadsworth Research Organization, New York, USA

CONTENTS

Acknowledgements	i
Abstract	ii
Contents	iv
List of Figures	vi
List of Tables	vii
List of Acronyms	viii
1. Introduction	1
1.1 General	1
1.2 Overview of the thesis	3
2. Brain computer interfaces	4
2.1. The physical brain	6
2.2. Measuring brain activity	10
2.3. Recording EEG activity	13
2.3.1 Electrodes	15
2.3.2 Electrode placement	16
2.3.3 Reference and bipolar recordings	17
2.3.4 Grounding	17
2.3.5 Artifacts	17
2.4. Electroencephalogram	19
2.4.1 Rhythmic brain activity	19
2.4.2 BCI based on rhythmic activity	20
2.5 Advantages of EEG over other methods	21
2.6 BCI approaches using EEG	23

2.6.1 Slow Cortical Potential	23
2.6.2 Mental Tasks	24
2.7 Errors in a BCI	25
3. Different BCI Systems	26
3.1 Visual Evoked Potential Detection	26
3.2 P300 detection	27
3.3 Slow cortical potentials	27
3.4 EEG Mu rhythm conditioning	28
3.5 EEG pattern recognition approach	29
4. Event related potentials	31
4.1 P300 potentials	33
4.2 BCIs based on Event related potential	35
4.3 EEG based Brain Computer Communication system	35
4.3.1 Data description	36
4.3.2 Signal processing of P300 component	41
4.3.3 Averaging	42
4.3.4 Peak picking method	42
4.4. Algorithm	43
5. Results and discussions	46
6. Conclusion and future scope	62
References	

v

List of Figures

Figure: 2.1 A BCI based on the classification of two mental tasks.	5
Figure 2.2: Brain Structures: cerebrum, cerebellum, limbic system, and brain stem	6
Figure 2.3: Projection neuron showing information flow	8
Figure 2.4: The brain's functional lobes	9
Figure 2.5: Example brain scans depicting spatial resolution. Computer Tomography (CT)	
is an X-ray imaging technique that does not provide functional information	11
Figure 2.6: Spatial (mm) vs Temporal (sec) Resolutions for Brain Graphing Methods	12
Figure 2.7: International 10-20 System of Electrode Placement	16
Figure 4.1: P300 waveform.	33
Figure 4.2: the user display for paradigm.	37
Figure 4.3: Electrode designations and channel assignment numbers	
as used in experiments.	39
Figure 4.4: The assignment of the variable Stimulus Code	40
Figure 5.1: GUI Based Brain Computer Communication System	46
Figure 5.2: Average Response of standard and oddball condition	48
Figure 5.3: 2d representation of time and amplitude values	50
Figure 5.4: Discriminability between standard and oddball as a function	
of time and channels.	51
Figure 5.5: Responses to the different columns at Cz 46	55
Figure 5.6: average responses of all letters of particular row	60
Figure 5.7: average responses of all characters	60

vi

List of Tables

Table 2.1: Brain imaging methods that can be used for BCI	
Table 5.1: Average response for standard and oddball	47
Table 5.2: Time course of p300 response	49
Table 5.3: ERP Response of 12 Stimuli	52
Table 5.4: Average response results for characters m,n,o,p,q and r	56

List of Acronyms

A/D	Analog-to-Digital	
ABI	Adaptive Brain Interface	
AC	Alternating Current	
BCI	Brain-Computer Interface	
CNV	Contingent Negative Variation	
CMAP	Compound Motor Action Potentials	
EEG	ElectroenCephalogram	
ECG	Electrocardiogram	
EMG	Electromyogram	
EOG	Electrooculargram	
EP	Evoked Potential	
ERD	Event-Related Desynchronization	
ERS	Event-Related Synchronization	
ERP	Event-Related Potential	
FMRI	Functional Magnetic Resonance Imaging	
LSP	Language Support Program	
MEG	Magnetoencephalography	
NCV	Nerve Conduction Studies	
PET	Positron Emission Tomography	
SCP	Slow Cortical Potential	
SNAP	Sensory Nerve Action Potentials	
TTD	Thought Translation Device	
VEP	Visual Evoked Potential	
VR	Virtual Reality	

viii

1. Introduction

1.1 General:

One of the most important and distinguishing aspects of humans is the ability to communicate. Communication between people is richer and more complex and than any other form of communication, and plays a vital role in any relationship. Similarly, as artificial devices become more complicated and play a rapidly waxing role in everyday life, communicating effectively with them becomes increasingly important. It is impossible to directly convey thoughts, emotions, or concepts between people. Instead, these must be translated into verbal or written statements, gesticulations, facial gestures, drawings, or other recognizable expressions. Though not typically regarded as such, much of human anatomy is designed to act as a natural interface, allowing people to convey ideas from one brain to another. Verbal and written messages are typically sent using the mouth and throat or the hands and are received by the ears or eyes, all of which are mediated by extensive processing mechanisms in the brain. While communication between humans has been extensively developed and studied, communication between people and devices - especially sophisticated electronic systems - is relatively embryonic. Only 60 years ago, state of the art computing systems like ENIAC or UNIVAC required punch cards for communication. An efficient interface is no less important that the device itself; imagine trying to use a modern computer with punch cards. Modern means of interfacing with a computer

such as a keyboard and mouse are vastly superior, but remain nonintuitive and are being continually developed.

The use of sophisticated computer tools such as real-time graphics, Multimedia, and ubiquitous computing, combined with future developments in 3-D representation, are creating a complex computational environment in which information overload is common. In such an environment, the usual modes of communicating with a computer, such as keyboard and mouse, are very slow and inefficient. The trend to solving this problem has involved the development of automated task managers, better visualization tools, and the development of more intuitive interfaces that recognize innate human skills, such as handwriting, gesture, and speech. As brain science and computer - technologies mature, it is inevitable that the ultimate intuitive interface will involve direct communication between the user's brain and a computer, or brain computer interface (BCI). This safe and non-invasive method of communication requires the wearing of a small device similar to a headset to detect brain electrical activity and communicate that activity to a computer or electronic device. This method has many potential advantages over current input modes.

A BCI is a real-time communication system designed to allow a user to voluntarily send messages or commands without sending them through the brain's natural output pathways. These systems can improve people's ability to convey information via two general avenues. First, they may restore some communication ability to severely disabled individuals, who are sometimes unable to communicate any other way. Second, healthy users may find BCIs an appealing means of supplementing or even replacing other interfaces for a

variety of reasons. BCIs are not currently in everyday use, and this is not likely to change in the near future. Their main drawback is their very poor information transfer rate. A typical speaker or skilled typist can easily send information above 100 words per minute, while the best BCIs currently available allow only a few words per minute. BCIs have other drawbacks as well; for example, they are more expensive than most other interfaces, require preparation to use, are not supported by common software, and may produce fears of invasive mind reading. However, growing attention to BCI research, as well as ongoing developments in relevant fields such as cognitive neuroscience, pattern recognition, electronics, computing, and brain imaging, provides grounds for optimism regarding the future of BCIs.

1.2 Overview of the thesis: This thesis is organized as follows

Chapter 1 as stated above serves as a general introduction to Brain Computer Interface.

Chapter 2 Describes the Human Braine and Electrical activity generated in brain, recording Electroencephalogram (EEG) Activity, BCI approaches using EEG and advantages of EEG over other methods.

Chapter 3 provides the brief discussion on Different BCI systems, that are divided by the type of brain activities used for control.

Chapter 4 describes the Event Related Potentials (ERP), P300 potentials and BCI based on ERP and also describes the algorithm for EEG Based Brain Computer Communication system that uses p300 potential as control signal.

Chapter 5 provides the details on the simulation program results.

Chapter 6 concludes the thesis with a final regard to the improvements for future development.

2. Brain-Computer Interfaces

A brain-computer interface (BCI) is a communication and control mechanism that does not rely on peripheral nerves and Muscles [17]. Fundamentally, BCI is a system to record functional activity directly from the brain, recognize the activity recorded, and control a device based on the activity recognized, is shown in Figure 2.1.

Ideally, brain imaging to record functional brain activity should be fast, fine grained, and nonencumbering for effective real-time device control. Practically, brain imaging devices today only partially fulfill these three constraints. Magnetoencephalography (MEG) is fast and fine grained, but requires a room full of equipment and the subject must remain still. Functional magnetic resonance imaging (FMRI) is fine grained, but requires a large machine that cannot be moved, and is slow in recording activity. Electroencephalography (EEG) is fast, inexpensive, and the subject is allowed a limited range of movement, however, it only records aggregate neuronal activity. Among these choices, EEG is the standard in BCI research because it is inexpensive and the activity recorded by EEG is backed by seventy-five years of research experience, while MEG and FMRI are relatively new and expensive technologies.

Recognition of brain activity is limited by the accuracy of the brain imaging technique used and confounded by the cacophony in the brain itself. Many algorithms have been employed to increase the classification rate of EEG BCIs. These methods include simple linear methods, such as averaging

EEG signals over multiple trials of the same stimulus [36], as well as correlations between individual trials and predetermined subject averages [19]. Machine learning algorithms have been used to improve BCI accuracy with techniques such as Independent Component Analysis (ICA) for the reduction of artifacts [27] and Support Vector Machines (SVMs) for increasing overall accuracy [8].

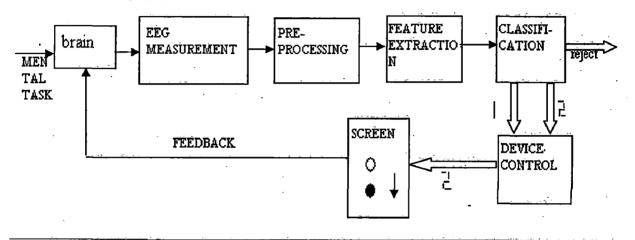


Figure: 2.1 A BCI based on the classification of two mental tasks.

BCI has also been used in computer applications for spelling [24], cursor control [17]. BCI is an interdisciplinary field combining research in cognitive neuroscience, signal processing, and computer science. This chapter covers the broad background required for brain-computer interfacing. The physical and functional anatomy of the brain is described with specific focus on aspects important in EEG BCI. Brain imaging methods are discussed and EEG is detailed in depth including the benefits of different electrical signals and the BCIs that utilize them.

2.1 The Physical Brain

The adult human brain contains 100 billion neurons spread through the cerebrum, cerebellum, limbic system, and brain stem shown in Figure 2.2

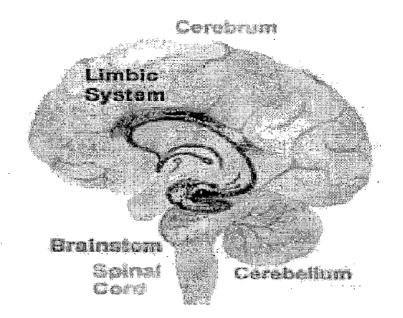


Figure 2.2: Brain Structures: cerebrum, cerebellum, limbic system, and brain stem [9]

The most important structure to brain-computer interfaces (BCIs) is the cerebrum's outer four millimeters (mm) of tissue called the cerebral cortex, which contains 20 billion neurons [13] generating the electrical activity that drives the typical electroencephalogram (EEG) BCI.

There are many different types of neurons in the central nervous system (brain and spinal cord) varying in diameter (0.004 mm to 0.1 mm), length (0.15 mm to 2 meters), and shape, among other attributes. The two main neuron classes in the cerebral cortex are pyramidal cells (pyramidshaped) and stellate cells (star-shaped). Pyramidal cells are longer than stellate cells and are oriented to form a dipole layer projecting electrical

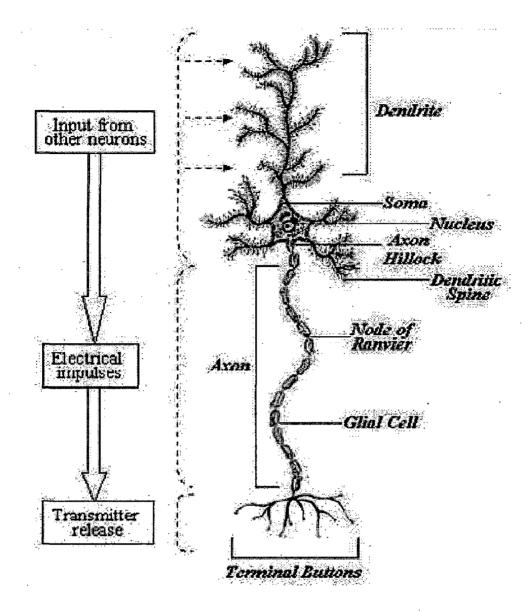


Figure 2.3: Projection neuron showing information flow [12]

Neuroscientists have shown that groups of neurons will fire in the same location on the cerebral cortex based on function. This has given rise to the functional map of the brain shown in Figure 2.4. In the functional map, the brain is divided into four lobes [12]: frontal, parietal, occipital, and temporal. The *frontal* lobe extends from behind the eyes to the top of the head and is responsible for analysis, planning, decisions, movement and motor skills, language production, and emotions. The *parietal* lobe extends from the frontal

lobe to about where the skull begins to steeply slope downwards and is responsible for body location and is the receiver of sensory information from the body.

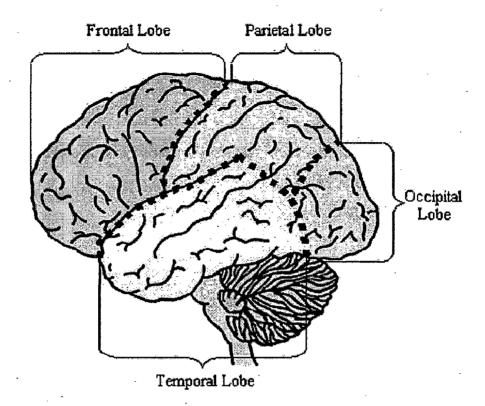


Figure 2.4: The brain's functional lobes [13]

The *occipital* lobe extends from the parietal lobe to the back of the head and sits above the cerebellum. The occipital lobe is responsible for processing visual information and has a direct link with the eyes. Finally, the *temporal* lobe extends along both sides of the head parallel to the ears and touches all three of the other lobes. The temporal lobe is involved with speech comprehension, recognizing objects, scenes, and faces, and maintaining autobiographical information in conjunction with the frontal lobe.

9[.]

2.2 Measuring Brain Activity

There are a variety of imaging devices that can be used for BCI. These devices include electroencephalogram (EEG), magnetoencephalography (MEG), positron emission tomography (PET), and functional magnetic resonance imaging (FMRI) described in Table 2.1

Method	Description
Electroencephalography(EEG)	Maps general brain activity using scalp
	electrodes
Magneto encephalography	Measures magnetic fields generated by
(MEG)	electrical currents at cell level
Positron emission tomography	The subject ingests radioactive tagged
(PET)	glucose. After the glucose enters the
	blood stream the PET machine measures
	the concentrations of glucose, which cor-
	responds to the brain's active areas.
Single-Photon Emission Computed	Similar to PET, but with poorer spatial
Tomography (SPECT)	resolution because it only measures a single
	photon
Functional magneto resonance	Based on Magnetic Resonance Imaging
imaging (FMRI)	(MRI) technology. FMRI can detect oxygen
	levels in blood to show variations in neural
	activity without ingesting radioactive
	markers.

Table 2.1: Brain imaging methods that can be used for BCI

Figure 2.5 depicts spatial resolutions for different brain imaging techniques.

Computer Tomography (CT) scans are the most fined grained, approximately 0.3 mm to 1 mm. Unfortunately, CT uses X-rays to scan the brain, which can damage cells. In addition, it does not provide functional information about the brain's activity. EEG provides a good functional map of the overall brain activity but has poor spatial resolution, ranging from 26.6 mm to 35.3 mm. Neurons' widths range from 0.004 mm (granule cell) to 0.1 mm (motor neuron)

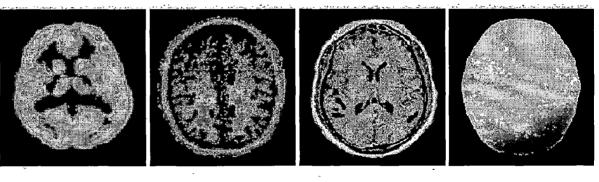


(a) CT Scan [19]

(b) MRI [33]

(c) fMRI [49]

(d) SPECT [19]



(e) PET [73]

(f) PET/MRI (Multi-Modal) [81] (g) MEG (Superimposed on MRI) [27] (h) EEG [68]

Figure 2.5: Example brain scans depicting spatial resolution. Computer Tomography (CT) is an X-ray imaging technique that does not provide functional information [16]

Figure 2.6 compares imaging methods' spatial resolution to temporal res-

olution. MEG provides the best spatial and temporal resolution, however, it requires a room full of expensive monitoring equipment and the subject's head cannot move during the recording. While EEG spatial resolution is poor, it has very good temporal resolution, which is important when translating rapidly changing brain activity to users' desires.

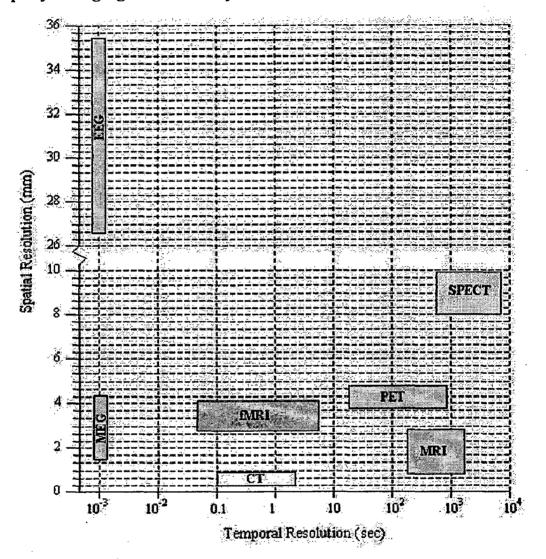


Figure 2.6: Spatial (mm) vs Temporal (sec) Resolutions for Brain Graphing Methods [12]

EEG signals are widely used in BCI research because they are fast temporally, inexpensive and less cumbersome than other methods (MEG, FMRI, SPECT, and PET require a room full of equipment), and non-invasive (the user wears a cap of electrodes) [41]. In addition, EEG signals can easily be combined with other techniques, such as FMRI, for BCI systems that require fine grained spatial resolution. For these reasons most BCI research, including this work, focuses on EEG.

2.3 Recording EEG Activity

This section details recording EEG from the scalp, known as surface EEG. To record EEG four types of equipment are required: electrodes, an operational-amplifier, an analog-to-digital (A/D) converter, and a computer. The electrodes acquire analog electrical signals from the scalp, which are then sent to the operational-amplifier for amplification. After amplification the signal is digitized by the A/D converter and transferred to a computer where they are interpreted in real-time using signal processing algorithms or stored for later processing. In BCI literature, interpreting signals for communication and control while the subject is using the BCI is referred to as online, while processing stored signals is referred to as offline. As already described when neurons fire they generate electrical activity that summates in the scalp. This electrical activity creates different electrical voltages (potentials) on the scalp, which are detected by electrodes. The voltages on the scalp from the neuron firing are very small, typically at most 50µV and needs to be increased to the sensitivity range of the A/D converter, which is usually ± 0.5 V to ± 10 V before further processing.

The scalp voltage is increased to the A/D converter's range with an operational amplifier, which is similar to an audio amplifier found in car and home theater systems. Amplifiers increase the voltage by a multiplicative constant

called *gain*, as shown in Equation 2.1 where V_i is the input voltage, g is the gain, and V_0 is the amplified output voltage.

$$V_o = V_i \times g \qquad \dots (2.1)$$

For example, a typical EEG amplifier gain is 50,000. Given an input of 10 μ V the output will be 500,000 μ V, which is 0.5 V, and within the range of an A/D converter.

The electrical potentials on the scalp are analog signals that need to be converted to digital representations for a computer to process them. Converting an analog signal to digital form is called *sampling*, because the continuous analog signal is sampled (recorded) at discrete time intervals. Two important aspects of analog to digital conversion are the sampling rate and resolution.

The *sampling rate* indicates how often the A/D converter samples the continuous signal. This rate is represented in units of Hertz (Hz), which are 1/seconds. If the sampling rate is 128 Hz, then the signal is sampled 128 times a second. The faster the sampling rate the more accurate the signal will be represented in digital form. The Nyquist theorem states the highest frequency that can be accurately reconstructed without error is half the sampling rate. In other words, to represent an analog signal without error in digital form the signal must be sampled at least twice its frequency. As shown in Section 2.4, brain signals have frequencies up to 30 Hz. To accurately represent 30 Hz beta signals in digital form the Nyquist theorem states the signal must be sampled at least at 60 Hz (2 x 30 Hz). If the beta signal is sampled at less then 60 Hz false frequency components will appear in the reconstructed signal.

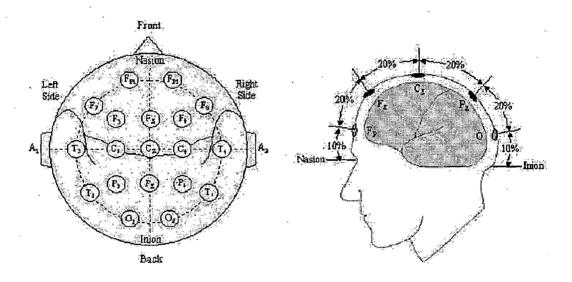
2.3.1 Électrodes

Electrodes conduct the electro cortical potentials from the scalp to an amplifier. Surface EEG electrodes are 8 to 9 mm in diameter and are composed of silver-silver chloride (Ag/AgCl), gold, or tin. Needle electrodes are generally not used for BCI as they are uncomfortable for the subject, may cause infection, and have poor recording quality. Electrodes are cup-shaped to hold electrolytic paste or gel depending on how they are affixed to the scalp. The electrolytic paste and gel aid the conductivity of the electrodes and help prevent motion artifact. For good quality recordings, the electrodes must be firmly attached to the scalp and the electrode impedance should between 100 and 5,000 Ω (Ohms).

Impedance is the resistance to current flow. If the impedance between the electrode and scalp is high, the brain's electrical activity will not be conducted through the electrodes properly and large differences in impedances between electrodes favor 60 Hz noise. Electrode impedance is measured by sending a weak alternating current through one electrode and recording it from a second electrode. With proper electrode application impedances can be reduced to less than 3,000 Ω . Only meters specifically designed to test scalp electrode impedances should be used. Impedance meters designed to test electrical circuits may send a large painful current to the patient, and can also polarize the paste or gel changing their conductive properties.

2.3.2 Electrode placement

The International 10-20 System of Electrode Placement, seen in Figure 2.7(a), was developed in 1958 by electroencephalographers to compare data using a common terminology and reference system, and defines the placement of twenty-one electrodes on the scalp. The system's name derives from the equal spacing of electrodes 10% and 20% of the distance between skull landmarks.



(a) (b) **Figure 2.7:** International 10-20 System of Electrode Placement. (a) Top view showing the 21 electrode positions. (b) Side view showing electrode positions at 10 and 20% of the distance between the nasion and inion measured over the top of the head [41]

The electrode position names consist of a letter followed by a number. The letter indicates the structural lobe below the electrode: Frontal, Central, Parietal, Occipital, and Temporal. Numbers indicate if the electrode is left, right, or on the midline. Odd numbers indicate left, even numbers indicate right and 'z' for 0 indicates on the midline. The system uses every other odd and even number starting with three and four to leave room for additional electrode placements.

2.3.3 Reference and Bipolar Recordings

EEG measures the potential difference (voltage) between two electrodes, i.e. the electrical signal from one electrode is subtracted from the other. In a bipolar recording, the two electrodes both measure cortical activity. In a reference recording, one electrode measures cortical activity while the other is placed on a body part without cortical activity, such as an earlobe. When recording in reference all electrodes measuring cortical activity are linked to a single reference electrode.

2.3.4 Grounding

Equipment and subjects must be properly grounded during EEG recordings for safety and to reduce noise [27]. A bony protuberance, such as the mastoid behind the ear, should be connected with an electrode to the EEG amplifiers electrode ground jack.

2.3.5 Artifacts

Artifacts are non-cerebral activity in the EEG that may masquerade as brain activity and otherwise obscure real brain activity. Artifacts appear because of the large amplification required to measure electrical brain activity, and may be technological or physiological in nature. The following is a list of the major artifacts that may occur when performing BCI experiments

Technical artifacts

• Electrode - Improperly attached electrodes and faulty wires can cause artifacts. An impedance checker should be used to verify that electrodes are properly attached. Electrode impedances should be less than 5,000Ω.

• 60 Hz interference - Nearby electrical equipment and power lines can induce rhythmic 60 Hz cycles (50 Hz in Europe) from alternating cur rent (AC) power. Proper grounding of the subject and equipment can reduce this interference. In addition, amplifiers typically have 60/50 Hz notch filters that remove this noise before amplification.

• Ground loop - 60 Hz interference that occurs when a ground electrode is shorted to an active electrode.

Physiological artifacts

• Oculographic - Eye movement and blinking can generate spikes of 200 to 410 μ V, which travel posteriorly. Eye electrical activity recordings, electrooculargram (EOG), are used to differentiate eye activity from cerebral activity. EOG is typically recorded from electrodes above and below the center of the eye, or above the eye and on the outer canthus. In BCI experimenters will generally reject trials with amplitudes greater than 50-90 μ V when classifying activity to account for electrooculargram (EOG) artifact.

• Muscle - Muscle contractions, such as talking, jaw clenching, and chewing, generate electrical activity, which may be seen in EEG.

• Cardiac - Electrical activity from the heart, electrocardiogram (ECG), can appear in EEG.

• Perspiration -Salt in perspiration creates a "salt bridge" between

electrodes that decreases inter-electrode impedances causing shorts.

• Motion - Head and body movement may move the leads and contacts, which causes wide wave artifacts. This can be corrected by asking the subject not to move.

2.4 Electroencephalogram (EEG)

Electroencephalogram (EEG) is the recording of electrical activity from the brain, discovered in humans by Hans Berger (1873-1941) in 1929. The electrical activity generated from neurons firing, Section 2.1, summates on the human scalp. Using EEG recording equipment, this electrical activity can be recognized and utilized in brain-computer interfaces (BCIs). This section reviews the signals generated by the brain, where they are recorded on the scalp, their functional significance, and their use in BCI.

2.4.1 Rhythmic Brain Activity

Rhythmic brain waves were the first brain signals discovered by Hans Berger [27]. Rhythmic brain waves are brain signals that occur continuously and repeat in amplitude, frequency, and waveform. These rhythmic signals are divided into frequency ranges named after Greek letters: delta δ , theta θ , alpha α , and beta β . The mapping of Greek letters and frequency ranges follows their chronological discovery, not a logical increasing in frequency.

Alpha

The alpha rhythm ranges between 8 and 13 Hz in normal adults and is distributed over the occipital, posterior temporal and parietal areas. The wave forms are monomorphic (regular in shape) with sharp points at the top or bottom, or sinusoidal. Alpha's amplitude is variable, but averages 50 μ V [27]. The rhythm is named 'alpha' for purely historical reasons. When Hans

Burger made his measurements he named the first rhythm he identified 'alpha' after the first letter in the Greek alphabet: α

Beta

The beta rhythm's frequency band is between 13 and 30 Hz and appears in three main types — frontal, widespread, and posterior — which vary in distribution and reactivity. These three beta patterns disappear in sleep, but frontal and widespread activity remain longer than alpha activity during drowsiness when beta becomes more dominant. Beta rhythm amplitude is typically lower than alpha amplitude, seldom exceeding 30 μ V [27]. Beta activity greater than 30 Hz is often referred to as gamma activity. **Delta and Theta**

The delta rhythm's frequency band is below 4 Hz; theta's is between 4 and 8 Hz. Both rhythms primarily occur in deep sleep [27] making them of little use in brain-computer interfaces; though, theta rhythms do appear in small unorganized amounts in normal adults.

Mu -

The Mu rhythm's frequency band is between 7 and 11 Hz and appears in the central and centroparietal regions as arch-shaped trains lasting a few seconds. Mu rhythms are more apparent during alpha blocking because Mu and alpha rhythms overlap in frequency range.

2.4.2 BCIs based on Rhythmic Activity

BCI using self-regulation of Mu and beta rhythm amplitude was developed by Wolpaw et al. [17]. After 5-10 half hour training sessions subjects can learn to increase and decrease the amplitude of the Mu or beta rhythm to control a mouse cursor and with sufficient training can achieve

information transfer rates up to 25 bits/min.

BCI based on the difference of Mu power at C3 and C4 using Cz as ground was developed by Pineda et al. [11]. Users were trained for 10 hours over five weeks to generate Mu activity under both C3 and C4 to move left in a virtual environment, and to generate less Mu in one hemisphere than the other to move the virtual character right. Transfer rates were not reported, but all subjects were able to demonstrate both types of control.

The brain-body interface Cyberlink [41], which uses a combination of electromyogram (EMG), EOG, and alpha and beta EEG for controlling various interfaces was studied by Doherty et al. [14]. They reported subjects with traumatic brain injuries achieved accuracy rates between 44 and 100%. Though it is unclear to what degree Cyberlink's control is directly from the brain.

2.5 Advantages of EEG Over Other Methods

EEGs offer five crucial advantages over other functional imaging approaches as the basis for a BCI.

First, it is currently impossible to measure changes in magnetic activity or blood flow without expensive and bulky equipment. This factor alone makes all functional imaging approaches other than EEGs impractical for a BCI designed to be used frequently. Scalp EEGs can be recorded with inexpensive and portable equipment. While the initial surgery to implant an intracranial monitoring system requires a hospital, EEGs can then be read for years without additional equipment.

> Second, preparing a subject for other recording approaches often

requires considerable time, risk, and at least one highly trained technician. PET and SPECT both require the injection of radioactive material. This adds considerably to preparation time and creates enough risk to the subject that neither technique could be used frequently enough to allow for consistent BCI use. MEGs and FMRIs are safe, and require less prep time than PET or SPECT, but nonetheless require a technician. A subject can be prepared for a laboratory EEG recording session in minutes. The individual who preps the subject needs very little training, and subjects can easily learn to prep themselves.

- Third, only EEGs and MEGs can measure brain function continuously and analyze it in real-time. A typical EEG recording session produces comparatively small datasets that can be analyzed with a meager office computer by an artificial system with no noticeable delay. PET, SPECT, and FMRIs can only take one snapshot of the brain every several seconds, and at least a few more seconds are required to process that data. While ongoing advancements in processor speed may soon allow any functional brain image to be processed in real-time, the limitations on sampling rate are much more entrenched and trenchant. This is also a serious drawback for other imaging approaches; their very low sampling rate would result in a very slow BCI.
- Fourth, because EEGs have been the predominant noninvasive methodology for studying brain function for decades, the relationship between EEGs and brain function is much better documented. For example, EEG changes resulting from movement imagery are known,

and many BCIs utilize these changes as a control signal. These movement-related changes in brain activity are much harder to pick up with other approaches, partly because of the low sampling rate of most approaches but also the relatively poor understanding of how movement imagery is reflected in FMRI, PET, SPECT, or MEG [18, 34].

Fifth, other approaches place additional constraints on the subject. All of them require the subject to remain still throughout the imaging session, while modern EEGs do not. FMRIs are extremely loud, making it very difficult to hear and concentrate on other tasks. All MRIs also require a very powerful magnetic field, making them unfeasible for many users and creating additional complications for any recording session.

The main drawback of scalp recorded electrophysiological signals is that they have poor spatial resolution. Despite their limitations, EEGs have proven to be a very useful and practical tool in experimental research. Compared to other means of detecting neural activity, such as PET or FMRI, EEG recording is fast, easy, safe, inexpensive, noninvasive, requires fairly little subject preparation, can be done on almost everyone, requires very little equipment (all of which is portable), and can be performed in a wide variety of noisy settings.

2.6 BCI approaches using EEG

2.6.1 Slow Cortical Potential (SCP)

. Slow cortical potentials (SCPs) are slow voltage changes generated in the cortex that occur over 0.5 to 10.0 seconds [15]. Birbaumer et al. [20]

studied users' ability to control the SCP's positive and negative amplitude with applications in BCI. Birbaumer's group developed the Thought Translation Device (TTD), which uses slow cortical potentials (SCPs) for two choice selections. In the TTD, a cursor moves from left to right across a screen at constant velocity. The cursor moves towards the top choice as the SCP becomes positive and the cursor moves towards the bottom choice as the SCP becomes negative. Selecting a choice takes 4 seconds. Users train in 1-2 hour sessions/week over weeks or months until they consistently achieve 75% or better accuracies, then they are switched to the Language Support Program (LSP). The LSP [20] extends the TTD two choice selection technique to spelling by presenting the user with two banks of letters. Each letter bank contains half of the alphabet. When the user selects a bank it is split in half and presented to the user again to chose. In this way the user can progressively split the bank in half to reach the desired letter. Users have achieved accuracies between 65 and 80% with information transfer rates of 0.75 to 15 bits/min.

2.6.2 Mental Tasks

Spontaneous EEG, resulting from a mental task, can also be to drive a BCI. Suppes [31] performed a study using EEG to discriminate seven mentally spoken words (first, second, third, yes, no, left, and right) with 71 to 86% accuracy. Ryu et al. achieved an 80% success rate discriminating between mental 'Yes' and 'No' with twelve subjects using artificial training neural networks. These studies did not attempt to control online BCI; however, Millan et al reported the Adaptive Brain Interface (ABI) uses a neural classifier to discriminate between mental states with online results.

2.7 Errors in a BCI

Two types of errors occur in BCI: selecting the incorrect choice and missing the correct choice, these are also referred to as false positive and false negative errors respectively. For many BCIs, the minimizations of false positive and false negative errors are diametrically opposed because reducing the number of incorrect selections increases the number of incorrect rejections and vice versa. In this case, it is better to reduce the number of incorrect selections at the expense of incorrect rejections because recovering incorrect selections can be more frustrating as the user must correct the error while incorrect rejections only require the user to wait for the appropriate choice to be presented again. If automatic error recovery is employed the number of incorrect rejections can be minimized without frustrating the user because incorrect selections are recovered without user involvement.

3. Different BCI Systems

Here some BCI systems are introduced. They are divided by the type of brain activities used for control.

3.1 VEP Detection

BCIs based on visually evoked potentials (VEP) are not truly BCI because user needs muscle control to turn his eyes to a certain point. But for comparisons they are included here.

VEPs applicability for BCI has been studied by three groups. Sutter's group [35] used a matrix of 64 kernels on a computer screen. The kernels were normal alphabets and commonly used English words. When a subject selects by looking a letter from the screen the English words on the matrix are changed to word beginning with that selected letter. Sutter switched 64 screen positions between red and green with lengthy binary sequence or in some trials by reversing a check board pattern. Each screen position was shifted 20ms in the binary control sequence relative to its neighbour, and the entire sequence was auto correlated with the VEP, which response lasts about 80ms, in overlapping increments beginning 20ms apart. The resultant vector was stored in a 64-position array of registers. When a coefficient remained greater than certain threshold and all the other coefficients for a certain time period, it was considered to have been selected by the subject. The VEP was measured with electrodes placed over the visual cortex at back of the skull. Experiment suggested that electrode placement and stimulation mode should optimize individually for each user for good target discrimination. This system was evaluated by seventy healthy subjects, who achieved response

times from one to three seconds after training period of 10-60 minutes.

3.2 P300 Detection

This system detects subjects P300 component from subjects event-related brain potential [38]. The P300 is a positive-going ERP with a latency of 300ms and it is triggered by a rarely-occurring stimulus that the subject is instructed to detect. This stimulus has to be of Bernoulli event i.e. one of two types, e.g. from two lights one flashes regularly and the other rarely. The observation of the rarely flashing light starts the P300. The EEG measurement was done by using a single electrode placed at Pz of the standard 10-20 system. The received signal was band pass filtered to 0.02 -35Hz and sampled at 50Hz.

The P300 was evoked by using "odd-ball" paradigm, where subject is asked to pay attention to some rarely happening stimulus by some non-motor way, such as counting the occurrences. This stimulus could be e.g. a light normally blinking green to suddenly blink red. A reliable detection of P300 requires averaging several samples of EEG. P300 detection from the EEG signal was studied with four different techniques: stepwise discriminant analysis, peak picking and covariance. Some of them have been explained in later sections.

3.3 Slow Cortical Potentials (SCP)

The Thought Translation Device (TTD) [20] is a BCI based on SCPs. In this approach the user learns to control the amplitude of his/hers SCP. This device is based on experiments with five subjects at their homes. The EEG recordings were made with portable EEG device using total of eight electrodes from frontal, central and parietal sections of the head. EEG signal was sampled at frequency of 256 Hz and filtered from eye-artifacts. Visual feedback is presented to the subject in a form of a "ball shaped light" that moves away or towards a target that is located at center of the computer screen, depending the level of the control at a given time. Also, the ball is highlighted when the subject has to produce negative SCP and flashes when positive SCP in needed. For the classification, the EEG is averaged in windows of 500ms moving in steps of 63ms. When the change in the amplitude is detected, it is visualized to the subject by a smiling face and a new trial begins. When the subject has stable performance of at least 75% of the trials correct, then he moves to the first level of the language support program. In this level I language support program, a letter is selected from an alphabet displayed on the computer screen by dividing it to two parts at every selection. So the alphabet gradually has only two letters to choose from and after the final selection the letter is added to current word that the subject is producing with the program. After the first two letters being selected, a erasing option is added to the screen for the user to edit out letters from the text field. It takes about two minutes to select a letter with the program.

3.4 EEG Mu rhythm Conditioning

In this method user controls the amplitude of a Mu-rhythm component in the EEG. Mu-Rhythm is detectable pattern in the EEG at 8-12Hz frequency range, centered about 9.1 Hz. The Mu-rhythm is Event-Related Desynchronization (ERD) that is desynchronized by movement, tactile simulation or planned movement. This approach is based on Kuhlman's [39, 40] approach and three groups have studied Mu -rhythms applicability to BCI.

Mu-rhythm amplitude of the subject was detected from the square-root of spectral EEG power at 9 Hz, using two electrodes located at near C3 in the standard 10-20 system [41]. Experiment set-up was such, that the subject tried to move cursor to a target placed randomly at somewhere at the top or the bottom of the computer screen. Cursor step size was varied by the operator of the system. Commonest i.e. easily achieved Mu-rhythms (< 4μ V) left the cursor in place or moved it downwards, while higher Mu-rhythms (> 4μ V) moved the cursor upwards. Observations made during the experiment were that there was no relationship between subjects muscular (EMG) activity and the Mu -rhythm. Also no connection was made between the subjects visual Mu-rhythm and Mu-rhythm.

Another similar setup was used by McFarland but with tighter time constraint. In this experiment the target moved from left to right side of the screen in eight second and subject had to move the cursor to one of the five vertical positions to intercept the target.

3.5 EEG Pattern Recognition Approach

Idea behind this approach is to take a kind of 'photograph' what is happening in the brain right now, instead of carefully waiting, timing and locating certain brain activity. Of course the ERDs, EPs etc. are used here also but rather as a combination than a single events that are searched. EEG signal was collected from 12 channels (Fp1, Fp2, Fz, C3, C4, Pz, F5, F6, F7, F8, O1 and O2) of the standard 10-20 system. Data was classified by two Multilayer perceptron (MLP) neural networks. The first was trained with average data and the second one for single-trial, on-line purposes. For the averaged data, the results were high, but for the on-line application they were less reliable. Keirn and Aunon [37] set out to find the best signals that could be differentiated by their EEG signal. They used Bayesian quadratic classifier to classify one of the five mental tasks that the subject was concentrating. These tasks were relaxing, non-trivial Multiplication problem, visualizing the rotation of three dimensional object in one's mind, mental composition of a letter to a friend and a visualizing numbers being written to a blackboard in increasing order as the previous is wiped before new is written. EEG data was recorded from six electrodes placed on P3, P4, O1, O2, C3, and C4 of the standard 1020 system. The features were power spectra extracted by using Wiener-Khincine method and later auto-regressive (AR) method, which proved out to be better. Between any mental tasks and a resting state, the classification results were between 80-90%.

4.0 Event Related Potentials (ERP)

Event-related potentials is a common title for the potential changes in the EEG that occur in response to a particular "event" or a stimulus. These changes are so small that in order to reveal them, EEG samples have to be averaged over many repetitions. This removes the "random" fluctuations of the EEG, which are not stimulus-locked. Event-related potentials can be divided into exogenous and endogenous. Exogenous ERPs occur up to about 100 ms after the stimulus onset. They depend on the properties of physical stimulus (intensity, loudness etc.). The potentials from 100 ms onward are called endogenous. They depend largely on psychological and behavioral processes related to the event.

Evoked potentials (EPs) is a subset of the ERPs, that rise in response to a certain physical (visual, auditory, somatosensory etc.) stimulus. A typical evoked potential is the *Visual evoked potential* (VEP) that reflects the output features of the entire visual pathway. The EEG over the visual cortex varies at the same frequency as the stimulating light.

In neurophysiology, an evoked potential (or "evoked response") is an electrical potential recorded from a human or animal following presentation of a stimulus, as distinct from spontaneous potentials such as electroencephalograms or electromyograms. Evoked potential amplitudes tend to be low, ranging from less than a microvolt to several micro volts, compared to tens of microvolts for EEG, millivolts for EMG, and often close to a volt for ECG. To resolve these low-amplitude potentials against the

background of ongoing EEG, ECG, EMG and other biological signals and ambient noise, signal averaging is usually required. The signal is time-locked to the stimulus and most of the noise occurs randomly, allowing the noise to be averaged out with averaging of repeated responses. Signals can be recorded from cerebral cortex, brainstem, spinal cord and peripheral nerves. Usually the term "evoked potential" is reserved for responses involving either recording from, or stimulation of, central nervous system structures. Thus evoked CMAP (compound motor action potentials) or SNAP (sensory nerve action potentials) as used in NCV (nerve conduction studies) are generally not thought of as evoked potentials, though they do meet the above definition. There are different types of evoked potentials namely, Steady state evoked potentials, Visual evoked potentials. In the next section, visual evoked potentials, somatosensory evoked potentials. What are visual evoked potentials?

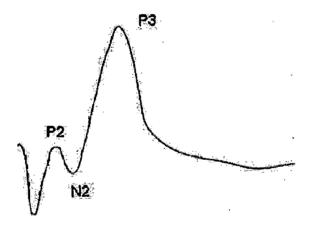
A visual evoked potential (VEP) is an evoked potential caused by sensory stimulation of a subject's visual field. Commonly-used visual stimuli are flashing lights, or checkerboards on a video screen that flicker between black on white to white on black [33](invert contrast).

Visual evoked potentials are very useful in detecting blindness in patients that cannot communicate, such as babies or non-human animals. If repeated stimulation of the visual field causes no changes in EEG potentials, then the subject's brain is probably not receiving any signals from his/her eyes. Other applications include the diagnosis of optic neuritis, which causes the signal to be delayed. Visual evoked potentials are also used in the investigation of basic functions of visual perception.

The term "visual evoked potential" is used interchangeably with "visually evoked potential". It usually refers to responses recorded from the occipital cortex. Sometimes, the term "visual evoked cortical potential" (VECP) is used to distinguish the VEP from retinal or subcortical potentials. Some specific VEPs are: **P300 Potentials**.

4.1. P300 Potentials

The P300 is a large brain signal that is evoked by novel and task relevant stimuli. These forms are designated P3a (novelty) and P3b (task relevance) [6]. The P300's name reflects that it is a positive signal that peaks **300** ms after the onset of stimulus. Most time related evoked potentials are named in this manner. The P300 is also referred to as the P3.



N1

Figure 4.1: P300 waveform.

The P3a appears frontally when the subject is aware of a novel or infrequent stimulus. For example, if the subject is presented with many low frequency tones intermixed with infrequent high frequency tones (e.g. lows tones occur five times as often as high tones), the high tones will evoke the P300 [5]. P3a experiments are often called *oddball* experiments referring to the infrequent stimuli being rare and different from frequent stimuli.

The P3b appears parietally when the subject is aware of a task relevant stimulus. For example, if the subject is repeatedly presented letters of the alphabet one letter at a time and is given a spelling task, the P300 will occur when the current letter the subject wants to 'type' is presented. The P300's amplitude is also smaller and may disappear if the subject is drowsy. The latency of the P300 increases with older subjects [5].The source site for the P300 in the brain is unknown; however, it is thought to be generated in the middle of the temporal lobe (medial-temporal); though, this is unproven. Because the P300 is evoked by many different tasks there may not be one source generator.

The P300 is a neural evoked potential component of the electroencephalogram (EEG). It is a late-appearing component of the event-related potential. P stands for positive voltage potential and 300 represents 300 millisecond post stimulus. Its amplitude increases with unpredictable, unlikely, or highly significant stimuli and thereby constitutes an index of mental activity. This event-related potential (ERP) appears as a positive deflection of the EEG voltage at approximately 300 ms. It is the signature of the users brain registering the event and typically occurs around 300ms after the infrequent event takes place It dominates at parietal electrode sites. The P300 is supposed to follow unexpected sensory stimuli or stimuli that provide useful information to the subjects according to his/her task [2].

History

Since the P300 is an extremely robust event-related potential, it is possible to see it without sophisticated analysis methods or devices. It was discovered early in the research of event-related potentials in 1965 by Sutter and colleagues [35]. Since then, an enormous amount of research has been done to study the nature of this deflection.

4.2 BCIs based on ERPs

The P300's robustness across multiple individuals and the lack of training required to utilize it makes it a desirable signal for BCIs. Donchin et al. [24, 38] used the P300 in a spelling BCI. Subjects were presented a six-bysix matrix of letters and numbers with intensifying rows or columns every 125 ms as stimuli. The subjects concentrated on a letter and mentally counted every time it intensified. In online trials 56% accuracy was achieved; offline processing showed communication rates of 7.8 characters/min at 80% accuracy and 4.8 characters/min at 90% accuracy. Bayliss [19] explored the P300 in environmental control using a virtual-reality environment where subjects were able to turn on or off a light, tv, and radio, and were able to make a virtual figure appear and disappear with Hi and Bye commands.

4.3 EEG Based Brain Computer Communication System.

The aim of this dissertation is to develop a Brain Computer Communication system, which predicts the correct character in each of the provided character selection epochs using the P300 event related potential. The P300 is a late positive wave that occurs between 250 and 800

milliseconds after the onset of a meaningful stimulus. Because of its robustness, the evoked electrical potential called P300, serves as a good candidate for an EEG-based computer interface. In these experiments, user focused on one out of 36 different characters. The objective in this dissertation is to predict the correct character in each of the provided character selection epochs.

4.3.1 Data description

The dataset has been obtained from Wadsworth research organization, New York USA. It represents a complete record of P300 evoked potentials recorded with BCI2000 using a paradigm described by Donchin[24] et al., 2000, and originally by Farwell and Donchin, 1988. In these experiments, a user focused on one out of 36 different characters. The objective here is to predict the correct character in each of the provided character selection epochs.

The user was presented with a 6 by 6 matrix of characters (see figure 4.2). The user's task was to focus attention on characters in a word that was prescribed by the investigator (i.e., one character at a time). All rows and columns of this matrix were successively and randomly intensified at a rate of 5.7Hz. Two out of 12 intensifications of rows or columns contained the desired character (i.e., one particular row and one particular column). The responses evoked by these infrequent stimuli (i.e., the 2 out of 12 stimuli that did contain the desired character) are different from those evoked by the stimuli that did not contain the desired character and they are similar to the

P300 responses previously reported (Farwell and Donchin, 1988, Donchin et al. [38]).

BCI2000 is a flexible Brain-Computer Interface research and development platform. It supports a variety of brain signals, signal processing methods, and user applications. It is currently used by 30 research groups for a variety of studies.

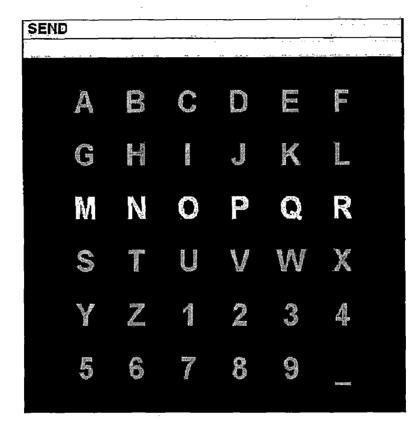


Figure 4.2: the user display for paradigm.

Data Collection

Signals have been collected (band pass filtered from 0.1-60Hz and digitized at 241Hz) from two subjects in five sessions each. Each session consisted of a number of runs. In each run, the subject focused attention on a series of characters. For each character epoch in the run, user display was as

follows: the matrix was displayed for a 2.5 s period, and during this time each character had the same intensity (i.e., the matrix was blank). Subsequently, each row and column in the matrix was randomly intensified for 100ms (i.e., resulting in 12 different stimuli – 6 rows and 6 columns). After intensification of a row/column, the matrix was blank for 75ms. Row/column intensifications were block randomized in blocks of 12. The sets of 12 intensifications were repeated 15 times for each character epoch (i.e., any specific row/column was intensified 15 times and thus there were 180 total intensifications for each character epoch). Each character epoch was followed by a 2.5 s period, and during this time the matrix was blank. This period informed the user that this character was completed and to focus on the next character in the word that was displayed on the top of the screen. The recorded 64 channel EEG signal is organized in one big matrix (Signal). The other relevant variables are described below. For each sample in the Signal matrix, associated events are coded using the following variables.

matrix is blank)

1...6 for intensified columns (1 ... left-most column)7...12 for intensified rows (7 ... upper-most row)

Stimulus Type: 0 when no row/column is being intensified or intensified row/column does not contain desired character 1 when intensified row/character does contain the desired character

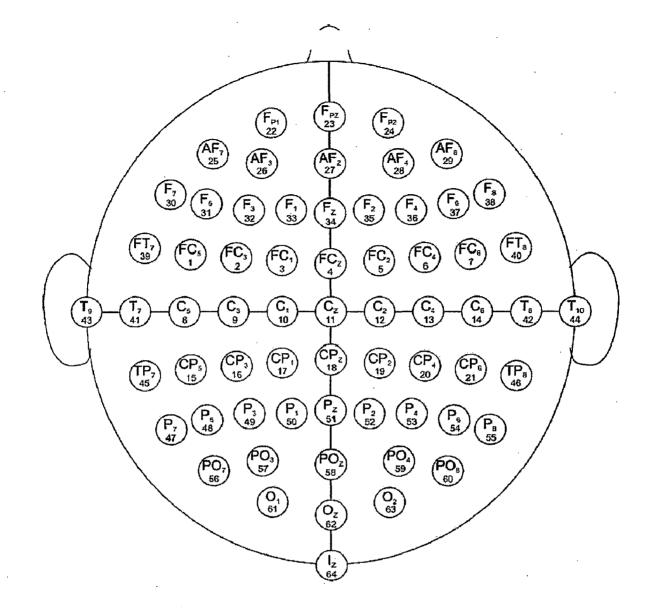


Figure 4.3: Electrode designations and channel assignment numbers as used in experiments.

This variable provides an easy access to the labels in the training sets in that it can be used to separate the responses that did contain the desired character from the ones that did not.

• For one or more channels, period of signal samples has been collected

at the start of each intensification, i.e., whenever Flashing changes from 0 to 1 (note: each character epoch of the data set starts at the first flash, i.e. Flashing=1 for the first data sample in each epoch).

• The signal sample has been accumulated in 12 separate buffers, according to the Stimulus Code of the corresponding stimulus. For each character epoch, each buffer should contain the 15 sample periods –one for each intensification of the given row/column. Each character in the matrix is represented by the row/column intersection.

The Figure 4.4 illustrates the assignment of the variable Stimulus Code to different row/column intensifications.

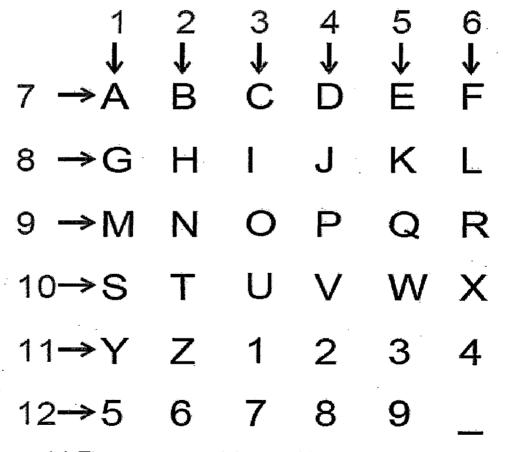


Figure 4.4: The assignment of the variable Stimulus Code to different row/column intensifications.

4.3.2 Signal processing of P300 component

The signal processing of evoked potentials remains a difficult and unsolved problem. Donchin noticed that in the P3 component of the evoked potential, not all P3 trials appear to have a good P3 peak. This may be due to a lack of "zeal" on the individual subject's part, normal subject signal variations, outside contamination of artifacts, or even just because of the low signal-tonoise ratio available from an EEG signal. It is not able that individual subjects may cause signal recognition problems and that signal processing cannot fix these problems. That is the job of the user interface. There are a variety of different techniques for dealing with recognition problems due to the noisiness of the signal and its occlusion by artifacts.

Not all P3 recognition techniques are suitable for use in an on-line BCI. Averaging over trials has been used to improve signal detection, but this technique requires a costly trade-off between recognition accuracy and the time taken to recognize a particular signal. In order to be useful in a BCI, this trade-off necessitates severely limiting the number of trials in an average. A compromise may be reached when single trials are only averaged when the recognition routine is unsure of its results. Peak picking and correlation are used individually for recognition of the P3 component. Recognition algorithms normally assume that the algorithm is responding to the presence of a P3 rather than the presence of one or more artifactual signals in raw EEG data.

4.3.3 Average

Traditionally, evoked potentials (EPs) are obtained by averaging EEG signals from specific electrode sites over many trials. Averaging to obtain an evoked potential contains the following benefits:

> It reduces the contribution from unrelated spontaneous EEG signals.

- > It reduces spurious noise.
- > It allows the observation of a response that would otherwise be unobservable.

An average may tell the clinician of an abnormality that a single trial could not, because of the natural variance in both the latency and morphology of an EP. Results suggest that P3 amplitude does not stabilize until approximately 20 trials have been averaged, although peak latency does not change significantly during this time frame.

4.3.4 Peak picking method

The simplest algorithm that is commonly used is called peak picking. The difference between a prototypical P3 and non-P3 (assuming not artifact) is the existence of a fairly large peak around 300 ms for the P3 that does not exist for the non-P3 trial. Thus, peak picking looks for trials with an amplitude difference greater than a specified voltage difference between the minimum and maximum voltage points within a specified time window. Peak picking has two parameters: the time window in which to look for the peak and the voltage difference threshold that is needed in order to declare the peak a P3 component. For recognition, the time window with the best results was between three and six hundred milliseconds. The voltage difference parameter was varied in experiments to yield the best result.

Peak picking offers the benefit of knowing when there is a P3 peak. As suggested by Donchin, there is not always a good peak in the appropriate time frame. In addition, peak picking suffers from the drawback of responding poorly in the presence of spurious high frequency noise and artifacts. Since single trials were recognized, it was necessary to an 8 Hz low pass filter in order to reduce this higher frequency noise contamination. Eye movements will contaminate the activity in the more anterior electrodes with the effect generally lessening towards the more posterior electrodes. If eye movements aren't accounted for in a peak picking situation, the subject may be able to achieve the desired results by moving the eyes rather than by a neural event. One of the goals of looking at the peak picking algorithm was to find out exactly what kinds of effects varying degrees of artifact had on recognition. As the data has been obtained from research organization there is no problem of artifacts. The data is free from artifacts and spurious high frequency noise. So peak picking algorithm offers greater advantages when data is free from artifacts.

4.4 Algorithm:-

Step1: start GUI

Step2: select the desired character from the list of alphabetsStep3: calculate trial length and convert it from milliseconds to samplesStep4: load data file for different sessions and different runs

Step5: evaluate loaded data file i.e. signal matrix and stimulus code, stimulus type etc

Step6: calculate the desired character using stimulus type and stimulus code

by which the desired character can be found

Step7: display the desired character

Step8: set trial numbers from 0 to 100 trials

Step9: calculate maximum stimulus code, initiate stimulus data and stimulus count

Step10: select the electrode location cz. for conditional loop to evaluate 50 trials each session for the corresponding electrode location

Step11: get indices of that particular trials e.g. from 0 to 50 trials

Step12: get data for these particular samples from trial data

Step13: apply **set Confilter**

Step14: calculate current stimulus type and stimulus code. Continuously update these values for different trials

Step15: if conditional loop to store values in two matrices depending on stimtypeStim type=0 then store values in avgdata1,else avg data 2

Step16: calculate average responses of stimuli with conditional loop stimulus=1 tomax stimulus code .if max stim code is 10 then loop1:10

Step17: calculate stimulus data

Step18: calculate average trials for each channel

Step19: conditional loop to plot figures

Step20: plot average responses of 36 grid positions

Step 21: plot response for all stimulus codes

Step22: using peak picking algorithm, (which looks for trials with an amplitude difference greater than a specified voltage difference between the minimum and maximum voltage points within a specified time window), find out the peaks of different grid positions from 300 to 400ms.

Step23: select the one with max peak as the result from BCI

Step24: display result

Step25: check whether the desired character and result from the bci are same and the corresponding letter has maximum peak at 310ms
Step26: end

5.0 Results and Discussions

In this chapter results have been presented and the corresponding figures have been plotted. The figure5.1 represents the GUI of EEG based communication system developed in this work. In this system there are nine characters as inputs namely b, c, d, f, g, h, r, s, and w. The data has been recorded in two sessions comprising of different runs. Each of the nine characters is associated with same/different sessions and different runs. After selecting the character, the average responses of all the characters are plotted and the response of the desired character is compared with other characters.

	COMMUNICA		-1VI	
Input Select Character	Select a Character		<u>ok</u>	
- Panel				
Difference	Standard/Oddball	Stimulus Response	Character Response	
		Result .		
Desired		Predicted		1

Figure 5.1 : GUI of EEG BASED BRAIN COMPUTER COMMUNICATION SYTEM

Table 5.1 represents the time course of average signal waveforms at cz locations. Here oddball represents the response of row/column that contained desired character and standard ball represents the row/column response that did not contain desired character. Values are tabulated below

· · · · · · · · · · · · · · · · · · ·	Samples 1 to 46		46 to 92	Samples	92 to	Samples	138 to
-		-		138		1 Š 6	
standard	oddball	standard	oddball	standard	oddball	standard	oddball
-382.439	-426.732	-523.51	-508.88	-403.76	-247.53	-361.41	-363.29
-427.512	-537.756	-517.66	-450.15	-175.06	-100.71	-284.24	-320
-602.537	-526.829	-427.12	-465.17	-320	-400.94	-268.24	-279.53
-468.488	-452.488	-428.88	-507.51	-285.18	-268.24	-352	-284.24
-444.683	-405.463	-629.46	-570.15	-311.53	-260.71	-295.53	-473.41
-410.537	-468.878	-482.73	-460.1	-312.47	-352.94	-461.18	-399.06
-448	-393.171	-480.78	-403.9	-359.53	-272.94	-272	-237.18
-384.585	-401.561	-395.71	-440.98	-345.41	-438.59	-212.71	-247.53
-362.537	-394.342	-410.54	-415.02	-449.88	-417.88	-309.65	-409.41
-360.585	-363.122	-398.05	-428.68	-455.53	-287.06	-372.71	-498.82
-399.415	-395.122	-387.51	-396.29	-320.94	-418.82	-490.35	-533.65
-340.683	-367.415	-372.68	-351.8	-380.24	-418.82	-486.59	-351.06
-405.463	-408	-378.54	-360.2	-528.94	-560	-434.82	-358.59
-355.707	-422.244	-327.02	-371.9	-516.71	-376.47	-331.29	-472.47
-433.756	-398.829	-406.83	-413.85	-318.12	-362.35	-517.65	-552.47
-374.829	-342.244	-381.46	-444.68	-286.12	-276.71	-442.35	-493.18
-365.268	-392.39	-461.07	-397.66	-225.88	-180.71	-495.06	-467.76
-352.976	-355.122	-357.07	-320.59	-248.47	-271.06	-419.76	-418.82
-330.342	-298.732	-381.46	-384.98	-329.41	-302.12		
-228.878	-299.317	-328.78	-326.24	-243.76	-176.94		
-347.902	-376.781	-336.39	-300.88	-205.18	-143.06		
-370.146	-439.22	-245.46	-327.61	-35.765	-24.471		
-487.61	-479.024	-357.27	-350.24	-74.353	11.2941		
-452.098	-421.268	-364.88	-431.8	-37.647	-103.53		
-397.268	-432.585	-470.05	-436.1	-80	0		
-426.342	-509.268	-443.51	-390.63	76.2353	210.824		
-603.122	-529.756	-358.24	-436.1	109.177	-7.5294		
-455.024	-444.683	-421.07	-496.2	-21.647	-37.647		

 Table 5.1: Average response for standard and oddball

				_			
-451.317	-400.39	-602.73	-530.54	-67.765	-11.294		
-399.805	-449.171	-463.8	-428.88	22.5882	16	1	
-453.268	-449.561	-438.05	-387.51	-22.588	-5.6471	1	· · · · · ·
-413.463	-428.878	-377.76	-428.29	-90.353	-92.235		*
-373.073	-416.195	-354.82	-366.12	-203.29	-213.65	<u> </u>	
-381.659	-360	-378.35	-329.41	-102.59	-96.941		· · · · · · · · · · · · · · · · · · ·
-432.976	-436.488	-539.29	-564.71	-115.76	-241.88	+	
-405.854	-449.951	-505.41	-416	-333.18	-438.59		+
-472.39	-488.39	-404.71	-410.35	-414.12	-322.82		
-437.659	-483.317	-309.65	-232.47	-306.82	-312.47	<u></u>	
-482.342	-434.146	-288	-445.18	-249.41	-336.94		
-428.488	-410.732	-352.94	-358.59	-354.82	-461.18		· · · · · · · · · · · · · · · · · · ·
-457.756	-484.293	-404.71	-378.35	-513.88	-415.06	- <u> </u>	- <u></u>
-415.22	-408.976	-324.71	-242.82	-344.47	-318.12	<u> </u>	<u></u>
-387.317	-359.805	-372.71	-341.65	-231.53	-304.94		<u></u>
-301.463	-372.878	-334.12	-380.24	-261.65	-187.29	· · · ·	
-409.951	-419.317	-396.24	-420.71	-475.29	-518.59	+ <u>-</u> (-)	
-402.342	-495.805	-402.82	-398.12	-365.18	-358.59	1	1

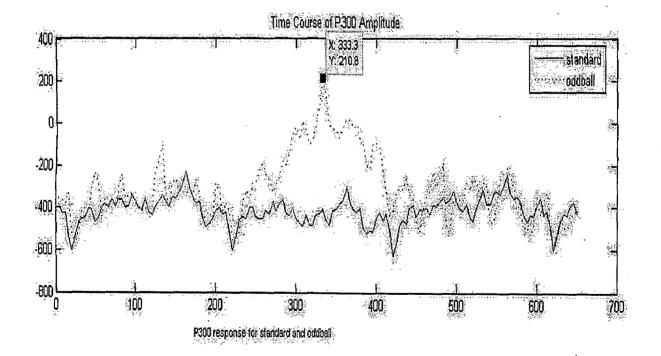


Figure 5.2: Average Response of standard and oddball condition

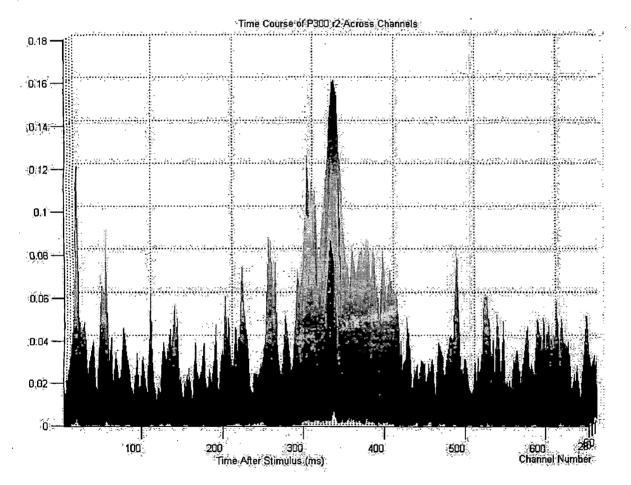
Average response of two conditions standard and oddball paradigms has been plotted in figure 5.2 using the values given in table 5.1. The oddball response in the figure indicates the p300 response of subject responding to some stimuli. The positive peak occurred in between 300-400msec indicates the presence of P300 ERPs which occur generally after 300 m sec of the stimuls onset.

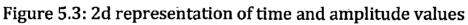
In this work the response of only one electrode position cz has been considered since P300 response is best reflected at cz location. Until now no reasons have been found as to why P300 is best reflected at cz locations. Table 5.2 indicates the values used to plot, the discriminability between standard and oddball as a function of time and channels.

Time course of p300 response for channel (11)								
0.0003	0.0013	0.1033	0.0142					
0.0017	0.0001	0.129	0.0007					
0.0017	0.0053	0.1146	0.0001					
0.0278	0.0003	0.0835	0.0008					
0.0025	0	0.0607	0.001					
0.0008	0.0007	0.0551	0.0038					
0.0006	0.0021	0.0404	0.0062					
0.0005	0	0.0672	0.0158					
0.0006	0.0084	0.0531	0.0059					
0	0.0025	0.0685	0					
0.0042	0.0001	0.0751	0.0004					
0.023	0.0015	0.0844	0.0027					
0.0137	0.0052	0.045	0.0029					
0.0018	0.0034	0.0809	0.007					
0.0006	0.0005	0.0496	0.0021					
0.0011	0.0017	0.0492	0.0016					
0.001	0.0018	0.0838	0.0022					
0.0001	0.0068	0.0583	0.0005					
0.0007	0.0007	0.0423	0.0029					
0.0072	0.0054	0.0234	0.0012					
0.0004	0.0123	0.0064	0.0018					
0.0016	0.0277	0.003	0					
0	0.0471	0.0288	0.0023					
0.0001	0.0172	0.0317	0.0002					
0	0.0146	0.0137	0.0053					
0.0001	0.0011	0.0086	0.0009					
0.0009	0.0071	0.0208	0.0007					

Table 5.2: Time course of p300 response

-			and the second
0.0002	0.0105	0.0021	0.0025
0.0004	0.017	0.0007	0.0028
0.0096	0.0314	0.0002	0.0055
0.016	0.0494	0.0058	0.0004
0.0193	0.0698	0	0.0044
0.0007	0.0822	0.0019	0.0003
0 .	0.0596	-0.01038	0.0002
0.0018	0.0961	-0.01365	0.0016
0.003	0.0658	-0.01692	0.0013
0.0001	0.0582	-0.02019	0.0031
0.0008	0.066	-0.02346	0.0007
0.0035	0.0785	-0.02673	0.00001







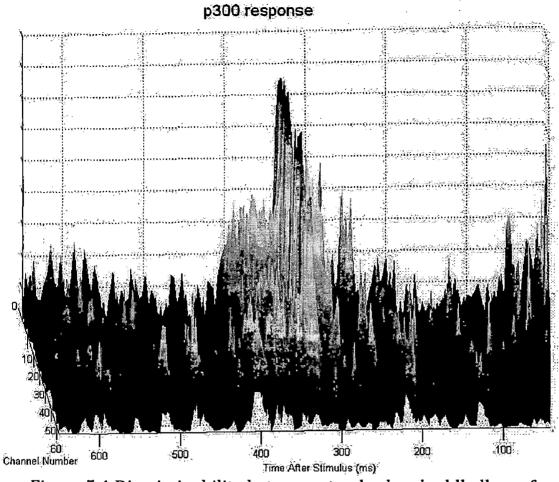


Figure 5.4:Discriminability between standard and oddball as a function of time and channels.

Figures 5.3 and 5.4 indicate the discriminability between standard and oddball as a function of time and channels. In this work channel cz has been considered. From figure it is clear that peak occurred after 300msec that indicates P300 response. Responses for all the channels are plotted in the figures but area of interest lies in channel cz.

The ERP response of the twelve stimuli has been given in the table 5.3

TABLE 5.3: ERP RESPONSES OF 12 STIMULI

$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.328 -0.5 0.526 -0.5 0.414 -0.57 0.598 -0.50 0.672 -0.5 0.718 -0.55 0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	4 -0.1244 8 -0.2596 2 -0.3342 5 -0.6347 6 -0.3342 8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.7 -0.61	-0.278 -0.196 -0.31 -0.63 -0.644 -0.624 -0.616 -0.484 -0.23 -0.268
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.414 -0.57 0.598 -0.50 0.672 -0.5 0.718 -0.55 0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	8 -0.2596 2 -0.3342 5 -0.6347 6 -0.3342 8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.7 -0.61 -0.652 -0.53 -0.454 -0.434 -0.5 -0.502	-0.31 -0.63 -0.644 -0.624 -0.616 -0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.598 -0.50 0.672 -0.5 0.718 -0.55 0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	2 -0.3342 5 -0.6347 6 -0.3342 8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.61 -0.652 -0.53 -0.454 -0.434 -0.5 -0.502	-0.63 -0.644 -0.624 -0.616 -0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.672 -0.5 0.718 -0.55 0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	5 -0.6347 6 -0.3342 8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.64 -0.652 -0.53 -0.454 -0.434 -0.5 -0.502	-0.644 -0.624 -0.616 -0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.718 -0.55 0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	6 -0.3342 8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.652 -0.53 -0.454 -0.434 -0.5 -0.502	-0.624 -0.616 -0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.714 -0.50 0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	8 -0.3556 8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.53 -0.454 -0.434 -0.5 -0.502	-0.616 -0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.704 -0.45 0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.546 -0.44	8 -0.2791 8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.454 -0.434 -0.5 -0.502	-0.484 -0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.888 -0.51 0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	8 -0.1938 2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.434 -0.5 -0.502	-0.23
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.504 -0.5 0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	2 -0.2542 2 -0.2684 4 -0.3627 8 -0.2702	-0.5 -0.502	
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$	0.532 -0.59 -0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	2 -0.2684 4 -0.3627 8 -0.2702	-0.502	-0.268
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	-0.48 -0.57 0.492 -0.39 0.546 -0.44 -0.41 -0.3	4 -0.3627 8 -0.2702		
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	0.492 -0.39 0.546 -0.44 -0.41 -0.3	8 -0.2702	-0 <i>4</i>	-0.396
-0.434 -0.4267 -0.29 -0.406 -0.226 -0.4462 -0.296 -1 -0.312 -0.256 -0.316 -0.474 -0.37 -0.3289 -0.44 -0.438 -0.1991 -0.27 -0.446 -0.274 -0.2436 -0.574 -1 -0.524 -0.1938 -0.322 -0.344 -0.148 -0.4249 -0.514 -1 -0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 -1 -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 -1 -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -1	0.546 -0.44 -0.41 -0.3		-0.4	-0.59
-0.312 -0.256 -0.316 -0.474 -0.37 -0.3289 -0.44 -0.438 -0.1991 -0.27 -0.446 -0.274 -0.2436 -0.574 -1.574 -0.524 -0.1938 -0.322 -0.344 -0.148 -0.4249 -0.514 -1.636 -0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 -1.636 -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 -1.598 -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -1.558	-0.41 -0.3		-0.42	-0.48
-0.438 -0.1991 -0.27 -0.446 -0.274 -0.2436 -0.574 - -0.524 -0.1938 -0.322 -0.344 -0.148 -0.4249 -0.514 - -0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 - -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 - -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -		4 -0.3502	-0.554	-0.404
-0.524 -0.1938 -0.322 -0.344 -0.148 -0.4249 -0.514 - -0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 - -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 - -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -	-0.524 -0.48	8 -0.4267	-0.54	-0.312
-0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 - -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 - -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -		8 -0.4142	-0.562	-0.338
-0.392 -0.1636 -0.492 -0.402 -0.388 -0.3289 -0.572 - -0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 - -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -	0.574 -0.38	2 -0.1956	-0.62	-0.232
-0.462 -0.1404 -0.516 -0.504 -0.494 -0.1369 -0.398 - -0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -	-0.512 -0.43	4 -0.1547	-0.64	-0.286
-0.416 -0.3093 -0.558 -0.478 -0.388 -0.1529 -0.196 -	0.376 -0.53		-0.584	-0.164
	-0.368 -0.34		-0.616	-0.166
	-0.312 -0.47		-0.482	-0 .204
	-0.158 -0.3		-0.528	-0.374
	-0.17 -0.34			-0.394
	0.498 -0.3			
	0.454 -0.3		-0.336	-0.236
	-0.54 -0.42		-0.28	-0.246
	0.434 -0.36		-0.288	-0.196
	-0.52 -0.4		-0.346	-0.38
	0.458 -0.34		-0.308	-0.536
	0.376 -0.20		-0.324	-0.318
	0.458 -0.15		-0.262	-0.456
	-0.408 -0.12			-0.586
	-0.26 -0.25		-0.11	-0.628
· · · · · · · · · · · · · · · · · · ·	0.208 -0.31		-0.022	-0.614
	-0.388 -0.27		0.06	-0.48
	0.418 -0.31		0	-0.438
	0.354 -0.44			-0.424
•	-0.214 -0.35		-0.032	-0.324
	-0.236 -0.37			-0.21
	-0.508 -0.46			-0.444
· · · · ·	0.414 -0.46			-0.69
	0.482 -0.34			
	0.692 -0.42		-0.068	-0.756
	0.686 -0.58			-0.832
	0.892 -0.64		-0.288	-0.686
	0.654 -0.47		-0.262	-0.492
	0.586 -0.64		-0.254	-0.374
	0.544 -0.46		-0.228	-0.332
	0.332 -0.51		-0.226	-0.332 -0.198
	0.332 -0.31		-0.210	-0.198 -0.466
	0.700 -0.0.7		-0.192 -0.284	-0.466 -0.456
		0.0029	-0.204	-0.400
	-0.41 -0.44			.0 504
		6 -0.6311	-0.416 -0.52	-0.594 -0.692

Results and discussions

							•	I.C	suns am		510115
-0.432	-0.528	-0.414	-0.484	-0.496	-0.5742	-0.63	-0.56	-0.544	-0.6844	-0.516	-0.534
-0.446	-0.4107	-0.438	-0.592	-0.212	-0.496	-0.662	-0.452	-0.54	-0,6489	-0.326	-0.344
-0.314	-0.4924	-0.4 06	-0.448	-0.326	-0.2809	-0.524	-0.312	-0.484	-0.7751	-0.408	-0.394
-0.36	-0.5067	-0.668	-0.448	-0.524	-0.2222	-0.326	-0.266	-0.426	-0.7716	-0.354	-0.242
· -0.274	-0.4338	-0.788	-0.38	-0.328	-0.2276	-0.422	-0.308	-0.514	-0.5404	-0.222	-0.286
-0.226	-0.512	-0.752	-0.29	-0.438	-0.224	-0.294	-0.192	-0.356	-0.6293	-0.356	-0.266
-0.194	-0.6062	-0.746	-0.306	-0.534	-0.1369	-0.324	-0.29	-0.434	-0.6631	-0.432	-0.35
-0.124	-0.4302	-0.618	-0.384	-0.64	-0.1191	-0.392	-0.366	-0.346	-0.656	-0.39	-0.51
-0.334	-0.4587	-0.364	-0.318	-0.534	-0.2116	-0.308	-0.47	-0.146	-0.7556	-0.464	-0.45
-0.484	-0.4302	-0.404	-0.502	-0.262	-0.2667	-0.166	-0.562	-0.228	-0.7022	-0.38	-0.204
-0.624	-0.5013	-0.418	-0.622	-0.354	-0.1351	- 0.1 06	-0.432	-0.424	-0.5973	-0.34	-0.264
-0.59	-0.512	-0.502	-0.32	-0.368	-0.256	-0.05	-0.23	-0.412	-0.4587	0.184	-0.488
-0.49	-0.5084	-0.45	-0.356	-0.296	-0.208	-0.184	-0.46	-0.408	-0.5653	-0.412	-0.41
-0.458	-0.5049	-0.714	-0.29	-0.276	-0.1796	-0.012	-0.4	-0.316	-0.4693	-0.412	-0.254
-0.458	-0.3129	-0.892	-0.18	-0.308	-0.08	0.016	-0.416	-0.286	-0.4124	-0.336	-0.3
-0.318	-0.4907	-0.69	-0.302	-0.404	-0.1689	-0.122	-0.51	-0.246	-0.6169	-0.496	-0.35
-0.42	-0.5991	-0.516	-0.306	-0.456	-0.1422	-0.282	-0.324	-0.144	-0.5084	-0.468	-0.456
-0.41	-0.3556	-0.438	-0.328	-0.518	-0.1529	-0.078	-0.392	0.096	-0.3964	-0.678	-0.472
-0.394	-0:5013	-0.382	-0.364	-0.594	-0.016	-0.242	-0.336	-0.034	-0.4338	-0.728	-0.52
-0.516	-0.6773	-0.286	-0.482	-0.566	-0.0516	-0.196	-0.37	-0.1	-0.3644	-0.818	-0.436
-0.436	-0.5511	-0.172	-0.634	-0.752	0.0693	-0.356	-0.57	-0.054	-0.4018	-0.66	-0.354
-0.342	-0.5262	-0.168	-0.594	-0.706	-0.0267	-0.384	-0.15	-0.05	-0.4	-0.688	-0.412
-0.48	-0.5991	-0.38	-0.416	-0.528	0.0356	-0.608	-0.174	-0.26	-0.4676	-0.68	-0.488
-0.366	-0.6027	-0.448	-0.376	-0.564	0.1884	-0.514	-0.368	-0.382	-0.4053	-0.728	-0.446
-0.432	-0.5582	-0.536	-0.368	-0.71	0.1973	-0.242	-0.27	-0.222	-0.4213	-0.626	-0.164
-0.216	-0.7022	-0.528	-0.312	-0.768	0.0942	-0.328	-0.342	0.056	-0.2418	-0.712	-0.124
-0.332	-0.6987	-0.37	-0.25	-0.73	0.1653	-0.212	-0.352	0.262	-0.3236	-0.568	-0.246
-0.5	-0.5902	-0.494	-0.422	-0.708	-0.0142	-0.206	-0.384	0.248	-0.3929	-0.542	-0.33
-0.452	-0.6293	-0.59	-0.696	-0.664	-0.0978	-0.34	-0.28	0.094	-0.4071	-0.536	-0.24
-0,442	-0.3716	-0.65	-0.716	-0.634	-0.2009	-0.182	-0.3	0.18	-0.4498	-0.368	-0.04
-0.416	-0.3324	-0.8	-0.648	-0.57	-0.1529	-0.144	-0.188	0.092	-0.4978	-0.438	-0.054
-0.346	-0.2471	-0.648	-0.596	-0.608	-0.1796	-0.452	-0.026	0.058	-0.4356	-0.322	-0.204
-0.408	-0.2862	-0.504	-0.388	-0.546	0.0338	-0.606	-0.08	-0.062	-0.3396	-0.392	-0.06
-0.306	-0.1298	-0.486	-0.384	-0.472	-0.0231	-0.616	0.06	0.074	-0.2364	-0.372	-0.102
-0.256	-0.3182	-0.4	-0.282	-0.504	0.0196	-0.712	-0.2	0.012	-0.4373	-0.452	-0.166
-0.48	-0.4569	-0.258	-0.392	-0.548	0.0178	-0.65	-0.154	-0.068	-0.3911	-0.57	-0.196
-0.58	-0.4427	-0.122	-0.506	-0.684	-0.0658	-0.668	-0.196	0.062	-0.3271	-0.532	-0.144
-0.388	-0.4516	-0.038	-0.47	-0.592	-0.1671	-0.8	-0.29	-0.004	-0.3627	-0.568	-0.062
-0.542	-0.384	-0.08	-0.6	-0.75	-0.1493	-0.876	-0.424	-0.028	-0.5476	-0.646	-0.116
-0.566	-0.4249	-0.218	-0.612	-0.988	-0.2382	-0.64	-0.482	-0.164	-0.5529	-0.55	-0.21
-0.524	-0.5582	-0.298	-0.524	-0.902	-0.2311	-0.598	-0.376	-0.194	-0.5938	-0.314	-0.384
-0.58	-0.736	-0.342	-0.77	-0.742	-0.2898	-0.626	-0.368	0.108	-0.4587	-0.296	-0.238
-0.494	-0.7431	-0.372	-0.552	-0.658	-0.2507	-0.58	-0.316	0.076	-0.3644	-0.118	-0.278
-0.444	-0.7538	-0.204	-0.57	-0.448	-0.2311	-0.448	-0.374	0.014	-0.3644	-0.182	-0.45
-0.428	-0.8284	-0.362	-0.55	-0.422	-0.432	-0.352	-0.52	-0.028	-0.3662	-0.298	-0.492
-0.328	-0.4889	-0.31	-0.586	-0.528	-0.4373	-0.41	-0.482	-0.216	-0.448	-0.37	-0.328
-0.422	-0.5529	-0.314	-0.738	-0.576	-0.3502	-0.516	-0.636	-0.538	-0.4907	-0.484	-0.342
-0.48	-0.8729	-0.526	-0.506	-0.676	-0.352	-0.612	-1.006	-0.484	-0.5724	-0.628	-0.392
-0. 4 0	-0.6667	-0.422	-0.53	-0.734	-0.332	-0.62	-0.914	-0.404 -0.416	-0.4569	-0.628 -0.664	-0.392 -0.4
-0.230	-0.4551	-0.422	-0.532	-0.734	-0. <u>1</u> 813	-0.694	-0.914	-0.448	-0.352	-0.664 -0.4	-0.4
-0.432 -0.652	-0.4533	-0.378 -0.166	-0.532	-0.5 -0.558	-0.1013 -0.1031	-0.694 -0.788	-0.72	-0.448 -0.548	-0.352 -0.3591	-0.4 -0.494	
-0.652	-0.4533 -0.6347	-0.166	-0.336	-0.556 -0.578							-0.272
-0.66 -0.66	-0.6347 -0.4462			-0.578	-0.1476 -0.3324	-0.664	-0.452	-0.364	-0.6756	-0.52	-0.158
-0.66 -0.558		-0.28	-0.178 0.356		-0.3324	-0.59 0.574	-0.41	-0.342	-0.3662	-0.44	-0.168
-0.000	-0.4053	-0.31	-0.356	-0.414	-0.2827	-0.574	-0.48	-0.436	-0.3289	-0.444	-0.094
					50						

53.

Results and discussions

								N.	suns ain	i discus	210112
-0.526	-0.5511	-0.392	-0.16	-0.288	-0.4836	-0.582	-0.626	-0.436	-0.5973	-0.574	-0.08
-0.498	-0.448	-0.278	-0.302	-0.188	-0.5938	-0.442	-0.67	-0.424	-0.64	-0.39	-0.216
-0.368	-0.4747	-0.344	-0.386	-0.284	-0.4907	-0.592	-0.592	-0.33	-0.4782	-0.348	-0.268
-0.33	-0.3342	-0.422	-0.302	-0.392	-0.3164	-0.57	-0.49	-0.376	-0.4889	-0.346	-0.302
-0.356	-0.3609	-0.484	-0.236	-0.416	-0.3271	-0.58	-0.484	-0.308	-0.6276	-0.51	-0.216
-0.286	-0.5102	-0.158	-0.182	-0.254	-0.288	-0.604	-0.564	-0.168	-0.5796	-0.41	-0.288
-0.278	-0.6489	-0.266	-0.356	-0.416	-0.2062	-0.53	-0.428	-0.416	-0.5173	-0.438	-0.038
-0.318	-0.7147	-0.376	-0.182	-0.506	-0.2258	-0.476	-0.188	-0.302	-0.544	-0.316	-0.042
-0.34	-0.5529	-0.222	-0.156	-0.476	-0.3307	-0.48	-0.396	-0.026	-0.5138	-0.22	-0.116
-0.434	-0.6951	-0.398	-0.28	-0.368	-0.4836	-0.22	-0.328	-0.466	-0.5867	-0.272	-0.138
-0.528	-0.4178	-0.446	-0.288	-0.122	-0.5049	-0.346	-0.398	-0.534	-0.6347	-0.176	-0.204
-0.45	-0.0889	-0.698	-0.132	-0.186	-0.448	-0.36	-0.418	-0.272	-0.6276	-0.206	-0.096
-0.582	-0.2418	-0.552	-0.182	-0.154	-0.4782	-0.43	-0.442	-0.224	-0.5618	-0.492	-0.074
-0.438	-0.1831	-0.472	-0.214	-0.5	-0.4391	-0.63	-0.308	-0.274	-0.6951	-0.522	-0.098
-0.508	-0.2738	-0.57	-0.18	-0.61	-0.3662	-0.572	-0.298	-0.36	-0.5849	-0.352	-0.186
-0.522	-0.3662	-0.482	-0.18	-0.432	-0.288	-0.366	-0.354	-0.28	-0.5493	-0.344	-0.2
-0.734	-0.4231	-0.41	-0.3	-0.42	-0.2311	-0.534	-0.368	-0.42	-0.464	-0.514	-0.28
-0.65	-0.4018	-0.638	-0.36	-0.59	-0.2116	-0.522	-0.554	-0.332	-0.3573	-0.528	-0.03
-0.708	-0.2098	-0.688	-0.356	-0.552	-0.2258	-0.252	-0.38	-0.34	-0.4889	-0.446	0.092
-0.78	-0.0889	-0.654	-0.32	-0.196	-0.3449	-0.122	-0.344	-0.36	-0.4462	-0.566	-0.076
-0.686	-0.0693	-0.618	-0.106	-0.062	-0.192	0.068	-0.536	-0.388	-0.6649	-0.47	-0.05
-0.78	-0.1796	-0.732	-0.224	-0.108	-0.1991	0.132	-0.55	-0.404	-0.752	-0.348	-0.252
-0.898	-0.2009	-0.604	-0.328	-0.15	-0.3876	0.17	-0.586	-0.57	-0.8178	-0.138	-0.266
-0.742	-0.2916	-0.372	-0.358	-0.138	-0 .3449	0.054	-0.444	-0.592	-0.7324	-0.106	-0.112
÷0.7	-0.4107	-0.374	-0.228	-0.26	-0.2293	0.19	-0.366	-0.59	-0.5831	-0.354	-0.134
-0.684	-0.6133	-0.216	-0.138	-0.386	-0.2151	0.212	-0.344	-0.336	-0.4587	-0.384	-0.302
-0.598	-0.5547	-0.14	-0.37	-0.466	-0.3324	0.032	-0.22	-0.13	-0.1458	-0.288	-0.246
-0.508	-0.3467	-0.138	-0.24	-0.18	-0.3004	0.07	-0.32	-0.114	-0.0693	-0.374	-0.358
-0.25	-0.5547	-0.314	-0.364	-0.296	-0.3093	-0.182	-0.302	-0.178	-0.0604	-0.54	-0.418
-0.142	-0.3876	-0.654	-0.33	-0.232	-0.4231	-0.374	-0.408	-0.182	-0.0587	-0.614	-0.406
-0.284	-0.3076	-0.52	-0.3	-0.264	-0.4569	-0.322	-0.38	-0.356	-0.1031	-0.69	-0.368
-0.34	-0.368	-0.572	-0.34	-0.47	-0.4942	-0.25	-0.296	-0.236	-0.1138	-0 .506	-0.424
-0.502	-0.4036	-0.766	-0.43	-0.562	-0.5938	-0.262	-0.264	-0.392	-0.2773	-0.484	-0.39
-0.434	-0.624	-0.636	-0.498	-0.482	-0.5636	-0.386	-0.354	-0.408	-0.3289	-0.566	-0.39 .
-0.554	-0.6489	-0.35	-0.456	-0.482	-0.6453	-0.354	-0.368	-0.408	-0.2098	-0.59	-0.35
-0.662	-0.6578	-0.312	-0.352	-0.576	-0.5404	-0.234	-0.37	-0.426	-0.32	-0.554	-0.386
-0.524	-0.6809	-0.078	-0.222	-0.41	-0.4124	-0.15	-0.452	-0.282	-0.3307	-0.67	-0.36
-0.532	-0.6276	-0.022	-0.252	-0.294	-0.544	-0.168	-0.416	-0.312	-0.2667	-0.628	-0.354
-0.584	-0.5262	-0.234	-0.12	-0.344	-0.5209	-0.346	-0.516	-0.176	-0.4071	-0.728	-0.548
-0.562	-0.5333	-0.284	-0.304	-0.436	-0.3804	-0.278	-0.44	-0.276	-0.4764	-0.53	-0.346
-0.606	-0.5156	-0.438	-0.406	-0.73	-0.3609	-0.526	-0.442	-0.598	-0.3502	-0.554	-0.41
-0.756	-0.5991	-0.56	-0.52	-0.858	-0.4533	-0.636	-0.622	-0.59	-0.5884	-0.568	-0.322
-0.804	-0.5049	-0.356	-0.316	-0.896	-0.5742	-0.626	-0.374	-0.528	-0.5191	-0.536	-0.378
-0.698	-0.4658	-0.104	-0.262	-0.97	-0.5084	-0.404	-0.428	-0.368	-0.4498	-0.422	-0.436
-0.83	-0.5991	-0.242	-0.17	-0.802	-0.5173	-0.392	-0.282	-0.466	-0.208	-0.492	-0.278
-0.9	-0.7431	-0.26	-0.17	-0.712	-0.5084	-0.168	-0.238	-0.48	-0.3182	-0.594	-0.276
-0.598	-0.7449	-0.004	-0.222	-0.59	-0.6062	-0.222	-0.268	-0.312	-0.2898	-0.516	-0.388
-0.704	-0.7449	-0.02	-0.222	-0.448	-0.4604	-0.326	-0.302	-0.374	-0.2133	-0.436	-0.300
-0.718	-0.736	-0.02	-0.302	-0.440 -0.644	-0.4004 -0.5244	-0.320	-0.382	-0.374	-0.2702	-0.430	-0.262
-0.710	-0.130	-0.024	-0.242	-0.044	-0.0244	-0.014	-0.002	-0.0	-0.2102	-0.072	-0.202

The averaged responses to each of the twelve stimuli have been given in the table 5.3. Stimuli 1-6 represent all rows and stimuli 8-12 represents all rows. The ERP response to all the rows and columns has been computed to identify the row and column with maximum P300 response. The figure 5.5 shows the responses to the different columns at Cz (stimuli 1-6) and rows (7-12) has been plotted.

ERP Responses To Each of 12 Stimuli									
	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~		$\sim$	~~ <u>+</u> ~~	<u> </u>				
-##E	180	200	300	400	500	600			
.::::::::::::::::::::::::::::::::::::::		بنجيبهم	ᡔ᠋᠆ᡔᡬᠯᠵ᠋᠆ᡔ			~~~~			
	100	200	300	400	500	600			
	<u></u>	$\sim\sim\sim\sim\sim\sim$		جريد فيجرح	~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~~	$\sim\sim\sim\sim\sim$			
	100	200	300	400	500	600			
	$\overline{}$	<u> </u>							
	100 	200	300	400	500	600			
.1888	100	200	200	400	<u></u>	600			
m8=			300	400	500 ⁶ محمد ا				
.1868	100	200	300	400	500	600			
-1688									
-1000	100	200	300	400	500	600			
. jail E	<u>جينية المناطقة من المناطقة المناطقة من من المناطقة من المناطقة من </u>		$\sim$		بمسليتين				
-1000	100	200	300	400	500	600			
			$\sim \sim \sim \sim$			حجليت			
	100	200	300	400	500	600			
.nelle~~~				$\sim + \sim \sim$					
ňœ	100	200	(300)	400	500	600,			
.1881									
	100	200	380	400	500	600			
.i88			$\sim$						
	ាហា	200	300	4∩∩	ะสาท	ភាព			

Figure 5.5: Responses to the different columns at Cz (stimuli 1-6) and rows 7-12)

Erp responses to all rows and columns have been plotted. The user task was to focus attention on characters and whenever the row/ column containing the desired letter flashes he counts the number of times it flashes. So in one way he is doing some mental task which means he is responding to the stimuli. Therefore the P300 potentials are evoked which are reflected in EEG.

In this work the results for the character"R" has been plotted. So the stimuli of the particular row and column i.e. 6 and 9 should have maximum P300 response.

In figure 5.6 the Averaged responses for each character in the matrix for channel Cz has been plotted. But average values only for letters m, n, o, p, q, r has been tabulated.

			·		· · · · · · · · · · · · · · · ·				
	average response results for characters m,								
		·	n,0,p,c	,r					
-478	-525	-504	-557	-566	-584				
-510	-499	-540	-636	-650	-581				
-526	-439	-346	-463	-453	-413				
-499	-380	-542	-448	-311	-266				
-315	-373	-382	-426	-346	-188				
-30	-81	-107	-243	-292	-391				
-426	-307	-222	-309	-295	-230				
-273	-495	-656	-549	-619	-532				
-540	-447	-414	-383	-525	-488				
-493	-399	-393	-394	-291	-314				
-235	-240	-356	-524	-501	-449				
-387	-372	-282	-282	-157	-214				
-308	-245	-196	-370	-374	-327				
-80	-35	-126	-179	-131	-162				
-144	-235	-116	-122	-274	-259				
-196	-285	-365	-359	-236	-209				
-215	-228	-272	-480	-482	-356				
-440	-600	-512	-501	-497	-481				
-461	-349	-353	-332	-227	-347				
-310	-183	-450	-531	-361	-403				
-356	-434	-401	-577	-491	-524				
-570	-537	-592	-734	-667	-645				
-510	-364	-311	-214	-162	-320				
-288	-447	-421	-481	-544	-403				

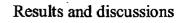
Table: 5.4 average response results for characters m, n, 0, p, q, r

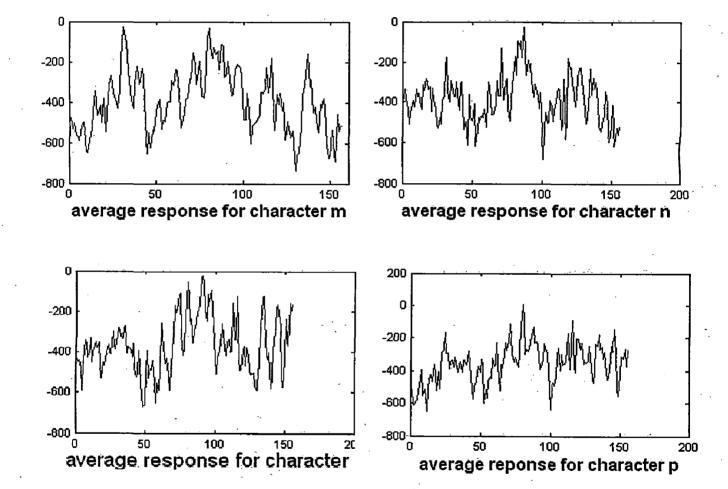
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-422	-380	-419	-602	-673	-666
-533	-648	-690	-455	-539	-509
-385	-	-385	-434.11	-506.11	-
	336.67				448.7
-416.67	-	-426.11	-337.33	-376	-
· · · ·	392.56				359.9
-395.44	-	-318	-343.56	-287.89	-
	435.33				298.8
-338.22	-	-447.89	-332.78	-395.22	-
<u>.</u>	326.67				430.6
-509.78	-	-474.56	-505.11	-390	-
	526.89				376.9
-225.56	-175	-348.33	-402.44	-296.11	-
					319.6
-375.11	-	-305.22	-405.56	-441.11	-
	374.56				307.3
-303.78	-534	-510.33	-495.78	-609	-
					366.3
-472.11	-	-473.56	-411.89	-612.33	-536
	491.22				
-475.33	-	-466.33	-473.89	-434	_
	488.22				520.1
-388.11	-	-329.11	-462.67	-462	-
	302.33				458.2
-410.44	-	-368.33	-371.56	-129.78	-
	299.44				267.7
-388.67	] -	-288.11	-429.56	-492.33	-
	302.56				390.1
-323.11	-	-171.11	-267.67	-95.778	-
	218.33				120.2
-94.556	-	-27.889	-153.11	-262.44	-
	174.11	1			190.3
-227.78	-206	-294.44	-376.11	-314	-
				-	333.6
-369.89	`	-352.44	-545.44	-678.44	-
ļ	428.22		ļ		541.3
· · · · · · · · · · · · · · · · · · ·	•	·	· · · · · · · · · · · · · · · · · · ·	<u> </u>	·

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-451.56	-	-499.33	-394.11	-420.67	-
	500.67	_•••••		. <u> </u>	493.6
-508.33	-	-580.56	-475.89	-180.44	-
	289.44				232.9
-228.56	-	-323.11	-421.56	-366.89	-
· .	316.89	. <u>.</u>			274.9
-224.44	-	-291.78	-385.44	-441.78	-
·	228.67				500.3
-474.67	] - [.]	-230.33	-366.33	-284.78	-
, , , , , , , , , , , , , , , , , , ,	342.33				331.8
-302	-	-516	-528.44	-541.89	-
	397.78	<u> </u>	· .	·	481.4
-469.78 -	-	-404.67	-556.78	-594.56	-
	351.11				516.4
-416.89	-	-611.56	-528.44	-559.44	-518
	532.56				
-434	-447	-441	-474	-589	-444
-346	-355	-428	-398	-332	-451
-401	-367	-348	-379	-352	-463
-526	-451	-466	-436	-401	-364
-398	-410	-297	-371	-384	-316
-284	-292	-325	-335	-278	-274
-404	-375	-379	-388	-423	-357
-489	-521	-508	-394	-546	-612
-672	-659	-497	-396	-525	-479
-489	-445	-547	-651	-554	-590
-482	-255	-316	-421	-457	-429
-515	-589	-468	-330	-171	-208
-193	-113	-109	-320	-415	-379
-236	-54	-123	-248	-235	-354
-295	-283	-206	-194	-163	-30
-21	-54	-191	-246	-117	-148
-95	-195	-263	-426	-505	-419
-413	-357	-262	-311	-373	-414
-351	-337	-399	-396	-163	-341
-339	-124	-432	-490	-485	-388

-373	-465	-381	-415	-485	-514
-507	-503	-568	-587	-482	-482
-276	-135	-126	-246	-418	-438
-404	-579	-522	-379	-369	-180
-167	-205	-280	-518	-575	-442
-236	-354	-370	-158	-197	-162
-515	-607	-613	-584	-581	-521
-455	-398	-554	-515	-557	-653
-505	-425	-427	-467	-363	-418





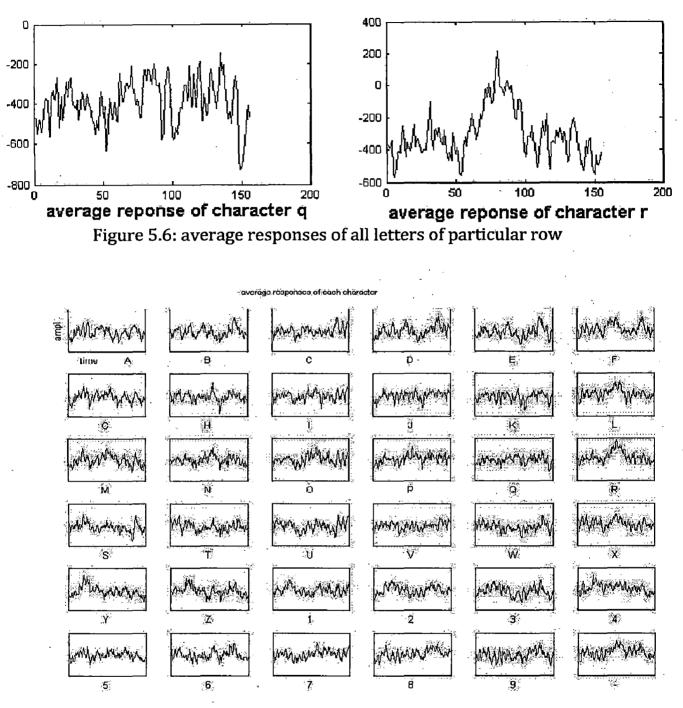




Figure 5.6 and 5.7shows the average responses of a particular row and responses of all characters respectively. The entire row containing character "R" has been plotted.

### Discussion

The sampling frequency of data is 240 Hz which means 240 samples per second. The data consists of a number of runs and session. The length of each run is 650 msec which when converted to samples is 156 samples. So the data have been plotted for 156 samples. The aim here is to find the P300 response which occurs after 300msec of the relevant stimuli. So 300msec is our target value. This 300msec when converted to samples is 72 samples. Although P300 wave is defined as a peak at 300 ms after a stimulus, it really occurs within 300 to 400 ms. So peak detection from samples 72 to 90 is done to detect the P300 response.

From the above figures indicating the character response of each character we can classify the samples having positive peak in between 300 to 350msec as the oddball condition. Once the samples containing p300 peaks are separated from the one that do not have any response it is easier to find out the peak of the particular character and find out the letter with maximum p300 peak. So the letter with maximum P300 peak in between 72 to 90 samples indicates that it is the desired character.

From the response of the figures it is clear that for character 'R' there occurred a positive peak at 80 th sample which indicates that it is the desired character. Letter 'R" is the intersecting element of the stimulus 6 and 9. From figure 5.5 stimuli 6 is having the maximum peak in between 300 -350msec and stimuli 9 is having peak. The response of every row and column are computed and the row and column having maximum response is found out. The intersecting element of that particular row and column is the desired character [2]. The intersecting element of stimuli 6 and 9 is the character "R". So character "R" is the desired letter. Initially "R" has been chosen as the desired character. The result from the algorithm is same as the one chosen at the beginning. So we can find out the desired character from the EEG data recorded during stimulus presentation.

6.0 Conclusions and Future Scope

The EEG based brain computer communication system designed in this work predicted the correct character in each of the provided character selection epochs using the P300 event related potential. In this work data from wadsworth organization have been used. Only one electrode location(cz)has been considered in detecting the P300 potentials. Averaging and peak picking algorithms have been used in this work for detection and classification of P300 potentials. Averaging to obtain an evoked potential contains the following benefits:

- It reduces the contribution from unrelated spontaneous EEG signals.
- It reduces spurious noise.
- ➢ It allows the observation of a response that would otherwise be unobservable.

Peak picking offers the benefit of knowing when there is a P3 peak. In this work, the responses of the 12 stimuli have been plotted and also the average response of the 36 letters used in detecting the desired letter has been plotted.

The EEG based brain computer communication system developed can provide basic communication and control functions to those with most severe neuromuscular disabilities.

#### **Future scope:**

BCI research is still in its infancy, its continued success depends on further exploration of neuroscience results, psychological methods, signal processing and machine learning algorithms, evaluation criteria, operation modes, and applications. The following list contains some proposals for further extensions to the work presented in this work.

• In this work averaging and peak picking algorithm have been used which yields better results when the data is free from artifacts and spurious high frequency noise. Peak picking offers the benefit of knowing when there is a P3 peak, but it suffers from the drawback of responding poorly in the presence of spurious high frequency noise and artifacts. As data has been has been imported which is a clean EEG data peak picking method is used for P300 detection. It achieved the accuracy of approximately 66% with some time delay.

•other methods such as support vector machines, SWDA, ICA used for classifying EEG signals to detect absence and presence of P300 component should be considered. These methods can be used for both online and offline analysis

•A latest and robust method for the detection of P300 is 'THE MEXICAN HAT WAVELET METHOD'. Developing a robust method using a few channels in P300 wave detection helps to move BCI to the realm of practicality. Better results may be achieved with this method.

For the future work, the use of a fuzzy logic system for classification of the generated features should be considered.

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