

AUDITORY BRAIN RESPONSE DETECTION USING A PORTABLE EEG HEADSET(EMOTIV EPOC)

by

Zeliha KOÇ SÖKER

BS, Computer Engineering, Fatih University, 2009

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**AUDITORY BRAIN RESPONSE DETECTION USING A
PORTABLE EEG HEADSET(EMOTIV EPOC)**

APPROVED BY:

Prof. Dr. Mehmed ÖZKAN
(Thesis Advisor)

Prof. Dr. Sadık KARA

Doc. Dr. Burak GÜÇLÜ

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ABSTRACT

AUDITORY BRAIN RESPONSE DETECTION USING A PORTABLE EEG HEADSET(EMOTIV EPOC)

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After the data acquisition phase, machine learning algorithms are applied to infer functions that can be used to classify signals. For reasons of practicality and simplicity, machine learning algorithms are usually divided into two modules: feature extraction and classification. The feature extraction module serves to transform raw neurophysiologic signals into a representation that makes classification easy. In other words, the goal of feature extraction is to remove noise and other unnecessary information from the input signals, while at the same time retaining information that is important to discriminate different classes of signals. Goal of feature extraction is to reduce the dimensionality of the data that has to be classified. After feature extraction, machine learning algorithms are used to solve two tasks. During training, the task is to infer a mapping between signals and classes. For this, the labeled feature vectors produced by the feature extraction module are used[10].

Keywords: EEG, ERP, Auditory Brain Response ABR.

ÖZET

TAŞINABİLİR EEG KAYDEDİCİSİ(EMOTIV EPOC) KULLANARAK İŞİTSEL BEYİN YANITI ALGILAMA

Türkçe tez özetini buraya yazınız. Özet bir sayfadan uzun olmamal ve referans içermemelidir.

Anahtar Sözcükler: Çeşitli, Anahtar, Sözcükleri, Buraya, Yazınız.

TABLE OF CONTENTS

ACKNOWLEDGMENTS	iii
ABSTRACT	iv
ÖZET	v
LIST OF FIGURES	viii
LIST OF TABLES	x
LIST OF SYMBOLS	xi
LIST OF ABBREVIATIONS	xii
1. INTRODUCTION	1
1.1 Motivation and Objectives	1
1.2 Outline of the Thesis	1
2. BACKGROUND	2
2.1 EVENT RELATED POTENTIALS	2
2.1.1 EEG	2
2.1.2 ERP	3
2.2 AUDITORY BRAIN RESPONSE	5
2.2.1 Human auditory system	5
2.2.2 Auditory Brain Response (ABR)	7
2.3 BLIND SOURCE SEPERATION	10
2.3.1 Principal Component Analysis	12
2.3.2 Independent Component Analysis	13
3. MATERIALS	15
3.1 Emotiv EPOC	15
3.2 Openvibe	16
3.3 Null-Modem Emulator (com0com)	16
3.4 Matlab-Eeglab	17
3.5 Weka	18
4. METHOD	19
4.1 Experiment Design	19
4.2 EEG Recordings	21

4.3	Signal Processing	22
4.4	Classification	25
5.	RESULTS	28
6.	DISCUSSION AND CONCLUSIONS	36
6.0.1	Discussion	36
6.0.2	Future Work	36
6.0.3	Conclusion	36
	APPENDIX A. SCRIPTS	37
A.1	Lua Script	37
A.2	MATLAB scripts	39
A.2.1	ICA Script	39
A.2.2	Feature Extraction Script	40
	REFERENCES	42

LIST OF FIGURES

Figure 2.1	Rhythmic EEG activity [1]	3
Figure 2.2	Visual representation of the cortex [2]	5
Figure 2.3	Anatomy and functional areas of brain [3]	6
Figure 2.4	Auditory System [4]	7
Figure 2.5	Central Auditory Pathway [5]	8
Figure 2.6	Primary auditory cortex. Brodmann's area 41-42 receives projections from the medial geniculate nucleus. Wernicke's area (secondary auditory area) is important for the interpretation of the spoken word. [6]	9
Figure 2.7	Idealized waveform of the computer-averaged auditory event-related potential (ERP) to brief sound. The ERP is generally too small to be detected in the ongoing EEG (top) and requires computer averaging over many stimulus presentations to achieve adequate signal noise ratios. The logarithmic time display allows visualization of the early brain-stem responses (Waves I-VI), the midlatency components (No, Po, Na, Pa, Nb), the 'vertex potential' waves (Pl, N1, P2), and task-related endogenous components (Nd, N2, P300, and slow wave). Source, Reprinted from Hillyard SA, Kutas M, 'Electrophysiology of Cognitive Processing.' Annual Review of Psychology 34 33 - 61, 1983. Copyright 1983, Annual Reviews. Used with permission from The Annual Review of Psychology, Volume 34	10
Figure 2.8	Principal component analysis (PCA) [?]	13
Figure 2.9	Independent component analysis (ICA) model [?]	14
Figure 3.1	Electrode locations used by the EPOC [7]	15
Figure 3.2	Specification of Emotiv Epoc [7]	16
Figure 4.1	Experiment procedure design in OPENVIBE	20
Figure 4.2	A recorded data on TestBench	21
Figure 4.3	Channel Data of EEG for 10 second	23

Figure 4.4	Component Data of EEG for 10 second	24
Figure 5.1	15 sec () 14 Channel EEG Data of one subject	29
Figure 5.2	14 Components of EEG Data of the same subject	29
Figure 5.3	14-Channel Silence Epochs For One Subject	30
Figure 5.4	14-Channel Sound Epochs For The Same Subject	30
Figure 5.5	Silence Component ERP epochs	31
Figure 5.6	Sound Component ERP epochs	31
Figure 5.7	Difference between silence and sound stimulation on 14 component	32
Figure 5.8	Difference between silence and sound stimulation ERP values for one component	32

LIST OF TABLES

Table 5.1	A portion of Feature Data	33
Table 5.2	Add caption	34
Table 5.3	=== Confusion Matrix ===	35

LIST OF SYMBOLS

a_{ij}	Description of a_{ij}
α	Description of α

LIST OF ABBREVIATIONS

AEP	Auditory Evoked Potential
VEP	Visual Evoked Potential

1. INTRODUCTION

In general terms, evoked potentials are electrical signals generated by the nervous system in response to a stimulus. Auditory evoked potentials (AEPs) are generated in response to an acoustic stimulus and AEPs are measured using electrodes on the surface of the skin or on the eardrum. Measuring the electrical response of auditory system gives many information about the status of individuals hearing.

Auditory brainstem response (ABR) audiometry is a neurologic test of auditory brainstem function in response to auditory stimuli.

1.1 Motivation and Objectives

1.2 Outline of the Thesis

2. BACKGROUND

2.1 EVENT RELATED POTENTIALS

2.1.1 EEG

Electroencephalography (EEG) is composed of two Greek words, "encephalon" (brain) and "graphein" (write). This is a diagnostic method to measure the electrical activity on the brain along the scalp over a period of time. German physiologist Hans Berger (1873-1941) recorded the first human EEG in 1924 [8].

The electric potential generated by single neuron cannot be picked up by EEG because it is far too small to be detected [9]. EEG can measure the summation of the synchronous activity of millions of neurons that have similar spatial orientation. If a pair of electrodes are attached to the surface of the human scalp and connected to a differential amplifier, as output of the amplifier a pattern of variation in voltage over time is seen. This voltage variation is known as the EEG. The amplitude of the voltage variation varies between nearly -100 and +100 microV, and its frequency ranges to 40 Hz or more.

Generally EEG waveforms are classified according to their amplitude, frequency, and location. The most familiar classification uses EEG waveform frequency, there are four major frequency bands on the EEG based on the brain functions. Alpha, beta, theta, and delta [10] [11]. The naming of the waves are related with the history. Alpha waves were among the first waves documented by Berger in 1920s.

- Delta Rhythms (0.5 - 4Hz) = Infants show irregular delta activity in the waking state, in adults it is associated with deep sleep.
- Theta Rhythms (4 - 8Hz) = These rhythms are frequently observed in young

children, and also in adults during phases of drowsiness or sleep.

- Alpha Rhythms (8 - 13 Hz) = These rhythms are particularly prominent in subjects who are relaxed and awake with their eyes closed are found on either side of the posterior regions of the head. Blocked or attenuated by attention, especially visual(occipitally), and mental effort.
- Beta Rhythms (14 - 30Hz) = Beta rhythms are associated with an activated cortex and can be observed during certain sleep stages. Occur in individuals who are alert and attentive to external stimuli or exert specific mental effort. The main points of observation are the frontal and central regions of the scalp.

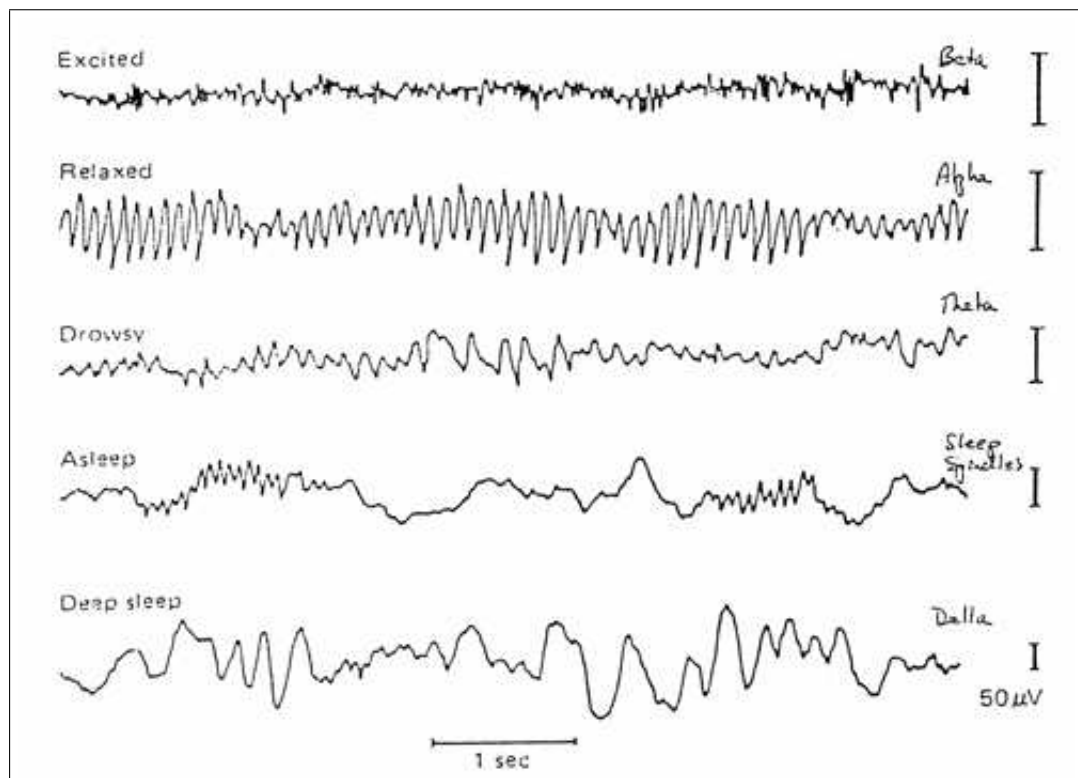


Figure 2.1 Rhythmic EEG activity [1]

2.1.2 ERP

If a stimulus is presented to a human subject while recording the EEG, we can define an epoch of the EEG that is time-locked to the stimulus. Within this epoch,

there may be voltage changes that are specifically related to the brain's response to the stimulus and it is known as event related potential. ERPs recorded from the scalp are not strictly depend on only one stimuli, they are related to 'a variety of processes that are invoked by the psychological demands of the situation' (Donchin et al. 1978, p. 350) and ERPs represent net electrical fields associated with the activity of sizeable populations of neurons. The individual neurons that comprise such a population must be synchronously active, and have a certain geometric configuration, if they are to produce fields that can be measured at the scalp[12].

Electrode locations are generally described with reference to the 10-20 system(Jasper 1958'). In this system, the location of an electrode is specified in terms of its proximity to particular regions of the brain (frontal, central, temporal, parietal, and occipital) and of its location in the lateral plane (odd number for left, the subscript z for midline, and even numbers for right). Although these electrode descriptors refer to particular brain areas, activity recorded at any particular scalp site is not necessarily attributable to activity in brain regions in close proximity to that site. This is because the brain acts as a volume conductor, meaning that electrical activity generated in one area can be detected at distant locations.

To obtain an ERP we need to record the voltage difference between two electrode sites. Recordings are based on the difference in voltage between each 'exploring' electrode and the same (common) reference electrode(s). To produce a waveform, the voltages at each of the electrodes are subtracted from each other by the amplifier. Electrical activity or noise that is common to both electrodes is canceled out and only the response voltage remains. This is called common mode rejection. The response voltage is then amplified. Popular reference selection is usually 'linked mastoid' reference, which consists of a linked pair of electrodes, one on each mastoid bone located behind each ear). The reference site is chosen so as to be relatively uninfluenced by the electrical activity of experimental interest[12].

There are some sections in the cerebral cortex that has with some specific functional activity in the brain. The cerebral cortex is divided into four sections, called

"lobes": the frontal lobe, parietal lobe, occipital lobe, and temporal lobe[2].

1. Frontal Lobe- associated with reasoning, planning, parts of speech, movement, emotions, and problem solving
2. Parietal Lobe- associated with movement, orientation, recognition, perception of stimuli
3. Occipital Lobe- associated with visual processing
4. Temporal Lobe- associated with perception and recognition of auditory stimuli, memory, and speech

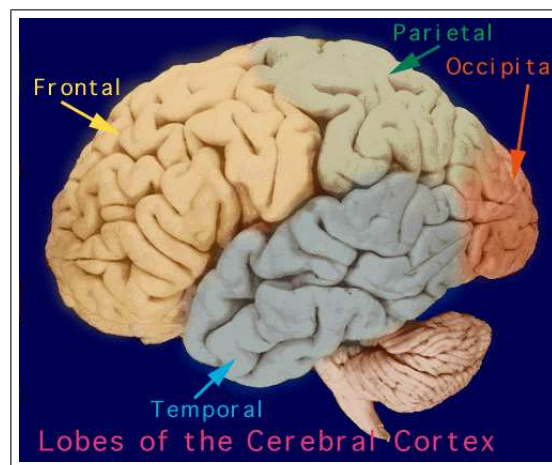


Figure 2.2 Visual representation of the cortex [2]

2.2 AUDITORY BRAIN RESPONSE

2.2.1 Human auditory system

The auditory system is the sensory system for the sense of sound waves. The system senses the sound(acoustical energy on the environment) and converts the acoustical energy into electrical energy to be processed and interpreted in the brain.

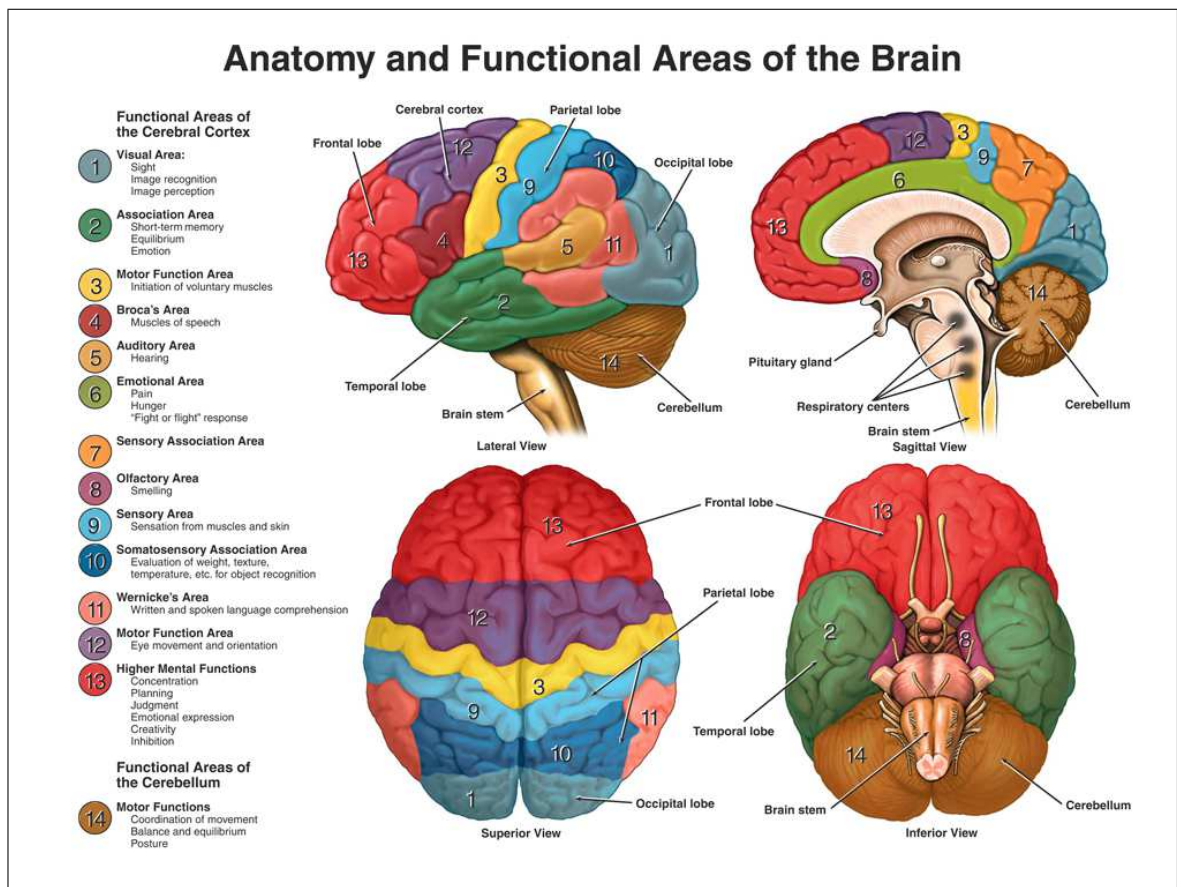


Figure 2.3 Anatomy and functional areas of brain [3]

The system has mainly two parts; Ear and auditory nervous system. The ear consists of three main parts; outer ear (ear + ear canal), the middle ear, and the inner ear. The working principle of all of these elements is not completely understood, but the functioning can be explained roughly.

The ear (scientifically 'pinna') collects the outer environment sound as an acoustical energy. The sound travels into ear canal. The ear canal boosts the sound and makes a little bit louder at certain frequencies. The travelled acoustical energy vibrates the eardrum.

The energy becomes mechanical energy with the movement of the eardrum. On the other side of the eardrum there are three tiny bones (ossicles) hammer, anvil and stirrup. These bones form the connection between the eardrum and the inner ear.

They increase and amplify the sound vibrations even more. The leveraged and boosted sound waves are transmitted to the inner ear.[13]

The inner ear (or the cochlea) is a spiral-shaped bony structure. It looks like the circular shell of a snail, and has a fluid filled tubes system. The mechanical energy transmitted by the inner ear vibrates oval window and the fluid on the cochlea. The energy becomes hydraulic energy, the fluid motion sets tiny hair cells in motion and the cells produce electrochemical energy to be sent to the brain.

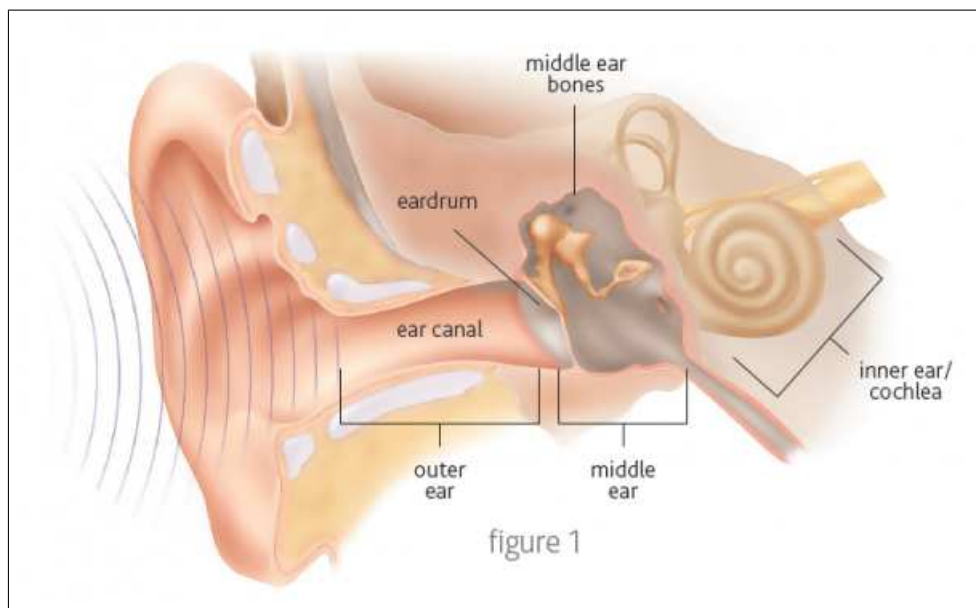


Figure 2.4 Auditory System [4]

2.2.2 Auditory Brain Response (ABR)

In general terms, evoked potentials are electrical signals generated by the nervous system in response to a stimulus. Auditory evoked potentials (AEPs) are generated in response to an acoustic stimulus and are measured using electrodes on the surface of the skin or on the eardrum. The ABR is a far-field recorded potential because the electrodes are placed on the scalp or on the ears, far from the potential generator, the cochlea. The auditory brainstem response is also commonly referred to as an ABR or BAER (brainstem auditory evoked response), depending on the region in which you live.

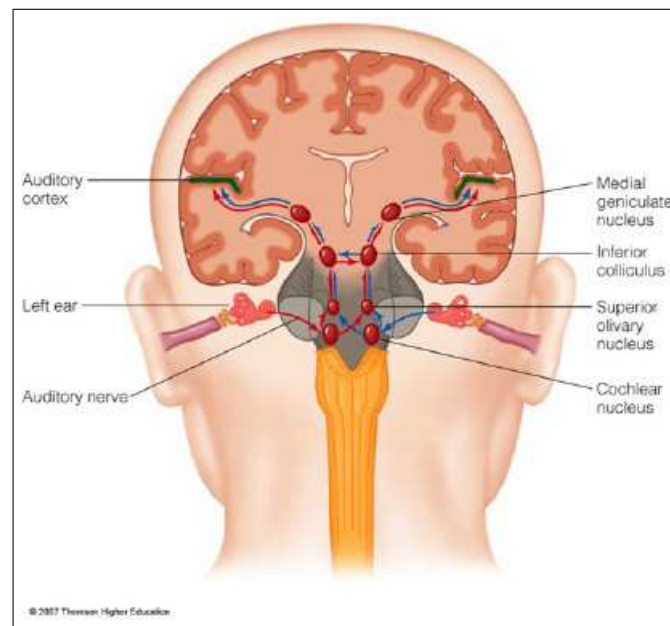


Figure 2.5 Central Auditory Pathway [5]

Electrochemical energy produced on the inner ear (cochlea) is transferred by the auditory nerve to the cochlear nucleus where the timing information on the sound is preserved, even enhanced. Then the output of the cochlear nucleus goes to the superior olivary nucleus in which the sound can be localized by discriminating the differences in arrival of the time to each ear or by considering the intensity of sound differences on each ear. The auditory stimulus is relayed to the inferior colliculus where the dorsal portion of it receives low-frequencies of sound, while the ventral portion receives high-frequencies of sound. Then the stimulus goes to medial geniculate nucleus which relays precise information to the auditory cortex regarding the frequency, intensity, and binaural properties of the sound [6].

The auditory stimulus is processed at the temporal lobe. The primary auditory cortex is the first region of cerebral cortex to receive auditory input. Perception of sound is associated with the left posterior superior temporal gyrus (STG). The neurons of the primary auditory cortex can be considered to have receptive fields covering a range of auditory frequencies. Primary auditory cortex is surrounded by secondary auditory cortex, and interconnects with it. These secondary areas interconnect with further processing areas in the superior temporal gyrus, in the dorsal bank of the

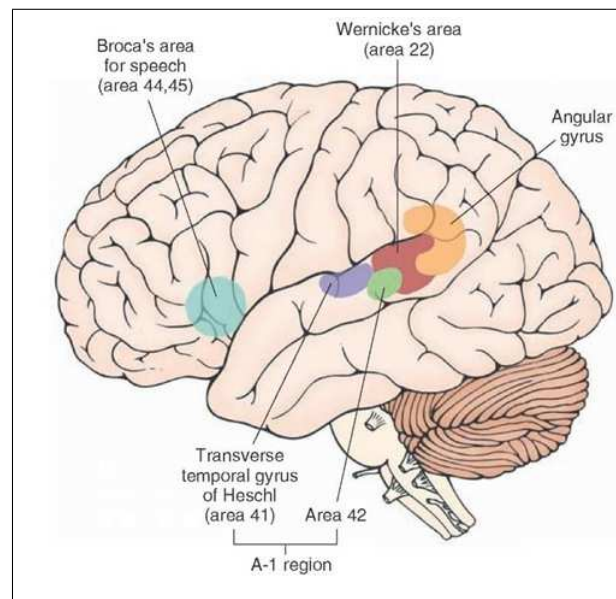


Figure 2.6 Primary auditory cortex. Brodmann's area 41-42 receives projections from the medial geniculate nucleus. Wernicke's area (secondary auditory area) is important for the interpretation of the spoken word. [6]

superior temporal sulcus, and in the frontal lobe. In humans, connections of these regions with the middle temporal gyrus are probably important for speech perception [14] [15].

10-20 system is used for electrode placement. For a two channel recording, Cz which is the top of the head, (or sometimes FPz, which is high forehead) A1 for the left ear and A2 for the right ear are used. Earlobe placement is typically used in the clinic. Sometimes M1 and M2 for mastoid placement is used as well.

The auditory stimulus can be a click, tone burst, or white noise. The ABR is an early potential, which means it occurs shortly after the onset of the stimulus. Auditory evoked potentials can be divided into three categories with different latencies.: 1. fast response - after 0-10 ms from the stimulus, 2. middle response - after 10-50 ms from the stimulus 3. slow response - after 50-500 ms from the stimulus.

Anatomical locations related to the the different waves of the AEP; wave I - auditory nerve, wave II - cochlear nuclei, wave III - superior olive, wave IV - lateral lemniscus, wave V - inferior colliculus. Waves I to V make up the brainstem potentials

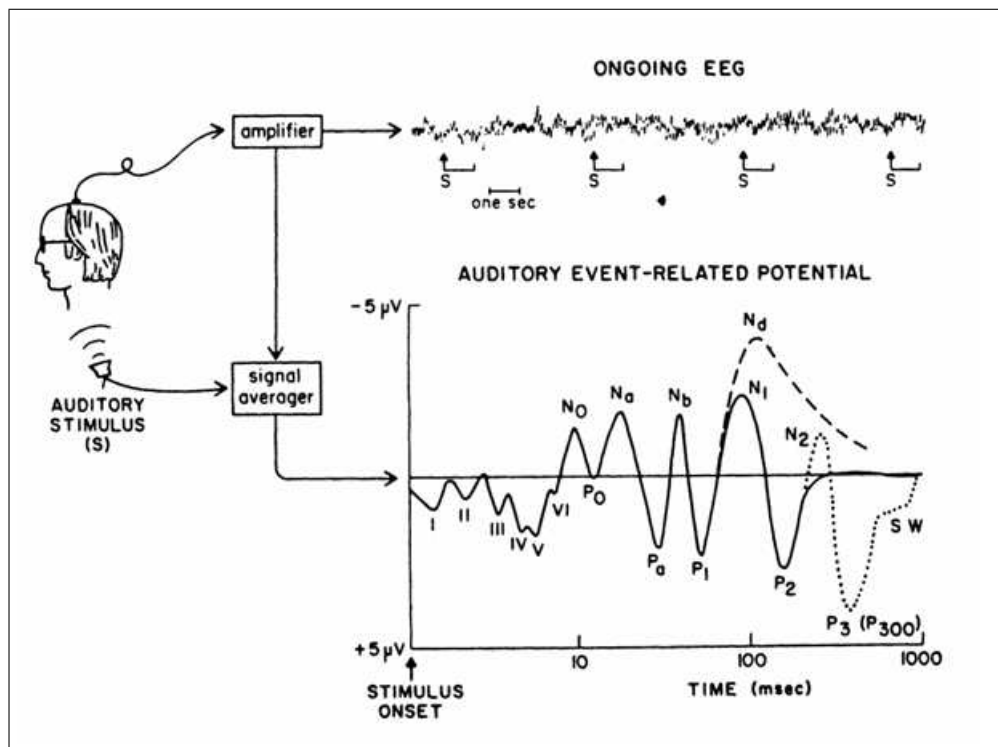


Figure 2.7 Idealized waveform of the computer-averaged auditory event-related potential (ERP) to brief sound. The ERP is generally too small to be detected in the ongoing EEG (top) and requires computer averaging over many stimulus presentations to achieve adequate signal noise ratios. The logarithmic time display allows visualization of the early brain-stem responses (Waves I-VI), the latency components (No, Po, Na, Pa, Nb), the 'vertex potential' waves (P1, N1, P2), and task-related endogenous components (Nd, N2, P300, and slow wave). Source, Reprinted from Hillyard SA, Kutas M, 'Electrophysiology of Cognitive Processing.' Annual Review of Psychology 34 33 - 61, 1983. Copyright 1983, Annual Reviews. Used with permission from The Annual Review of Psychology, Volume 34

(BAEPs). The thalamus (medial geniculate ganglion) and the auditory cortex (temporal lobe) make up the middle and late waves (N, P) of the AEP.

2.3 BLIND SOURCE SEPERATION

Blind source separation also known as blind signal separation, is the separation of a set of original source signals from a set of mixed signals, without the help of the information about the source signals or the mixing process.

An essential problem in many disciplines especially in neural network research, is to find an appropriate representation of multivariate data. For the sake of conceptual

and computational ease, the representation is often looked for as a linear transformation of the original data. Principal component analysis (PCA) and the newer method Independent component analysis (ICA) are the well-known linear transformation methods. PCA method is based on variance, covariance, eigenvectors whereas the ICA method is based on statistical independence(nongaussianity, entropy,negentropy)

The problem definition on the BSS problem can be formulated as below. If the observed signals are formulated as

$$X(t) = [x_1(t), x_2(t), x_3(t), \dots, x_n(t)]$$

And the original source signals as

$$S(t) = [s_1(t), s_2(t), s_3(t), \dots, s_m(t)]$$

The problem is to find a set of basis vectors that transforms the recorded signals into a set of original source signals.

$$X(t) = AS(t)$$

Here, A is the unknown mixing matrix of dimensions $n \times m$. Using the mixing matrix A, it is then possible to project the components back to reconstruct the original data.

$$S'(t) = WX(t) \text{ is the source component estimation}$$

The BSS method then tries to find the corresponding unmixing matrix W that best estimates the original source signals.

$$X(t) = W^1 S'(t) = AS'(t) = AWX(t)$$

2.3.1 Principal Component Analysis

Principal component analysis (PCA) is a useful statistical technique that is used in application fields such as image compression, face recognition and, it is a common method to find patterns in high dimensional data. PCA is a method to find a linear transformation of the data that maximizes the variance of the transformed data. Using PCA, the transformation is constrained to be orthogonal. The process for computing the principal components of a set of multidimensional data is based on the common statistical concepts of variance, covariance and eigenvectors.

Algorithm

1. Normalize the data to zero mean and unit variance
2. Compute the coveriance matrix of the normalized data

$$\Sigma = \frac{1}{n} \sum_{i=1}^n x^{(i)} x^{(i)T}$$

3. Find top k eigenvectors of (Σ)

To apply the algorithm singular value decomposition(SVD) is used. <SVD states that for any $A \in R^{m \times n}$, matrix A can be decomposed to

$$\underbrace{\begin{bmatrix} A \end{bmatrix}}_{m \times n} = \underbrace{\begin{bmatrix} U \end{bmatrix}}_{m \times n} \underbrace{\begin{bmatrix} A \end{bmatrix}}_{n \times n} \underbrace{\begin{bmatrix} A \end{bmatrix}^T}_{n \times n}$$

Where D is a diagonal matrix containing the singular values of A (σ)

$$\begin{bmatrix} \sigma_i & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_n \end{bmatrix}$$

U's coloumns are the eigenvectors fo AA^T V's coloumns are the Eigenvectors of $A^T A$

To get the top k eigenvectors, X (observed data) ?? can be written as $XUDV^T$ then top k columns of V are the top k eigenvectors of $X^T X \Sigma$

PCA is eigenvector-based multivariate analyses. PCA's principle action can be thought of as enlightening the internal structure of the data in a technique that best explain the variance of the data. PCA can provide to the user a lower-dimensional image, a "shadow" of this object that includes the most informative part of the data. By computing the first few principal components, the dimension of the original data is reduced on the transformed data. PCA finds a set of orthogonal axes in the data then rotating the axes and representing the original data on the rotated axes provides principle components of the original data.

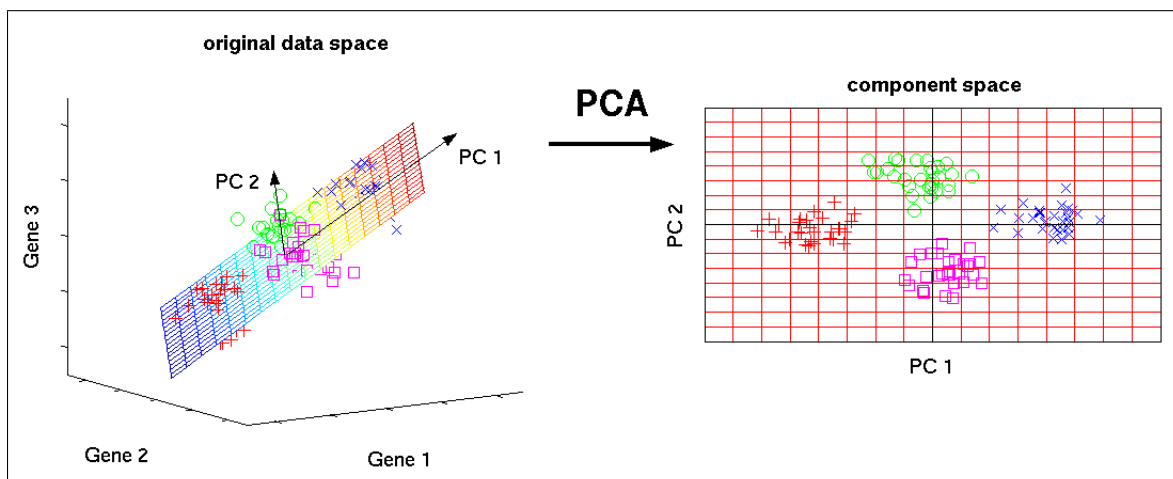


Figure 2.8 Principal component analysis (PCA) [?]

In the Figure 2.3.2 three dimensional gene expression data is converted to(reduced) two dimensional data. A two dimensional plane which represent the highest variance of the data is constructed, then rotated to present a two dimensional component space.

2.3.2 Independent Component Analysis

ICA is a technique to separate independent sources linearly mixed in several observations. The assumption on the ICA method is that the observed signals are pro-

duced from a mixture of several separate(independent) source signals. The well-known example of ICA is the 'cocktail party problem'. In the cocktail party, there is several independent sound sources (music, individual's voices, noise from the outside environment etc.) and there are also a number of microphones set up in the room to record a mixture of all the sounds (sources). Using the data recorded from all of the recording channels (microphones),ICA try to transform recorded data into a set of the original independent source signals.The goal is to find a linear representation of non-Gaussian data so that the components are statistically independent.

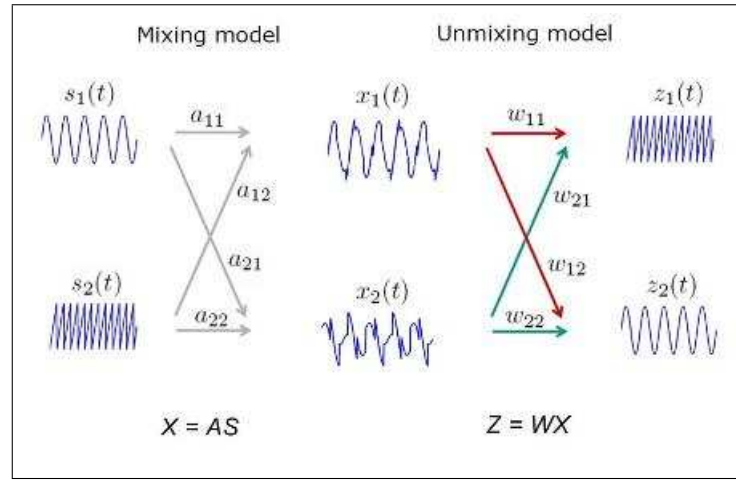


Figure 2.9 Independent component analysis (ICA) model [?]

Algorithm

Original Sources (n speakers) as S Signal from speaker j at time i as $S_j^{(i)}$

k = index of speakers we observe $X^{(i)} = AS^{(i)}$ and $X_j^{(i)} = \sum_{k=1}^n A_{jk} S_k^{(i)}$

goal is to find $W = A^{-1}$ so that $S^i = WX^i$

kurtosis Definition of Kurtosis For univariate data Y1, Y2, ..., YN, the formula for kurtosis is:

where μ is the mean, σ is the standard deviation, and N is the number of data points.
Alternative Definition of Kurtosis The kurtosis for a standard normal distribution is

three. For this reason, some sources use the following definition of kurtosis (often referred to as "excess kurtosis"):

This definition is used so that the standard normal distribution has a kurtosis of zero. In addition, with the second definition positive kurtosis indicates a "peaked" distribution and negative kurtosis indicates a "flat" distribution. Which definition of kurtosis is used is a matter of convention (this handbook uses the original definition). When using software to compute the sample kurtosis, you need to be aware of which convention is being followed. Many sources use the term kurtosis when they are actually computing "excess kurtosis", so it may not always be clear.

<http://www.itl.nist.gov/div898/handbook/eda/section3/eda35b.htm>

3. MATERIALS

3.1 Emotiv EPOC

The EPOC neuroheadset reads electrical activity in the brain using EEG technology and then it sends this information to a computer through wireless signals.

The EPOC neuroheadset uses a set of 14 sensors and 2 references to tune into electric signals produced by the brain to detect the user's thoughts, expressions and even feelings in real time. [7] It has a software called TestBench which is used to real-time display of the Emotiv headset data stream, the display includes the raw EEG data, contact quality of the electrodes, FFT, gyro wireless packet acquisition/loss display, marker events and battery level of the headset.[16] EEG neuroheadset does not require gel on the scalp; it should be moisturized with saline solution before usage.

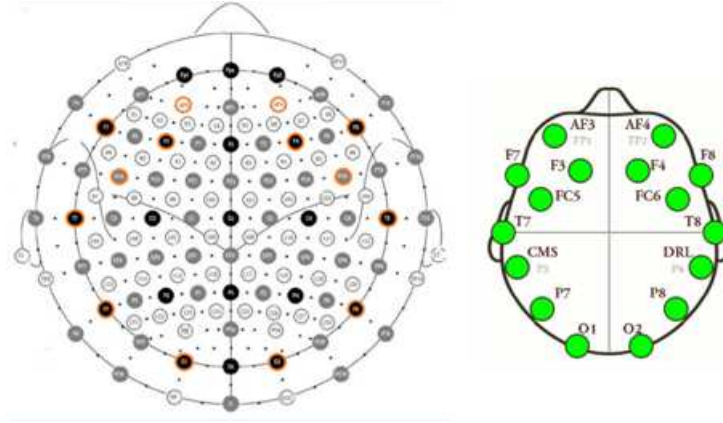


Figure 3.1 Electrode locations used by the EPOC [7]

We have used that neuroheadset and TestBench software to record the EEG data from subjects under auditory stimulus.

Number of channels	14 (plus CMS/DRL references)
Channel names (Int. 10-20 locations)	AF3, AF4, F3, F4, F7, F8, FC5, FC6, P3 (CMS), P4 (DRL), P7, P8, T7, T8, O1, O2
Sampling method	Sequential sampling, Single ADC
Sampling rate	~128Hz (2048Hz internal)
Resolution	16 bits (14 bits effective) 1 LSB = 0.51 μ V
Bandwidth	0.2 - 45Hz, digital notch filters at 50Hz and 60Hz
Dynamic range (input referred)	256mV pp
Coupling mode	AC coupled
Connectivity	Proprietary wireless, 2.4GHz band
Battery type	Li-poly
Battery life (typical)	12 hrs
Impedence measurement	Contact quality using patented system

Figure 3.2 Specification of Emotiv Epoc [7]

3.2 Openvibe

OPENVIBE is free and open source software platform. It can be used to design and test brain computer interfaces. It consists of several software modules and these modules can be easily integrated to design BCI applications. It has acquisition client box to acquire signals from some supported devices(EMOTIV EPOC is supported), the signal processing boxes to filter and process signals and visualization boxes to show the signals in real time [17].

We have used the OPENVIBE platform to design the experiment procedure. It has been used to design an auditory oddball paradigm. "Clock-stimulator", "Lua Stimulator", "Sound Player" and "Run Command" modules of OPENVIBE are used. (For a detailed description see "METHOD" section)

3.3 Null-Modem Emulator (com0com)

The Null-modem emulator is a virtual serial port driver for Windows; it is open source software and can be downloaded freely under GPL license.

The Null-modem emulator can be used to create virtual COM port pairs and it can be used to connect one COM port based application to another. Two COM ports are created for each COM port pair. The output to one of the port pairs is the input from other port [18].

We have used that software to connect OPENVIBE and EMOTIV TestBench software. We have created a pair of virtual COM port. We have used one of these ports in OPENVIBE to write the marker value on that port. We have used the other port in TestBench in order to import marker value while recording the EEG. Since the output of one port is the input of the other, TestBench is received the marker value which is sent by OPENVIBE while recording EEG.

3.4 Matlab-Eeglab

EEGLAB is a toolbox for Matlab environment. It can be used for processing event-related and continuous EEG data. It has some features like graphical user interface, open source plug-in facility, independent component analysis (ICA), time/frequency analysis, artifact rejection, and several useful interactive plotting functions for the visualization of the single-trial and averaged data [19].

We have used the EEGLAB toolbox for the processing of the recorded EEG data. Some facilities of EEGLAB toolbox such as filtering, independent component analysis, artifact rejection, epoch extraction and averaging are used. Raw EEG data recorded by EPOC is processed and some features are extracted from data using MATLAB-EEGLAB.

3.5 Weka

WEKA is open source data mining software written in JAVA. It has a many machine learning algorithms to use in data mining tasks. It contains tools for data classification, regression and clustering [20].

We have used WEKA for classification of data. The extracted features of the data are given to the WEKA software and the data is classified.

4. METHOD

Auditory brain response detection is done in three main parts:

- Experiment Design
- EEG Recordings
- Signal Processing
- Classification

4.1 Experiment Design

An experiment for the detection of Auditory Brain Response is designed using auditory oddball paradigm and OPENVIBE environment.

A pure tone, 0.2 sec sound file is created, with the frequency of 1000Hz. Playing procedure is designed in OPENVIBE environment, a "clock stimulator box" is used to stimulate the marker generator at every second. "Clock stimulator" is used to trigger stimulation at fixed frequency. This box produces stimulations at specific times depending on its configuration. It is configured to produce one stimulation (stimulation id=OVTK_StimulationId_Label_00) at every second. Then, the stimulation label is sent to a "Lua Stimulator" box. Lua Stimulator generates some stimulations according to a Lua script. Lua script is a simple programming language. It can be used for high-level operations and it does not need compilation. The Lua script code is arranged to produce two different stimulation labels randomly one for the sound, other one for the silence marker. The script generates the random stimulation as frequency distribution of %20 for the sound, %80 for the silence (ODDBALL PARADIGM REFERENCE), (APPENDIX). "Lua Stimulator" generates two outputs as the result of lua script.

(OVTK_StimulationId_Label_02 for silence and OVTK_StimulationId_Label_03 for sound).

"Sound Player" box is triggered by "OVTK_StimulationId_Label_03" stimulation and plays the 0.2 sec 1000Hz sound. The first "Run Command" box is also triggered by the "OVTK_StimulationId_Label_03" stimulation and it writes the number '3' indicating the sound as a marker for TestBench recording.

Second "Run Command" box is triggered by the "OVTK_StimulationId_Label_02" stimulation and it writes the number '2' indicating the silence as a marker for TestBench recording.

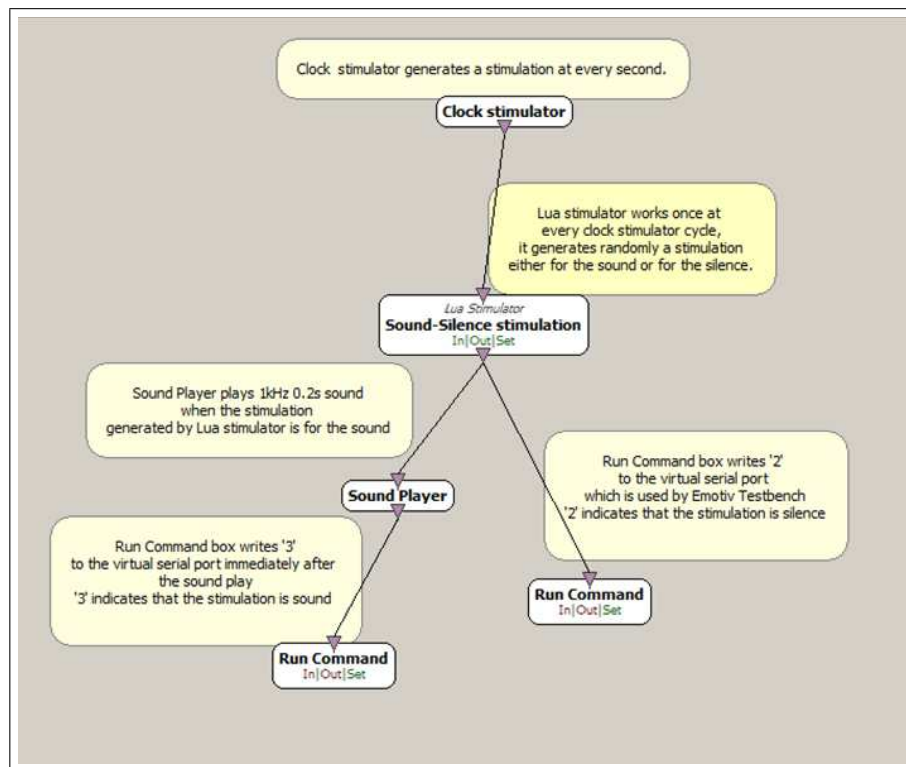


Figure 4.1 Experiment procedure design in OPENVIBE

4.2 EEG Recordings

Epoc neuroheadset is prepared to be used; its sensors are moisturized by contact lens solution. It is placed on the subject's head and the connection qualities of the sensors are checked for each sensor using the Emotiv Control Panel and TestBench. Recording is done after being sure about the connection quality of the sensors. A subject on a silent room has listened to the sound, which is played by OPENVIBE, with an earphone. TestBench is arranged to get the marker value from a serial port. The TestBench and Openvibe have run at the same time. Openvibe has played the sound and sent a marker at every second when TestBench receives that marker and saves the EEG data of the subject. The EEG recording procedure is repeated for 13 person (8 male, 5 female). All of the participants volunteered for the experiment. The experiment is done for each subject three times with about 3 minute EEG recordings.

The below figure shows a recorded data 4.2

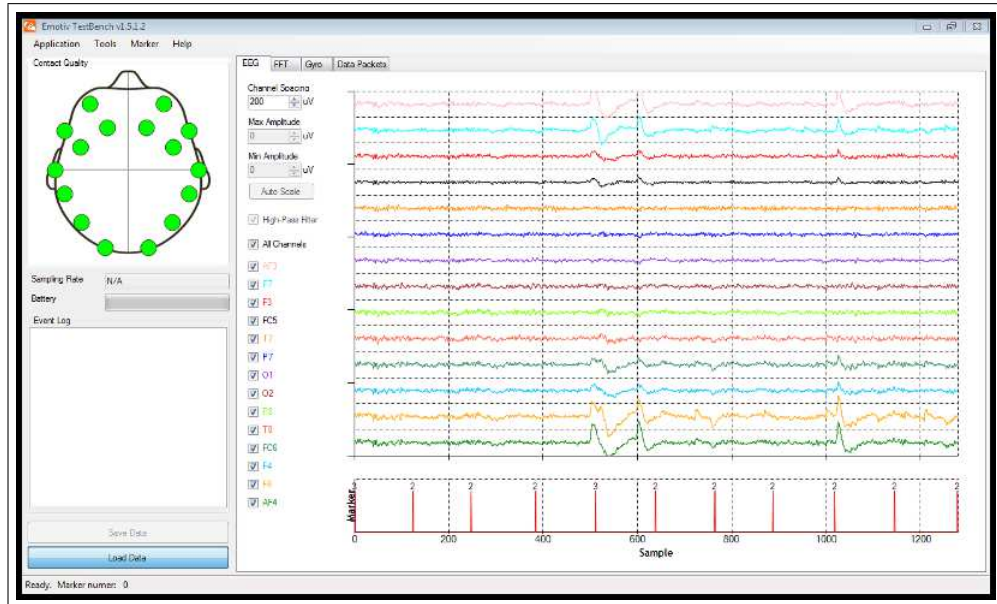


Figure 4.2 A recorded data on TestBench

4.3 Signal Processing

The data recorded by the Testbench is in the type of 'edf' file. The data is converted to csv file and processed in MATLAB. EEGLAB plug-in is used for processing. The recorded data is imported to the EEGLAB. The event channel (marker values are added to data as an extra channel) is set and channel location file [?] is imported. EEG data is filtered by using linear finite impulse response (FIR) filtering with 1Hz high pass filtering and 50Hz low pass filtering. After filtering the extreme values on the recorded data are removed.

Independent component analysis is done on the data. ICA has computed the "ICA weight matrix" for the recorded data. ICA weight matrix is computed by rotating the axis, and minimizing the Gaussianity of the projection on all axes [21]. Multiplying the Weight matrix with the EEG data gave us the maximally independent components on the EEG data. ICA is a blind separation method. The simple known application of ICA is "cocktail party problem" where the microphones on a room take the speech signals produced by many individuals. Underlying independent sources (speech of each individual) can be extracted using ICA (a demo can be seen on the web page of ICA research group at Helsinki University [22]). The ICA solution to the cocktail party problem is first adopted to the decomposition of EEG on 1996 (Makeig) and subsequent work over the next dozen years or more has confirmed the ability of ICA to identify both functionally and temporally independent source signals in multi-channel EEG or other electrophysiological data [23].

If a stimulus is presented to a human subject while recording EEG, an 'epoch' of the EEG that is time locked to the stimulus can be defined [12]. Within this epoch there may be some voltage changes that is related with the brain's response to that stimulus, and event related potential (ERP) is a set of voltage changes contained in this epoch of EEG. In most cases the ERP waveform is small in relation to the EEG waveform. To extract the signal (time locked-ERP) from the noise (background EEG) "averaging is" used as a signal extraction technique most commonly [12]. Since the EEG activity that is not related (time locked) with the event will randomly vary across

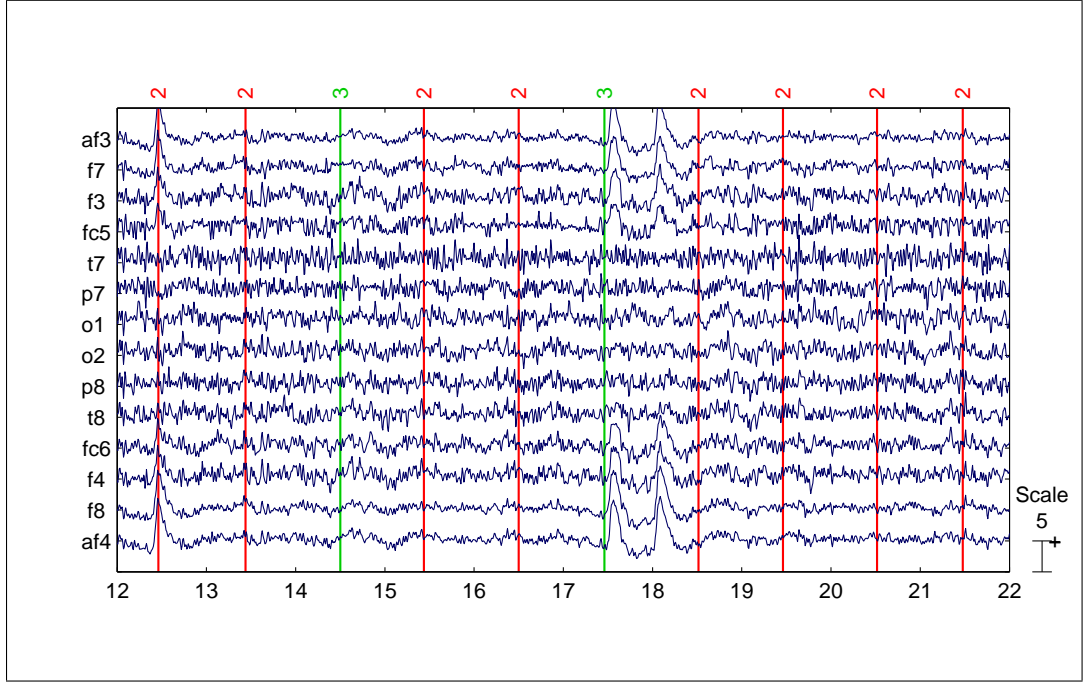


Figure 4.3 Channel Data of EEG for 10 second

epochs, this average background EEG will tend to become zero. Therefore the time locked average ERP will largely represent activity of the brain related with the given event. This averaging technique also deals with the rejection of two major sources of artifact, movement of the eyes and eye blinks, because these artifacts occur randomly across epochs, averaging reduces the effect of artifacts. In this thesis the epoch begins with 500ms before the stimulus and ends with 1000ms after the stimulus. The epochs are extracted from the EEG using the markers on the data. The silent epochs are extracted by taking the EEG data part, 500ms before and 1000ms after the marker '2'. All the extracted silent epochs are averaged and an ERP waveform for the silent is obtained. The same thing is done for sound epochs using the marker '3' after averaging the epochs, an ERP waveform for the sound is obtained too. Epoch averaging is also done for the ICA components.

The ERP waveform for the sound and silence is compared.

For the feature extraction part, five feature for the sound and silence ERPs are calculated separately. The calculated values are written to an 'arrf' file format to be

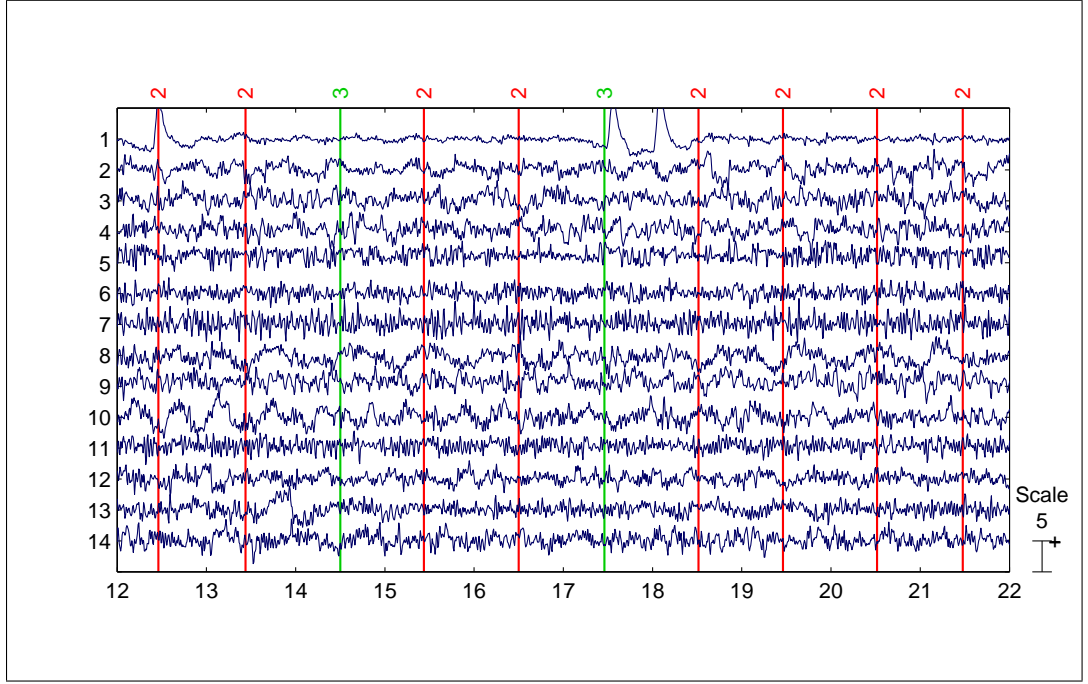


Figure 4.4 Component Data of EEG for 10 second

used later on the classification part.

Firstly the energy of the ERP signal is calculated The energy of a discrete-time signal is:

$$E_d = \sum_{k=1}^n (|x(k)|)^2 \quad (4.1)$$

As the second feature the maximum power of the signal is calculated by taking the square of each data point on the ERP signal and taking the maximum of the squares.

$$MaximumPower = \max(|x(k)|^2) \quad (4.2)$$

As the third and fourth feature, the peak values of the ERP signal is taken.

Maximum peak value and minimum peak value of the ERP signal is taken out.

As the last feature average power of power spectral density (PSD) of the ERP is calculated. Power spectral density is the average of the Fourier transform magnitude squared. It is calculated by using the Equation 4.3

$$\frac{1}{2T} \left| \int_{-T}^T f(t) e^{-j2\pi ft} dt \right|^2 \quad (4.3)$$

PSD is calculated using the Signal Processing Toolbox on MATLAB.[24] A.2.2

A MATLAB script is written to extract the features A.2.2. The script has run for all of the recordings, it has computed the feature values and it wrote them to a text file. Since the subject count is 13, recording count for each subject is 3 and the features are extracted for each sound and silence part separately, total number of feature data is 78. The feature data is converted to an 'arff' file to be used in WEKA for classification.

4.4 Classification

Classification is done using a simple probabilistic classifier, naive Bayes classifier, it is based on applying Bayes' theorem with strong (naive) independence assumptions.[25] [26] If we show each data instance as attribute values consisting of n-dimensional vector :

$$X = (x_1, x_2, x_3, \dots, x_n) \quad (4.4)$$

and each class value which the data instance is assigned as m-dimensional vector

$$C = (C_1, C_2, C_3, \dots, C_m) \quad (4.5)$$

The classifier assigns the data X , to class C_i if and only if

$$P(C_i|X) > P(C_j|X) \text{ for all } j \text{ such that } 1 \leq j \leq m, j \neq i \quad (4.6)$$

The Bayes' Theorem states that

$$\underbrace{P(C_i|X)}_{\text{posterior probability}} = \frac{\underbrace{P(X|C_i)}_{\text{likelihood}} \underbrace{P(C_i)}_{\text{prior probability}}}{\underbrace{P(X)}_{\text{normalising factor (equal for all classes)}}} \quad (4.7)$$

If we assume that all of the attributes are independent to each other (this is why the model is called 'naive') we can write the likelihood as:

$$P(X|C_i) = \prod_{k=1}^n P(x_k|C_i) \quad (4.8)$$

with the independence assumption, the Bayes' rule can be rewritten as :

$$P(C_i|x_1, x_2, \dots, x_n) = \frac{P(x_1|C_i) \times P(x_2|C_i) \times \dots P(x_n|C_i) \times P(C_i)}{P(x_1, x_2, \dots, x_n)} \quad (4.9)$$

The model on 4.9 can be used efficiently in categorical attributes, but since we use numerical attributes, we need to use probability density function (pdf). Assuming the probability distribution of an attribute follows the normal (Gaussian) distribution, the probability density function can be written as:

$$f(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} \quad (4.10)$$

By using the mean and the standard deviation of each attribute for each class outcomes, we can compute the pdf value at any given decision point. By using the pdf values in Naive Bayes' rule we can obtain the probabilities corresponding to each class.

We used the WEKA machine learning software tool to generate and test Naive Bayes model. The feature data in 'arff' format is used for classification. The file is

given to WEKA as input to generate Naive Bayes model. As the test option '10-fold cross validation' is used. The option randomly breaks the dataset into 10 partitions of size $n/10$. For each selected partition, analysis is done on all the partitions except the selected one(training set), and validating the analysis on the selected subset(validation set or testing set).The procedure is repeated 10 times and the overall validation result is found by calculating the average over the rounds.

After generating and running Naive Bayes Model, the results about the classification are shown as confusion matrix (contingency table). By using the confusion matrix, Chi Square test is used to test statistical significance.

5. RESULTS

After every experiment, the recorded EEG data is converted to 'csv' format and used in MATLAB - EEGLAB to be processed. The data is filtered with 1Hz high pass filter and 50Hz low pass filter.

Independent component analysis is done on the filtered data. When ICA is applied to a matrix of EEG scalp data, it finds an 'unmixing' matrix of weights (W) that, when multiplied by the (channels by time points) scalp data matrix, gives a matrix of independent component (IC) activities. This is the process of ICA decomposition of the data into maximally temporally independent processes, each with its distinct time series and scalp map [23]. In our case, ICA has converted the 14 channel EEG data to 14 independent components. ICA is done before the epoch extraction in order to use the same weight matrix for sound and silence parts.

The figures below (Fig.5.1) (Fig.5.2) show the channel and component graph of the EEG data. The difference between scalp EEG and components can be clearly seen on the graphs.

After finding ICA weight matrix and ICA components, epoch extraction is done for silence and sound parts on the data. Epoch duration is given as -0.5sec to 1sec distance to the marker value. The epochs are extracted and averaged to have an ERP signal for silence and sound parts separately.

ERP signal for a subject data, with 14 channel graphs can be seen on Fig.5.3 and Fig. 5.4. ERP signals of 14 components are shown on Fig.5.5 and Fig. 5.6.

The graphs clearly shows the reaction of brain to the auditory stimulation.

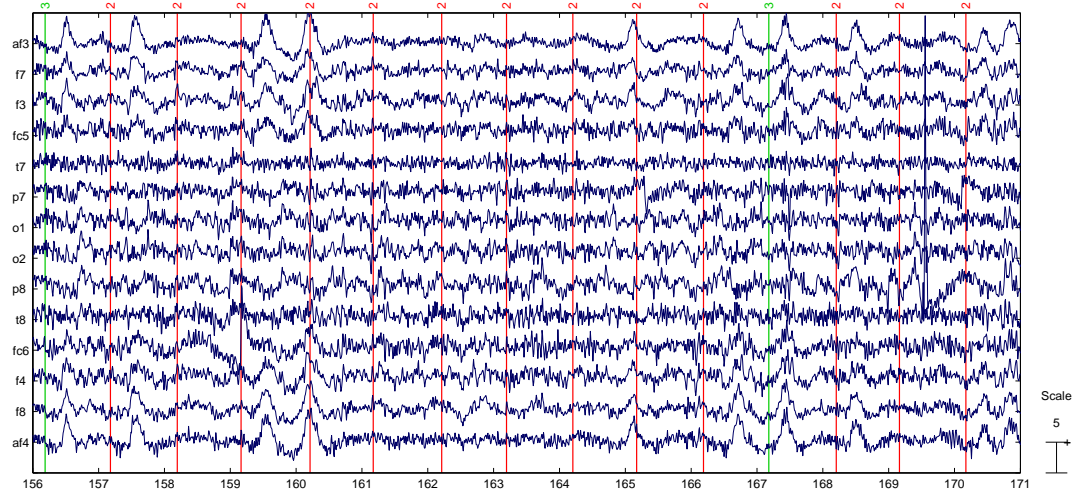


Figure 5.1 15 sec () 14 Channel EEG Data of one subject

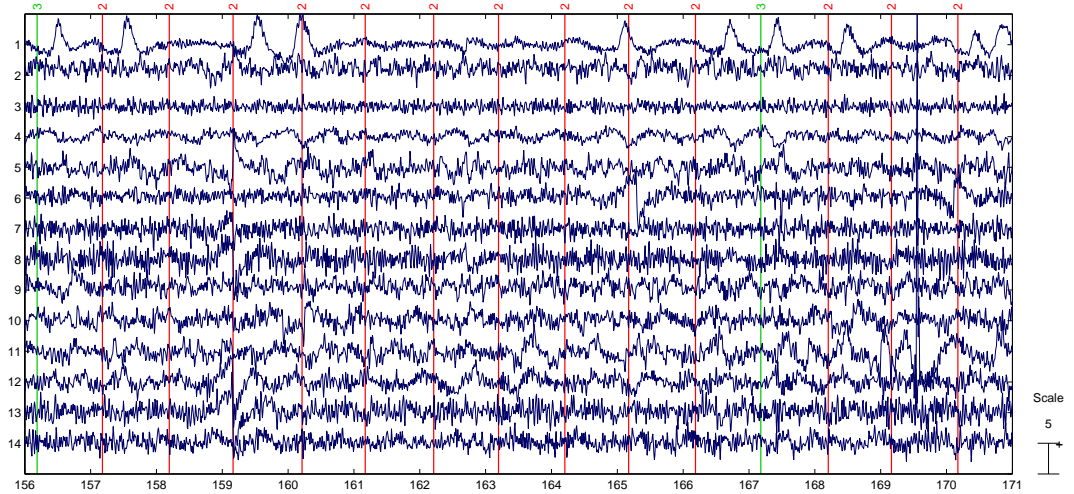


Figure 5.2 14 Components of EEG Data of the same subject

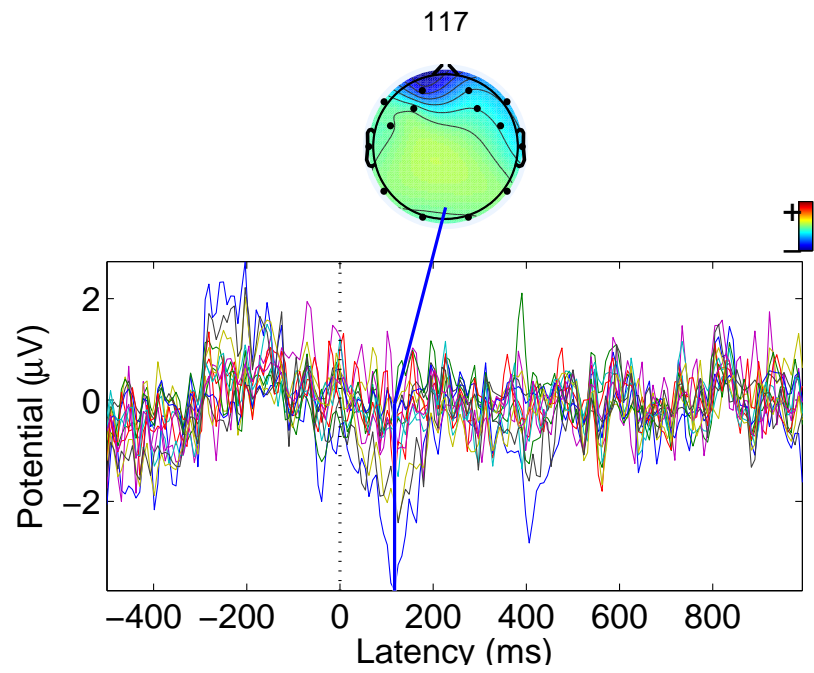


Figure 5.3 14-Channel Silence Epochs For One Subject

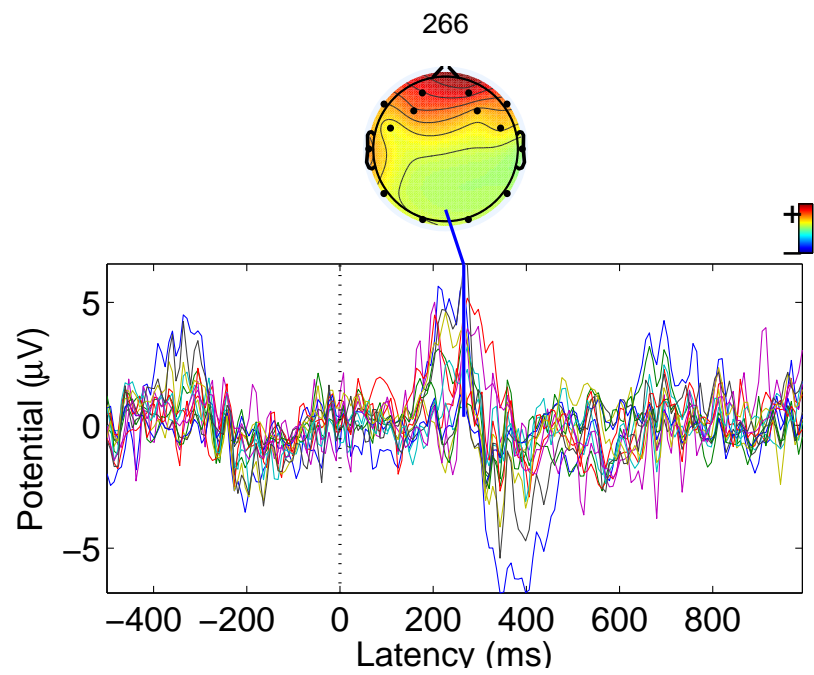


Figure 5.4 14-Channel Sound Epochs For The Same Subject

Largest ERP components of silence

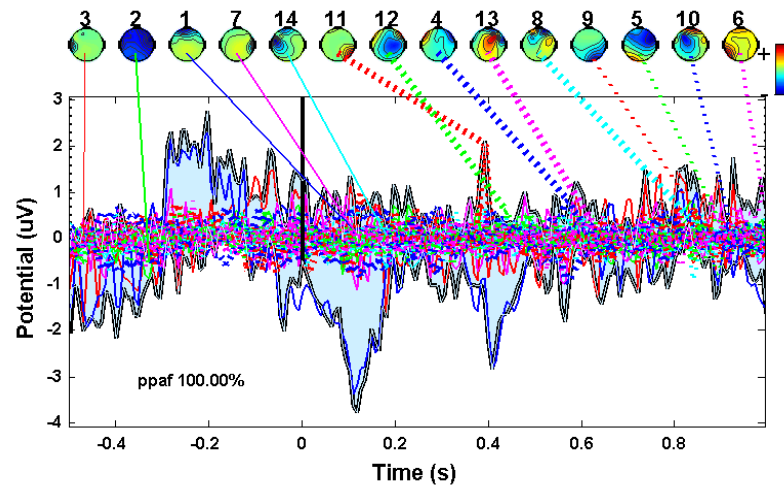


Figure 5.5 Silence Component ERP epochs

Largest ERP components of sound

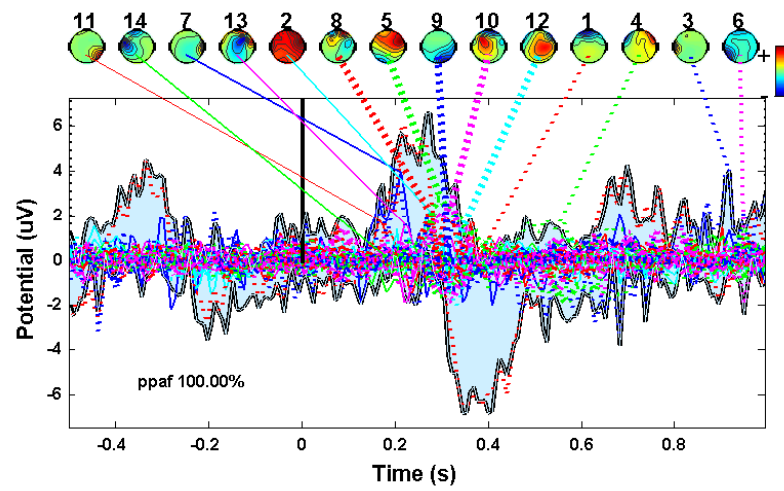


Figure 5.6 Sound Component ERP epochs

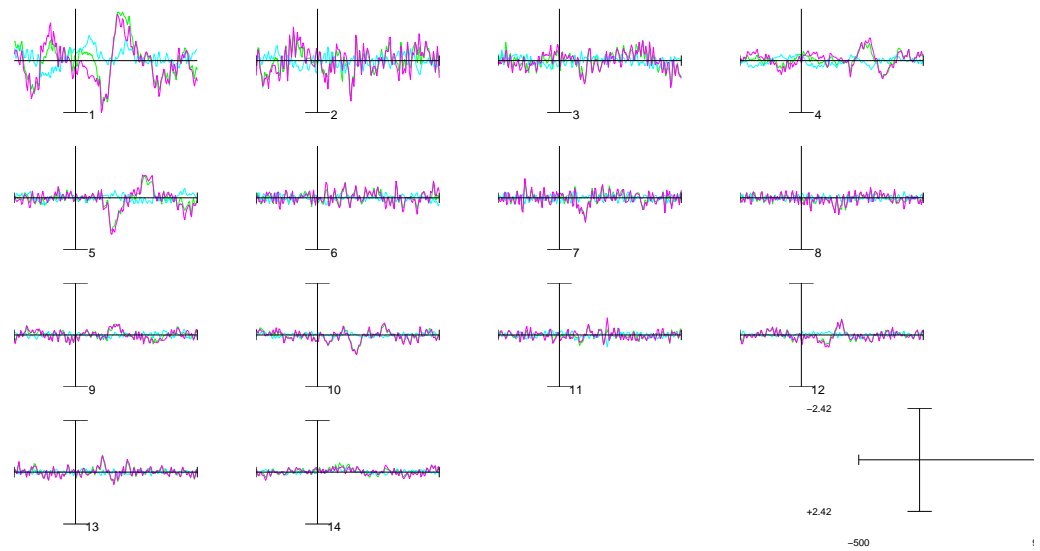


Figure 5.7 Difference between silence and sound stimulation on 14 component

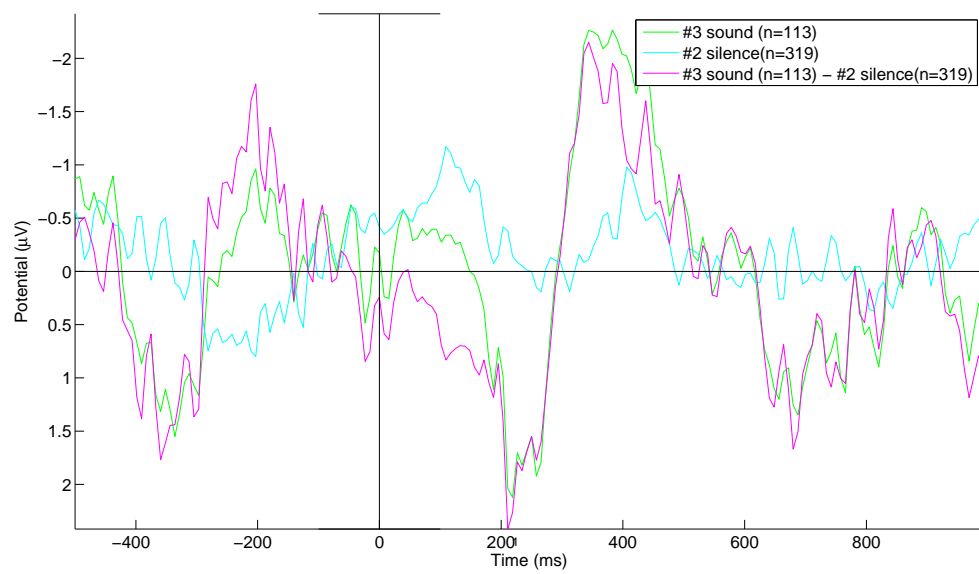


Figure 5.8 Difference between silence and sound stimulation ERP values for one component

After obtaining the ERP waveforms for sound and silence, features are extracted from the ERP signals to be used in classification.

Energy of the silence ERP signal and sound ERP signal are calculated for each data. Ratio between 'sound ERP signal energy' and 'silence ERP signal energy' was nearly '2.99'

Similarly the calculated values of max(Power), max(ERP), min(ERP), and psd was sufficiently different for sound and silence ERPs.

The 'arff' file is created using the below structure 5.1

Table 5.1
A portion of Feature Data

Class	Energy	Max(Power)	Max(ERP)	Min(ERP)	avgpower(psd)	DATA
silence	101,174	4,9757	1,7354	-2,2306	0,2656	2[4]*1. data
sound	399,578	30,0184	5,4789	-2,7854	1,0894	
sound	460,824	23,0129	4,7972	-4,2591	1,238	2[4]*2. data
silence	83,5073	3,2581	1,4461	-1,805	0,2242	
silence	248,142	9,2121	3,0351	-2,9061	0,6514	2[4]*3. data
sound	352,725	12,4246	2,7906	-3,5249	0,9397	
sound	545,989	20,1643	4,0489	-4,4905	1,4927	2[4]*4. data
silence	151,443	5,3839	1,8331	-2,3203	0,3995	
silence	54,8195	2,374	1,3519	-1,5408	0,1465	2[4]*5. data
sound	285,908	17,5339	2,993	-4,1873	0,7568	
sound	371,1252	11,5162	3,3935	-3,2788	0,9803	2[4]*6. data
silence	140,622	6,6623	2,5812	-1,3618	0,3697	
sound	660,8268	17,8225	4,2217	-3,9777	1,7461	7. data

Mean and standart deviation of extracted feature values can be seen on Table 5.2

Table 5.2
Add caption

	silence	sound	
Mean	135.9289	404.5848	Energy
Std. Dev.	71.1357	172.9513	
Mean	5.1507	15.2929	max(Power)
Std. Dev.	2.7637	6.7159	
Mean	1.9365	3.6087	max(ERP)
Std. Dev.	0.5301	0.9098	
Mean	-1.967	-3.2229	min(ERP)
Std. Dev.	0.6315	0.7985	
Mean	0.3667	1.0901	psd
Std. Dev.	0.1957	0.4715	

Table 5.3
 === Confusion Matrix ===

	a	b	Total	<- classified as
	34	5	39	a = silence
	7	32	39	b = sound
Total	41	37	78	

Classification based on this 5.2 feature values are done using the Naive Bayes' classifier on WEKA. 10-fold cross validation is used the classification results were like the following:

Correctly Classified Instances = 66 =>84.6154 %

Incorrectly Classified Instances = 12 =>15.3846 %

Using the confusion matrix Chi-square statistics test is done.

Calculated Chi Square value for the confusion matrix =35.677

Degrees of freedom of the contingency table df=1

Level of alpha p=.05

Chi Square value in the table at p=.05 and df=1 -> Chi Square=3.84

The result of Chi-square test states that with the <5% error probability the extracted features and the NaiveBayes algorithm correctly classifies the sound and silence class on the subjects who participated in the experiment.

6. DISCUSSION AND CONCLUSIONS

6.0.1 Discussion

6.0.2 Future Work

6.0.3 Conclusion

APPENDIX A. SCRIPTS

A.1 Lua Script

```

1  dofile("../share/opencvib-plugins/stimulation/luastimulator-stim-codes.
    lua")
2
3  — this function is called when the box is initialized
4  function initialize(box)
5      io.write("initialize has been called\n");
6
7      — inspects the box topology
8      io.write(string.format("box has %i input(s)\n", box:
          get_input_count()))
9      io.write(string.format("box has %i output(s)\n", box:
          get_output_count()))
10     io.write(string.format("box has %i setting(s)\n", box:
          get_setting_count()))
11     for i = 1, box:get_setting_count() do
12         io.write(string.format(" — setting %i has value [%s]\n",
            i, box:get_setting(i)))
13     end
14
15 end
16
17 — this function is called when the box is uninitialized
18 function uninitialize(box)
19     io.write("uninitialize has been called\n")
20 end
21
22 — this function is called once by the box
23 function process(box)
24     io.write("process has been called\n")
25
26     — enters infinite loop
27     — cpu will be released with a call to sleep
28     — at the end of the loop

```

```

29     while true do
30
31         -- gets current simulated time
32         t = box:get_current_time()
33
34         -- loops on all inputs of the box
35         for input = 1, box:get_input_count() do
36
37             -- loops on every received stimulation for a
38             -- given input
39             for stimulation = 1, box:get_stimulation_count(
40                 input) do
41
42                 -- gets the received stimulation
43                 identifier, date, duration = box:
44                     get_stimulation(input, 1)
45
46                 -- logs the received stimulation
47                 io.write(string.format("At time %f on
48                     input %i got stimulation id:%s date:%s
49                     duration:%s\n", t, input, identifier,
50                     date, duration))
51
52                 -- discards it
53                 box:remove_stimulation(input, 1)
54
55                 a = math.random(5)
56
57                 if a == 1 then
58                     box:send_stimulation(1,
59                         OVTk_StimulationId_Label_03, t, 0)
60                 else
61                     box:send_stimulation(1,
62                         OVTk_StimulationId_Label_02, t, 0)
63                 end
64             end
65         end
66     end
67 end

```

```

59
60             — releases cpu
61             box:sleep()
62         end
63 end

```

A.2 MATLAB scripts

A.2.1 ICA Script

```

1  cigdem3 = importdata('C:\Users\Toshiba\Desktop\cigdem3.csv');
2  eegdatacigdem3 = cigdem3.data;
3  eegdatacigdem3(:,17:35) = [];
4  eegdatacigdem3(:,1:2) = [];
5  eegdatacigdem3 = eegdatacigdem3';
6  eeglab
7  EEG = pop_importdata('data',eegdatacigdem3,'srate',128); % import data
      from MATLAB array
8  EEG = pop_chanevent(EEG, 15,'edge','leading','edgelen',0); % event
      channel
9  EEG = pop_chanedit(EEG, 'load',{ 'C:\openvibe\P300New\emotiv.ced' '
      filetype' 'autodetect' }); % channel locations
10 EEG = pop_eegfilt(EEG, 1, 0, [], [0]); % highpass filtering at 1Hz
11 EEG = pop_eegfilt(EEG, 0, 50, [], [0]); % low pass filtering at 50Hz
12 eeglab redraw
13
14 EEG = eeg_checkset( EEG );
15 EEG = pop_runica(EEG, 'icatype','runica','dataset',1,'options',{ 'extended
      ' 1});
16 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
17 EEG = pop_epoch( EEG, { '2' }, [-0.5 1], 'epochinfo', 'yes');
18 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1,'setname','silence','
      gui','off');
19 EEG = eeg_checkset( EEG );
20 EEG = pop_rmbase( EEG, [-500 0]);
21 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
22 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 5,'retrieve',1,'study'

```

```

    ,0);
23 EEG = eeg_checkset( EEG );
24 EEG = pop_epoch( EEG, { '3' }, [-0.5 1], 'epochinfo', 'yes');
25 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1, 'setname', 'sound', '
    gui', 'off');
26 EEG = eeg_checkset( EEG );
27 EEG = pop_rmbase( EEG, [-500 0]);
28 save('C:\Users\Toshiba\Desktop\ALLEEGcigdem3.mat', 'ALLEEG');
29 clear

```

A.2.2 Feature Extraction Script

```

1 eeglab
2 load('C:\Users\Toshiba\Desktop\~ZSOKER~\dataBilisimPersonel\cigdem\
    ALLEEGCigdem3.mat')
3 eeglab redraw
4 [EEG ALLEEG CURRENTSET] = eeg_retrieve(ALLEEG,1);
5 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1, 'retrieve', 2, 'study'
    ,0);
6 EEG = eeg_checkset( EEG );
7 EEG = pop_rmbase( EEG, [-500 0]);
8 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
9 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 2, 'retrieve', 3, 'study'
    ,0);
10 EEG = eeg_checkset( EEG );
11 EEG = pop_rmbase( EEG, [-500 0]);
12 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
13 EEG = eeg_checkset( EEG );
14 [erp1 erp2 erpsub time sig] = pop_comperp( ALLEEG, 0, 3, 2, 'addavg', 'on', '
    addstd', 'off', 'subavg', 'on', 'diffavg', 'on', 'diffstd', 'off', 'tplotopt'
    , { 'ydir' -1 });
15 saveas(figure(2), 'C:\Users\Toshiba\Desktop\~ZSOKER~\dataBilisimPersonel\
    cigdem\cigdem3Component', 'fig');
16 saveas(figure(2), 'C:\Users\Toshiba\Desktop\~ZSOKER~\dataBilisimPersonel\
    cigdem\cigdem3Component', 'bmp');
17 close(figure(2))
18 d=erp1; d1=sum(d);
19 energy=sum(d.^2);

```

```

20 power=(d1.^2);
21 energy=sum(power);
22 maxpower=max(power);
23 maxErp=max(d1);
24 minErp=min(d1);
25
26 Fs = 128; x1=d1;
27 nfft = 2^nextpow2(length(x1));
28 Pxx1 = abs(fft(x1,nfft)).^2/length(x1)/Fs;
29 Hpsd1 = dspdata.psd(Pxx1(1:length(Pxx1)/2),'Fs',Fs);
30 power1=avgpower(Hpsd1);
31 fid=fopen('C:\Users\Toshiba\Desktop\matlabData.txt','a');
32 fprintf(fid,'%5s %4.4f %4.4f %4.4f %4.4f %4.4f \n\n','sound',energy,
    maxpower,maxErp,minErp,power1);
33 fclose(fid);
34 d=erp2; d1=sum(d);
35 energy=sum(d.^2);
36 power=(d1.^2);
37 energy=sum(power);
38 maxpower=max(power);
39 maxErp=max(d1);
40 minErp=min(d1); Fs = 128; x1=d1;
41 nfft = 2^nextpow2(length(x1));
42 Pxx1 = abs(fft(x1,nfft)).^2/length(x1)/Fs;
43 Hpsd1 = dspdata.psd(Pxx1(1:length(Pxx1)/2),'Fs',Fs);
44 power1=avgpower(Hpsd1);
45 fid=fopen('C:\Users\Toshiba\Desktop\matlabData.txt','a');
46 fprintf(fid,'%5s %4.4f %4.4f %4.4f %4.4f %4.4f \n\n','silence',energy,
    maxpower,maxErp,minErp,power1); fclose(fid); clear

```

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