AUDITORY BRAIN RESPONSE DETECTION USING A PORTABLE EEG HEADSET

by

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ABSTRACT

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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. Measuring the electrical response of auditory system gives many information about the status of individuals hearing. Auditory brain response (ABR) is an AEP and can be detected using EEG technology and signal processing techniques.

In this thesis, an ABR detection system has been implemented. Experiment procedure was designed using auditory oddball paradigm. An acoustic stimulus has been sent to the subject and a marker about the stimulus has been sent to the recording software simultaneously while recording EEG. A low cost, wireless EEG headset was used to record EEG data under auditory stimulus from 13 subjects. Raw EEG data has been processed by using epoch extraction, event related potential (ERP) averaging, and independent component analysis (ICA) methods. Some features were extracted about the auditory stimulus. Then the extracted features were used to classify the data to understand if hearing has occurred or not under given stimulation. Results of the experiments showed that the implemented ABR detection system detected the sound and silence stimulation with 85% accuracy.

Keywords: EEG, ERP, Auditory Brain Response ABR.

ÖZET

TAŞINABİLİR EEG KAYDEDİCİSİ KULLANARAK İŞİTSEL BEYİN YANITI ALGILAMA

Genel olarak, uyarılmış potansiyeller sinir sistemi tarafından bir uyarıcıya yanıt olarak üretilen elektrik sinyalleridir. İşitsel uyarılmış potansiyeller (AEPs) akustik uyarana yanıt olarak oluşturulur. İşitme sisteminin elektriksel tepkisinin ölçülmesi bireylerin işitme durumu hakkında birçok bilgi verir. İşitsel beyin yanıtı (ABR) bir işitsel uyarılmış potansiyeldir(AEP) ve EEG teknolojisi ile sinyal işleme teknikleri kullanılarak tespit edilebilir.

Bu tezde, bir ABR algılama sistemi tasarlanmıştır. Deney prosedürü 'auditory oddball paradigm' kullanılarak dizayn edilmiştir. EEG kaydı sırasında, deneye katılan kişiye akustik uyaran, EEG kaydedilen yazılıma da uyaran hakkında bir işaretleyici eş zamanlı olarak gönderilmiştir. 13 denekten işitsel uyaran altında EEG verilerini kaydetmek için düşük maliyetli, kablosuz bir EEG kayıt cihazı kullanılmıştır. Kaydedilen EEG datası 'epoch' ayrıştırma, olaya ilişkin potansiyel (ERP) ortalaması alma ve bağımsız bileşen analizi (ICA) yöntemleri kullanılarak işlenmiştir. EEG datasından işitsel uyaran hakkında bazı ayırt edici özellikler çıkarılmıştır. Daha sonra, çıkarılan bu özellikler, verilen stimülasyon altında işitmenin oluşup oluşmadığını anlamak amacıyla verileri sınıflandırmak için kullanılmıştır. Deneylerin sonuçları, uygulanan ABR algılama sisteminin % 85 doğruluk payı ile ses ve sessizlik stimülasyonlarını tespit ettiğini göstermiştir.

Anahtar Sözcükler: EEG, ERP, İşitsel Beyin Yanıtı, ABR.

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LIST OF SYMBOLS

$X(t)$	Observed Signal
$S(t)$	Source Signal
$S'(t)$	Source Component Estimation
A	Mixing Matrix
W	Unmixing Matrix
σ	Singular Values of a Matrix
$s_i(t)$	Signal From source 'i' at time 't'
E_d	Energy of a Discrete Time Signal
$P(C_i|X)$	Probability of Given Data 'X' to be in Class 'i'

LIST OF ABBREVIATIONS

AEP	Auditory Evoked Potential
ABR	Auditory Brain Response
EEG	Electroencephalography
EMG	Electromyography
ECG	Electrocardiography
ERP	Event Related Potential
ICA	Independent Component Analysis
PCA	Principal Component Analysis
SVD	Singular Value Decomposition
PSD	Power Spectral Density
PDF	Probability Density Function
IC	Independent Component

1. INTRODUCTION

1.1 Motivation and Objectives

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 scalp or on the eardrum [1] [2]. Measuring the electrical response of auditory system gives many information about the status of individuals hearing. Auditory brain response(ABR) can be detected using EEG technology and signal processing techniques. ABR can be used for adults and also for newborn babies to test their hearing ability[3]. Since hearing has critical effect on the development of learning, speech and communication skills, early recognition of hearing loss and early intervention diminish the delays on language and learning development.

Extracting information from EEG is a complicated task because EEG signals are recorded from the scalp, far away from the origin of activity and contains many artefacts[4]. Recorded EEG signal is the sum of EEG source activities and non-brain source artefacts such as eye movement, muscle (EMG), cardiogenic (ECG) artefacts plus external instrumental noise[5]. EEG/ERP researchers try to find methods to seperate recorded EEG signals into set of activities originating from different source domains[6][7].

Event related potential(ERP) trial averaging method is used by researchers to reduce complexity of event-related EEG data[5][8]. If an experimental event(stimulus) is presented to a subject while recording the EEG, an epoch of the EEG that is time-locked to the stimulus can be defined[9]. If count of these epochs is large enough, extracted and averaged epochs give information about the processing of that event on the brain. This is because the event related activation will occur on all epochs and contributes to the averaged ERPs, whereas the remaining EEG(noise) tends to

become smaller and smaller by means of 'phase cancellation'[10]. An acoustic stimulus is presented to subject while recording the EEG, to get the information about auditory brain response to the acoustic stimulus.

Independent component analysis (ICA) as a signal proccessing method that receives increasing interest. The ICA problem is to seperate statisticaly independent sources(inputs) which have been linearly mixed on the observations(outputs). It is first used for speech seperation(cocktail-party problem)[11] and shortly after applied to EEG signal source seperation[10]. Since brain acts as a volume conductor, meaning that electrical activity generated in one spot can be detected at different locations, ICA is helpful to seperate indepedent activities produced on the brain as well as non-brain artefacts[6].

The objectives of the study can be stated as follows :

- To design an experiment procedure for the auditory brain response detection.

- To record the EEG data under auditory stimulus using the experiment procedure.

- To test the low cost, wireless Emotiv Epoc neuroheadset EEG recording device as an EEG research tool.

- To process EEG signal using independent component analysis and extract the features to identify silence and sound stimulus.

- To classify the extracted features to get the information about if hearing occurs or not.

1.2   Outline of the Thesis

Remaining chapters are prepared as follows.

In Chapter 2, Event Related Potentials (ERPs) are explained giving some information about brain structure, EEG and extraction of event related potentials from EEG. In that chapter we also mention from the auditory brain response explaining how human auditory system works and how ABR is generated as well as how it can be detected using EEG. Additionally, blind source separation methods (Principal Component Analysis and Independent Component Analysis) are explained.

In Chapter 3, Materials that are used in the study containing the experiment design (Emotiv EPOC, Openvibe, Null-Modem Emulator), signal processing (Matlab-Eeglab), and classification(Weka) are explained briefly.

In Chapter 4, Experiment design, EEG recording procedure, signal processing methods and classification methods that are used in the study are explained.

In Chapter 5, Results of the study are given.

In Chapter 6, Results of the study are discussed, and feature work is explained.

2.   BACKGROUND

2.1   EVENT RELATED POTENTIALS

2.1.1   EEG

Electroencephalography (EEG) is composed of two Greek words, "graphein"(write) and "encephalon" (brain). 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 [12].

The electric potential produced by single neuron cannot be picked up by EEG because it is too far and too small to be detected [13]. EEG can measure the summation of the synchronous activity of millions of neurons whose spatial orientation are similar. If an electrode pair is 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 vary between nearly -100 and +100 microV, and its frequency ranges to 40 Hz or more.

Generally EEG waveforms are classified according to their location, amplitude and frequency. 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 [14] [15]. 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 parts of observation are the frontal and central regions of the scalp.
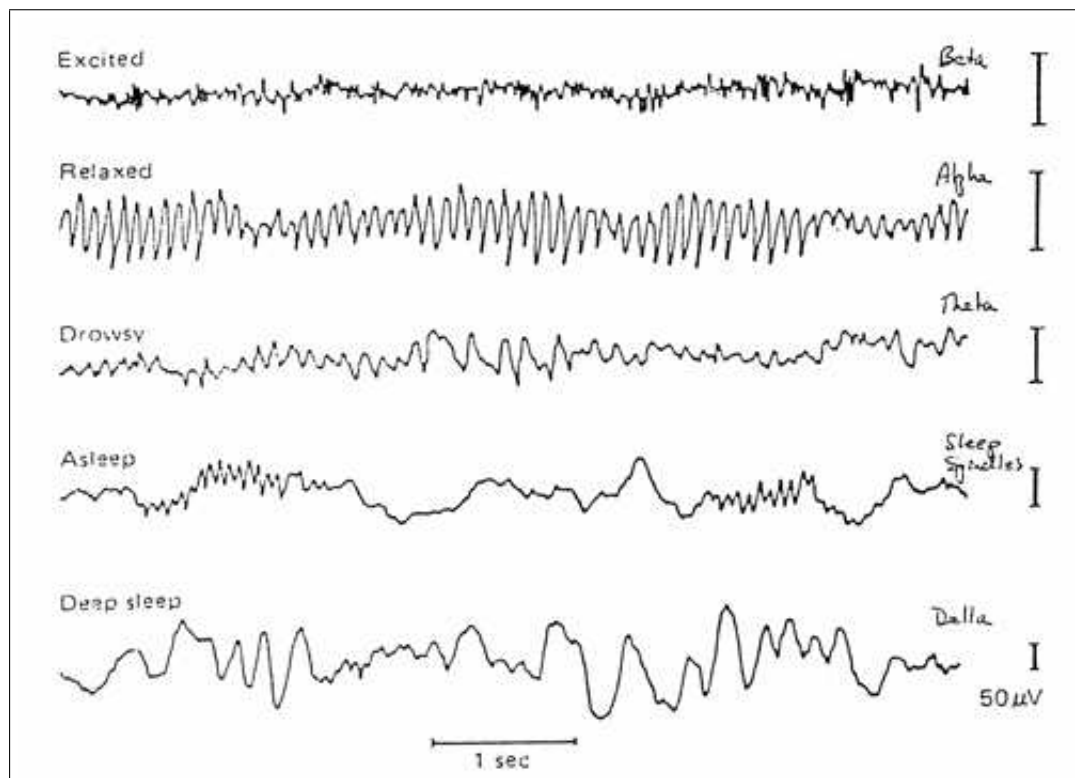
Figure 2.1 Rhythmic EEG activity [16]

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. In 1970s Donchin had stated that 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 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 electrical fields that can be measured at the scalp[17].

Electrode locations are generally expressed 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 (even numbers for right, the subscript z for midline and odd number for left). Although these electrode descriptors refer to particular brain areas, activity recorded at any particular scalp location is not necessarily attributable to activity in brain regions in close proximity to that location. This is because the brain acts as a volume conductor, meaning that electrical activity generated in one spot can be detected at far-away 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 both electrodes are subtracted from each other by the amplifier. Noise or electrical activity that is common to both electrodes is canceled out and what's left is only the response voltage. This is called common mode rejection. Then the response voltage is 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[17].

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

temporal, frontal, parietal, and occipital lobe [18].

1. Frontal Lobe- associated with planning, reasoning, movement, parts of speech, problem solving, and emotions

2. Parietal Lobe- associated with orientation, movement, perception of stimulus, and recognition

3. Occipital Lobe- associated with visual processing

4. Temporal Lobe- related with perception and recognition of speech, auditory stimuli, and memory
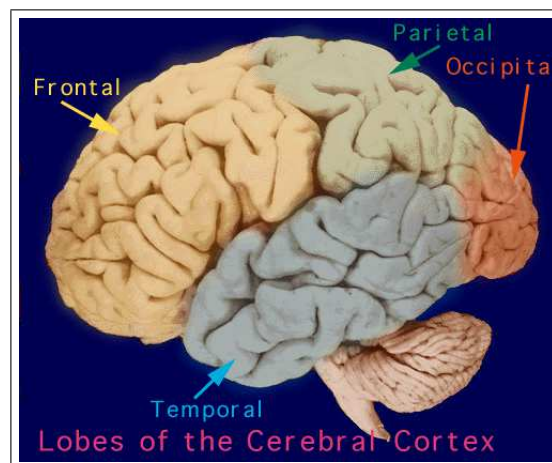
Figure 2.2 Visual representation of the cortex [18]

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.
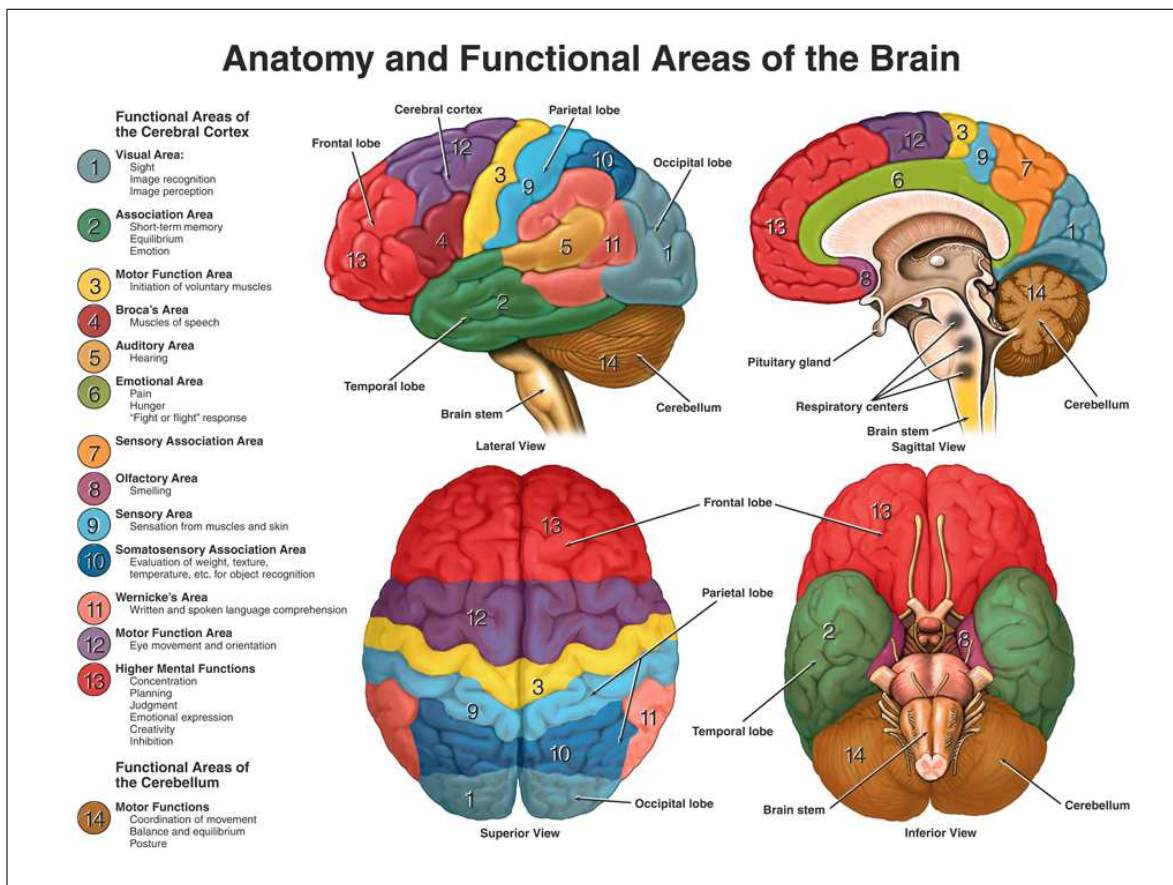
Figure 2.3 Anatomy and functional areas of brain [19]

The system has mainly two parts; Auditory nervous system and the ear. The ear consists of three main parts; outer ear, 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) stirrup, hammer, and anvil. 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.[20]

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.
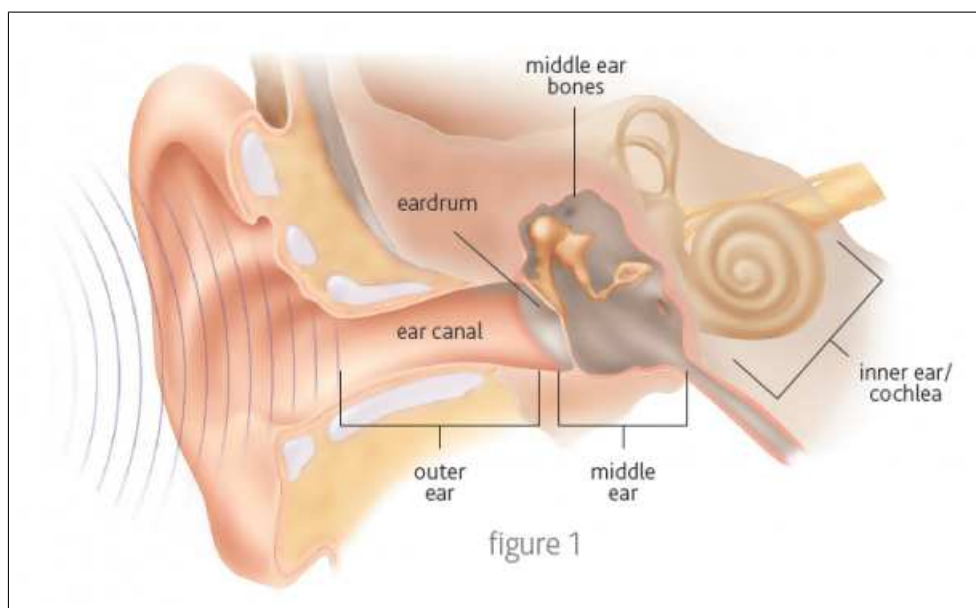
Figure 2.4 Auditory System [21]

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 AEPs are measured using electrodes on the surface of the skin or on the eardrum. Auditory Brain Response (ABR) is a kind of auditory evoked potential and it is a far-field recorded potential because the electrodes are placed on the scalp or on the ears, far away from the potential generator, the cochlea[22]. The auditory brainstem response is also commonly referred to as an ABR or brainstem auditory evoked response (BAER), depending on the region in which you

live.
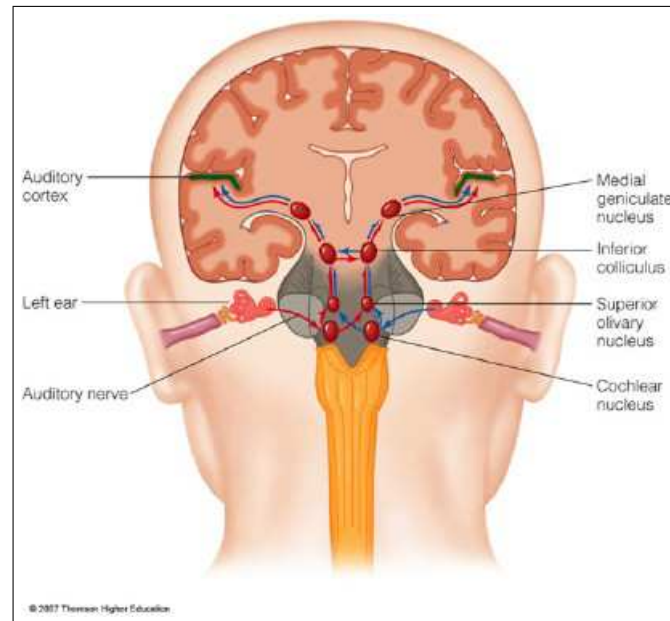
Figure 2.5 Central Auditory Pathway [23]

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 [24].

The auditory stimulus is processed at the temporal lobe. The first region of cerebral cortex is primary auditory cortex to receive acoustic input. Perception of sound is associated with the left posterior superior temporal gyrus (STG). The neurons of the primary auditory cortex are thought to have receptive fields covering a range of auditory frequencies. Primary auditory cortex is surrounded by secondary auditory cortex, and intersects with it. These secondary areas intersect with further processing
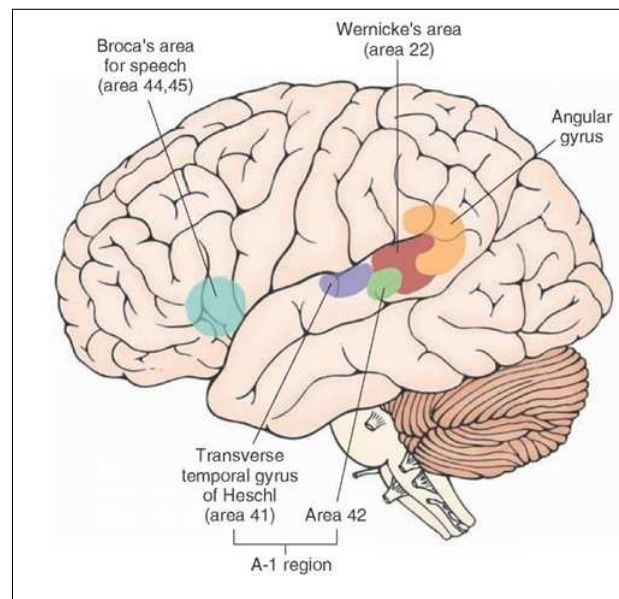
Figure 2.6 Primary auditory cortex. Broadman's area 41-42 receives projections from the medial geniculate nucleus. Wernicke's area (secondary auditory area) is important for the interpretation of the spoken word. [24]

areas in the superior temporal gyrus, in dorsal part of the superior temporal sulcus, and in frontal lobe. In humans, association between these regions with the middle temporal gyrus is possibly important for speech perception [25] [26].

Auditory stimulus processing can be detected using EEG. 10-20 system is used for electrode placement. For a two channel recording, Cz which is the top of the skull, (or FPz, which is high forehead) A1 for the left ear and A2 for the right ear are used. Earlobe placement or sometimes M1 and M2 for mastoid placement is used as well in the clinic.[22]

The auditory stimulus can be a click, tone burst, or white noise. The auditory brain response arises shortly after the beginning of the stimulus so it is called an early potential. AEPs 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 are; wave I - auditory nerve, wave II - cochlear nuclei, wave III - superior olive, wave IV - lateral
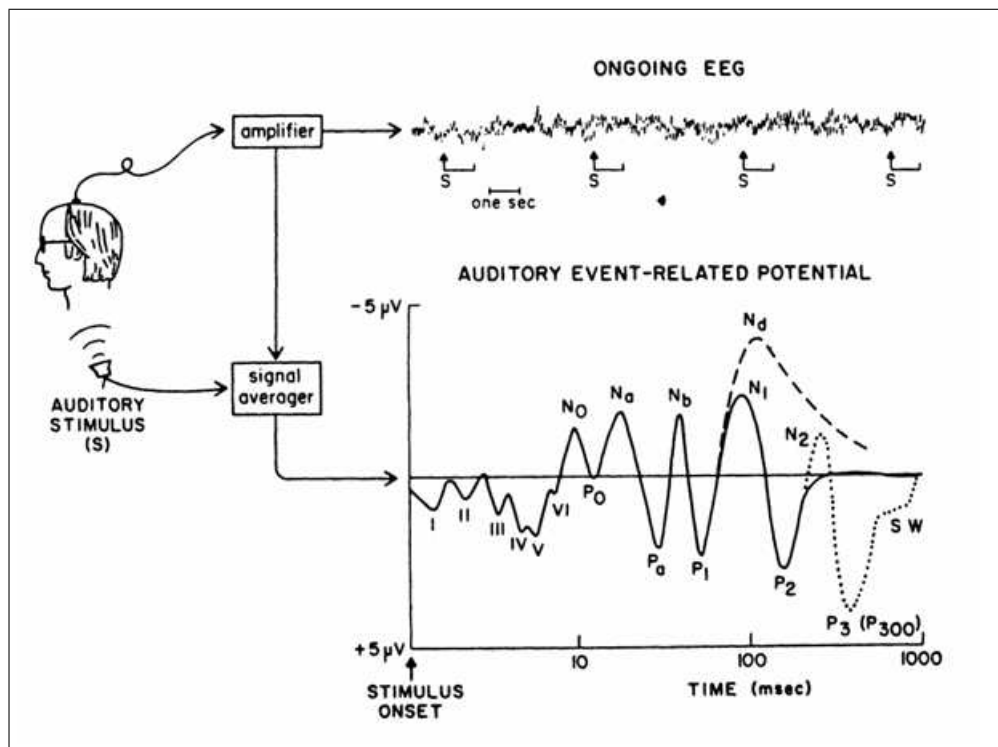
Figure 2.7 Idealized waveform of the computer-averaged auditory event-related potential (ERP) to brief sound. The ERP is generally too small to be detected in the ongoing EEG (top) and requires computer averaging over many stimulus presentations to achieve adequate signal noise ratios. The logarithmic time display allows visualization of the early brain-stem responses (Waves I-VI), the rnidlatency 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

lemniscus, wave V - inferior colliculus. Waves I to V make up the brainstem potentials (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, can be described as the separation of a set of original source signals from a set of mixed signals, without the help of the knowledge about the source signals or the integration 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

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

And the original source signals as

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

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 × m. Using the mixing matrix A, it is then possible to project the components back to reconstruct the original data.

$$S'(t) = WX(t)$$

Where $S'(t)$ 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. 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.

PCA algorithm can be summarized as [27]

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

$$\underbrace{\begin{bmatrix} A \end{bmatrix}}_{m \times n} = \underbrace{\begin{bmatrix} U \end{bmatrix}}_{m \times n} \underbrace{\begin{bmatrix} D \end{bmatrix}}_{n \times n} \underbrace{\begin{bmatrix} V \end{bmatrix}}_{n \times n}^{T} \tag{2.1}$$

Where D is a diagonal matrix and contains the singular values of A, (σ)

$$D = \begin{bmatrix} \sigma_i & 0 & 0 & 0 \\ 0 & \sigma_{i+1} & 0 & 0 \\ 0 & 0 & \ddots & 0 \\ 0 & 0 & 0 & \sigma_n \end{bmatrix}$$

U's columns are the eigenvectors fo AA^T and V's columns are the eigenvectors of $A^T A$.

To get the top k eigenvectors, X (observed data) can be written in Equation 2.1 as $X = UDV^T$ then top k columns of 'V' are the top k eigenvectors of Σ

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.

PCA can be demonstrated using the Figure 2.3.2. In that figure 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)

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
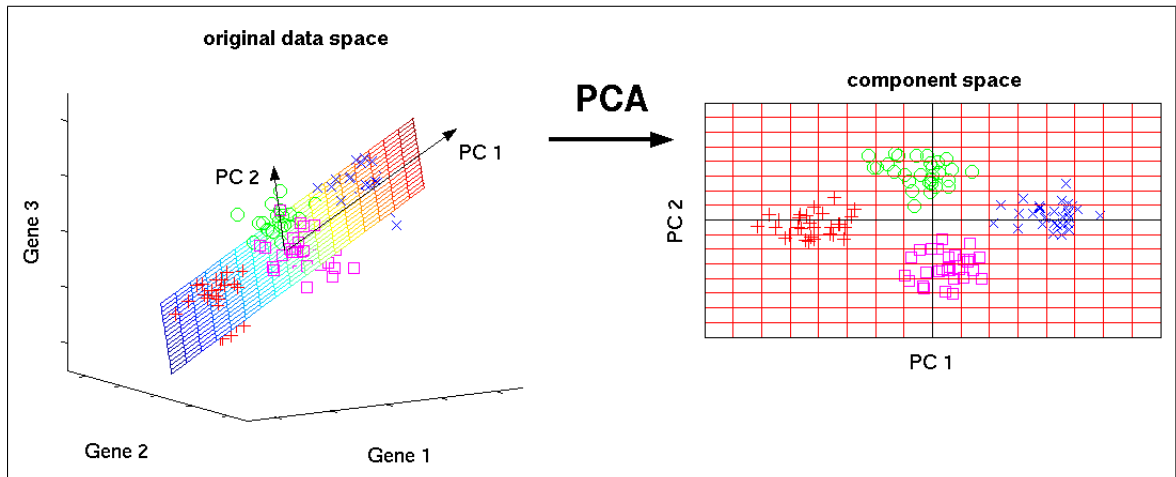
Figure 2.8 Principal component analysis (PCA) [28]

produced 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 original independent source signals. The goal is to find a linear representation of non-Gaussian data with the intention that the components are statistically independent.
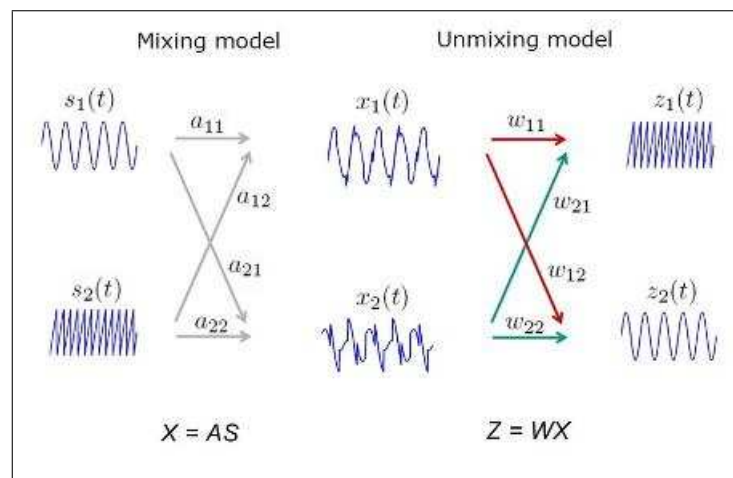
Figure 2.9 Independent component analysis (ICA) model [29]

ICA does not require orthogonality of the components and it can be thought as

a higher order generalization of PCA. ICA tries to make components to have minimum mutual information, there are some ICA algorithms that measures the non-Gaussianity of the components using higher order statistics [30][31]. By the help of central limit theory, relation between non-Gaussianity and statistical independence can be understood. Central limit theory states that the sum of independent random variables tend to become more gaussian than each variable. So if the sources $S_i(t)$ in ICA is assumed to be independent, the observed signal $X_i(t)$ will be more gaussian by the central limit theorem. For the closest approximation to the real sources, the unmixing vector W is found such that it maximizes the independence on all of the source components(S'(t)). There are several ways to measure components' independence. While some methods try to minimize mutual information, others try to maximize non-Gaussianity.

There are several ICA algorithms, some of them are called, Kernel-ICA [32], Infomax Ica [33], RADICAL[34], Fast Ica [35], JADE [36]. Infomax Ica and Fast Ica are probably the most known and used algorithms. For the measurement of non-Gaussianity entropy-negentropy and kurtosis methods can be used. Kurtosis is a measure to understand whether the probability distribution of data is 'peaked'(super-Gaussian) or 'flat'(sub-Gaussian) relative to normal distribution (Gaussian). Positive kurtosis means the data is super-Gaussian whereas negative one means the data is sub-Gaussian.

If we define original sources (e.g. n speakers) as $S(t)$, signal from source i (e.g. i'th speaker) at time t as $s_i(t)$, the observed signal can be expressed as $X(t) = AS(t)$ and $X_i = \sum_{k=1}^{n} A_{ik}s_k$ Then our goal is to find $W = A^{-1}$ so that $S(i) = WX(t)$

ICA model has mainly two ambiguities.

- The variances of the independent components cannot be determined. Since $X = AS$ and both S and A are unknown, any scalar multiplier in the sources S can be cancelled by dividing the mixing matrix A by the same scalar, so the

magnitudes of the independent components could not be determined correctly. Fortunately the problem can be resolved by normalizing the data to zero mean and unit variance, but still the sign of the components are unknown and in most applications luckily the sign of the components are insignificant.

- The order of the independent components can not be determined. Since one component can be computed as the sum of unmixing matrix coefficients multiplied by the observed signals, we can freely change the order in the summation and any of the independent components can be called as first one.

ICA algorithm [37] :

- Normalize the data to zero mean and unit variance

- Initially start with a random W matrix

- Measure non-gaussianity or mutual information (entropy-negentropy) of the components

- Iteratively update W to have maximum non-gaussian components.

Despite the fact that at first ICA is used for "cocktail party problem" and succeeded, also it is used for EEG processing and have satisfactory results [10].
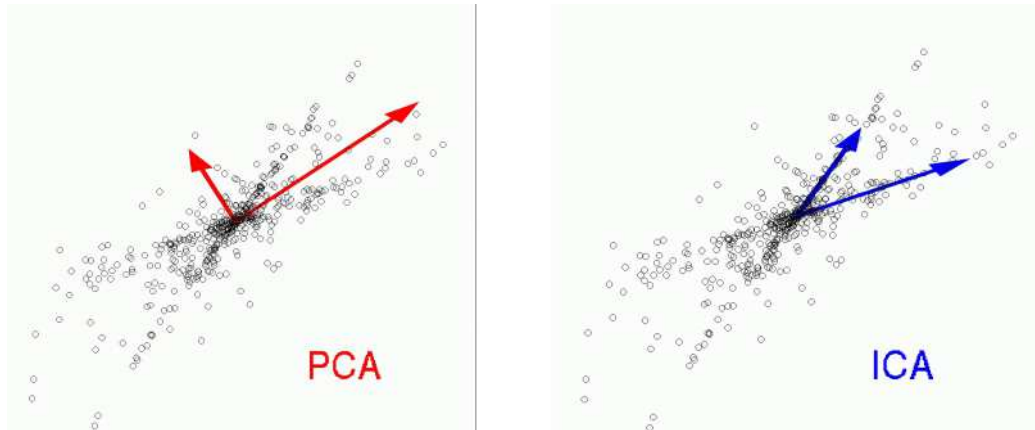
Figure 2.10 Principal Components and Independent Components of a normalized data [37]
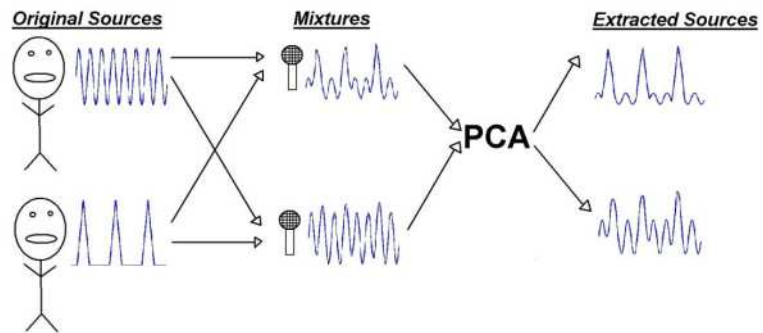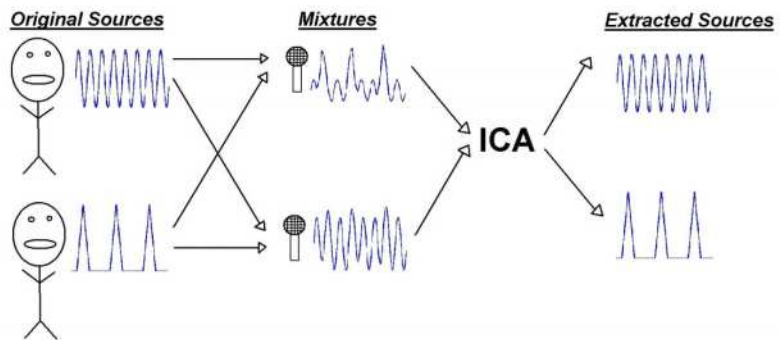
Figure 2.11 PCA and ICA solution of 'cocktail party effect' [38]

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. [39] 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.[40] EEG neuroheadset does not require gel on the scalp; it should be moisturized with saline solution before usage.
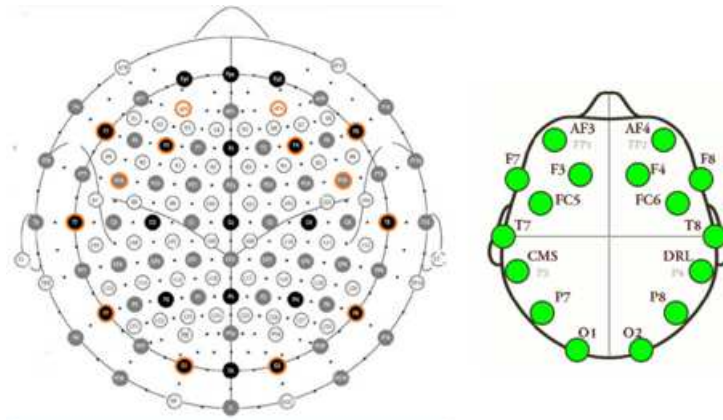
Figure 3.1 Electrode locations used by the EPOC [39]

The Epoc neuroheadset has been used as a gaming tool and recently it also used by research purposes [41][42][43] 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 = 0.51µV
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 [39]

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 [44].

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 [45].

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 [46].

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. Row 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 [47].

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 four 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[48] [49] 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(Appendix A.1). "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 (Fig.4.1).

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 Test-Bench recording.
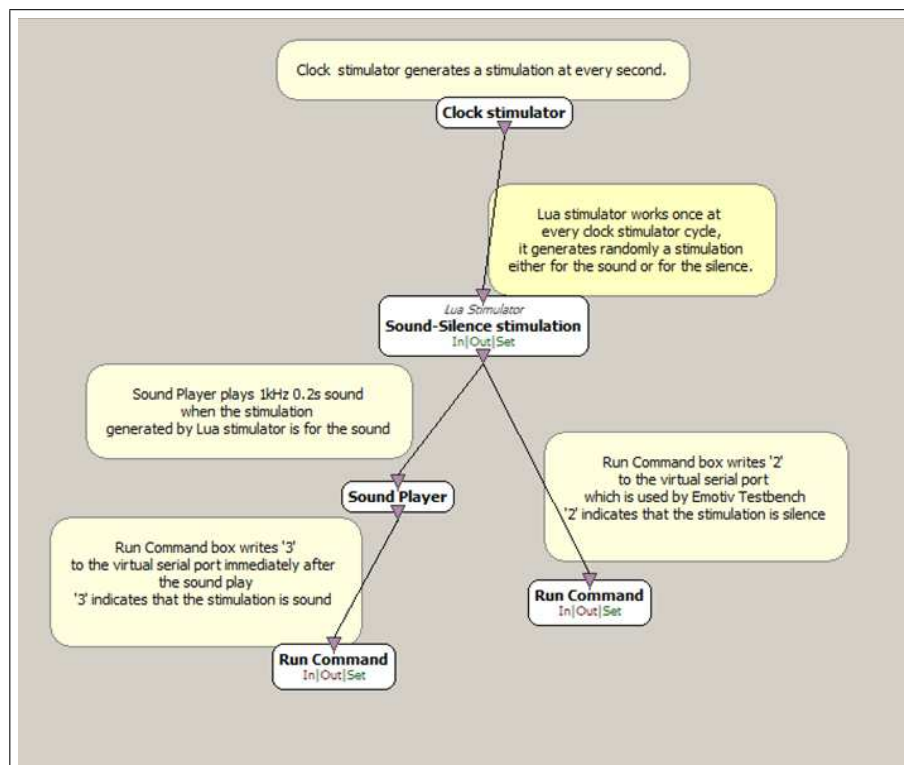
Figure 4.1 Experiment procedure design in OPENVIBE

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. 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 repeted for 13 people (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
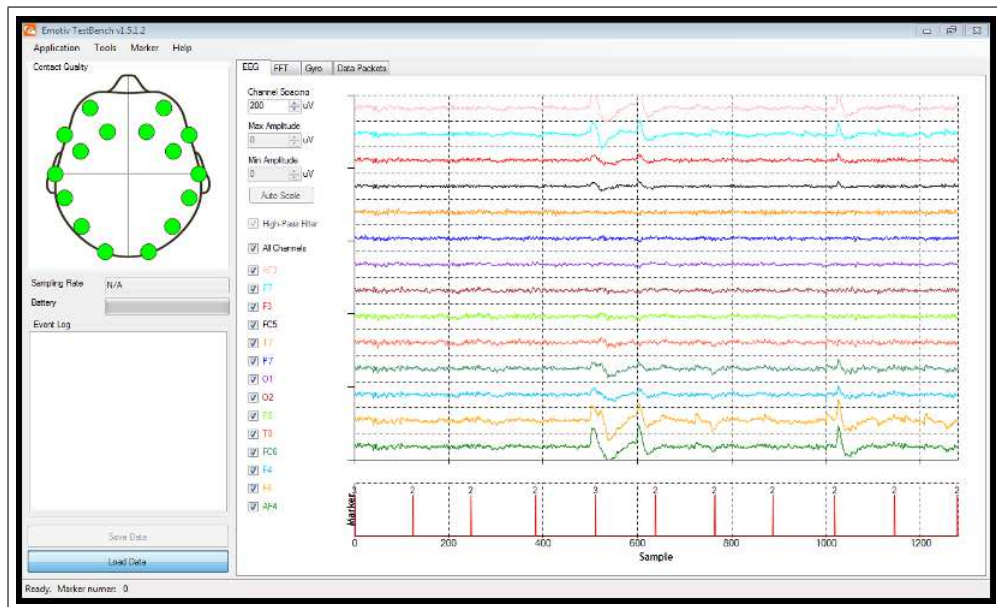
Figure 4.2 A recorded data on TestBench

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 [50] 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 [51]. Multiplying the Weight matrix with the EEG data gave us the maximally independent components on the EEG data.The ICA solution has been used firstly to the cocktail party problem and it 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 [52].
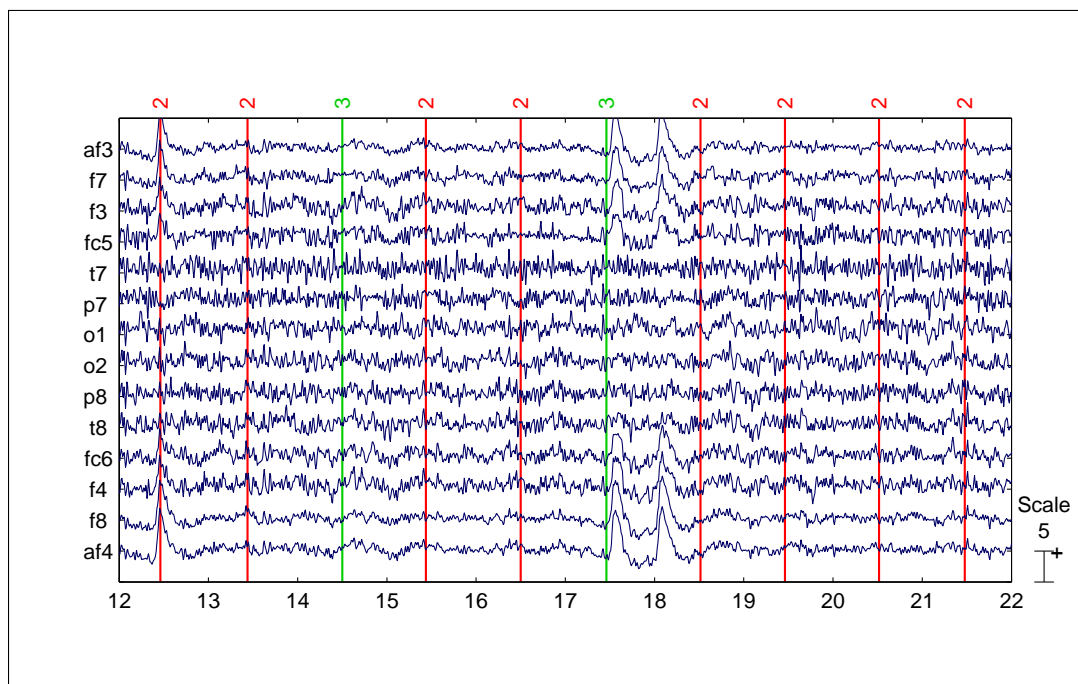
Figure 4.3 Channel Data of EEG for 10 second

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 [17]. 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)
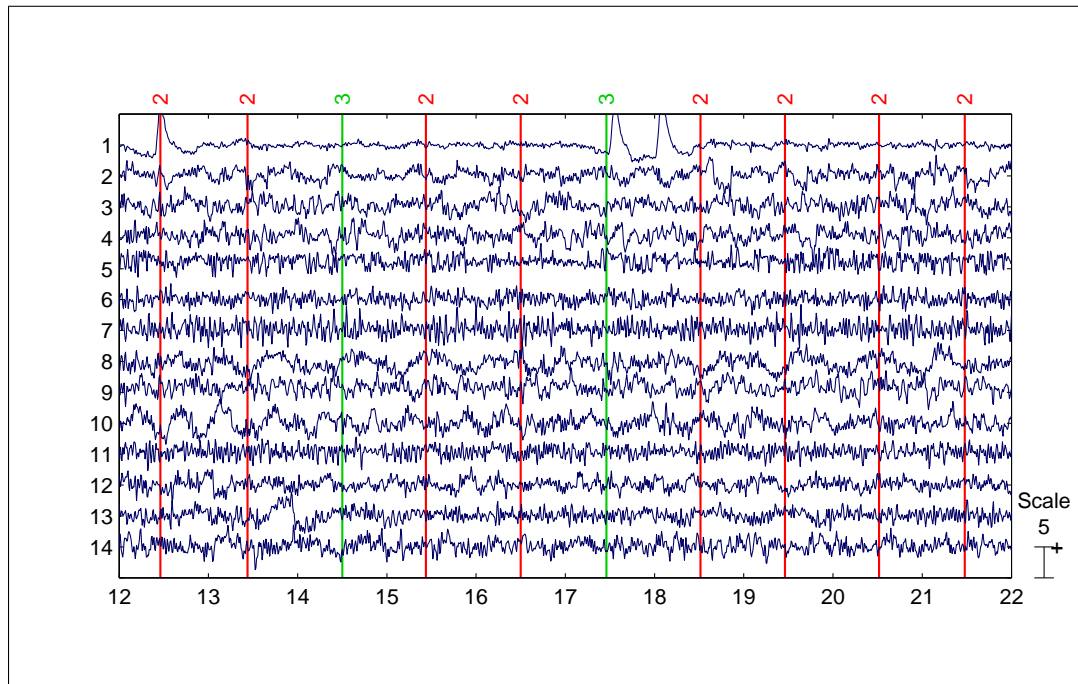
Figure 4.4 Component Data of EEG for 10 second

"averaging" is used as a signal extraction technique most commonly [17]. Since the EEG activity that is not related (time locked) with the event will randomly vary across epochs, this average background EEG will tend to become zero. Therefore the time locked average ERP will largely represent activity of the brain, that is 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 study 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 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 used later on the classification part.

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

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

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.

$$Maximum Power = max(|x(k)|^2) \tag{4.2}$$

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

$$\frac{1}{2T} \mid \int_{-T}^{T} f(t)e^{-j2\pi ft}dt \mid^2 \tag{4.3}$$

PSD is calculated using the Signal Processing Toolbox on MATLAB.[53] (Appendix A.2.2)

A MATLAB script is written to extract the features (Appendix 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[54] [55].

If we show each data instance as attribute values consisting of n-dimensional vector as:

$$X = (x_1, x_2, x_3, ..., x_n) \qquad (4.4)$$

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

$$C = (C_1, C_2, C_3, ..., C_m) \qquad (4.5)$$

The classifier assings the data X, to class C_i if and only if the probability of given data 'X' to be in class 'i' is bigger than all of the probabilities for each class.

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

The Bayes' Theorem states that

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

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:

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

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

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

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:

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

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 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 whole dataset(size=n) 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.

As the second method for classification, the data has been spectrally analyzed. The averaged epoch signals have been converted to frequency domain, power of the signal for 5Hz intervals has been computed and written to an 'arff' file seperatly for the sound and silence parts of the data.

Signal processing procedure is also applied without using ICA. Feature values are extracted using the averaged ERP waveform and data is classified to understand if ICA gives better results or not.

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 [52]. 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. We can say that the first component on Fig.5.2 is probably eye-blink artefact.

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 of one of the subject's 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.
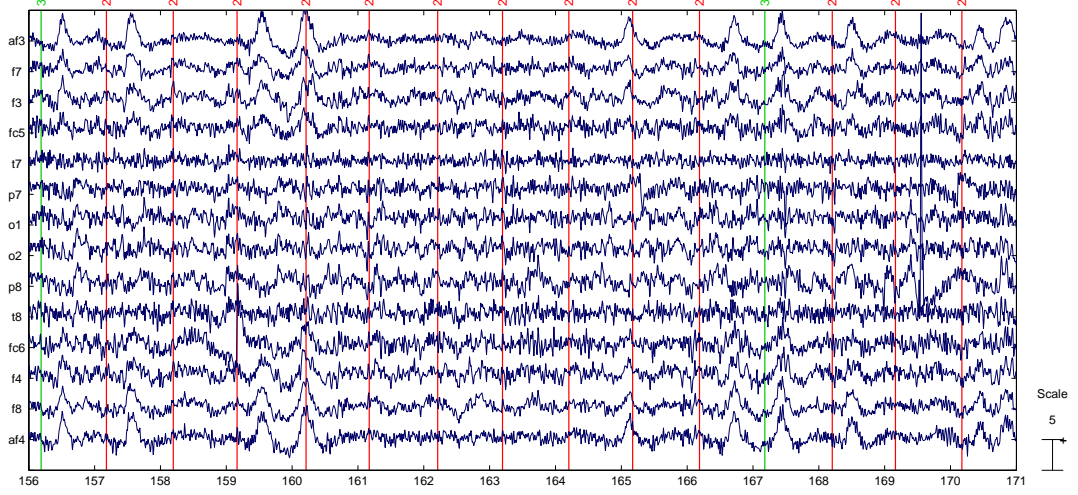
Figure 5.1 15 sec part of 14 Channel EEG Data for one subject
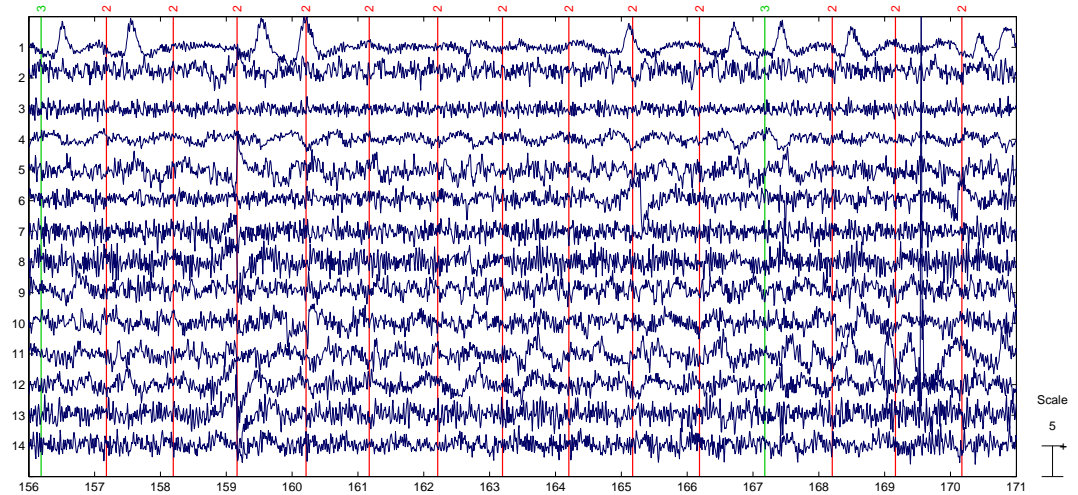
Figure 5.2 14 Components of EEG Data of the same subject
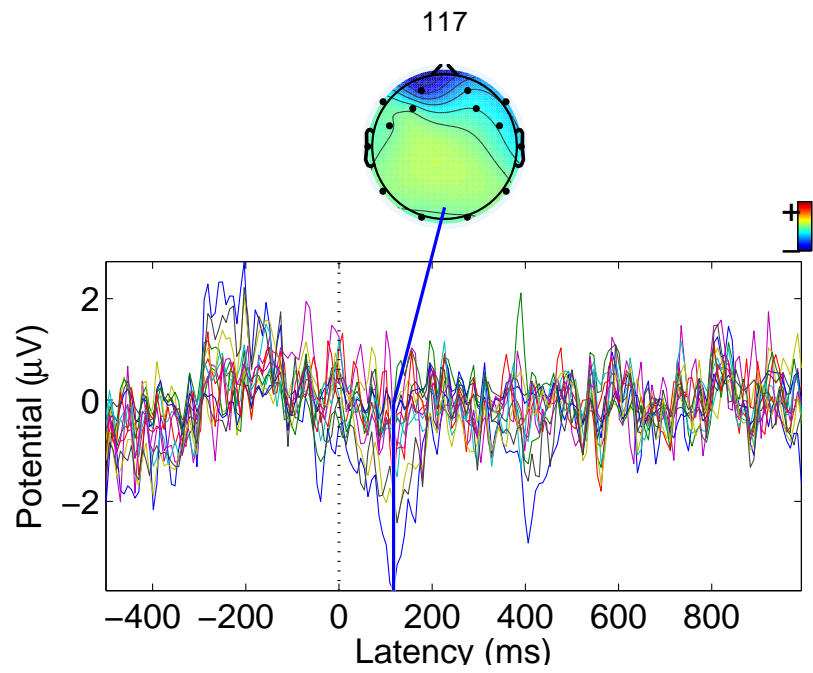
Figure 5.3 14-Channel Silence Epochs For One Subject
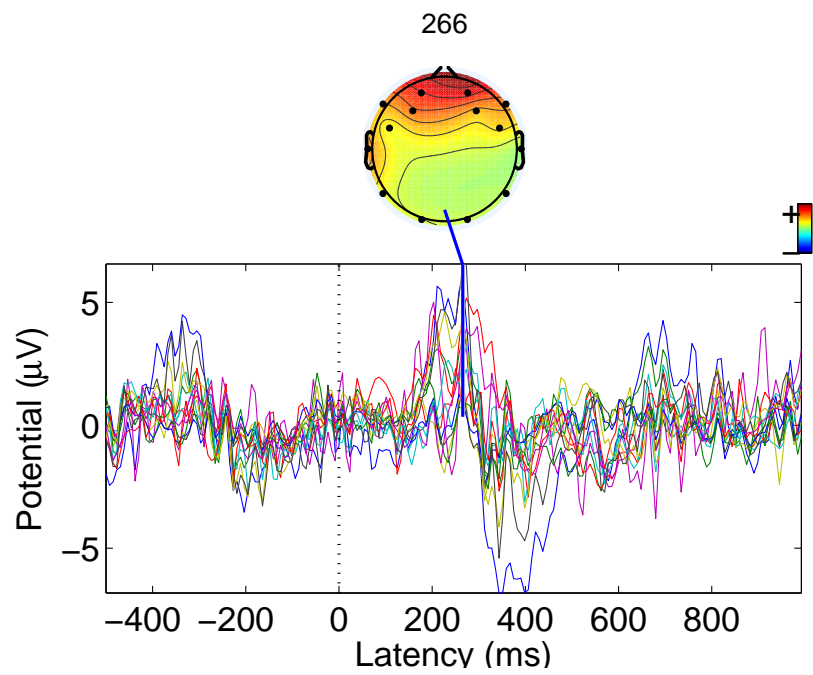
Figure 5.4 14-Channel Sound Epochs For The Same Subject

Largest ERP components of silence
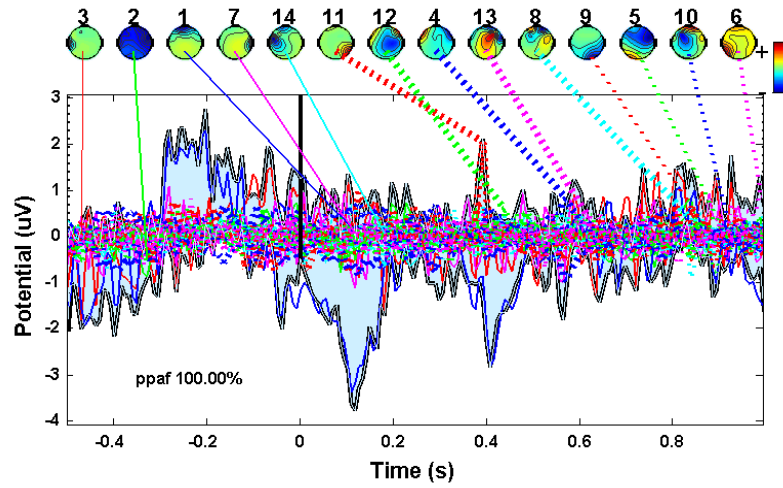
Figure 5.5 Silence Component ERP epochs

Largest ERP components of sound
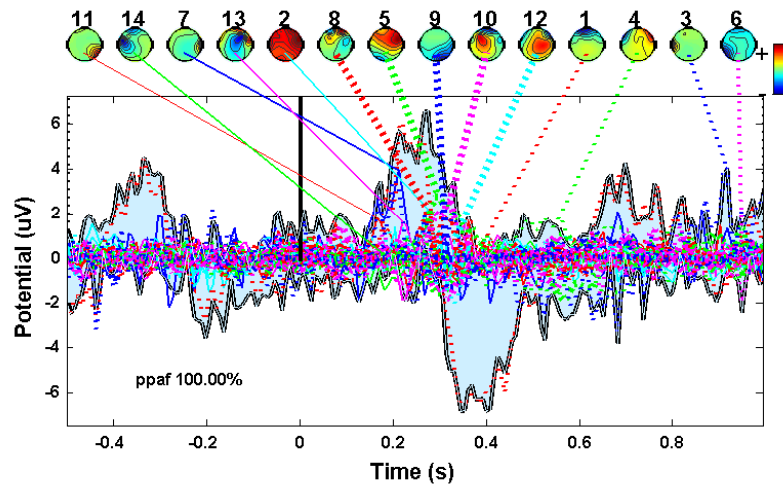
Figure 5.6 Sound Component ERP epochs
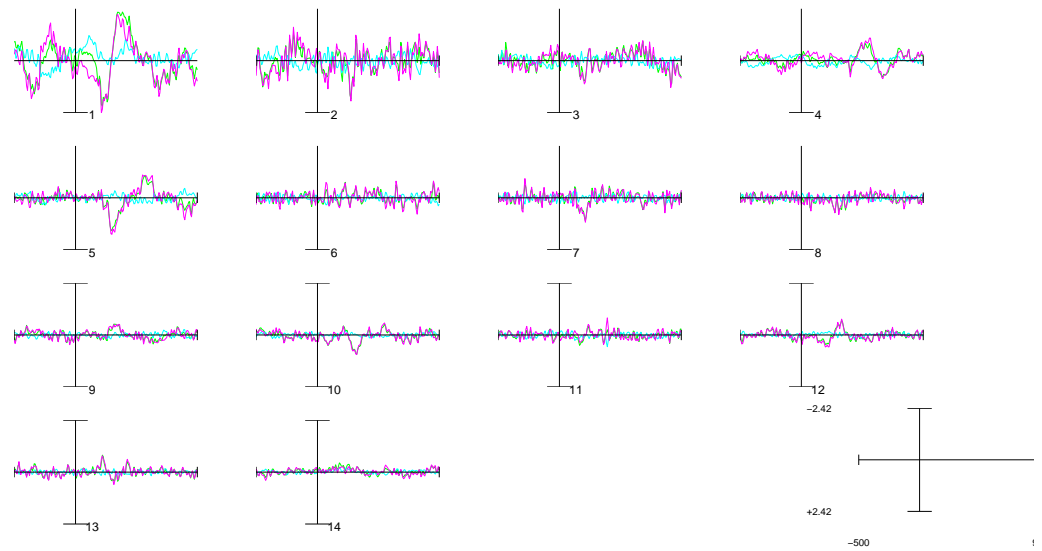
Figure 5.7 Difference between silence and sound stimulation on 14 components
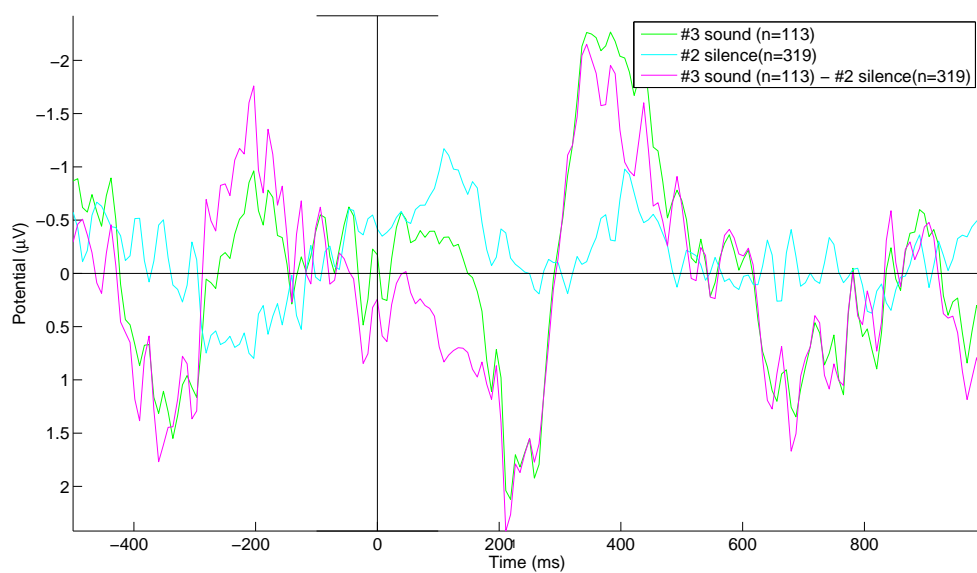
Figure 5.8 Difference between silence and sound stimulation ERP values for one component

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.

Mean and standard deviation of extracted feature values can be seen on Table 5.1. The values for each feature attribute have been tested with t-test. T-test result shows that all of the attributes were significantly different($p=0.05$) on sound and silence stimulus.

Table 5.1
Mean and standard deviation of extracted features

	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	

Classification based on this 5.1 feature values are done using the Naive Bayes' classifier on WEKA. 10-fold cross validation is used. The classification results were like the following:

Table 5.2
Confusion Matrix

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

Correctly Classified Instances = 66 =>84.6154 %
Incorrectly Classified Instances = 12 =>15.3846 %

Using the confusion matrix Chi-square statistics test is done. Since the calculated Chi Square value for the confusion matrix exceeds the value on the Chi-square table with degree of freedom=1 and probability level p=.05 we can conclude that the results are statistically significant.

Visualization of the feature matrix can be seen on Fig. 5.9

After calculating the component ERP features and confusion matrix, the data has been processed without using the ICA method, only averaged ERP waveform is used for feature extraction and classification.

Mean and standard deviation of extracted feature values without ICA can be seen on Table 5.3.

Classification based on this 5.3 feature values are done using the Naive Bayes' classifier on WEKA. The classification results were like the following:
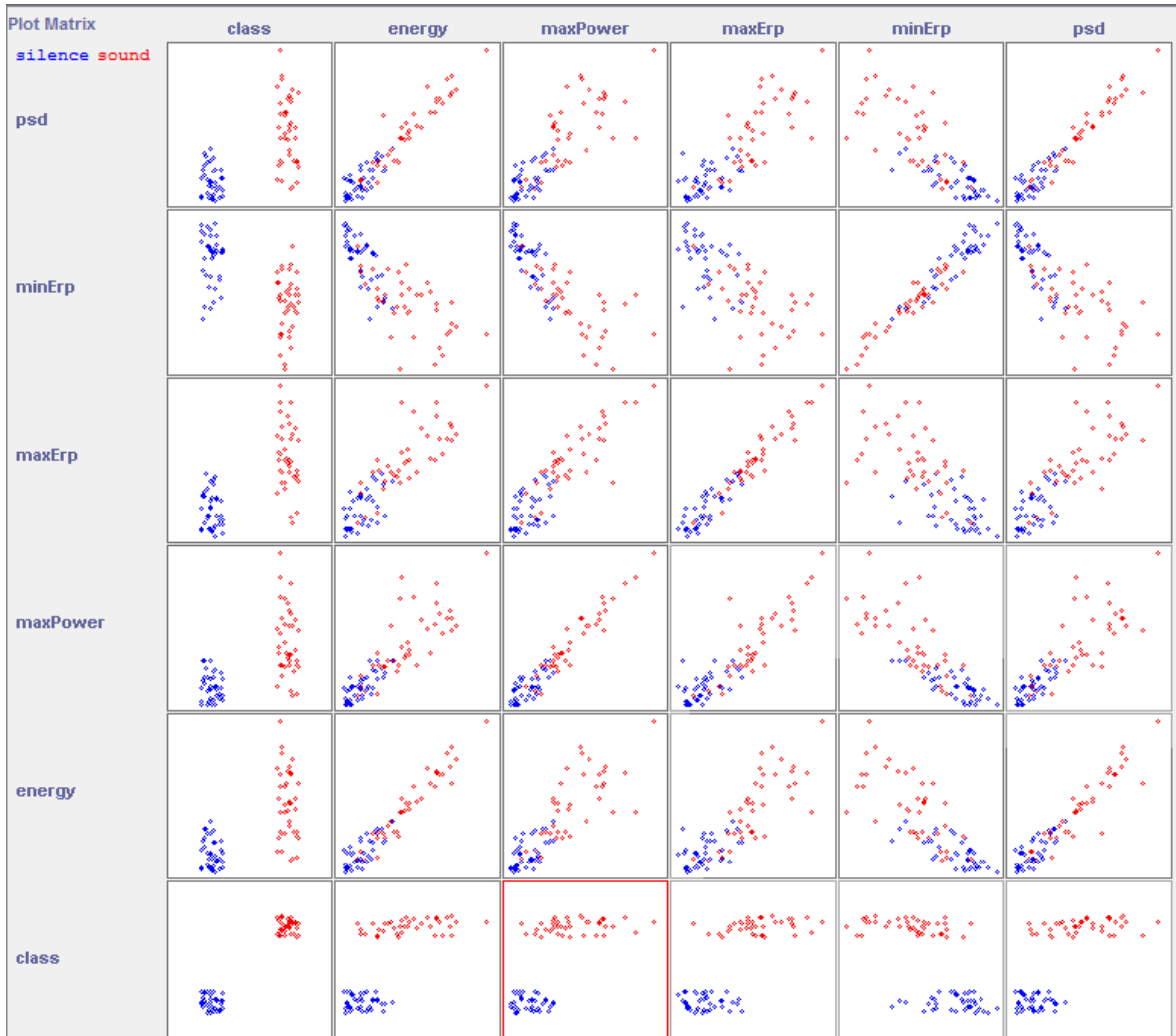
Figure 5.9 Visualization Of The Feature Matrix

Table 5.3
Mean and standard deviation of extracted features without ICA

	silence	sound	
Mean	21792.3391	66224.9683	Energy
Std. Dev.	20395.6439	52102.9801	
Mean	853.2856	2730.5141	max(Power)
Std. Dev.	765.2978	1689.8934	
Mean	24.487	47.4115	max(ERP)
Std. Dev.	9.0257	15.7767	
Mean	-24.0846	-38.4194	min(ERP)
Std. Dev.	11.3488	14.6854	
Mean	58.1975	180.8601	psd
Std. Dev.	54.7966	143.6188	

Correctly Classified Instances = 60 =>76.9231 %

Incorrectly Classified Instances = 18 =>23.0769 %

Table 5.4
Confusion Matrix Without ICA

a	b	Total	<– classified as
34	5	39	a = silence
13	26	39	b = sound
Total 47	31	78	

As the result of second feature extraction method(5Hz interval power spectral analysis), power spectral density graph of one subject for sound and silence stimulus can be seen on Fig 5.10. Blue line indicates sound stimulus, red line indicates silence one. The peaks on the graph does not represent the signal energy on the specific frequency. The area under the graphs for some interval represent the energy of the signal on the specific frequency interval.
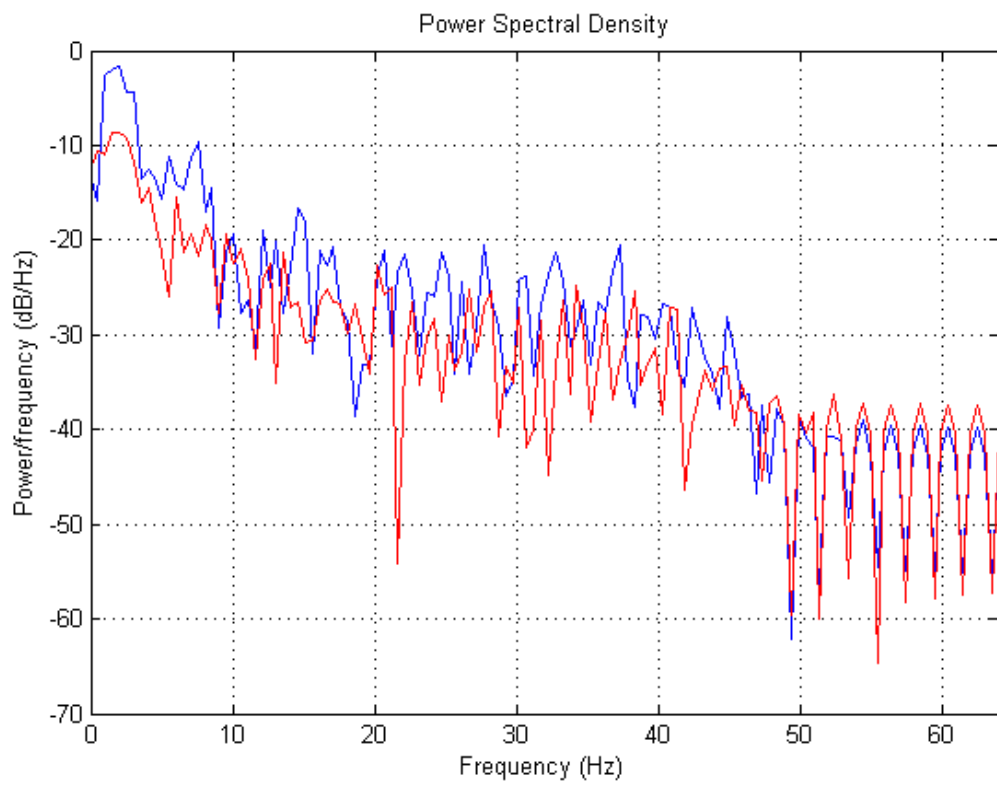
Figure 5.10 Power Spectral Density Graph of One Subject

Mean and standard deviation of extracted feature values by using the second feature extraction method can be seen on Table 5.5. The values for each attribute(each frequecny interval) have been tested with t-test. T-test result shows that all of the attributes were significantly different(p=0.05) on sound and silence stimulus.

Table 5.5
Mean and standard deviation of extracted features (5Hz-interval power spectral analysis)

	silence	sound	
Mean	206.719	651.2974	a1_5
Std. dev.	130.9761	421.3211	
Mean	61.3815	160.7035	a5_10
Std. dev.	94.0506	129.1714	
Mean	26.9712	80.8319	a10_15
Std. dev.	31.0792	51.5866	
Mean	13.0691	46.1994	a15_20
Std. dev.	8.6364	26.0112	
Mean	9.8814	27.0544	a20_25
Std. dev.	5.6849	13.0509	
Mean	10.1745	25.1873	a25_30
Std. dev.	7.2879	14.9639	
Mean	9.9987	27.3729	a30_35
Std. dev.	10.7062	20.4041	
Mean	5.8562	17.1211	a35_40
Std. dev.	5.1604	10.412	
Mean	2.3317	6.7368	a40_45
Std. dev.	1.4298	4.2871	
Mean	0.3861	1.025	a45_50
Std. dev.	0.2962	0.6752	

Classification based on this (Table 5.5) feature values are done using the Naive Bayes' classifier on WEKA. 10-fold cross validation is used. Classification results using 5Hz-interval power spectral analysis have been found like the following (Table 5.6)

Table 5.6
Confusion Matrix (5Hz-interval power spectral analysis)

a	b	Total	<– classified as
34	5	39	a = silence
6	33	39	b = sound
Total 41	37	78	

Correctly Classified Instances = 67 =>85.8974
Incorrectly Classified Instances = 11 => 14.1026

Results for spectral analysis method can be seen as a feature matrix on Fig. 5.11

Classification is also done by using the results on 5Hz-interval power spectral analysis without ICA. Classification results have been found like the following (Table 5.7)

Correctly Classified Instances = 59 =>75.641 %
Incorrectly Classified Instances = 19 => 24.359 %

Table 5.7
Confusion Matrix Without ICA(5Hz-interval power spectral analysis)

a	b	Total	<– classified as
33	6	39	a = silence
13	26	39	b = sound
Total 46	32	78	
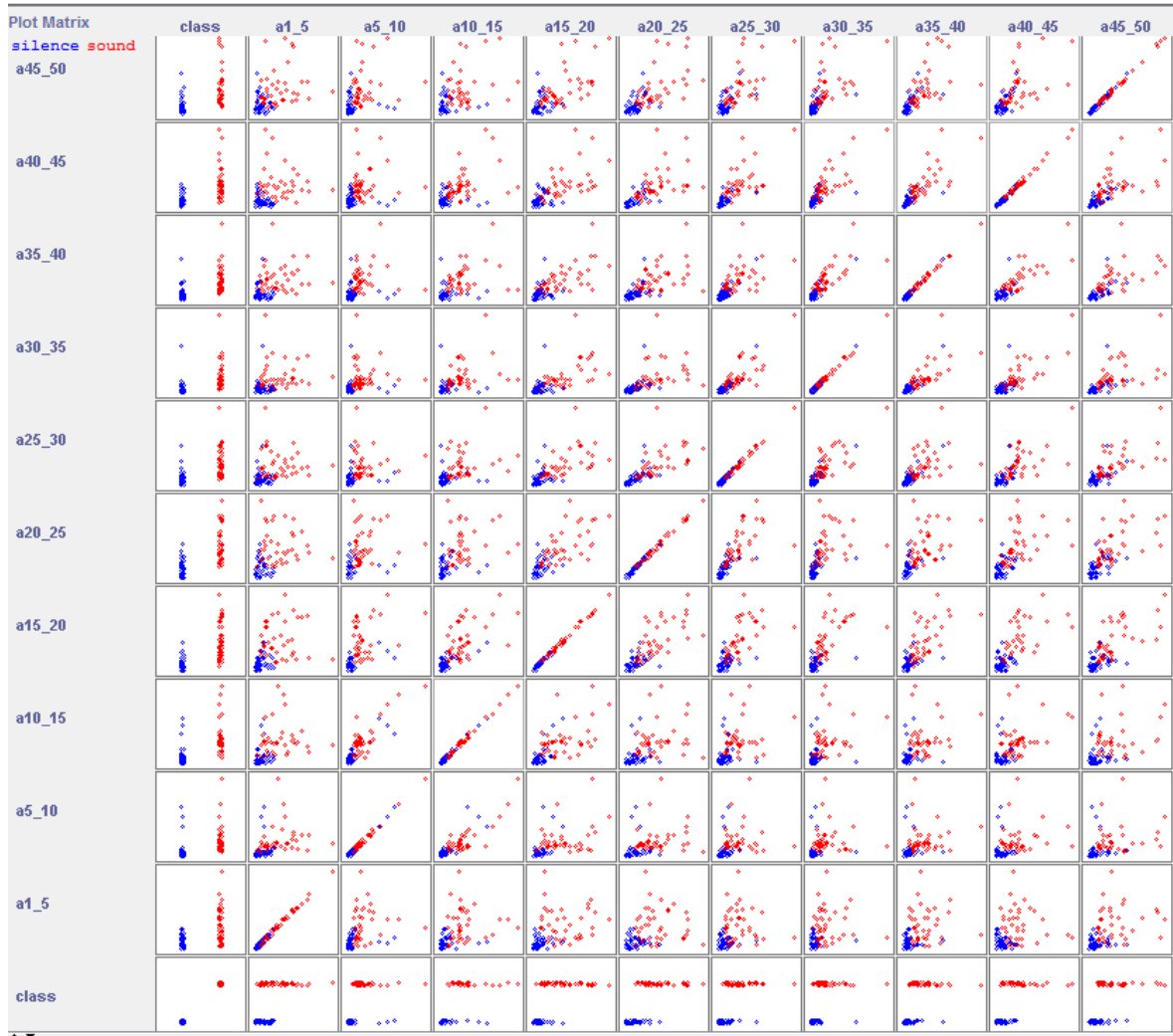
Figure 5.11 Visualization Of The Feature Matrix For 5Hz Interval Spectral Power

6. DISCUSSION AND CONCLUSIONS

6.1   Discussion

6.1.1   Experiment Design

In the experiment design, implemented auditory oddball paradigm gave us the opportunity to detect selective attention to given auditory stimulus. Sound and silence stimulus are presented randomly with the ratio of 1/5 to identify the brain response to the sound stimulus accurately. Sound stimulus was pure tone and duration has been chosen as 0.2 second in order to identify the stimulus effect in 1 second duration epochs.

6.1.2   EEG Recording

EEG data is recorded using Emotiv TestBench software, acoustic stimulus marker has been sent using different program(Openvibe) via virtual serial port. There were nearly 100 ms delay between sending of marker to the Testbench recording and playing the sound on sound player box when we use same stimulator for marker send and to open sound player box on Openvibe, this delay has been decreased by not using the same stimulator but stimulating the sending of marker with the playing of sound.

EEG data recording time has been chosen as nearly 3 minute in order not to make the subjects get bored because if the subjects are annoyed with the length of experiment the artifacts (e.g. eye movement, muscle, eyeblink ..) on the recording increases. Another reason for not using a long experiment duration is the adaptation process on the brain, because if same stimulus is presented in long duration, brain adapts to that stimulus and begins to ignore it.

6.1.3 Signal Processing

Raw EEG data has been filtered and some extraordinary voltage values has been substracted. Then independent component analysis is done on the filtered data, ICA has been done before the epoch extraction and averaging because ICA gives better results with more data points. Epochs of EEG data has been extracted using the markers and averaged for the sound and silence stimulations seperately. Phase difference on each epoch caused averaged silence epochs to become smaller on amplitude. Acoustic stimulation make the sound epochs to be on nearly the same phase so that the resulting averaged sound epochs reflects the brain response to the stimulus.

6.1.4 Classification

To classify the feature extracted data 10-fold cross validaiton is used with Naive Bayes classifier. Cross validation gave us the opportunity to use all of the feature data on both training and testing parts.

6.2 Future Work

It is shown in the study that the method can be used to seperate sound and silence stimulations with nearly 85% correctness on 13 subject with 78 data (39 silence, 39 sound), but the results may be compared with the clinical instrumentation to get better idea about the system's performance.

Brain adaptation process may be considered deeply and effective long time duration for the experiments may be obtained. An audiometer can be implemented by using different frequency and dB level sound as stimulators.

6.3 Conclusion

The study shows that experiment design and signal proccessing procedure can be a starting point of new experiments for the auditory brain response detection using portable, wireless and low cost eeg headsets. Even though the headset(EPOC) used in the study is thougt as a game tool it is shown that it can be used for research purposes on auditory response detection with the help of improved signal proccessing techniques.

APPENDIX A. SCRIPTS

A.1   Lua Script

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

```
31  -- at the end of the loop
32  while true do
33
34  -- gets current simulated time
35  t = box:get_current_time()
36
37  -- loops on all inputs of the box
38  for input = 1, box:get_input_count() do
39
40  -- loops on every received stimulation for a given input
41  for stimulation = 1, box:get_stimulation_count(input) do
42
43  -- gets the received stimulation
44  identifier, date, duration = box:get_stimulation(input, 1)
45
46  -- logs the received stimulation
47  io.write(string.format("At time %f on input %i got stimulation id:%s date
        :%s duration:%s\n", t, input, identifier, date, duration))
48
49  -- discards it
50  box:remove_stimulation(input, 1)
51
52  a = math.random(5)
53
54  if a == 1 then
55  box:send_stimulation(1, OVTK_StimulationId_Label_03, t, 0)
56  else
57  box:send_stimulation(1, OVTK_StimulationId_Label_02, t, 0)
58  end
59
60  end
61  end
62
63  -- releases cpu
64  box:sleep()
65  end
66  end
```

A.2   MATLAB scripts

A.2.1   ICA Script

```
1  rawdata = importdata('C:\Users\Toshiba\Desktop\data.csv');
2  eegdataS1 = rawdata.data; %Subject1 EEG data
3  eegdataS1(:,17:35) = [];
4  eegdataS1(:,1:2) = [];
5  eegdataS1 = eegdataS1';
6  eeglab
7  EEG = pop_importdata('data',eegdataS1,'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 % ced file is taken from http://neurofeedback.visaduma.info/
       emotivresearch.htm
11 EEG = pop_eegfilt(EEG, 1, 0, [], [0]); % highpass filtering at 1Hz
12 EEG = pop_eegfilt(EEG, 0, 50, [], [0]); % low pass filtering at 50Hz
13 eeglab redraw
14
15 EEG = eeg_checkset( EEG );
16 EEG = pop_runica(EEG, 'icatype','runica','dataset',1,'options',{'extended
       ' 1});
17 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
18 EEG = pop_epoch( EEG, {  '2'  }, [−0.5               1], 'epochinfo', 'yes');
19 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1,'setname','silence','
       gui','off');
20 EEG = eeg_checkset( EEG );
21 EEG = pop_rmbase( EEG, [−500      0]);
22 [ALLEEG EEG] = eeg_store(ALLEEG, EEG, CURRENTSET);
23 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 5,'retrieve',1,'study'
       ,0);
24 EEG = eeg_checkset( EEG );
25 EEG = pop_epoch( EEG, {  '3'  }, [−0.5               1], 'epochinfo', 'yes');
26 [ALLEEG EEG CURRENTSET] = pop_newset(ALLEEG, EEG, 1,'setname','sound','
       gui','off');
```

```
27  EEG = eeg_checkset ( EEG );
28  EEG = pop_rmbase ( EEG, [−500      0]);
29  save ('C:\Users\Toshiba\Desktop\ALLEEGS1.mat', 'ALLEEG');
30  clear
```

A.2.2 Feature Extraction Script

```
1   eeglab
2   load ('C:\Users\Toshiba\Desktop\ALLEEGS1.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\s1Component', 'fig');
16  close (figure (2))
17  d=erp1; d1=sum (d);
18  energy=sum (d.^2);
19  power=(d1.^2);
20  energy=sum (power);
21  maxpower=max (power);
22  maxErp=max (d1);
23  minErp=min (d1);
24
25  Fs = 128; x1=d1;
26  nfft = 2^nextpow2 (length (x1));
27  Pxx1 = abs (fft (x1, nfft)).^2/length (x1)/Fs;
```

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

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