Original Article

# ICA-Based Imagined Conceptual Words Classification on EEG Signals

**Ehsan Imani[1], Ali Pourmohammad[2], Mahsa Bagheri[1], Vida Mobasheri[1]**

*[1]Malek Ashtar University of Technology, Tehran, Iran, [2]Amirkabir University of Technology, Tehran, Iran*

## Abstract

Independent component analysis (ICA) has been used for detecting and removing the eye artifacts conventionally. However, in this research, it was used not only for detecting the eye artifacts, but also for detecting the brain-produced signals of two conceptual danger and information category words. In this cross-sectional research, electroencephalography (EEG) signals were recorded using Micromed and 19-channel helmet devices in unipolar mode, wherein Cz electrode was selected as the reference electrode. In the first part of this research, the statistical community test case included four men and four women, who were 25–30 years old. In the designed task, three groups of traffic signs were considered, in which two groups referred to the concept of danger, and the third one referred to the concept of information. In the second part, the three volunteers, two men and one woman, who had the best results, were chosen from among eight participants. In the second designed task, direction arrows (up, down, left, and right) were used. For the 2/8 volunteers in the rest times, very high-power alpha waves were observed from the back of the head; however, in the thinking times, they were different. According to this result, alpha waves for changing the task from thinking to rest condition took at least 3 s for the two volunteers, and it was at most 5 s until they went to the absolute rest condition. For the 7/8 volunteers, the danger and information signals were well classified; these differences for the 5/8 volunteers were observed in the right hemisphere, and, for the other three volunteers, the differences were observed in the left hemisphere. For the second task, simulations showed that the best classification accuracies resulted when the time window was 2.5 s. In addition, it also showed that the features of the autoregressive (AR)-15 model coefficients were the best choices for extracting the features. For all the states of neural network except hardlim discriminator function, the classification accuracies were almost the same and not very different. Linear discriminant analysis (LDA) in comparison with the neural network yielded higher classification accuracies. ICA is a suitable algorithm for recognizing of the word's concept and its place in the brain. Achieved results from this experiment were the same compared with the results from other methods such as functional magnetic resonance imaging and methods based on the brain signals (EEG) in the vowel imagination and covert speech. Herein, the highest classification accuracy was obtained by extracting the target signal from the output of the ICA and extracting the features of coefficients AR model with time interval of 2.5 s. Finally, LDA resulted in the highest classification accuracy more than 60%.

**Keywords:** *Artificial neural network (ANN), blind source separation (BSS), brain–computer interfaces (BCIs), electroencephalography signals (EEG signals), independent component analysis (ICA), linear discriminant analysis (LDA)*

## Introduction and Related Studies

### Overview and concepts

In the interdisciplinary studies, such as brain–computer interfaces (BCIs) and also diagnostic and cognitive applications, the human brain can be studied. Studies may include brain imaging or the use of brain signals. Brain signals are collected by the electrodes placed on the scalp and then processed until special features that indicate the user's intentions are extracted. These signals contain physiological artifacts such as eye blinks and eye movements and nonphysiological artifacts such as 50 Hz alternating current; various methods were proposed for removing these artifacts by researchers.[1] Most of the researches on brain signals were performed to evaluate the various algorithms to remove artifacts and compare them with each other. Electroencephalography (EEG) studies were based on the two main paradigms: (1) event-related potentials (ERPs) and (2) the raw brain signals by EEG. Numerous studies were performed related to the ERPs.

*Address for correspondence:* Dr. Ali Pourmohammad, Amirkabir University of Technology, Tehran, Iran. E-mail: pourmohammad@aut.ac.ir

**Website:** www.jmss.mui.ac.ir



**How to cite this article:** Imani E, Pourmohammad A, Bagheri M, Mobasheri V. ICA-based imagined conceptual words classification on EEG signals. J Med Sign Sens 2017;7:130-44.

According to the results of these studies, the brain momentary reaction to a word or phrase was observed in a particular potential, but these words or phrases were not separable as per the concept. For example, the P600 wave of the ERP appeared to equally deal with two phrases with different concepts, in which the verb and subject did not match with each other or have other grammatical mistakes.[2] In addition, some research was done on the raw brain signals to extract emotions such as anger, happiness, and sadness.[3] So far, the studies were about separating words and their concepts in the covert speech based on cerebral images, and also a number of studies have used the EEG signal directly. However, the detection was done only on two syllables or a particular vowel. Therefore, we continued to investigate these studies.

## Review of previous studies

For doing the project in the best possible way, the first priority was to get to know the nervous system and the physiology of the human brain.[4] Nervous system is the most organized and complicated system of the human body. Nervous system consists of the following two major parts: central and environmental nervous systems. The central part is the part that is located in the bone chambers (spinal and cranial). This part includes the brain hemispheres, the cerebellum, the midbrain, the brain bridge, the medulla oblongata, and the spinal cord. The human brain consists of two hemispheres, the right and the left hemispheres. Each hemisphere includes some lobes such as the frontal lobe, the parietal lobe, the temporal lobe, and the occipital lobe. Researches on the human brain show that different areas of the brain cortex do a particular work. The most important communicational areas are as follows: (1) the parietal-occipital-temporal area, (2) the parietal-frontal area, and (3) the limbic area. The parietal-occipital-temporal communicational area consists of the following four parts: analysis area of the spatial coordinates of the body, word understanding area (Wernicke area), visual word processing area (the angular gyrus), and the area of naming the objects. The main area of understanding the words, known as Wernicke, is the most important part of the brain related to the high clever level of the brain functions, because all these functions are based on speech. The angular gyrus area is the lowest part of the posterior parietal lobe that is located right under the Wernicke area and from the back is also connected to the occipital lobe visual areas. If this area gets damaged and the Wernicke area survives, so visual experiments current from the visual cortex to the Wernicke area will be stopped. Hippocampus is located in the most interior part of the temporal lobe and does the memory storage process. Loss of the hippocampus causes human inability to consolidate memory, and the person loses his data transferring power to the other brain areas.[5] According to the obtained results from studying the human brain anatomy regarding the ability to produce words, Wernicke area, angular gyrus area, and hippocampus have a close relationship with the occipital lobe. Studies on positron emission tomography (PET) images in 2006 showed different levels of the brain activity when presented with different vision, hearing, and speech tasks. This result showed that the occipital lobe was involved in much more activities than the other parts of the brain.[6,7]

A study was performed in 2010 on people belonging to the age range of 5–18 years to understand their ability to produce covert speech and to discover the processing procedure, speech production, and the order of activities in different areas. This study was performed using functional magnetic resonance imaging (fMRI) method, with 336 persons participating. The number of participants and their age range made this study unique. The procedure was to repeat one of the motivator words such as full or drink in a covert way. Thereafter, by using fMRI imaging, brain activities of different areas were recorded. Independent component analysis (ICA) was applied for finding the relation between areas. This statistical analysis extracted the different sources from which the data was combined. The visual imagination area and the words semantic processing area, located in the occipital lobe, had a great impact on producing covert and overt words.[8] fMRI is one of the other ways for recognizing and comparing the activities of different areas in covert and overt states while experimenting completing words. The procedure was to show the volunteer a part of a word, for example three letters cou, and he should complete the word in the way that the first three letters of the intended word be the same with the first three letters of the shown word, for example cousin. In overt state, the volunteer should repeat expressing the word, and, in the covert state, he was asked to repeat it just in his mind. Ten participants were examined in six overt and six covert experiments. It could be seen that in producing covert and overt words, the occipital and the temporal lobes were active.[9]

Most of the studies performed regarding the covert speech on the brain signals depended on previous studies in ERP by using P300, N400, and P600 components. These methods had a good performance in recognizing large number of characters, but they were slow in doing this, and the speed was about several characters per minute. Some of the studies used directly the EEG signals that provided a good speed in recognition, but they were just done in recognition of the two special syllables or vowels. In a published article in 2010, three persons took part in an experiment related to imagination of two vowels, /u/ and /a/, and their EEG signals were recorded for further processing. In this experiment, the volunteers were asked to the following three methods by showing them every motivator: (1) /a/ vowel, imagination of opening the mouth and expressing the word; (2) /u/ vowel, imagination of rounding the lips and expressing the word; (3) control, doing nothing. During each study, 50 repetitions were performed; therefore, totally 150 repetition were performed. In the classification level, for all the repetitions, the window was considered for 0–500 ms (starting with showing the visual sign), and EEG data was divided as two subsets, training and testing. Training consisted of 30 repetitions, and testing consisted of 20 repetitions that are selected randomly from a set of 50 repetitions. Training and testing sets were fed to the support vector machine (SVM). This process tested the subsets 20 times by choosing randomly one of the subsets, training or testing. The overall performance of the classification was in the range of 68–78%; therefore, it can be used in BCI systems.[10] In addition, in another research in 2010 in California University on seven volunteers, imagination of two syllables, /ba/ and /ku/, was done in three different rhythms. The procedure showed one of the syllables, /ba/ or /ku/, for the first 0.5 s, and then the next 1 s would be silence. The recorded EEG signal for this time period would be used as the basic power spectrum. During 3 s rhythm sings will be shown. In a time interval of 6 s, volunteers would imagine the syllable with represented sign and requested rhythm. For removing noise and reducing data dimensions, second-order blind identification (SOBI) was used. For the four SOBI primary components, time and spectral features of the Hilbert spectrum (HS) were extracted. HSs represent nonfixed data accurately than other methods such as Short Time Fournier Transform (STFT) and scale wavelet compression. Results for classification of three rhythms depicted that the average performance among all the volunteers, using SOBI components, was 58.05%.[11]

In a research in 2012 on patients who had lost their speech power because of disorder in the nervous system by using visual stimulation signals and choosing letters from a virtual keyboard with P300 evoked potential signal, the person could make his sentences with a high accuracy about 85%.[12,13] In the researches that Hobe performed during 2009 till 2010, the participants were asked to think about control of something in cyberspace by sending orders to the device by imagining them, for example moving the cursor using EEG signals.[14,15] In addition, vertical and horizontal cursor movements could be controlled by concentration level of user.[16,17] For increasing the performance of BCI system, choosing proper features, which were well separatable and were using high accuracy classifiers, should be considered. In addition, by using feedback, effecting parameters on person's imagination could be recognized, and, by removing confounding factors, performance could be optimized.[18,19] Pfurtscheller *et al.*[20] used the C3 and C4 EEG signal channels for detecting the movement imagination of the right and left hands with an average detection error from 5.8 to 32.8%. In addition, Palaniappan *et al.*[21] discriminated three out of five mental activities, according to the power of brain signal components in 0–50 Hz using autoregressive (AR) coefficients, Burg algorithm, and phase separators, and reported 93% accuracy. In a study in 2013,[22] for discriminating the brain signals in a BCI system based on the movements of the right and left hands using extracted features of the wavelet coefficients, different kinds of classifiers were studied, wherein the research resulted classification error rate of 14% using linear discriminant analysis (LDA), 43% using SVM, and 10% using Weighted Majority Voting (WMV), in which these classifiers outperformed the multilayer perceptron with 26% error rate. In this study, the sampling rate was 128 Hz, and also a band-pass filter of 0.5–30 Hz was used. In addition, the represented task consisted of 240 signs, and 140 signs were used for training, and the remaining signs were used for test.

### The importance of research

The results of the studies on the anatomy of the brain in the covert speech, PET images, fMRI images, and studies on the head topography at the imaginary speech in the covert syllables and vowels communications showed that the occipital lobe activity was more than the other brain areas in seeing the words and images. In addition, it could be seen that the occipital lobe had a great impact in producing overt and covert words. Because of the low cost and high acceptance of noninvasive brain signal (EEG) recording in BCI systems, the purpose of this research was to find a signal that had high accuracy in detection and separation of two conceptual categories of the words danger and information by using traffic signs in the first part and four main directions (up, down, left, and right) in the second part. ICA was used for detecting and removing the eye artifacts conventionally. However, in this research, it was used not only for detecting the eye artifacts, but also for detecting the brain-produced signals of two conceptual danger and information category words.

## Materials and Methods

### Description of the volunteers and factors affecting research

In this cross-sectional study, the statistical population included eight volunteers, four males and four females belonging to the age group of 25–30 years. Volunteers were physically and mentally healthy, and, before recording their brain signals, they were given the necessary recommendations and also a written permission was obtained for recording their brain signals. Parameters that must be observed to prevent any failure to this research included the following: (1) the task should not be long, (2) volunteers must be given training before signal recording procedure, and (3) laboratory should have ideal conditions such as temperature, lighting, ventilation, and walls empty of boards. All of these items were checked and controlled before recording signals.

### Description of signal recording equipment

Recording process was performed by using a 64-channel Micromed: (Micromed S.p.A. a Socio Unico) Via Giotto, 2 – 31021, Mogliano Veneto (TV) - ITALY 19-channel helmet → 19-channel Micromed helmet in unipolar mode. The Cz electrode was selected as reference electrode, and the entire head surface was covered by 18 left electrodes according to the 10–20 standard protocol. Sampling frequency was 1024 Hz, and recording channels were FP1, FPz, FP2, F8, F4, Fz, F3, F7, T4, C4, C3, T5, P3, P4, T6, O1, Oz, and O2; one channel was considered as the earth.

### Description of the task

Before recording EEG signals, a task was already designed to be shown to them for recording their signals. For designing the task, three groups of traffic signs were chosen with different shapes and colors. In each group, there were six signs with different subjects but having the same major concept.

The characteristics of the first group were the following: the common concept was danger that was shown with red color and triangle shape [Figure 1a]. The characteristics of the second group were the following: the common concept was information with blue color and square or rectangular shape [Figure 1b]. The characteristics of the third group were the following: the signs that belong to Republic of Ireland regarding danger concept were the same with the first group, but the signs about color and shape were different (yellow or orange and rhombus shape) [Figure 1c]. Recording from each volunteer lasted 10 min and 35 s. In the first 95 s, volunteers would be taught the kind (danger or information) and the subjects of the signs, and then signs one by one in orders would be shown for 15 s in a manner that their subjects were not mentioned under them. After representing each sign, a black screen within 15 s showed the rest time. Signs according to the order of Figure 2 would be shown from left to right. The volunteers were asked to imagine the subject of each sign after seeing that the concept could be comprehensible. For example, the person after watching the sign of slippery road evoked the concept of danger by imagining driving in this condition. The person's convenience was an important factor in thinking and

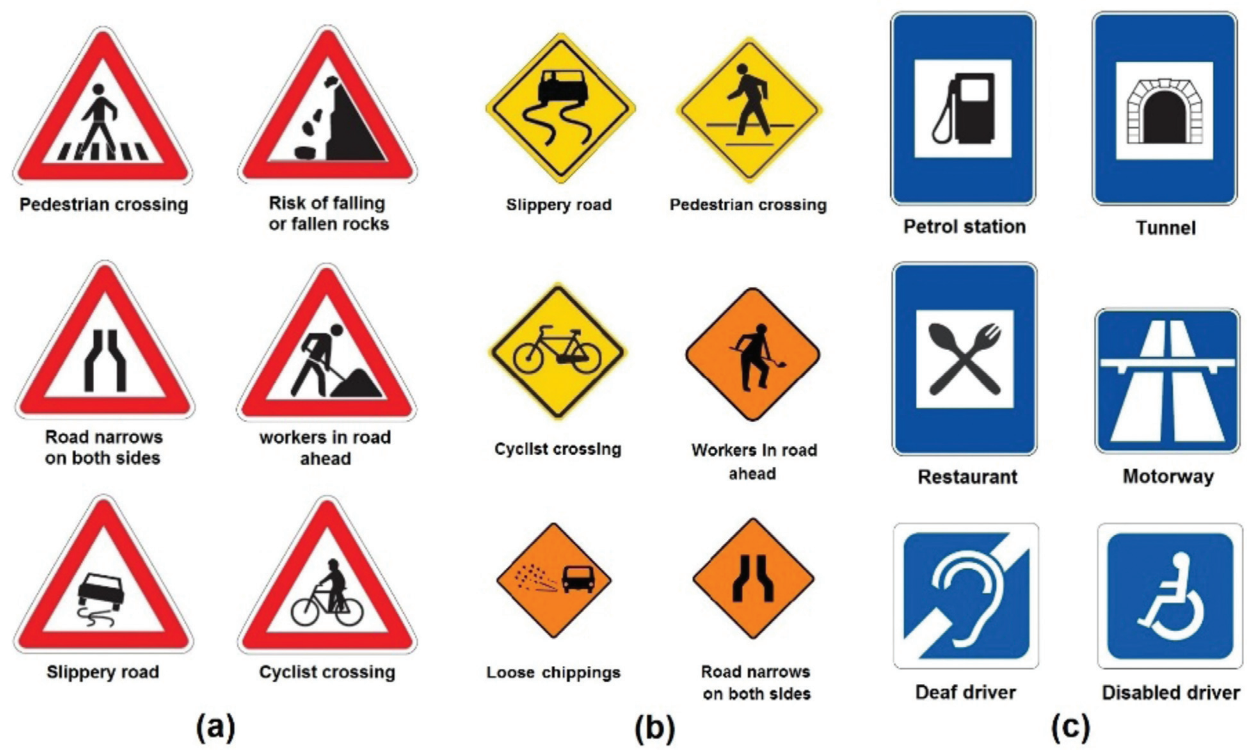


**Figure 1: (a) Red triangle traffic signs that refer to the concept of danger with six different topics. (b) Orange/yellow rhombus traffic signs that refer to the concept of danger with six different topics. (c) Blue square or rectangular traffic signs that refer to the concept of information with six different topics**

**Figure 2: 18 pictures of traffic signs were randomly projected for 15 s to the volunteers**

recording time, as there was no problem with eye blinks in thinking time, and the volunteers just should avoid vigorous shaking of the head and the body.

Eventually, three volunteers, two men and one woman, who had the best results, were chosen out of eight participants. In the designed task, at first a white blank screen appeared for 15 s, and, during this time, the volunteer was asked to make a peace of his mind. After this period of time, one of the direction arrows (up, down, left, and right) appeared, and the person must imagine them in this time before a 15 s black screen as the rest time [Figure 3]. These steps were repeated randomly 24 times for each person (each direction six times), which took 12 min. Before training, a volunteer got to know the task and its levels and was asked to concentrate just on the desired arrow by imagining that and not to repeat the corresponding word in his brain.

## Description of the method

The research was conducted in two parts. In the first part, the research showed the task of traffic signs and recorded their EEG signals. We concluded that the target signals would be chosen in the way that had the most correlation with the occipital lobe (O1, Oz, and O2 electrodes).

In the second part, after showing the task of directions (right, left, up, and down) and recording their EEG signals, by applying FastICA algorithm and correlation function the target signals were selected based on the most correlation with the occipital lobe. Thereafter, by feature extraction and applying classifications, separation of the directions was tried.

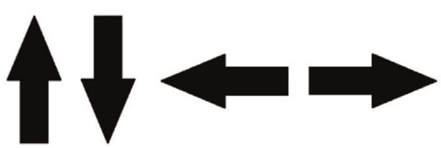

**Figure 3: Four main directions were up, down, left, and right**

In the first part, after showing volunteers the task of traffic signs and recording their signals and then removing the first 5 s of each signal, by applying FastICA algorithm, recorded signals would be decomposed to their components with independent resources. After applying FastICA, correlation function would be applied on recorded signals (mixed signal of outputs of the electrodes and independent signals). After applying correlation function, the target signals would be chosen in the way that had the most correlation with the occipital lobe (O1, Oz, and O2 electrodes).

According to Figure 4, in the second part, after representation of the task to the selected volunteer and recording the EEG raw data, the signals should be preprocessed to be prepared for feature extraction and classification. These levels of all five steps were described as follows.

First step in the preprocessing was separation of the image intervals and classification of them into right, left, up, and down categories. In the second step, down sampling was performed; therefore, sampling rate reduced from 1024 to 256 Hz. In the third step, for the stationary in statistical data and also for the addition to training and test data (records), the signal was divided into some segments and considered the overlapping for all segments. In this research, six different implementations (0.5, 1, 1.5, 2, 2.5, and 3 s) for window size were studied, and 50% overlapping was used. In the final step, direct current components of the signals were ignored.

In the second step, for eliminating the noises and artifacts, and separation of the dependent sources, ICA algorithm applied to the signals. In a BCI systems, EEG signals would be fed to the computer or any other processing system such as digital signal processing cards after recording for more processes. The BCI unit extracted the features to reach to a distinct criteria for different EEG signals, and then based on these features, they would be classified.[23] Blind source separation (BSS) extracted the signal sources from a few sensors, which recorded and

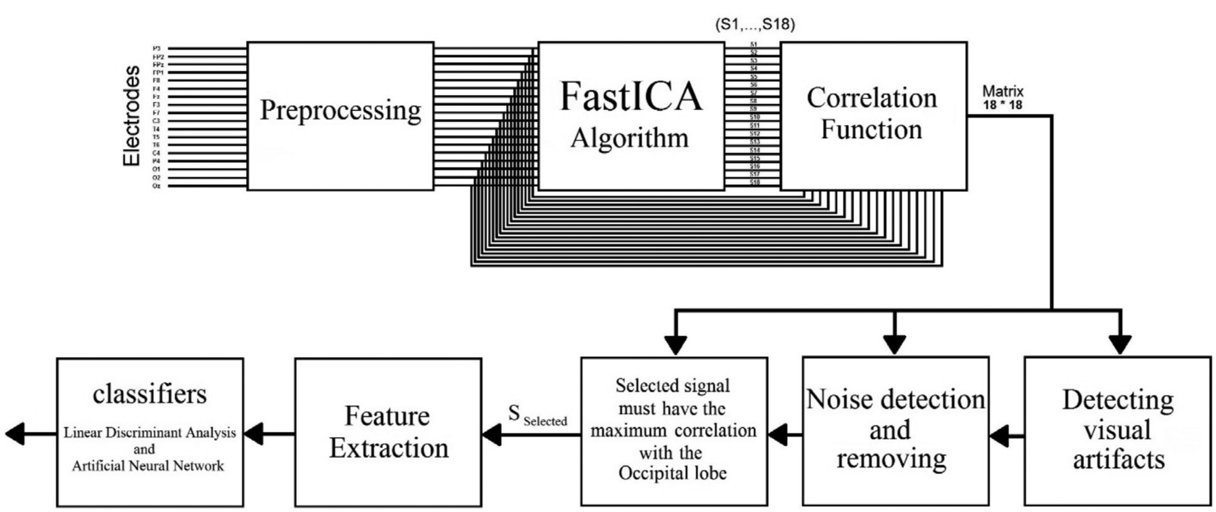


**Figure 4: Method for selecting the semantic signals (target signals) and the order of levels for discriminating directions. Preprocessing included removing direct current frequency, applying correlation function, separating 50 Hz ICA artifacts, downsampling from 1024 to 256, applying algorithm and EEG noises, and choosing target signal. Thereafter, feature extraction level was determined and classifiers (LDA and ANN) were applied**

combined the signals.[24] One of the most common BSS methods was ICA. ICA decomposed signals to their components with independent resources.[25] One of the most common ICA algorithms was FastICA.[26]

After applying ICA to the mixed signals, in the third step, by applying a correlation function, the target signal was separated from each of the words up, down, left, and right, which were studied for getting discriminated in feature extraction level.

After applying the mentioned preprocesses to the EEG signals, in the fourth step, specified features could be extracted. In this research, statistical features, parameter-based features, and frequency band power based features were extracted. AR model, one of the parameter-based features, was extracted from (with) order of 1–15 by using Burg method. Statistical features that were selected were mean, standard deviation, kurtosis, skewness, and moments of $1^{st}$ up to $22^{nd}$ order. Frequency band power based features were calculated in frequency bands of 1–4, 4–8, 8–12, 12–30, and 8–30 Hz. Ultimately, optimized feature with the highest classification accuracy was obtained.[27]

In the fifth step, classifiers were studied. The most important part of a BCI was classifier, which assigned each part of the EEG signal to the appropriate mental activity class according to extracted features. In this study for classification of extracted features, LDA and artificial neural network (ANN) were used. Operation of ANN with different number of hidden layers (1, 2, 3) and different number of neurons (10, 20, 30) and different classification functions (purlin, logsig, tansig, and hardlim) were investigated, and optimum implementation of ANN with highest classification accuracy was determined. Classification accuracies were calculated with $K = 10$ ($K$ stands for $k$-fold cross-validation). 10% of extracted features were test data, and others were training data. Thereafter, classification was performed, and a value for classification accuracy was obtained. This process was repeated ten times, and in each repeat, other new features added to the test data category. Thus, all the features were at least one time considered as test data. Finally, the average of accuracy obtained from each repeat was resulted as main accuracy. In this study, operation of LDA and ANN was also compared.

After recording signals, the data would be stored in a matrix in MATLAB software, and also in this research, data analysis methods and implementing algorithms were performed using MATLAB. For checking accuracy of FastICA algorithm, according to Figure 5, two audio signals were combined by a random matrix and separated through FastICA algorithm. Herein, S1 represented number 2, and S2 signal represented number 5.

### Artificial network classifier

An ANN was an interconnected group of nodes akin to the vast network of neurons in the brain. Herein, each circular node represented an artificial neuron, and an arrow represented a connection from the output of one neuron to the input of another. The word network in the term "ANN" referred to the interconnections between the neurons in the different layers of each system. An example system had three layers. The first layer had input neurons, which sent data via synapses to the second layer of neurons, and then via more synapses to the third layer of the output neurons. More complex systems would have more layers of neurons, some having increased layers of input and output neurons. The synapses stored parameters called "weights" that manipulated the data in the calculations. An ANN was typically defined by three types of parameters [Figure 6]:

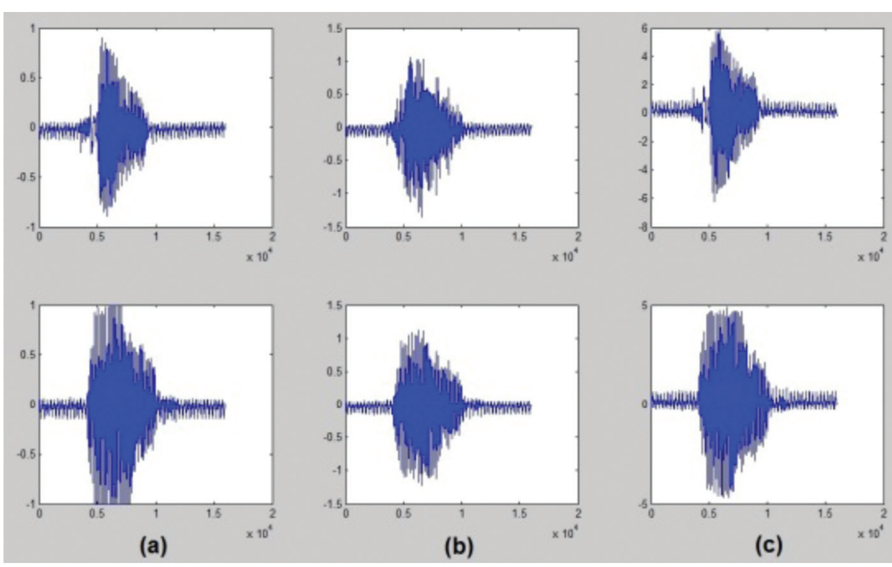


**Figure 5: (a) Two audio signals. (b) Two audio signals mixed randomly. (c) Two mixed audio signals separated from each other perfectly with FastICA algorithm**

(1) The interconnection pattern between the different layers of the neurons.

(2) The learning process for updating the weights of the interconnections.

(3) The activation function that converted a neuron's weighted input to its output activation.[28]

### Linear discriminant analysis

Accordingto $(x) = W^t X + \omega_0$, a discriminant function that was a linear combination of the components of **x** could be written as follows: wherein, **w** was the weight vector and $w0$ the bias or threshold weight. A two-category linear classifier implemented the following decision rule: decide $\omega_1$ if $g(\mathbf{x}) > 0$ and $\omega_2$ if $g(\mathbf{x}) < 0$. If $g(\mathbf{x}) = 0$, **x** could ordinarily be assigned to either class. Figure 4 shows the mentioned decision rule. LDA by making a linear margin separated the two classes. This method tried to interpret an independent variable as a linear combination of the other features. This variable was a label in LDA method. To implement a multiclass classification, a linear discriminant function separated each class from each of the classes [Figure 7].[28]

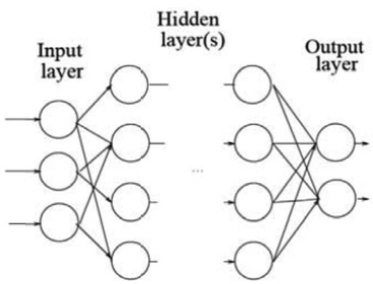


**Figure 6: Different layers of a neural network**[28]

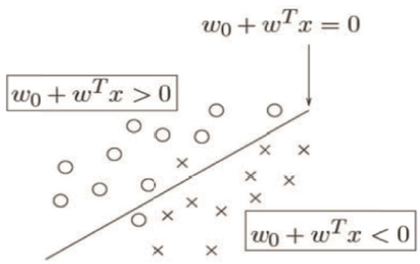


**Figure 7: The decision rule in a linear two-class classifier**[28]

## Simulations and the Results

After recording EEG signals from eight volunteers, the results showed that, for two of the eight volunteers in the rest time, alpha waves were observed with a very high power from back of the head, but in thinking time, it was different. According to this, alpha waves in changing the task from thinking to rest, it took for two volunteers at least 3 and at most 5 s till they went to absolute rest. Therefore, to analyze the thought signals of everyone, the first 5 s of 15 s were deleted. Figures 8 and 9 show, respectively, two of the male 1 EEG signals of his rest and think.

Table 1 shows the amounts of correlation between EEG signals and the output of FastICA algorithm of EEG signals. As was seen, S3 was the source of the occipital lobe, S8 was the source of the parietal and occipital lobes, S9 was the source of the frontal and temporal lobes on the left hemisphere, S10 was the source of the right temporal lobe, S15 and S16 were the sources of eye movements, and S18 was the source of eye blinks. According to the results obtained from PET and fMRI, cognitive processing was performed in the occipital and temporal lobes with visual information. Therefore, the FastICA algorithm was applied to the EEG signals, and autocorrelation function was applied to the EEG signals and the output of FastICA algorithm of EEG signals. A selected signal must have the maximum correlation with signals of the occipital lobe. By applying the FastICA algorithm to the EEG signals in Figure 10, ocular artifacts consisted of eye blinks and eye movements detected and separated from EEG signals as depicted in Figure 11. In the first part for the task of traffic signs, Table 2 displays the mean of

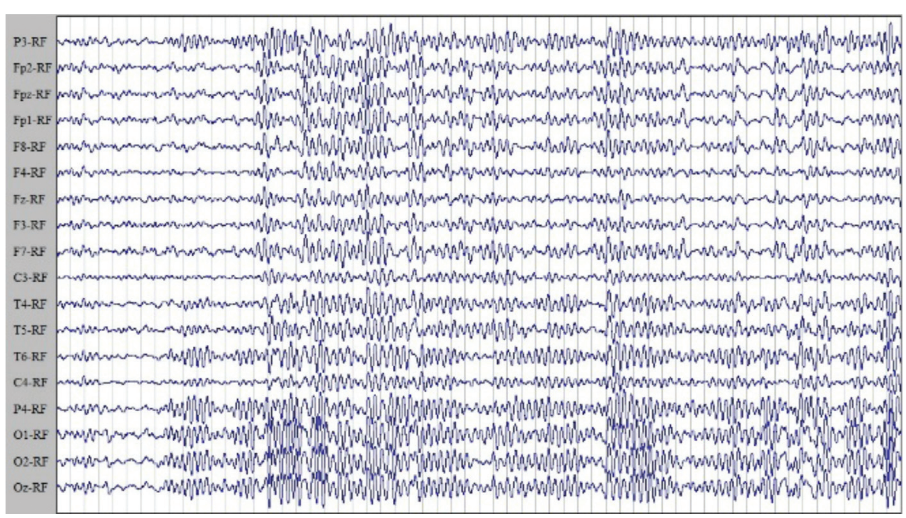


**Figure 8: Sample 15 s of rest for male 1**

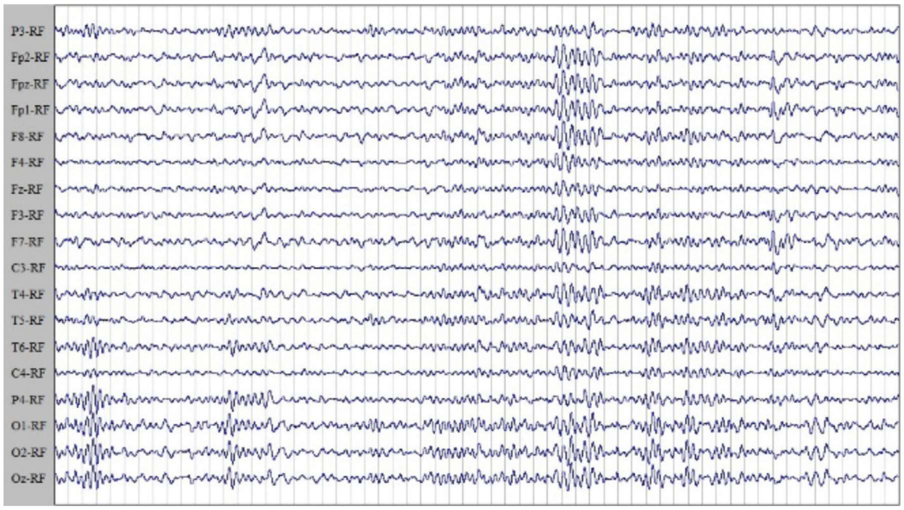


**Figure 9: Sample 15 s of think for male 1**

**Table 1: The amounts of correlation between EEG signals and the output of FastICA algorithm of EEG signals**

| | S1 | S2 | S3 | S4 | S5 | S6 | S7 | S8 | S9 | S10 | S11 | S12 | S13 | S14 | S15 | S16 | S17 | S18 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| P3 | 0.2 | 0.1 | 0.3 | 0 | 0.1 | 0.1 | 0 | 0.7 | 0.3 | 0.2 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0 | 0.2 | 0.2 |
| FP2 | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0.2 | 0.2 | 0.1 | 0.1 | 0 | 0 | 0 | 0.2 | 0.1 | 0 | 0.9 |
| FPz | 0 | 0 | 0 | 0.1 | 0 | 0 | 0 | 0.2 | 0.2 | 0.1 | 0 | 0 | 0.1 | 0 | 0.2 | 0.1 | 0 | 0.9 |
| FP1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0.2 | 0.2 | 0.1 | 0 | 0 | 0.1 | 0 | 0.2 | 0 | 0.1 | 0.9 |
| F8 | 0 | 0.1 | 0.1 | 0 | 0.1 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0.1 | 0.1 | 0.2 | 0 | 0.2 | 0.1 | 0 | 0.8 |
| F4 | 0 | 0 | 0.1 | 0.2 | 0 | 0 | 0 | 0.3 | 0.2 | 0.2 | 0.2 | 0.2 | 0.1 | 0.2 | 0.4 | 0.2 | 0.1 | 0.7 |
| Fz | 0 | 0 | 0.1 | 0.2 | 0.2 | 0.2 | 0.1 | 0.3 | 0.1 | 0.2 | 0.1 | 0.3 | 0 | 0 | 0.5 | 0.2 | 0.1 | 0.6 |
| F3 | 0.1 | 0.1 | 0.1 | 0.1 | 0.3 | 0.1 | 0.1 | 0.2 | 0.3 | 0.2 | 0 | 0.1 | 0 | 0 | 0.3 | 0.1 | 0.1 | 0.7 |
| F7 | 0.1 | 0 | 0.1 | 0 | 0.1 | 0 | 0.1 | 0.2 | 0.4 | 0.2 | 0 | 0 | 0.2 | 0 | 0.3 | 0 | 0.2 | 0.8 |
| C3 | 0.1 | 0.1 | 0.2 | 0.1 | 0.3 | 0.2 | 0.1 | 0 | 0.6 | 0.3 | 0.1 | 0.3 | 0.1 | 0.1 | 0.2 | 0 | 0.2 | 0.2 |
| T4 | 0 | 0.1 | 0.1 | 0 | 0.3 | 0.2 | 0.1 | 0.1 | 0.3 | 0.4 | 0.1 | 0 | 0.4 | 0 | 0.2 | 0.3 | 0.4 | 0.3 |
| T5 | 0.3 | 0.1 | 0.4 | 0.1 | 0.1 | 0.1 | 0.1 | 0.3 | 0.5 | 0.5 | 0.1 | 0.2 | 0.1 | 0 | 0.1 | 0.2 | 0.1 | 0 |
| T6 | 0 | 0 | 0.1 | 0.3 | 0.2 | 0.1 | 0 | 0.3 | 0.4 | 0.5 | 0 | 0.1 | 0 | 0.2 | 0.1 | 0.5 | 0.2 | 0 |
| C4 | 0 | 0.2 | 0.2 | 0.4 | 0.2 | 0.3 | 0.1 | 0.1 | 0.1 | 0.6 | 0 | 0.1 | 0.1 | 0.2 | 0.2 | 0.4 | 0.1 | 0.2 |
| P4 | 0 | 0 | 0.2 | 0.4 | 0.3 | 0.1 | 0.1 | 0.6 | 0.2 | 0.3 | 0.1 | 0.1 | 0.1 | 0.3 | 0 | 0.2 | 0.1 | 0.2 |
| O1 | 0.2 | 0.1 | 0.6 | 0.1 | 0 | 0.2 | 0.1 | 0.5 | 0.3 | 0.2 | 0.1 | 0.1 | 0.2 | 0.1 | 0 | 0.1 | 0 | 0.3 |
| O2 | 0 | 0 | 0.6 | 0.1 | 0.2 | 0.1 | 0 | 0.4 | 0.2 | 0.4 | 0.1 | 0.1 | 0.2 | 0.1 | 0 | 0.2 | 0 | 0.2 |
| Oz | 0.1 | 0 | 0.6 | 0.1 | 0.1 | 0.1 | 0 | 0.4 | 0.3 | 0.2 | 0.3 | 0.1 | 0.3 | 0.2 | 0.1 | 0.1 | 0 | 0.3 |

correlation of six selected signals with the amounts obtained from electrodes on the scalp in each group for all of the volunteers. It could be seen that difference between concept of danger and information existed for male 1 in F3, F7, and C3 (the frontal lobe of the right hemisphere), for male 2 in Fz, F4, F8, T4, T5, and C4 (the frontal lobe of the right hemisphere and the temporal lobe of the right and left hemispheres), for male 3 in Fz, F3, F7, T5, T6, C3, P3, and P4 (the frontal lobe of the left hemisphere and the temporal and parietal lobes of the right and left hemispheres), for male 4 in Fz, F8, T4, T5, and T6 (the frontal lobe of the right hemisphere and the temporal lobe of the right and left hemispheres), for female 1 in F3, F7, P3, and T5 (the frontal, temporal, and parietal lobes of the left hemisphere), for female 2 in F8, T4, and T6 (the frontal, temporal, and parietal lobes of the left hemisphere), for female 3 in F4, F8, C4, T4, and T6 (the frontal and temporal lobes of the right hemisphere) and for female 4 in F8, F7, C4, P4, and T4 (frontal hemispheres and the temporal and parietal lobes of the right hemisphere).

According to Table 3, the danger and information signals were separated perfectly for 3/8 volunteers, and the obtained difference between the concept of the danger and information signals was observed in the right hemisphere for five volunteers and in the left hemisphere

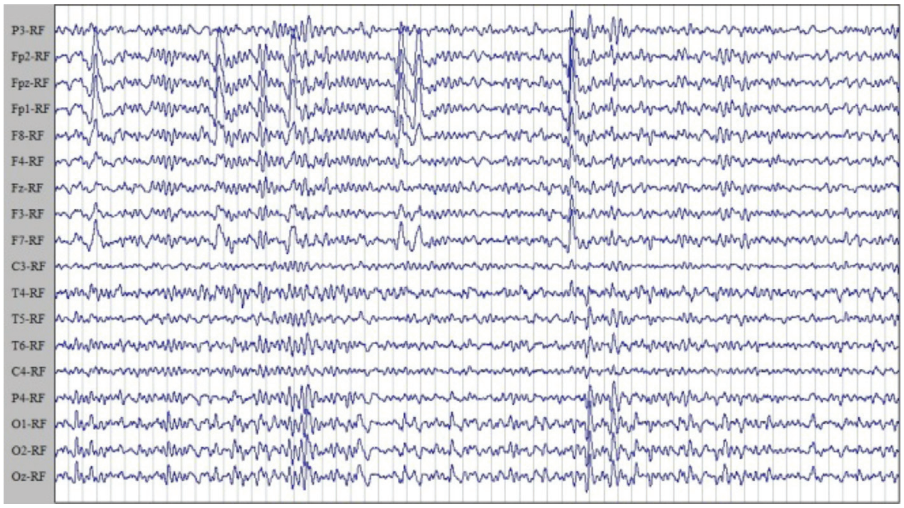

**Figure 10: EEG signals recorded from the information of traffic signs from one of the volunteers in 15 s**

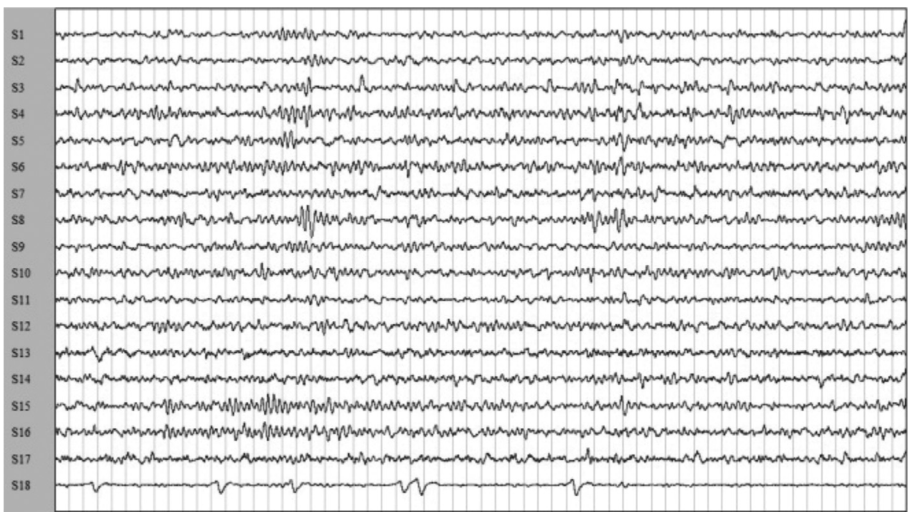

**Figure 11: The output of FastICA algorithm of EEG signals showed in Figure 10. S18 is the source of eye blinks. S15 and S16 are the sources of eye movements**

for three of them. In Table 4, the amounts of mean squared error and correlation of danger and information signals for volunteers from Table 2 were shown. According to Table 5, the maximum correlation and minimum mean squared error for signs of group (a) were between female 3 and female 4, the maximum correlation and minimum mean squared error for signs of group (b) were between male 2 and female 4, and the maximum correlation and minimum mean squared error for signs of group (c) were between female 2 and female 4. Table 6 shows the amounts of mean squared error and correlation for each volunteer between group (a) and group (b) with common titles. The result of LDA classifier for all the features and six different window sizes for three selected subjects in task 2 were depicted in Table 7. Classification accuracy for AR coefficient features of 1–15 order and moments of 1$^{st}$ up to 22$^{nd}$ order and also power in 1–4, 4–8, 8–12, 12–30, 8–30 frequency bands in the highest accuracy are also reported.

As shown, 2.5 s window size and AR coefficient model feature resulted in highest classification accuracy. Because of better results for AR coefficient features, for comparison between different orders of AR coefficient features, a diagram is illustrated in Figure 12. This diagram illustrated classification accuracy of LDA classifier for all three volunteers in different orders (1–15) of AR coefficient. According to this diagram, AR coefficient feature of order 15 showed better results for all three volunteers. Table 8 shows results of 36 different implementations of ANN classifier with different number of layers and neurons and different classification functions. In this table, classification accuracy for all three participants, for 2.5 s window size and AR coefficient extracted feature of order 15, is illustrated. The result specified that there was no significant difference between different implementation of ANN, except hardlim function, which did not show suitable classification accuracy. Table 9 shows classification accuracy of LDA and ANN (two layers, 20 neurons, and purlin function) classifier for 2.5 s

**Table 2: The mean of correlation of the six selected signals for eight volunteers with the amounts obtained from electrodes on the scalp in each group**

| Volunteer | Sign | P3 | FP2 | FPz | FP1 | F8 | F4 | Fz | F3 | F7 | C3 | T4 | T5 | T6 | C4 | P4 | O1 | O2 | Oz |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Male 1 | a | 0.35 | 0.23 | 0.23 | 0.23 | 0.30 | 0.20 | 0.17 | 0.27 | 0.35 | 0.25 | 0.40 | 0.37 | 0.42 | 0.32 | 0.42 | 0.50 | 0.55 | 0.55 |
| | b | 0.43 | 0.30 | 0.35 | 0.35 | 0.35 | 0.27 | 0.23 | 0.33 | 0.37 | 0.35 | 0.37 | 0.37 | 0.45 | 0.37 | 0.42 | 0.40 | 0.47 | 0.43 |
| | c | 0.33 | 0.20 | 0.15 | 0.15 | 0.25 | 0.23 | 0.17 | 0.13 | 0.18 | 0.18 | 0.37 | 0.32 | 0.47 | 0.33 | 0.52 | 0.45 | 0.48 | 0.47 |
| Male 2 | a | 0.27 | 0.22 | 0.15 | 0.15 | 0.30 | 0.17 | 0.15 | 0.12 | 0.23 | 0.23 | 0.52 | 0.22 | 0.45 | 0.33 | 0.43 | 0.42 | 0.47 | 0.43 |
| | b | 0.28 | 0.22 | 0.13 | 0.10 | 0.37 | 0.17 | 0.17 | 0.20 | 0.23 | 0.25 | 0.43 | 0.33 | 0.40 | 0.38 | 0.42 | 0.40 | 0.53 | 0.52 |
| | c | 0.27 | 0.17 | 0.13 | 0.13 | 0.15 | 0.07 | 0.08 | 0.12 | 0.25 | 0.27 | 0.28 | 0.42 | 0.40 | 0.22 | 0.40 | 0.55 | 0.50 | 0.47 |
| Male 3 | a | 0.48 | 0.10 | 0.13 | 0.10 | 0.22 | 0.18 | 0.20 | 0.18 | 0.18 | 0.30 | 0.25 | 0.43 | 0.33 | 0.17 | 0.42 | 0.52 | 0.47 | 0.50 |
| | b | 0.45 | 0.15 | 0.15 | 0.13 | 0.20 | 0.20 | 0.23 | 0.23 | 0.27 | 0.35 | 0.32 | 0.47 | 0.43 | 0.35 | 0.42 | 0.48 | 0.45 | 0.47 |
| | c | 0.30 | 0.07 | 0.07 | 0.07 | 0.15 | 0.12 | 0.10 | 0.08 | 0.08 | 0.15 | 0.25 | 0.27 | 0.23 | 0.18 | 0.28 | 0.57 | 0.52 | 0.58 |
| Male 4 | a | 0.38 | 0.22 | 0.17 | 0.18 | 0.43 | 0.35 | 0.18 | 0.25 | 0.23 | 0.27 | 0.53 | 0.32 | 0.55 | 0.53 | 0.42 | 0.30 | 0.53 | 0.52 |
| | b | 0.47 | 0.28 | 0.17 | 0.27 | 0.33 | 0.20 | 0.13 | 0.18 | 0.30 | 0.23 | 0.42 | 0.30 | 0.47 | 0.35 | 0.55 | 0.38 | 0.52 | 0.52 |
| | c | 0.47 | 0.15 | 0.17 | 0.20 | 0.28 | 0.23 | 0.28 | 0.23 | 0.28 | 0.33 | 0.27 | 0.48 | 0.28 | 0.27 | 0.33 | 0.47 | 0.53 | 0.50 |
| Female 1 | a | 0.42 | 0.18 | 0.15 | 0.23 | 0.12 | 0.22 | 0.30 | 0.28 | 0.30 | 0.47 | 0.28 | 0.55 | 0.32 | 0.20 | 0.22 | 0.55 | 0.43 | 0.48 |
| | b | 0.43 | 0.18 | 0.13 | 0.17 | 0.22 | 0.13 | 0.15 | 0.27 | 0.30 | 0.47 | 0.37 | 0.53 | 0.45 | 0.30 | 0.35 | 0.50 | 0.50 | 0.53 |
| | c | 0.38 | 0.28 | 0.25 | 0.18 | 0.20 | 0.18 | 0.22 | 0.15 | 0.15 | 0.27 | 0.27 | 0.38 | 0.45 | 0.37 | 0.48 | 0.48 | 0.53 | 0.53 |
| Female 2 | a | 0.48 | 0.17 | 0.15 | 0.17 | 0.28 | 0.15 | 0.20 | 0.30 | 0.32 | 0.33 | 0.43 | 0.45 | 0.42 | 0.27 | 0.43 | 0.47 | 0.47 | 0.48 |
| | b | 0.28 | 0.17 | 0.17 | 0.17 | 0.33 | 0.30 | 0.17 | 0.13 | 0.08 | 0.20 | 0.38 | 0.23 | 0.45 | 0.48 | 0.32 | 0.47 | 0.47 | 0.42 |
| | c | 0.42 | 0.17 | 0.17 | 0.13 | 0.22 | 0.23 | 0.28 | 0.25 | 0.13 | 0.15 | 0.35 | 0.32 | 0.37 | 0.32 | 0.32 | 0.47 | 0.43 | 0.38 |
| Female 3 | a | 0.37 | 0.12 | 0.10 | 0.15 | 0.20 | 0.17 | 0.20 | 0.20 | 0.23 | 0.27 | 0.43 | 0.40 | 0.48 | 0.35 | 0.45 | 0.53 | 0.55 | 0.57 |
| | b | 0.33 | 0.10 | 0.10 | 0.08 | 0.18 | 0.17 | 0.13 | 0.15 | 0.08 | 0.17 | 0.43 | 0.33 | 0.47 | 0.43 | 0.40 | 0.43 | 0.47 | 0.43 |
| | c | 0.37 | 0.10 | 0.12 | 0.12 | 0.08 | 0.13 | 0.17 | 0.17 | 0.20 | 0.20 | 0.27 | 0.33 | 0.40 | 0.23 | 0.38 | 0.45 | 0.40 | 0.40 |
| Female 4 | a | 0.42 | 0.18 | 0.17 | 0.15 | 0.25 | 0.18 | 0.17 | 0.18 | 0.20 | 0.27 | 0.43 | 0.33 | 0.48 | 0.40 | 0.48 | 0.50 | 0.47 | 0.50 |
| | b | 0.33 | 0.15 | 0.12 | 0.12 | 0.27 | 0.22 | 0.23 | 0.13 | 0.22 | 0.22 | 0.48 | 0.33 | 0.47 | 0.43 | 0.50 | 0.42 | 0.52 | 0.45 |
| | c | 0.38 | 0.20 | 0.20 | 0.20 | 0.17 | 0.22 | 0.32 | 0.20 | 0.15 | 0.23 | 0.37 | 0.33 | 0.47 | 0.28 | 0.40 | 0.50 | 0.47 | 0.45 |

**Table 3: The difference between concept of danger and information in the hemispheres for each volunteer**

| Volunteer | Electrode | Hemisphere | Hand |
|---|---|---|---|
| Male 1 | F3–F7–C3 | Left | Right |
| Male 2 | Fz–F4–F8–T4–C4 | Right | Left |
| Male 3 | Fz–F3–F7–T5–C3–P3 | Left | Right |
| Male 4 | Fz–F8–T4–T6 | Right | Left |
| Female 1 | F3–F7–P3–T5 | Left | Right |
| Female 2 | F8–T4–T6 | Right | Right |
| Female 3 | F4–F8–C4–T4–T6 | Right | Left |
| Female 4 | F8–C4–P4–T4 | Right | Left |

window size by using AR coefficient feature of order 15 for all three volunteers. LDA classifier shows better results than ANN.

## Discussion on the Results

According to the definition of BCI system, it is a system that makes direct connection between the brain and the world outside that is not dependent on the conventional neuromuscular brain channels; only brain signals can be used to build a BCI system, and according to the available facilities, the most economical method is recording EEG signals. On the other hand, because the BCI system is directly in contact with people and is a noninvasive method used to record EEG signals and also to increase acceptance, the EEG signal recording must be performed with the least number of electrodes. On the other hand, the selected mental activities should be consistent with the system output types such as computer cursor movements. In this study, noninvasive signal recording, according to the high percentage accuracy in separating words concepts, is one of the strong points for BCI applications. Although selected mental activities somewhat are not consistent with the mental activities related to the BCI systems, and it is one of the weak points, the results show that subjective perceptions and mental imagery are effective to improve the accuracy of separating the words and their concepts.

In the first part, according to the results, for seven of the eight volunteers, danger and information signals were well separated; these differences for five of the eight volunteers were observed in the right hemisphere, and, for the other three volunteers, the differences were observed in the left

**Table 4: The amounts of mean squared error and correlation of danger and information signals for volunteers from Table 2**

| Volunteer | Danger (a) − danger (b) | | Danger (a) − information (c) | | Danger (b) − information (c) | |
|---|---|---|---|---|---|---|
| | Mean squared error | Correlation | Mean squared error | Correlation | Mean squared error | Correlation |
| Male 1 | 0.3165 | 0.9 | 0.3173 | 0.9 | 0.4888 | 0.8 |
| Male 2 | 0.2291 | 0.9 | 0.4186 | 0.8 | 0.3996 | 0.8 |
| Male 3 | 0.2670 | 0.9 | 0.4068 | 0.9 | 0.5673 | 0.8 |
| Male 4 | 0.3754 | 0.8 | 0.5813 | 0.4 | 0.4637 | 0.6 |
| Female 1 | 0.3271 | 0.8 | 0.5270 | 0.5 | 0.4090 | 0.8 |
| Female 2 | 0.5304 | 0.6 | 0.3808 | 0.8 | 0.3375 | 0.8 |
| Female 3 | 0.2670 | 0.9 | 0.4068 | 0.9 | 0.5673 | 0.9 |
| Female 4 | 0.1967 | 0.9 | 0.2596 | 0.9 | 0.3151 | 0.8 |

**Table 5: The maximum correlation and minimum mean squared error for signs of groups**

| Sign | Volunteer | Mean squared error (MSE) | Correlation |
|---|---|---|---|
| Group (a) | Female 3 − female 4 | 0.1905 | 1 |
| Group (b) | Male 2 − female 4 | 0.2272 | 1 |
| Group (c) | Female 2 − female 4 | 0.2184 | 0.9 |

**Table 6: The amounts of mean squared error and correlation for each volunteer between group (a) and group (b) with common titles**

| Volunteer | Slippery road | | Road workers | | Cyclist crossing | | Road narrows on both sides | | Pedestrian crossing | |
|---|---|---|---|---|---|---|---|---|---|---|
| | Mean squared error | Correlation | Mean squared error | Correlation | Mean squared error | Correlation | Mean squared error | Correlation | Mean squared error | Correlation |
| Male 1 | 0.5477 | 0.7 | 0.5292 | 0.5 | 0.6633 | 0.6 | 1.1402 | 0.4 | 0.6557 | 0.2 |
| Male 2 | 0.9110 | 0.2 | 0.6928 | 0.6 | 0.7071 | 0.6 | 0.5477 | 0.8 | 0.7211 | 0.5 |
| Male 3 | 0.7681 | 0.8 | 0.6928 | 0.8 | 0.8185 | 0.5 | 0.5916 | 0.7 | 1.1180 | 0 |
| Male 4 | 0.5831 | 0.8 | 1.3416 | 0.1 | 0.7550 | 0.9 | 0.6856 | 0.6 | 0.7874 | 0.6 |
| Female 1 | 0.8307 | 0.7 | 0.7874 | 0.6 | 0.9381 | 0.1 | 0.7000 | 0.6 | 0.4123 | 0.8 |
| Female 2 | 0.6633 | 0.5 | 1.0198 | 0 | 0.9274 | 0.5 | 0.6325 | 0.5 | 0.5099 | 0.8 |
| Female 3 | 0.4796 | 0.8 | 0.6083 | 0.7 | 0.6557 | 0.6 | 1.0724 | 0.2 | 0.7071 | 0.9 |
| Female 4 | 0.7550 | 0.6 | 0.8888 | 0.3 | 0.5657 | 0.7 | 0.9747 | 0.5 | 0.8000 | 0.5 |

hemisphere. Except female volunteer 2, the amounts of mean squared error between [group (a) and group (c)] and [group (b) and group (c)] were more than the amounts of mean squared error between [group (a) and group (b)], which suggested that danger and information signals were perfectly separated for seven out of eight volunteers. The amount of correlation between [group (a) and group (b)] was more than the amounts of correlation between [group (a) and group (c)] and [group (b) and group (c)] for male 2 and male 4; however, for the remaining volunteers, measurement of correlation was not suitable for separation. Male 4 had the best separation of danger and information signals, and female 2 had the worst separation; therefore, the data in this case was invalid.

There were different shapes and colors in danger signs of group (a) and group (b); nevertheless, both groups had the same results in all electrodes for all volunteers. Traffic signs refer to the concept of danger, and include two groups with different shapes and colors [red triangle (a) and orange/yellow rhombus (b)]. Five traffic signs, two by two in groups (a) and (b), had the same subjects. The amounts of mean squared error and correlation was shown for each sign. It is clear that shape and color do not have any effect on the separation of the traffic signs. For example, male 1 had further concentration on signs of slippery road, road workers, and cyclist crossing and generated similar signals according to goal signal. Male 2 had further concentration on signs of road narrows on both sides;

**Table 7: The highest classification accuracies of LDA for different features and six time window states**

| Feature | Volunteer 1 | | | | | | Volunteer 2 | | | | | | Volunteer 3 | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Time | | | | | | Time | | | | | | Time | | | | | |
| | 0.5 | 1 | 1.5 | 2 | 2.5 | 3 | 0.5 | 1 | 1.5 | 2 | 2.5 | 3 | 0.5 | 1 | 1.5 | 2 | 2.5 | 3 |
| AR coefficient | 54.50 | 54.90 | 59.20 | 64.30 | 67.89 | 61.20 | 53.10 | 54.60 | 55.20 | 60.80 | 63.41 | 60.60 | 55.80 | 56.20 | 56.90 | 57.30 | 60.49 | 59.20 |
| Average | 34.09 | 35.26 | 35.98 | 37.34 | 37.02 | 36.89 | 30.12 | 30.99 | 30.25 | 32.61 | 33.58 | 31.06 | 30.80 | 32.10 | 33.23 | 33.86 | 35.68 | 34.99 |
| Standard deviation | 43.87 | 43.99 | 45.50 | 45.66 | 47.89 | 44.25 | 39.89 | 40.58 | 41.34 | 42.75 | 41.68 | 41.03 | 41.58 | 42.76 | 44.95 | 45.06 | 47.21 | 44.89 |
| Moment | 35.29 | 36.27 | 36.98 | 37.59 | 38.94 | 39.15 | 31.02 | 31.59 | 32.59 | 33.19 | 34.93 | 32.78 | 30.28 | 30.89 | 33.38 | 35.20 | 36.26 | 34.17 |
| Kurtosis | 32.89 | 33.43 | 33.02 | 35.89 | 37.12 | 37.21 | 36.17 | 32.00 | 32.74 | 32.86 | 34.82 | 35.91 | 32.15 | 33.89 | 33.91 | 35.02 | 36.68 | 36.13 |
| Skewness | 32.80 | 34.03 | 37.12 | 38.21 | 38.98 | 40.21 | 37.23 | 31.36 | 31.89 | 33.27 | 34.85 | 35.84 | 32.45 | 33.85 | 33.98 | 34.29 | 37.00 | 37.25 |
| Power | 44.25 | 44.85 | 46.52 | 46.66 | 48.59 | 45.26 | 40.01 | 40.90 | 42.01 | 43.58 | 42.23 | 42.01 | 42.20 | 43.90 | 43.10 | 45.85 | 46.65 | 46.56 |

**Table 8: Classification accuracy in different states of neural network for 2.5 s window length and AR feature of order 15**

| Volunteers | The number of layers | Neural network functions | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Purlin | | | Logsig | | | Tansig | | | Hardlim | | |
| | | The number of neurons | | | The number of neurons | | | The number of neurons | | | The number of neurons | | |
| | | 10 | 20 | 30 | 10 | 20 | 30 | 10 | 20 | 30 | 10 | 20 | 30 |
| Volunteer 1 | 1 | 58.60 | 56.23 | 57.52 | 59.24 | 58.17 | 57.41 | 55.96 | 55.89 | 59.39 | 26.76 | 27.01 | 26.55 |
| | 2 | 58.50 | 60.16 | 59.26 | 56.68 | 57.20 | 56.14 | 58.89 | 60.02 | 56.47 | 27.33 | 26.36 | 27.48 |
| | 3 | 56.85 | 57.73 | 56.52 | 57.32 | 57.99 | 57.15 | 56.65 | 57.86 | 55.61 | 26.85 | 26.35 | 27.01 |
| Volunteer 2 | 1 | 48.63 | 50.70 | 50.91 | 45.42 | 46.35 | 47.33 | 48.56 | 48.43 | 48.88 | 26.53 | 26.85 | 26.36 |
| | 2 | 50.37 | 49.94 | 49.97 | 45.58 | 47.33 | 48.32 | 45.38 | 48.13 | 47.29 | 25.99 | 26.56 | 25.69 |
| | 3 | 48.33 | 52.31 | 50.25 | 45.72 | 48.92 | 51.70 | 44.89 | 47.22 | 51.78 | 27.12 | 27.82 | 27.01 |
| Volunteer 3 | 1 | 49.79 | 48.27 | 49.31 | 48.46 | 53.01 | 54.98 | 51.66 | 54.74 | 57.72 | 27.14 | 26.12 | 26.85 |
| | 2 | 50.69 | 51.52 | 49.02 | 46.68 | 50.47 | 48.24 | 50.93 | 51.25 | 51.76 | 26.89 | 25.78 | 26.15 |
| | 3 | 52.65 | 49.12 | 54.75 | 45.91 | 49.51 | 55.09 | 45.22 | 50.49 | 53.62 | 26.94 | 27.16 | 27.02 |

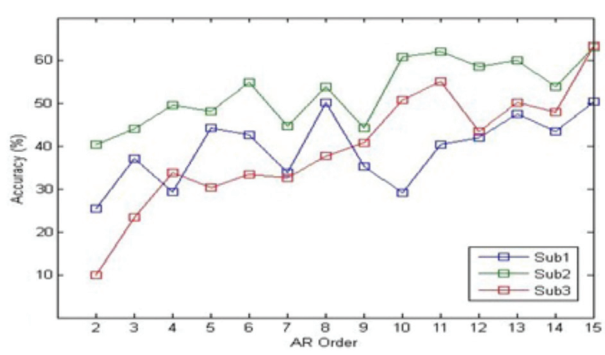


**Figure 12: Diagram of discrimination accuracy of LDA according to the AR coefficients of order 1–15**

male 3 had further concentration on signs of slippery road and road workers; and male 4 had further concentration on signs of slippery road and cyclist crossing. Female 1 had further concentration on signs of cyclist crossing and slippery road, female 2 had further concentration on sign of pedestrian crossing, female 3 had further concentration on signs of pedestrian crossing, slippery road, and road workers, and female 4 had further concentration on signs of cyclist crossing and slippery road.

To compare the results of this research with the results of the other similar previous researches,[8] it is noteworthy that in the research in which ICA algorithm and fMRI were used for detection and separation of two conceptual categories of the words, the process was to repeat one of the words full or drink in a covert way. Thereafter, by using fMRI image analysis, brain activities of different areas were recorded during the test, and ICA was used for finding communication between different areas; however, because of using brain imaging, only location features were extracted. The advantages of our research compared to the mentioned one is that more volunteers with wider age ranges participated and also locating accuracy is higher. Both of the researches have used ICA algorithm for detection and separation of conceptual categories of the words, and the advantages of the research, which is performed in this study, due to using EEG signals are high temporal and location extraction accuracy according to the concepts of the words.

Next, there is also a similar study[9] that had performed the test of completing words on fMRI images by using ICA algorithm, that such as mentioned issues, the advantages of the research which is done in this article is using EEG signals with high temporal and location accuracy that is more suitable for using in BCI systems. Both of the researches somewhat are the same in the number of volunteers. Two other studies[10,11] were performed on EEG signals, wherein the participants in the two experiments were tested to imagine vowel and syllable, respectively. For separating EEG signals and reducing data dimensionality, classification of SVM was used in the study,[10] as well as modified SOBI algorithm was used in study.[11] The advantages of our research are recording EEG signals for more volunteers and also using the words and their concepts with mental imagery instead of using vowels and syllables; the weak point is the lack of considering spectral features. According to the available signals, it is possible that in future spectral features be investigated along with the temporal and location features. Of course, usage of the spectral features and time–frequency processing due to the complexity and volume of processing is not recommended in BCI systems, because BCI systems should be processed as real-time [Table 10].

The results of these studies show that the occipital lobe had a fundamental role for semantic processing and covert word generation in humans. The results show that the occipital lobe activity was more than other brain areas during seeing words and images. In this experiment, so as to compare the obtained results with the studies that were performed on the brain anatomy, PET and fMRI images, and also brain topography in imagined speech in the covert syllables and vowels communications, the target signal after applying the ICA algorithm was selected in the way that it had maximum correlation with the occipital lobe. Finally, the results of this study confirmed the results of the other similar previous researches.

**Table 9: Classification accuracy in neural network (two layers, 20 neurons, and purlin function) and AR coefficient feature for 2.5 s window length of order 15**

| Volunteers | Classification | |
|---|---|---|
| | Artificial neural network | Linear discriminant analysis |
| Volunteer 1 | 60.16 | 67.89 |
| Volunteer 2 | 50.70 | 63.41 |
| Volunteer 3 | 48.27 | 60.49 |

Simulation results show that from classification of main directions, window size of 2.5 s was the best. In this aspect, 2 s window size was the next best choice. Considering feature extraction results, AR coefficients had the highest classification accuracy among the other options. According to the results of this study, we claim that AR coefficients are the best features. Simulation results confirmed that coefficients of order 15 gave higher classification accuracy for all three participants. The aforementioned results hold for both ANN and LDA. Simulations showed no considerable change in the accuracy of ANN for different number of hidden layers or number of neuron in each layer and different classification function. In the case of using hardlim classification, accuracy was considerably degraded; therefore, we concluded that this function was not appropriate for this case study.

As mentioned, a number of hidden layers and number of neurons in each layer, along with the classification function, make no difference in the performance of ANN; therefore, we use the setup with the shortest volume of computation, which reasonably will take less time. We used one hidden layer with ten neurons in each of the layers and also used purlin function, which was computationally more efficient. Comparing the results of ANN and LDA classifiers showed that LDA outperformed ANN in the classification accuracy domain and run time as well.

It is worth mentioning that the results of this study are in agreement with the results of the previous studies on the human brain anatomy, fMRI images, and head topography

**Table 10: Comparing the results of this research with the results of the other similar previous researches**

| | Covert speech by studying fMRI images[8] | Test of completing words[9] | Detection and separation of imagination of two vowels /u/ and /a/[10] | Classification of imagination of two syllables /ba/ and /ku/[11] | Detection and separation of two conceptual categories of the words danger and information |
|---|---|---|---|---|---|
| Number of volunteers | 336 | 10 | 3 | 7 | 8 |
| Age range | 5–18 | – | – | – | 25–30 |
| Task | Words | Words | Vowel | Syllable | Concept of the word |
| Recording | fMRI | fMRI | EEG | EEG | EEG |
| Algorithm | ICA | ICA | SVM | SOBI | ICA |
| Feature | Location | Location | Temporal | Temporal and spectral | Temporal and location |

during covert speech. Results of the previous researches showed that usage of evoked potential was more effective than using raw brain signal analysis in the mental activities classification accuracy. Although this was kind of a shortcoming for raw brain signal based analysis, this method could separate more different classes of activities. This was due to the fact that evoked potential only responded to the immediate brain reactions. The results confirmed those obtained from previous studies using AR coefficients for feature extractions. Comparison of the results of ANN and LDA classifiers showed that LDA outperformed ANN as well, and this was in agreement with the results of Ahangi *et al.*[22]

Scientific limitations in this study included few number of volunteers in the limited age range, limited mental activities in the designed task, and lack of the facilities such as brain imaging equipment with EEG signal recording and other obstacles that we are trying to fix in subsequent studies.

## Conclusion

In this experiment, in the first part, classification of two cognitive groups of words using EEG signals was investigated. In this study, ICA algorithm was used not only for detection and separation of the ocular artifacts from the EEG signals, but also for detection and classification of two cognitive groups of words. In the proposed method, after applying ICA algorithm to the EEG signals, the autocorrelation function was calculated between the EEG signals and the output signals of ICA algorithm. The signal with the maximum correlation, with the signals of the occipital lobe, was selected as a target signal. The simulations showed that according to the output signals of the FastICA algorithm from the recorded mixed signals, the ocular artifacts including eye blinks and eye movements could be simply detected and separated from the EEG signals. In addition, the results showed that ICA algorithm as one of the BSS algorithms is a suitable algorithm for recognizing the word concept and its place in the brain.

The results of this experiment were the same with the results that were obtained from PET, fMRI, and topographic data of volunteers, who produced in their imagination one of two syllables in one of three different rhythms, wherein the cognitive processing was performed in the occipital and temporal lobes with visual information. The cognitive processing or concept processing activates different lobes for each word in the brain.

In this research, the brain signals of the volunteer were recorded when imagining the image of four main direction arrows (up, down, right, and left) using EEG method. This was to implement the designed interface. At the preprocessing step, ICA algorithm was used to do artifact and noise elimination and detect target signal as well. After the preprocessing step, the raw data feature extraction took place. Simulation results showed that the best features resulted when the AR coefficients of order fifteen were used. According to the extracted features, each piece of the signal was classified to the appropriate class among the allowed ones.

In this study, LDA and ANN are used for classification of extracted features. The operation of ANN with different number of hidden layers (1, 2, and 3), different number of neurons (10, 20, and 30), and different classification functions was investigated, and the optimum state of ANN with highest classification accuracy was determined. LDA was more efficient in terms of processing time and classification accuracy. In the existence of four different classes (each corresponding to one of the main directions), the measured classification accuracy outperformed previous results.

The results of this research can be used in designing a BCI system for people, especially those with disabilities, and also, by applying a feedback (using the characteristics of the target signal), it can be used in training the patients with brain injury, Alzheimer disease, and Attention Deficit Hyperactivity Disorder (ADHD) children. Further studies to verify and expand the results of this study are recommended.

### Acknowledgments

Facilities for this study in the Department of Rehabilitation, Iran University of Medical Sciences were provided by Dr. Mahdi Akbari, and we appreciate his sincere help. We also thank all the participants in this research.

### Financial support and sponsorship

Nil.

### Conflicts of interest

There are no conflicts of interest.

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