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Deception Detection Method using Independent Component Analysis of EEG signals

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Abstract*— Deception detection has vital legal and medical applications; however the reliability of ways for the differentiation between truthful and deceptive responses continues to be restricted. Deception detection is additional accurately achieved by activity the brain correlates of lying in a personal. For the analysis of the tactic, many participants were passed through the designed Guilty Knowledge test (GKT) paradigm and their individual brain signals were recorded. The electroencephalogram (EEG) signals were recorded. To enhance signal noise ratio (SNR) of P300 components, the Independent component analysis (ICA) method was adopted which helps in reducing the noise and plotting original non-artifacted EEG signals. And then group of features such as morphological features and wavelet features were extracted from the reconstructed wave-form. Finally, the two class of extracted feature were classified with help of classifier. The efficiency achieved in this method is 83%. The method presented in this project improves the efficiency of GKT and deception detection in comparison with previous reported methods

Index Terms— *Electroencephalogram, Guilty knowledge test, Independent component analysis*.

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I. Introduction

Deception Detection is one of the most emotive and hotly debated of all human technological endeavors. The ability to notice deception has necessary legal, ethical and clinical implications, and has recently received revived interest from the scientific community. Deception is ubiquitous in human societies and is essential for proper social interactions. Lying is a complex process requiring suppression of the truth, communication of a coherent falsehood, contextual knowledge of that false situation, and modifications and changes of behaviors to convince the receiver of one's actions [1]. This complex and universal process would seem amenable to detection by brain imaging. The ability to measure noninvasively the Correlates of lying in the brain within an individual could offer a significant improvement over currently available tools to detect deception. In the early ages technique called deception detection via analysis of verbal and nonverbal behavior had been developed. In this they examined the hypotheses that a systematic analysis of nonverbal behavior could be useful in deception detection and that lie detection would be most accurate if both verbal and nonverbal indicators of deception to be consider. Results revealed several nonverbal and verbal indicators of deception. If only nonverbal behavior is considered 78% of the lies and truths could be correctly classified. An even the percentage of correct classification can be higher when all three detection techniques were taken into account. But this is completely hypothetical results based so is not liable. There are the basic ways to catch liars (A) by observing them how they behave their movements, whether they smile or steal gazes, pitch of their voice, rate of speech likewise. (B) By listening to them what they says analyzing there speech content, (C) By measuring physiological responses [2] [3]. Some liars may act innocent during the test if they are skilled enough to deceive and some innocent may found guilty because of fear and nervousness [1] [4] [5]. This is not reliable method.

Currently, the most widely used technique for the quantitative discrimination between deceptive and truthful responses is polygraph test, which measures activity of the peripheral nervous system to detect deception .This method measure nonspecific peripheral emotional/autonomic arousal that might or might not be associated with lying. By their very nature, polygraph measurements provide an extremely limited and indirect view of complex underlying brain processes. Consequently, a number of other recording modalities have recently been investigated for the possible application to deception detection; Another emerging technique is FMRI. MRI is a medical imaging technique using high magnetic fields and non-ionizing electromagnetic radiation to produce high resolution, three-dimensional (3D) tomographic images of the body is distinguished from regular (structural) MRI by the speed of acquisition of each 3D image . In fMRI, continuous pictures of the complete brain area unit nonheritable once each few seconds, that is quick enough to look at changes within the regional blood volume and flow that area unit related to psychological feature activity. Blood activity level dependent (BOLD) imaging is currently getting used within the magnetic resonance imaging technique most typically utilized in neuroscience BOLD depends on the difference in the magnetic properties of the contents of the blood vessels and the surrounding brain tissue as well as the magnetic difference between oxygenated and deoxygenated hemoglobin. BOLD fMRI does not show absolute regional brain activity; rather, it indicates relative changes in regional activity over time [6] [7].

In this paper we will discuss about the new method of deception detection using electroencephalograph (EEG)

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analysis of guilty and truthful suspect. Here the most powerful technique Independent component analysis is used to separate the EEG signal as EEG signal is superposition of many signal arising from brain and different. Buried in the EEG are signals that reveal information about brain processes. These signals are detected by changes in timing in the EEG after events such as listening to a sound or seeing a picture. The resulting signal is called an event related potential (ERP), which clearly stands above the background brain activity. The ERP can be divided into several basic components represented as positive or negative fluctuations in the ERP waveform at different delays after the stimulating event.ERP component contains signals such as P1, P2, N1, N2, N400 and P300. The signals generally arising after 250 milliseconds are thought to reflect higher level cognitive processes such as memory or language. The P300 is a specific electrical brain wave that is triggered whenever a person sees a object familiar to him. The P300 waves have been understood in electrophysiology to mean that the subject is able to consciously identify and categorize a stimulus. For example, if a subject has been listening to trombone noises and a flute tone is played, a P300 wave will appear 300 ms later on the EEG machine. The P300 event-related potential can be used to determine concealed knowledge that only a criminal would know. By putting details of the crime arbitrarily among an inventory of non-relevant things, one will distinguish criminal from national. If an individual recognizes a detail of the crime, it produce a P300 EPR and is likely guilty of, or at least familiar with, the crime [8] [9] [10] [11].

II. PROPOSED METHOD

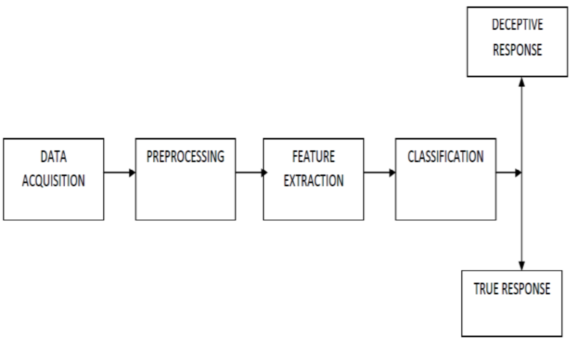

Fig.1 Block Diagram of Proposed Method

The brief idea about the method is that first acquiring the EEG recording of the person under test with the help of Guilty Knowledge Test, then after signal acquisition performing some basic filtering operation on the acquired data so as to increase the SNR of signal and reduce some percent of noise. As we know that the EEG signal consist of the many superimposed signal so by applying powerful Independent Component Analysis algorithm we will get refined and independent signals from mixed EEG signal. After applying ICA we will get the clear read of signal and so feature extraction is performed. Various features are extracted from the EEG signal which is most widely used in previous research for lie detection. For classification here I have used Hamming distance classifier.

A. Data acquisition

The EEG recording will be made using Ag-AgCl electrode placed on the scalp. Signals were recorded according to international standard 10/20 from 18 channels using RMS India system with 256 Hz sampling frequency for bipolar montages.

1. Guilty knowledge test

The guilty knowledge test, has recently drawn considerable attention among researchers. This test presents a set of question items to an examiner, which include one crime related item (critical item) and several control items (noncritical items). Items are selected so that an innocent examinee (i.e., one who does not possess the information) would be unable to distinguish the critical item from the noncritical items.

Participants: The participants in this test are 3 healthy right handed person of age between 12 to 14. They had no previous history of neurological or mental abnormalities.

Protocol: In a classroom of 15 students examiner declared test after 1 hour and kept test papers on table itself and left the classroom. Then student allowed to staying in a classroom and examiner was observing them from outside so that student should not notice. After some time two students came in front and saw the test paper and then sat on their positions. Examiner was observing them. After that, test was conducted and then those two students who are guilty and some innocent students were taken to the hospital to conduct GKT test. EEG recordings of all students were recorded while performing GKT.

B. Preprocessing: Independent Component Analysis

The EEG is composed of electrical potentials arising from several sources. Each source (including separate neural clusters, blink artifact, or pulse artifact) projects a unique topography onto the scalp known as 'scalp maps'. These maps are mixed according to the principle of linear superposition. Independent component analysis (ICA) attempts to reverse the superposition by separating the EEG into mutually independent components or scalp maps that is why the method used in the study is independent component analysis (ICA). ICA is a signal processing technique that models a set of input data in terms of statistically independent variables, it is able to separate independent components produced by distinct sources from linearly mixed signals. The basic ICA model can be described below as.

$$X = As(t)$$

Where $s(t) = [s_1(t)\ldots\ldots s_m(t)]^T$ is a source signal vector , $x(t)=[x1(t),\ldots,xn(t)]$ stands for the vector of mixtures, and A denotes the [n×m] mixing matrix . The minimal required apriori information is the independence of the source signals and the fact that at most one of the signals can have Gaussian distribution [12] [13].

1. FastICA Algorithm for fixed iteration

FastICA learning rule finds direction i.e. unit vector W such that the projection $w^T x$ maximizes nongaussianity. Nongaussianity here is measured by approximation of negentropy. It is based on the fixed point iteration scheme [14].

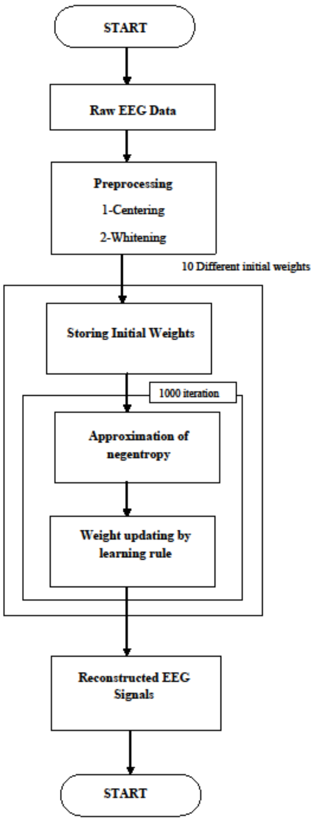

Fig.2 Flowchart of FastICA for fixed iteration.

C. *Feature Extraction*

A group of features were defined and evaluated in this study. These features have shown good performances in similar studies and hence, were believed to be useful as well for this application.

1. Morphological Features

These features are previously used by Kalatzis et al. in discriminating depressive persons from normal to detect P600 wave. Features are defined and calculated as below

(1) Latency (maximum): This latency time that is the time where maximum value of a signal appears.

$$\text{Latmax} = \{t|s(t) = s_{max}\}$$

Where s(t) is the signal trial for 1000ms and s_{max} is the maximum signal value in this interval.

(2) Amplitude (max): The maximum signal value

$$S_{max} = \max\{s(t)\}$$

(3) Latency/Amplitude ratio: it is the ratio of time at which signal value is maximum and maximum value at that point.

$$\text{LAR} = t_{Smax} / s_{max}$$

(4) Latency (minimum): This latency time is the time where minimum value of a signal appears.

$$\text{Latmin} = \{t|s(t) = s_{min}\}$$

(5) Amplitude (min): The minimum signal value

$$S_{min} = \min\{s(t)\}$$

(6) Peak-to-Pick (PP,pp):

$$pp = s_{max}\text{-}s_{min}$$

Where s_{max} and s_{min} are maximum and minimum signal values.

$$S_{max} = \max\{s(t)\}$$
$$S_{min} = \min\{s(t)\}$$

(7) Peak-to-Peak time window(PPT, t_{pp}):

$$t_{pp} = t_{Smax\text{-}}\ t_{Smin}$$

(8) Peak-to-peak slop (PPS,s_{pp}) :

$$s_{pp} = \frac{pp}{t_{pp}}$$

2. Wavelet Feature

Discrete wavelet coefficients were also used as a group of features which were extracted from the single trials. Three step wavelet transform is used. Symlets function were use as a mother wavelet.

D. *Classification*

Classification of obtained features was done with the help of Hamming distance classifier. First the features of training set data are calculated and are stored in a vector at their respective indexes. Then features of testing samples were calculated and again a feature vector of testing set is made. Now this feature vector of testing sample is compared with each training set feature vector with the help of hamming distance and then the value of hamming distance is stored in the respective places with their indexes. For classification minimum valued hamming distance is considered.

III. RESULT

The raw EEG signals collected after GKT is first preprocessed by applying ICA which gives near to original EEG signal. FastICA algorithm is used which is one of the powerful algorithm for ICA which separates the complex signals. ICA is applied on all 18 electrode data. The results are shown below. EEG signals before applying ICA and After applying ICA

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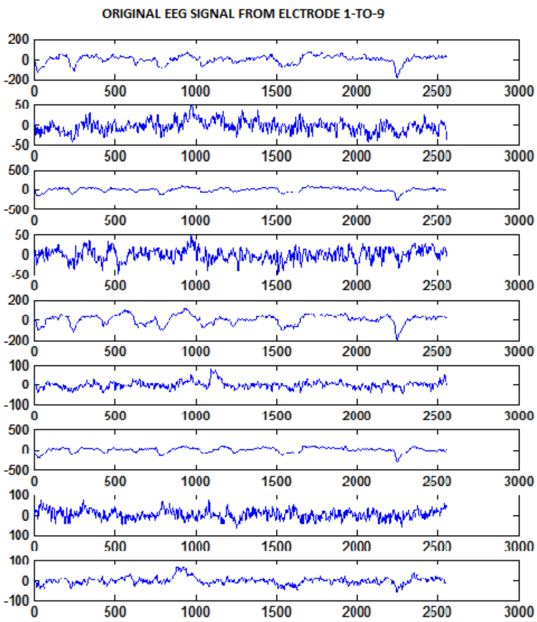

Fig.3(A) Original EEG signals from electode 1-to-9

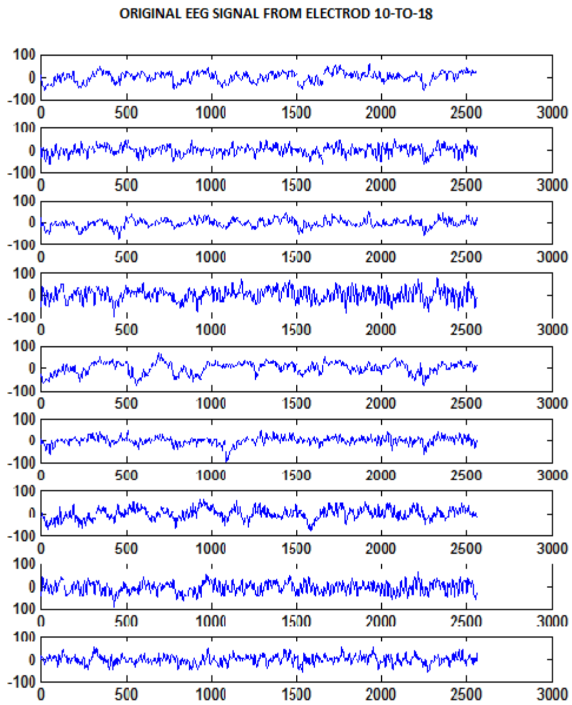

Fig.3(B) Original EEG signals from electode 10-to-18

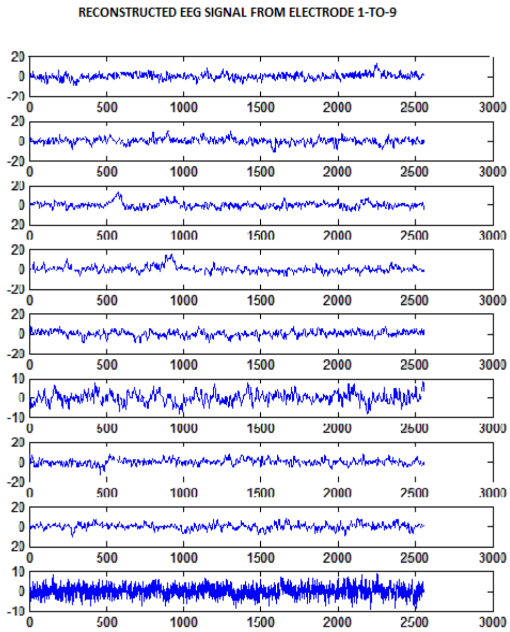

Fig. 4(A) Reconstructed EEG signal from electrode 1-to-9

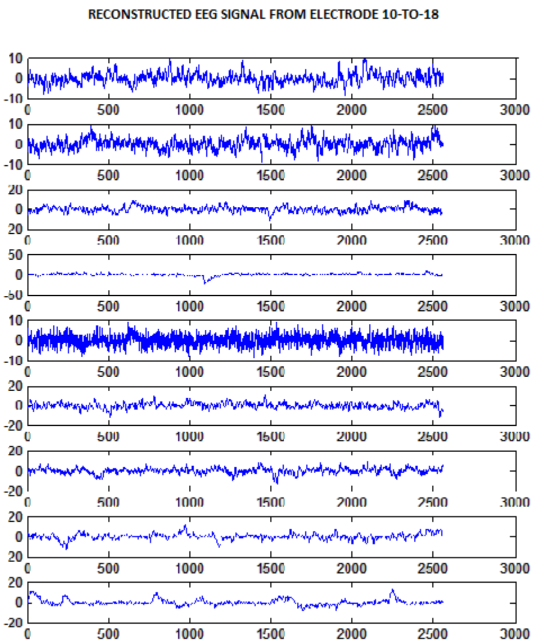

Fig.4 (B) Reconstructed EEG signal from electrode 10-to-18

After preprocessing, processed data is further used for feature extraction and classification.

The features of training set is calculated and stored in the respective index position in a vector. After calculating feature vector of whole training dataset test signal is loaded. After preprocessing feature vector of test signal is calculated. Then this test signal vector is compared with each of training set vector with the help of hamming distance classifier. After comparing two vectors the hamming distance value is stored at each index. Then minimum value of hamming distance is considered for the true and deceptive responses as per the signals stored in the training dataset.

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Following are the final results which are classifying true and deceptive signals.

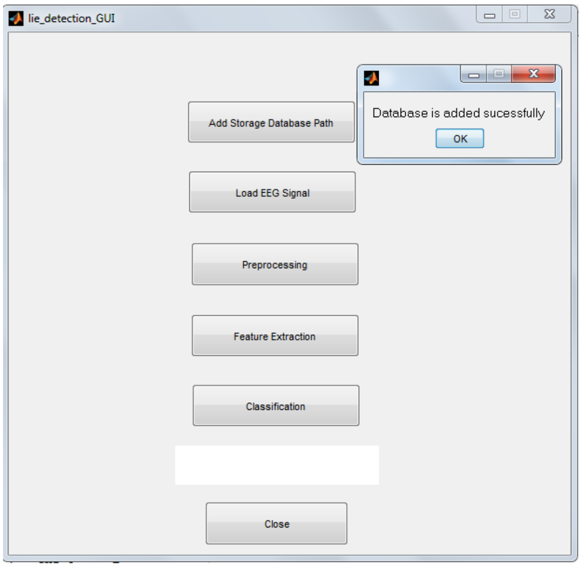

Fig5. Loading training Set.

After this test signal is loaded. Then preprocessing is performed on this signal then feature extraction performed and feature vector is created.

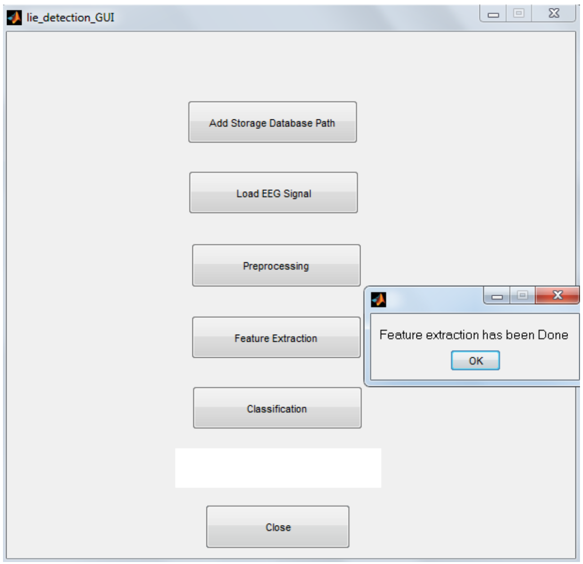

Fig.6 Preprocessing and feature extraction of Test signal

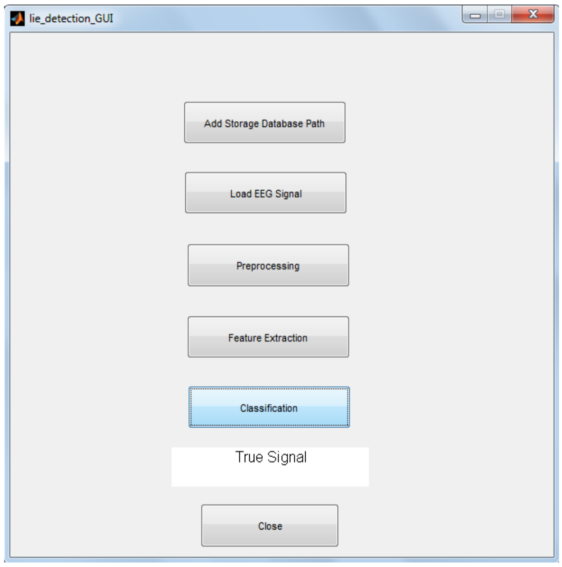

Fig.7 (A) Classification of test signal(True response)

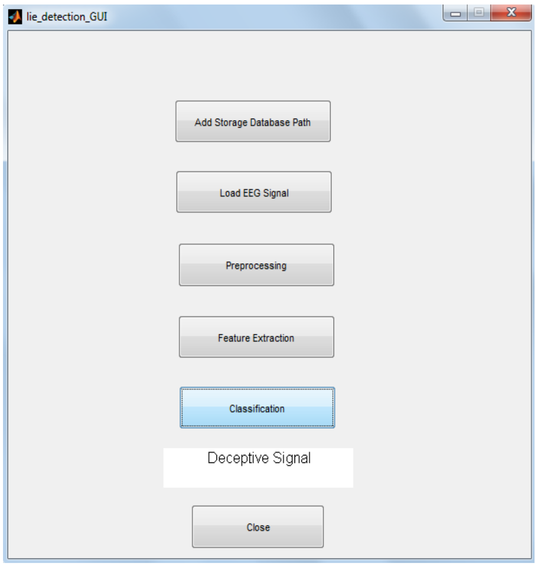

Fig.7 (B) Classification of test signal (Deceptive response)

IV. CONCLUSION AND FUTURE WORK

The aim of this preliminary study was to implement independent component analysis as one of the powerful denoiseing technique to classify the complex valued EEG signal which is implemented successfully. And then two classes of features such as morphological feature and wavelet were extracted. These features are proven to be the robust features for detection of P300 wave which is considered to be a ERP generated when person lies. The efficiency of this method is 83%. Based on these preliminary results, the application of morphological and wavelet transform based features to deception detection appears promising.

From our discussions in the preceding chapters as well as with our implementation and experimental results, we can confirm that the approach yields results up to our satisfaction. However, we have identified some other changes in the guilty knowledge to increase the efficiency. Some other electrode like Fz can also be used to get the guilty information. Classification can be done using more efficient classifier for large dataset.

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