

A Novel Method Based on Empirical Mode Decomposition for P300-Based Detection of Deception

Abdollah Arasteh, Mohammad Hassan Moradi, and Amin Janghorbani

Abstract—Conventional polygraphy has several alternatives and one of them is P300-based guilty knowledge test. The purpose of this paper is to apply a new method called empirical mode decomposition (EMD) to extract features from electroencephalogram (EEG) signal. EMD is an appropriate tool to deal with the nonlinear and nonstationary nature of EEG. In the previous studies on the same data set, some morphological, frequency, and wavelet features were extracted only from Pz channel, and used for the detection of guilty and innocent subjects. In this paper, an EMD-based feature extraction was done on EEG recorded signal. Features were extracted from all three recorded channels (Pz, Cz, and Fz) for synergistic incorporation of channel information. Finally, a genetic algorithm was utilized as a tool for efficient feature selection and overcoming the challenge of input space dimension increase. The classification accuracy of guilty and innocent subjects was 92.73%, which was better than other previously used methods.

Index Terms—Empirical mode decomposition, event-related potentials (ERP), feature selection, genetic algorithm, guilty knowledge test (GKT), P300.

I. INTRODUCTION

DETECTION of deception from subject's physiological characteristics has legal, moral, and clinical implications. This topic has especially been paid attention, and recently, several methods have been developed for this purpose in the scientific community [1]. Among all these approaches, conventional polygraphy is the oldest and most extended approach [2]. Respiration pattern, cardiovascular measurements and electrodermal response (EDR) are the most ordinary physiological parameters used in polygraph. These parameters are often extracted from structures which are controlled by the autonomic nervous system. In a polygraphic test, these parameters are recorded with a polygraph while an examiner asks some relevant and irrelevant questions from the subject.

Manuscript received October 26, 2015; revised June 2, 2016; accepted July 1, 2016. Date of publication July 13, 2016; date of current version September 1, 2016. The associate editor coordinating the review of this manuscript and approving it for publication was Prof. Mauro Barni.

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Digital Object Identifier 10.1109/TIFS.2016.2590938

The subject's guilt or innocence can be deduced from variation of these recorded parameters.

Wide variety of measures were applied in GKT studies including measures of Autonomic Nervous System (ANS), Central Nervous System (CNS) such as ERP, and fMRI based measures. However, CNS measures showed more reliability than other measures [3]. ANS and CNS measures were investigated simultaneously in [4], and the results showed that CNS measures achieved better results than ANS ones, yet superior results based on combination of these measures suggested that these measures complement each other.

P300 (also known as P3) is one of the endogenous ERPs which are extensively examined for cognitive tasks. This wave appears in response to meaningful rare stimuli (often called odd ball stimuli). Its scalp distribution is defined as amplitude variations along middle line of head (Cz, Fz and Pz channel).

The P300-based "Guilty Knowledge Test" (GKT) is a test which utilizes P300 amplitude as an index for recognition of concealed information. In fact GKT is a method that facilitates psychophysiological detection of prior knowledge of crime scene details, which is known only by guilty person involved in the crime, and by authorities, police, etc [5], [6].

GKT is based on the assumption that familiar topics among several unfamiliar homogenous topics will be followed by different responses. Often in a P300-based GKT, three types of stimuli are presented to the subject:

1. Probe (P), which is related to concealed information and is known only by guilty persons and authorities, so the guilty subjects know this stimulus while innocent persons do not.
2. Irrelevant (I), which is irrelevant to the crime therefore both innocent and guilty subjects are unfamiliar with this stimulus.
3. Target (T), which is often irrelevant to the crime, but all subjects are requested to have a reaction (such as pushing a button) while this stimulus is shown to them.

The numbers of irrelevant stimuli are more than two other kinds of stimuli, so P and T stimuli are taken into account as rare stimuli. T stimuli force subject to cooperate with the authorities, because not responding to these stimuli indicates subject's carelessness, which may lead to test failure. T stimuli are rare and the subjects know about them, so invoke P300 wave. In the later analysis of the probes, T stimuli are used as

an ordinary subject's P300 [7]. Nonetheless the theory that the T-Type P300 is the classic meaning of standard P300 definition is sometimes wrong [8].

The basic assumption in P300 based GKT is: if the subject has the crime information which exists in the probe stimuli, because of the rare nature of these stimuli, a P300 wave similar to the T-Type P300 is invoked. On the other hand, if the subject has no information about the probe stimuli, these stimuli are similar to irrelevant stimuli which do not invoke P300 wave, or the invoked P300 wave by these stimuli has negligible amplitude.

There are two basic approaches for EEG analysis in GKT: the first one is, bootstrapped amplitude difference (BAD) which is based on assessment of the similarity between the P-Type and the T-Type P300 amplitudes. For the guilty subjects, one expects that $P > I$ while for the innocent one, there is no difference between P-type and I-type P300 amplitudes [8]. The second approach introduced by Farwell and Donchin [7], is called bootstrapped correlation difference (BCD). In this method, P and T cross correlation will be compared with P and I cross correlation. P-T cross correlation is expected to be greater than the P-I cross correlation in the guilty subjects, and the opposite is expected in the innocent subjects.

In addition to these basic approaches, different signal processing and feature extraction techniques were applied in GKT. In [9], independent component analysis was used to enhance P300 SNR, and three groups of time, frequency and wavelets features were extracted from p300 and classified with SVM to detect guilty subjects. Nonlinear and chaotic analysis is another method that was used as a feature extraction method in GKT [10]. Wavelet features are of the most frequent groups of features that were used in several GKT studies [11]–[15].

One of the pioneer studies in which wavelet features were extracted for classification of guilty and innocent subjects was [14] and [15]. Three groups of features, morphological, spectral and wavelet, were extracted from Pz channel and optimal feature vector was selected with genetic algorithm and classified using LDA classifier.

The dataset of current study is the same dataset used in [14], and the aim of this study is re-analysis of this dataset with a different feature extraction method based on Empirical Mode Decomposition (EMD).

EMD is a transformation introduced by N. E. Huang in recent years [16]. This is a suitable method for non-stationary and nonlinear signal processing, it is an adaptive method for decomposing a signal into AM-FM modulated components called Intrinsic Mode Function (IMF) where each one is related to a physical characteristic existing in the signal nature.

Whereas most of biological signals have nonlinear and non-stationary characteristics, EMD is a good choice for processing of biological signals, such as EEG, which is one of the most complicated signals. EEG is difficult to process because of its nonlinear, non-stationary or even chaotic nature [17]–[20]. EMD has been used in different signal processing tasks such as de-noising and signal enhancement [21]–[23], feature extraction [24], [25] and other signal processing aspects [26]–[28].

Escalante et al applied an EMD based method in P300 detection task for BCI application [24]. In this study, IMFs of containing P300 and without P300 reference signals were considered as basis functions to represent EEG single trials, and the coefficients of expansion based on all basis functions were considered as a feature vector. These features can represent the similarity between each EEG trial with reference signals.

This method was chosen as the basic method of this study for feature extraction. The results of this method are the labels of a single trial EEG. These labels are not applicable in GKT in this naive form. The first modification of this algorithm is using single trial labels to vote on guilt or innocence of the subject. In addition to this modification, feature extraction was done on all three channels of recorded EEG, Cz, Fz and Pz rather than just Pz channel as previous studies have carried out on the same dataset [14]. This modification was done in order to use the specific information of P3a subcomponents of P300, which are dominant in Cz and Fz channels rather than Pz [29]. The input of the basic method was single trial EEG, which has low Signal to Noise Ratio (SNR). Another step of enhancement of the basic method is application of SNR enhancement methods such as EEG averaging, to improve the results of GKT. Extraction of features from all three channels resulted in increase of feature vector dimension. The classification results based on all features were not satisfactory; therefore, to improve the results, genetic algorithm was applied to select optimal feature vector.

The rest of the paper is organized as follows: in section II, first, the protocol of experiments and characteristic of the collected data is explained. Afterward, the EMD algorithm and feature extraction method with EMD are explained and finally, feature selection method with genetic algorithm is described. The result of this method is presented in section III. Finally, in section IV the paper is concluded with a summary of the study and the discussion of the results.

II. MATERIALS AND METHODS

A. Data Acquisition

EEG Signals used in this study were recorded in the BSP Laboratory of Biomedical Engineering School of Amirkabir University of Technology. The data were recorded primarily by Abootalebi and used first in [14]. Sixty-two subjects (59 males, 3 females) took part in signal recording task. They were generally undergraduate or graduate students and all had normal or corrected vision. The EEG was recorded using Ag/AgCl electrodes placed at the Fz (Frontal), Cz (Central) and Pz (Parietal) sites (10–20 international system). All sites were referenced to linked mastoids, and the subjects were grounded at the forehead. Electrooculogram (EOG) was recorded from sub and supraorbital electrodes (above and below the right eye). EEG was amplified and digitized at a rate of 256 samples per second. Digitized data were subsequently analyzed offline using MATLAB software. Before data analysis, all data were digitally filtered using a band-pass filter in the range of 0.3–30 Hz. This is the frequency range which is used typically in P300-based GKT studies [8].

All subjects were trained, and then performed a mock crime scenario. The subjects have been told to choose guilty or innocent role in the first round (first experiment), and then switch their role in the next round (second experiment). After a training phase about the protocol, a box – containing a jewel – was given to the subject. The examiner left the room and permitted the subject to perform his role in the scenario. In this step the subject could choose and implement one of two possible roles (guilty/innocent). The guilty subject opened the box, checked and investigated the jewel precisely and imagined that he/she has stolen the jewel. The subject was asked to memorize the jewel details, so he/she could have acted as the actual robber. For reassurance, the subject was asked to write the detail of the object on a piece of paper, and deliver it after the test. The innocent subject has never opened the box, and thus, had no information about the object. This protocol is a single-probe protocol similar to protocols which are usually used by Rosenfeld *et al.* [8].

Then the examiner returned to the room and executed the P300-based GKT protocol. After the attachment of electrodes and start of the recording, stimuli consisting of single pictures of five pieces of jewelry, were presented randomly and successively on a monitor to the subjects. Each item remained 1.1 s on the screen, of which 1s was used for processing. The inter-stimulus interval was 2s. During the test, pictures of five items (for example: ring, wristwatch, necklace, earring, and hairpin) were randomly presented one at a time (each with 30 iterations, so we had $5 \times 30 = 150$ recorded trials for each subject). These objects contained one target, one probe, and three Irrelevants. The probe was the object in the box. The target was another object, which had been previously presented to the subject in the training phase at the start of the protocol.

One push button was given to each hand of the subject, right click as “YES”, and left click as “NO”. The subjects were asked to reply to the items by pressing one of the two buttons; “YES” for familiar items and “NO” for unknowns. This task had already been practiced during the training phase. The subjects also were instructed to try to hide their information about the probe item in the guilt condition and to behave mentally as innocent. Any covert action was permitted, provided that it did not disarrange the totality of the test, and was not observable to the examiner either by visual inspection of the subject or from the recorded signal. Hence, actions such as voluntary blinking or body movement detected by the examiner were not permitted. Indeed, all subjects were supposed to press “YES” for targets and “NO” for the probes and the Irrelevants. Thus, guilty and innocents, both replied honestly to targets and Irrelevants; but for probes, the guilty subjects replied falsely while the innocents answered honestly. Subjects with more than 10% error in correct clicking for all stimuli were removed from the analysis.

Each subject took part in two experiments (playing guilty role and innocent role) in which the boxes and all displayed jewels were different. The jewel in the box was a gold coin in the first experiment and a hairpin in the second experiment. Therefore, with 62 subjects, a total number of 124 tests were performed. 32 subjects chose the innocent role and 30 subjects chose the guilty role in their first experiment. A few test

results were removed due to improper implementation of the protocol by the subject or inappropriately recorded signals. Finally, 59 guilty cases and 51 innocent cases (almost balanced class distribution) were chosen to be used in the current study.

B. EMD Algorithm

In this section EMD algorithm that plays the main role in the implementation of the proposed method will be introduced.

EMD decomposes complicated signals into a few components called Intrinsic Mode Function (IMF). Each IMF has some specifications:

- (1) The number of extrema (maxima and minima) is equal to number of zero crossings of the signal or differs only by one
- (2) They are locally symmetric and the mean of top and bottom envelope of each IMF is zero

Decomposition of the original signal into IMFs is called Sifting Process, which is an iterative algorithm until some conditions are satisfied. The sifting process stops when any of the following criteria are reached:

- (1) The residual signal energy becomes less than a predefined threshold
- (2) The residual signal is a monotonic function that cannot be decomposed into more IMFs

The sifting process can be summarized into the following steps:

- (0) Assign $i = 1$
- (1) Find all extrema (maxima and minima) of the signal $x(n)$
- (2) Get the envelopes of minima ($e_{\min}(n)$) and maxima ($e_{\max}(n)$) of the signal $x(n)$
- (3) Compute the mean of minima and maxima envelopes: $m(n) = \frac{e_{\min}(n) + e_{\max}(n)}{2}$
- (4) Compute the difference of the main signal and the mean signal: $h(n) = x(n) - m(n)$
- (5) Continue the steps 1-4 with $h(n)$ as a new signal or stop depending on stopping criteria in [16], and assign $c_i(n) = h(n)$ and continue the process with the residual signal $x(n) - h(n)$ as a new $x(n)$ and increase i by one.

After performing the sifting process, the original signal can be written as the sum of its IMFs ($c_i(n)$) [16]:

$$x(n) = \sum_{i=1}^N c_i(n) \quad (1)$$

As discussed in [16], the IMFs are not only some components extracted from the original signal sum of which is equal to the original signal, but also each of them is related to a physical characteristic existing in the signal nature. It is true that the frequency content of the IMFs is decreased from the first to the last, but each of them has a frequency band, rather than a single frequency with respect to sinusoidal waves as reference. They are also suitable (locally narrow-band) for Hilbert Transform. In Fig. 1, a single P-Type (Probe) trial signal from Pz channel of a guilty subject and its IMFs are shown.

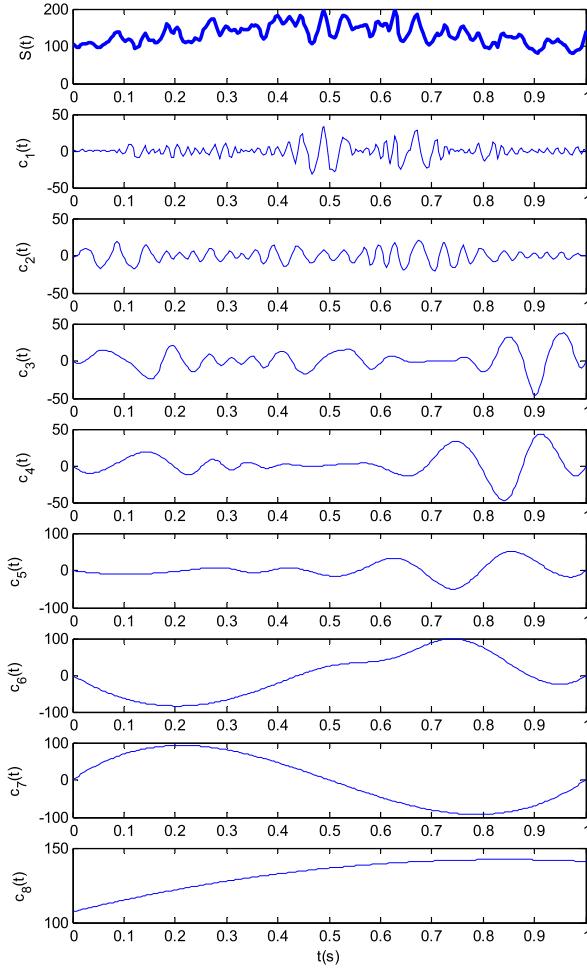


Fig. 1. A P-Type (Probe) single trial of a guilty subject and its IMFs (Pz channel).

C. Feature Extraction

Raw data are not suitable for classification, so often by certain methods, a vector (called feature vector) with specific dimension is extracted from the original signal. In recent years EMD-based feature extraction methods have been used for the classification of various types of signals.

Expanding a signal over a basis is widely used as a feature extraction method [30]. As mentioned in section II.B, IMFs are related to natural characteristics of the signal, so expansion coefficients of a signal over IMFs of a reference signal with predetermined desirable properties, can be treated as a feature for the measure of the similarity between them.

The aim of GKT is investigation of similarity between Probe and Target or Irrelevant stimuli, so obtaining proper reference signals for guilty and innocent subjects and expanding a Probe based on their IMFs will result in coefficients which can be used as a feature for classification.

Escalante et al applied such an approach for classification of single trial records of Cz channel of BCI speller dataset. Based on this approach, the reference signals for GKT problem were built.

In this study, first, all trials containing P300 and all trials without P300 were averaged separately to obtain two reference

signals, $R_1(n)$, $R_2(n)$ respectively. $R_1(n)$ is the reference of trials with P300 and $R_2(n)$ is the reference of the trials without P300:

$$R_1(n) = \frac{1}{K_1} \sum_{i=1}^{K_1} x_{1,i}(n), \quad R_2(n) = \frac{1}{K_2} \sum_{i=1}^{K_2} x_{2,i}(n) \quad (2)$$

K_1 and K_2 are the number of the trials with P300 ($x_{1,i}(n)$) and without P300 ($x_{2,i}(n)$) respectively.

There are several choices for calculation of reference signals (R_1 and R_2) from the dataset. One choice is applying target trials for calculating R_1 wave and irrelevant (non-target) trials for calculating R_2 . This is important that the original signals to be classified are probe signals, so if the maximum classifier adaptation and generalization is desired in the training process, it is better to use guilty person's probe signals as the reference of trials containing P300 wave (R_1), and innocent person's probe signals as the reference of trials without P300 wave (R_2). These signals were also used in [14] and [15] for feature extraction and classification, so the final reference signals were chosen as mentioned for better comparison between past studies and the current study.

Then EMD algorithm was applied to these reference signals and their IMFs were obtained:

$$R_1(n) = \sum_{i=1}^{M_1} c_{1,i}(n), \quad R_2(n) = \sum_{i=1}^{M_2} c_{2,i}(n) \quad (3)$$

In Eq. (3) M_1 and M_2 are the numbers of the IMFs of R_1 and R_2 respectively, and $c_{1,i}(n)$, $c_{2,i}(n)$ are their IMFs. Thus, each record $x(n)$ can be expanded based on $c_{1,i}(n)$ or $c_{2,i}(n)$:

$$x(n) \simeq \sum_{i=1}^{M_1} b_{1,i} c_{1,i}(n) = \hat{x}_1(n)$$

$$x(n) \simeq \sum_{i=1}^{M_2} b_{2,i} c_{2,i}(n) = \hat{x}_2(n) \quad (4)$$

In Eq. (4) $b_{1,i}$ and $b_{2,i}$ are expansion coefficients based on IMFs of reference signals, R_1 and R_2 . These coefficients were calculated from pseudo-inverse equation and least square error constraint [31] as follows:

$$A_1 b_1 = \hat{x}_1$$

$$A_2 b_2 = \hat{x}_2 \quad (5)$$

$$A_1 = \begin{bmatrix} c_{1,1}(0) & c_{1,2}(0) & \cdots & c_{1,M_1}(0) \\ c_{1,1}(1) & c_{1,2}(1) & \cdots & c_{1,M_1}(1) \\ \vdots & \vdots & \ddots & \vdots \\ c_{1,1}(N-1) & c_{1,2}(N-1) & \cdots & c_{1,M_1}(N-1) \end{bmatrix}$$

$$A_2 = \begin{bmatrix} c_{2,1}(0) & c_{2,2}(0) & \cdots & c_{2,M_2}(0) \\ c_{2,1}(1) & c_{2,2}(1) & \cdots & c_{2,M_2}(1) \\ \vdots & \vdots & \ddots & \vdots \\ c_{2,1}(N-1) & c_{2,2}(N-1) & \cdots & c_{2,M_2}(N-1) \end{bmatrix} \quad (6)$$

$$b_1 = [b_{1,1} \quad b_{1,2} \quad \cdots \quad b_{1,M_1}]^T = (A_1^T A_1)^{-1} A_1^T \hat{x}_1$$

$$b_2 = [b_{2,1} \quad b_{2,2} \quad \cdots \quad b_{2,M_2}]^T = (A_2^T A_2)^{-1} A_2^T \hat{x}_2 \quad (7)$$

Based on above relations, b_1 and b_2 were calculated using the fact that minimizing error of $|\hat{x}_1 - x|$, $|\hat{x}_2 - x|$ with least square error constraint, leads to this answer for non-square matrices A_1 and A_2 . After calculating coefficient vectors b_1 and b_2 , each or both of them can be used as features for classification.

The primary results of applying this approach, showed poor performance of this method for GKT problem. In [24], only results of Cz channel were reported based on single trial classification, but single trial classification in GKT is not so beneficial, and the classification of subjects is the main goal. So, firstly the method was adapted by applying voting, meaning that in N classified single trials, the majority label was assigned as subject's label. This approach significantly improved the accuracy of subject classification.

Some studies suggest that P300 complex has 2 subcomponents P3a and P3b (classic P300). The P3a subcomponent is generated during the attentional focus process of the primary discrimination task [32]. This subcomponent has frontal-central maximum amplitude. P3b would appear as another subcomponent which is subsequent of P3a, if activation of attention resources caused promoted memory operations. It is the reflection of the brain activity during memory usage, which has parietal maximum amplitude [29], [33]. Based on these evidences, attentional focus of the subject to the probe stimulus can provide clues about guilt or innocence of the subject. So, it may be useful to use Fz and Cz channels information in which the P3a amplitude is maximal, in addition to Pz channel in which P3b is maximal.

Based on abovementioned points, in this study, not only Cz channel was used, but also Fz and Pz channels and their combination were used for feature extraction and classification.

Single trial classification accuracy in P300 detection task is not acceptable due to low Signal to Noise Ratio (SNR) of trials. In order to improve the classification accuracy, enhancement of SNR should be performed. Noise of EEG signal is usually modeled as AWGN, so using mean of single trials leads to better SNR and more reliable results [34], so the effect of using mean of single trials instead of just one trial as input, was investigated and the results are presented in the results section (Section III). Superimposed grand-average of T-Type, P-Type and I-Type trials for guilty and innocent subjects is shown in Fig. 2. The procedure of feature extraction is depicted in Fig. 3 schematically.

D. Classification and Validation

There are several classifiers for classification of feature vectors, but Linear Discriminant Analysis (LDA) is simple and has an acceptable time of training and accuracy. LDA is also appropriate for feature selection with genetic algorithm (which is discussed later), because genetic algorithm is a very time consuming task, and quick training means a significant decrease in time cost.

Cross-validation is essential in order to determine final accuracy. There are several cross validation methods. One of the most reliable cross validation methods is Leave-One-Out cross validation (LOOCV) [35], in which one feature vector

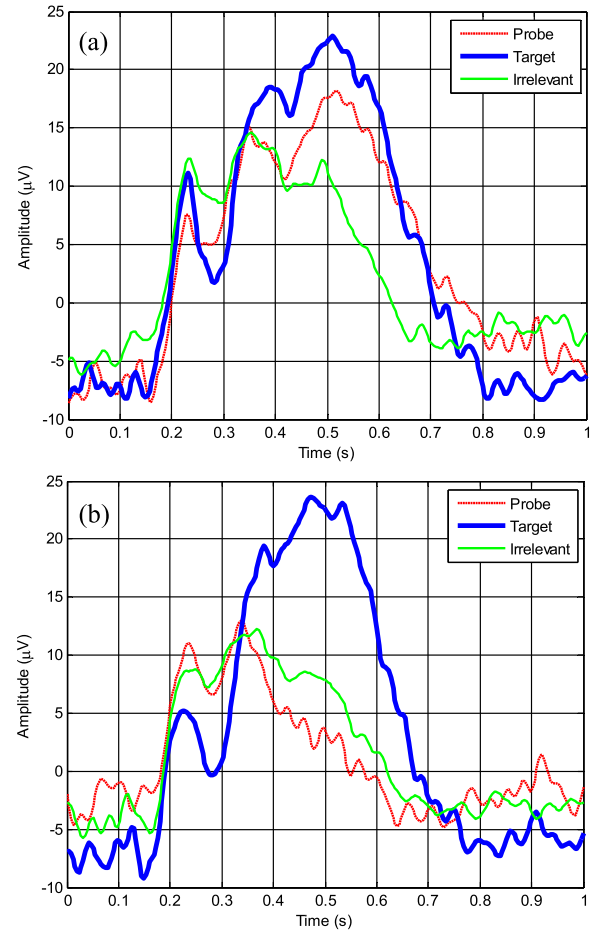


Fig. 2. Superimposed grand-average of T-Type, P-Type and I-Type trials for: (a) guilty subjects; (b) innocent subjects.

is selected as test vector, and all of the other feature vectors are used as the training set. Then, the test vector is classified with trained classifier, and this procedure is repeated for all of feature vectors as test vector. The percent of correct classified vectors is assumed as the classification accuracy. One of the advantages of this method is stable accuracy result in spite of other methods like K-fold; however, the classifier must be trained for each feature vector, and the computational cost of this algorithm is higher than other methods.

E. Feature Selection

Feature vectors of three channels can be used simultaneously and simply by concatenating them to form a feature vector with a higher dimension. The results of this method were not so desirable and no improvements were observed. One reason for this result is that increasing the dimension of feature vectors, increases the number of the necessary training data (needed for achieving an acceptable accuracy of classification) exponentially. Increasing the dimension of feature vectors also increases the complexity of classifier and makes it harder to converge to an optimal decision region, because it can vary with large degrees of freedom [36]. One of the current methods for solving this problem is called dimension reduction, which means shortening the dimension

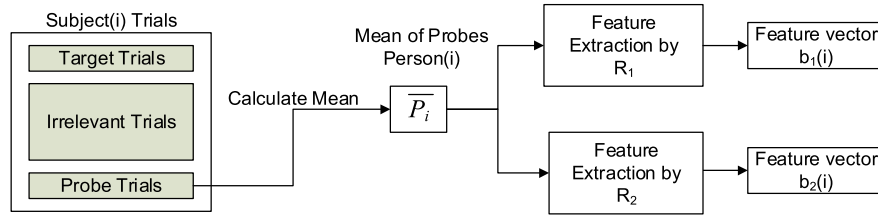


Fig. 3. The procedure of feature extraction.

of feature vectors by omitting some features which have minimum discrimination for classification. These features are redundant and their data exist somehow in other features and do not help the classifier to discriminate different feature vectors.

Several methods could be applied for selecting suitable features from all of the extracted features. The best method for finding global optimum features is testing all possible combinations of N features (2^N possible combinations) which increases intractably large by increasing features number and can be used only for small N (approximately $N < 20$) and could be used only for single channel feature selection. Another solution for feature selection is genetic algorithm [37]. Using a genetic algorithm for satisfying a minimum or maximum condition is one of the usual approaches in solving optimization problems. In this method, a number of numeric strings (often 1 and 0) are considered as chromosomes. Each chromosome contains a special coded number that is equivalent to a solution to the problem. Then, in a special process and by means of some “operators”, a new generation of chromosomes is produced from the previous generation. Some well-known operators that have been defined in the field of genetic algorithm are described below:

- Reproduction: is an operator in which the most fitted chromosomes (those with the best corresponding solutions) are transferred to the next generation directly.
- Crossover: is one of the operators in which a portion of one chromosome is combined with a portion of another chromosome in order to produce a new one.
- Mutation: is an operator in which a few random chromosomes are produced.

The fitness function is a criterion that determines a solution’s degree of optimality. Greater value of the fitness function shows the more optimal solution.

There is a straightforward method for using genetic algorithm in feature selection. In this method, chromosomes are coded with binary codes and each bit indicates the existence or absence of a feature in the selected feature vector. For example, if the i^{th} bit is 1, the i^{th} feature would be selected, and if the i^{th} bit is 0, the i^{th} feature would be omitted. It is obvious that the most fitted chromosome is the one that maximizes the accuracy of classification based on its associated feature vector. So in each generation, based on binary bits of each chromosome, the selected features of all feature vectors are given to the classifier, and the overall accuracy of the classification is determined as the output of the fitness function of each chromosome and is used for production of the next generation. This process is very time-consuming, and its time is related directly to the initial

TABLE I
GENETIC ALGORITHM PARAMETERS

Genetic Algorithm Parameters	Value
Initial population	20
Number of generations	100
Number of reproductions	6
Number of crossovers	13
Number of mutations	1
Crossover method	Uniform binary mask
Best chromosome selection method	Roulette wheel

TABLE II
RESULTS OF CLASSIFICATION ACCURACY BASED ON THE EXTRACTED FEATURES FROM EACH CHANNEL WITH T-TYPE AND I-TYPE SIGNALS AS REFERENCE

Selected Channel	Accuracy (%)
Fz	66.36%
Cz	60.00%
Pz	74.55%

population and the number of generations to proceed. If the initial population and the number of generations increase, the time cost of the algorithm will be high, but on the other hand, the probability of finding a more efficient solution will also be higher.

In this study, 20 chromosomes were selected as initial population, and the algorithm was progressed to the generation 100. Percent of reproduction, crossover and mutation were chosen to be 30%, 65% and 5% respectively. The roulette wheel algorithm [38] was used for selection of the most fitted chromosomes. Cross over was done uniformly with a random mask. LOOCV method was used for computation of the fitness function for each chromosome. A summary of genetic algorithm parameters which were used in this study are given in Table I.

III. RESULTS

A. Classification Results

In this section, the results of the proposed method in the current study are presented.

As discussed in section II.C, several choices were available for building reference signals, but after investigation of results, the best performance was achieved by choosing guilty and innocent probe signals as reference. For example, Table II shows the performance of classification based on features extracted from T-Type and I-Type trials as reference for three separate channels. The best result in this approach is related

TABLE III
ACCURACY, SENSITIVITY AND SPECIFICITY RATES BESIDE AUC OF ROC FOR EACH METHOD OF FEATURE EXTRACTION AND CLASSIFICATION

	Method	Measures	Channel(s)				Maximum number of correctly classified subjects
			Cz	Fz	Pz	Cz-Fz-Pz	
1	Escalante et al (Single Trial)	Accuracy	0.5909	0.5819	0.5760	0.5752	-
		Sensitivity	0.5995	0.5800	0.5783	0.5766	
		Specificity	0.5835	0.5835	0.5740	0.5740	
		AUC of ROC	0.6143	0.6098	0.6112	0.6005	
2	Adapted Escalante et al (Voting on Single Trial Labels)	Accuracy	0.7727	0.7727	0.8000	0.7455	88
		Sensitivity	0.7647	0.7451	0.7647	0.7451	
		Specificity	0.7797	0.7966	0.8305	0.7458	
		AUC of ROC	0.8588	0.8445	0.8800	0.8219	
3	Enhanced Adapted Escalante et al (Voting and Feature Selection)	Accuracy	0.8273	0.8182	0.8364	0.8455	93
		Sensitivity	0.8431	0.8431	0.8627	0.8431	
		Specificity	0.8136	0.7966	0.8136	0.8475	
		AUC of ROC	0.8488	0.8554	0.8930	0.8850	
4	Abootalebi et al (With Feature Selection)	Accuracy	-	-	0.8636	-	95
		Sensitivity			0.8627		
		Specificity			0.8644		
		AUC of ROC			0.8759		
5	Current Study (SNR Enhancement, Without Feature Selection)	Accuracy	0.7455	0.7182	0.7727	0.8000	88
		Sensitivity	0.7451	0.7451	0.7843	0.7647	
		Specificity	0.7458	0.6949	0.7627	0.8305	
		AUC of ROC	0.7411	0.7677	0.8564	0.8711	
6	Current Study (SNR Enhancement, With Feature Selection)	Accuracy	0.7727	0.7909	0.8636	0.9273	102
		Sensitivity	0.8039	0.8431	0.8235	0.9608	
		Specificity	0.7458	0.7458	0.8983	0.8983	
		AUC of ROC	0.7714	0.8116	0.8966	0.9252	

to Pz channel and is equal to 74.55% which is not acceptable, and 28 subjects were misclassified, so in the remained results, the reference signals were guilty and innocents probe signals.

The first implemented method was naive algorithm presented by Escalante et.al, in [24]. The best result in this approach was achieved by Cz channel features, which was 59.09%, and the Area Under Curve (AUC) of Receiver Operating Characteristic (ROC) was 0.6143. As can be seen in Table III, the sensitivity and specificity of this method are approximately equal.

As discussed in section II.C, labeling on single trials is not the final goal of GKT, so voting was done after classification of single trials for each subject and the majority class among labels was assigned to subject as final label. Correct classification rate after this adaptation is maximal on Pz channel features and is equal to 80%. It should be mentioned that sensitivity in this method is less than specificity (Table III). Up to this point, only 88 out of 110 subjects were classified correctly.

Also it can be seen from Table III that combining feature vectors from three channels together, drops the classification accuracy, because of increase in input dimension and harder convergence of classifier with rather large set of parameters. Selecting optimal or sub-optimal features from all channels could enhance the performance of classification, so genetic algorithm has been applied for feature selection (as described in section II.E) and classifying single trials, and then final classification accuracy was calculated after voting on majority label of single trials for each subject. This approach resulted in 84.55% correct classification rate on three channels feature vector together, and the accuracy on the other single channels

was less (see Table III). After this modification, the number of correctly classified subjects reached 92 out of 110 subjects. The result is rather reasonable now after two steps of modification, but the previous studies has shown slightly better accuracy.

Investigation of the effect of SNR Enhancement using single trial averaging showed rather moderate results, but the point here is without any feature selection, combination of all three channels features, is now superior to all single channel results. This fact shows the promotion of feature discrimination of Cz and Fz channels as a result of SNR enhancement.

Final results belong to classification accuracy after feature selection, which was the best result in all classification measures among all methods. The accuracy in this method was maximum in combination of features of all three channels which was 92.73%, meaning correct classification of 102 subjects out of 110.

B. Statistical Analysis of Classification Results

In the previous section, only the primary accuracy of the classification was reported in each step, but the results could be investigated more deeply. One important classification output is the sensitivity of classification, which means the number of guilty subjects classified correctly. Sensitivity is very important in GKT, and is a benchmark for acceptance or rejection of a GKT method in real world applications [39]. The final proposed method's sensitivity (96.08%) is superior to other methods (Table III). This is a significant achievement in the results of classification in GKT problem.

Another benchmark for a classification result is AUC of ROC which is available in Table III. It can be seen that the

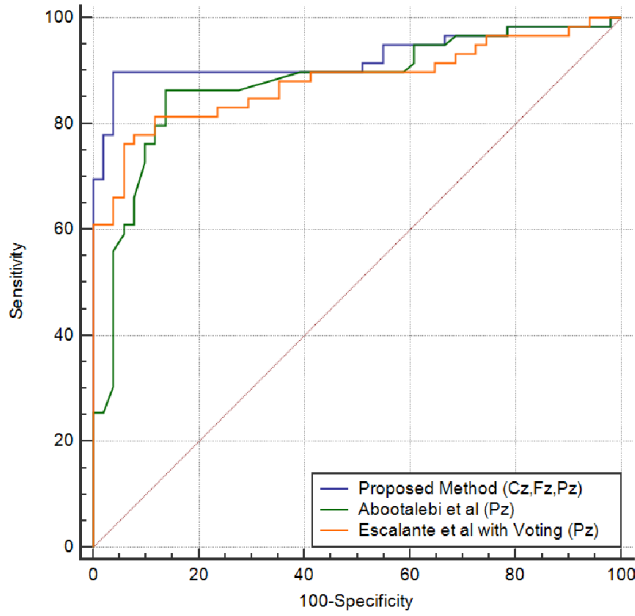


Fig. 4. ROC of three selected methods (axis scales are percentage).

TABLE IV
PAIRWISE ROC STATISTICAL COMPARISONS BETWEEN
THREE SELECTED METHODS

Compared Methods	p-value
Escalante et al ^a - Abootalebi et al	0.8929
Proposed Method- Abootalebi et al	0.1873
Proposed Method- Escalante et al	0.0793

^aMethod 2 in Table III – Pz Channel

final proposed method has the largest AUC (0.9252). The ROC of different methods could be compared statistically to show the difference between various methods of classification. Fig. 4 shows ROC for three chosen methods from Table III, and related pairwise ROC comparisons are shown in Table IV. The values in the Table IV are calculated based on DeLong et al method [40], and show rather acceptable difference between the proposed method and both Escalante et al and Abootalebi et al methods.

There is another advantage in proposed method and that is the separability of classes. LDA outputs a discrimination number for each input feature vector which is not crisp. Usually, a threshold is used to label the output of LDA as negative or positive class. Performing Kruskal-Wallis test [41] and drawing boxplot of LDA output for each method, shows a good raise of inter-class discrimination for the proposed method (Fig. 5, Table V).

IV. DISCUSSION AND CONCLUSION

In this study, a novel method for EEG feature extraction and its application in P300-based GKT was introduced and discussed. This method was based on feature extraction from EEG trials by means of EMD, and had better results in P300-based GKT than the previous studies [14], [15]

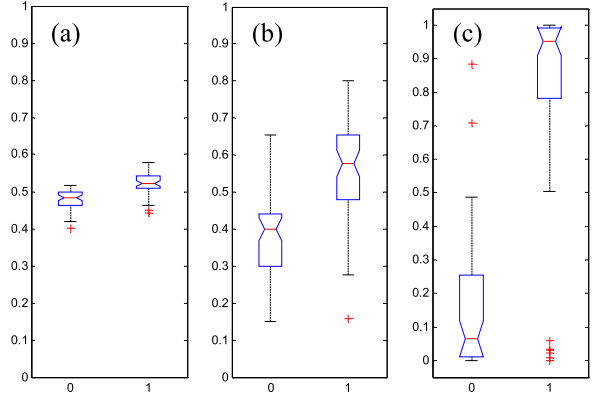


Fig. 5. The box plots of 3 methods discrimination output of classifier: (a) Escalante et al with voting – Pz channel. (b) Abootalebi et al – Pz channel. (c) Proposed method – All three channels after feature selection.

TABLE V
KRUSKAL-WALLIS TEST RESULTS FOR SEPARABILITY
OF THREE SELECTED METHODS

Compared Methods	p-value
Escalante et al ^a	7.1733×10^{-12}
Abootalebi et al	1.1895×10^{-11}
Proposed Method	1.72876×10^{-14}

^aMethod 2 in Table III – Pz Channel

TABLE VI
NUMBER OF FEATURES AND SELECTED FEATURES FROM
EACH CHANNEL IN THE PROPOSED METHOD

Channel	Number of Features	Number of Selected Features	Percent of Selected Feature
Cz	15	7	46.6%
Fz	11	5	45.5%
Pz	10	8	80.0%

on the same dataset. In addition, changing the feature domain from wavelet coefficients and morphological features in [14] and [15] into a new feature domain, can lead future studies to further improvements of discrimination between guilty and innocent subjects. The p-values in Table V and box plots of Fig. 5 suggest better inter-class discrimination for the proposed method. This discrimination helps for generalization and real world application of proposed method.

The dominance of the proposed method is significant in sensitivity, which is very high (0.9608) with respect to other methods. AUC of this method is also high (0.9252).

One of the advantages of the proposed method in the current study is the use of all three recorded channels, while in the previous studies, only the Pz channel was used due to the dimensionality problem and classifier complexity, and there was no evidence of final result improvement. However, the number of selected features in proposed method of current study is shown in Table VI, and it can be observed that the Pz channel percentage of selected features is almost twice the other two channels, and this fact confirmed the importance of this channel.

This is suitable to use data effectively as much as we can, because the data were recorded once, and every channel and

trial type (such as P-Type, T-Type and I-Type trials) may have useful information for more discrimination between guilty and innocent subjects.

One of the improvement fields for future works is modification of the genetic algorithm parameters in a manner that leads to better classification accuracy. For this purpose, the genetic algorithm parameters should be changed for further and more effective search in the domain of parameters. The genetic algorithm used in this study was not very complicated for two reasons:

- First: the results of this study could be comparable to the previous studies
- Second: the main focus in this study was in the area of feature extraction and new feature domain, not in genetic algorithm

So, changing the parameters of genetic algorithm and using a more suitable method and parameters may result in better classification accuracy.

One new approach which can be considered for more investigation in the future is classification based on each subject's trials himself/herself, rather than classification with respect to all subjects' trials. It means feature extraction from T-Type and I-Type single trials (or averaged trials) and then classifying P-Type trials.

Changing the classifier and using more efficient classifiers like SVM or cascade of classifiers also could be a good alternative in the whole process, which may lead to better results.

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