Research Journal of Applied Sciences, Engineering and Technology 4(17): 2995-3004, 2012
ISSN: 2040-7467

Submitted: December 28, 2011 Accepted: January 03, 2012 Published: September 01, 2012

Combination of Designed Immune Based Classifiers for ERP Assessment in a P300-Based GKT

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Abstract: Constructing a precise classifier is an important issue in pattern recognition task. Combination the decision of several competing classifiers to achieve improved classification accuracy has become interested in many research areas. In this study, Artificial Immune System (AIS) as an effective artificial intelligence technique was used for designing of several efficient classifiers. Combination of multiple immune based classifiers was tested on ERP assessment in a P300-based Guilty Knowledge Test (GKT). Our experimental results showed that the proposed classifier named Compact Artificial Immune System (CAIS) is a successful classification method and can be competitive to other classifiers such as K-Nearest Neighbourhood (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). Also, in the experiments, it was observed that using the decision fusion techniques for multiple classifier combination lead to better recognition results. The best rate of recognition by CAIS was 80.90% that has been improved in compare to other applied classification methods in our study.

Keywords: Artificial immune system, ERP, guilty knowledge test, lie-detection, P300

INTRODUCTION

Recording the brain potentials as one of the old non-invasive techniques has been applied for studying the brain functions (Abootalebi *et al*., 2004). This technique which is common used method measures event-related changes in the Electroencephalogram (EEG) known as Event-Related Potentials (ERPs). ERPs which are electrical brain waves have been extensively studied in the P300 waves. The P300-based Guilty Knowledge Test (GKT) utilizes P300 amplitude as an index of actual recognition of concealed information (Ben-shakhar and Elaad, 2002). This test has been suggested as an alternative approach for conventional polygraphy which is applied for psycho physiological detection of prior knowledge of crime details that would be known only by the guilty person and also police or other authorities (Ben-shakhar and Elaad, 2002). The designed GKT was applied to several subjects and their respective brain signals were recorded. After removing the noise of signals and pre-processing stages; for analysis of signals, some suitable features were extracted and then, our new hybrid method consisting of combination the decision of different classifiers produced by Compact Artificial Immune System (CAIS) was applied.

Multiple classifier combination as a technique that combines the decision of several classifiers is used in a wide range of pattern recognition fields (Bi *et al*., 2008). When there are several competing classifiers available, it is better to combine them to get a more accurate classifier by a combination function.

Artificial Immune System (AIS) is a bio-inspired computational intelligence method that has been employed in a wide variety of different application areas such as pattern recognition (Kudo and Sklansky, 2000), machine learning (Suliman and Rahman, 2010), data mining (Chen *et al*., 1996), statistic (Coutinho, 1980), control (Lie *et al*., 2000), Optimization (Tan *et al*., 2008) and classification (Bereta and Burczynski, 2006). The natural immune system has many properties which make it desirable as a source of inspiration to design the computational algorithms. Typical examples of these properties including: recognition, learning, memory, self-regulation, adaptation and robustness. AIS like other Artificial Intelligence techniques can learn new information, save data, recall the learned information and finally perform different tasks such as pattern recognition.

In pattern recognition domain, the first work that suggested a computational system inspired from natural immune system was performed by Farmer *et al*. (1986). In this work, the authors proposed a model based on the idiotypic network theory which explained the immune memory mechanism and could be applied for pattern recognition tasks. This work suggested that the biological

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immune system can be considered as a learning system and used as an inspiration to build machine learning techniques. Cook and Hunt followed these ideas to develop an algorithm for DNA sequence classification (Cook and Hunt, 1995) .

After that, a modified algorithm was proposed by Timmis *et al*. to expand a general technique for data reduction and clustering (Timmis *et al*., 1999). Forrest *et al*. proposed an algorithm inspired from the mechanism used by immune system to train the T-cells to recognize antigens and prevent them from attacking to the body's own cells (Forrest *et al*., 1994). This algorithm which was named Negative Selection (NS) is based on self/non-self recognition as one of the interesting mechanism of the adaptive immune system and different versions of this algorithm were applied for pattern recognition tasks (Chen, 2003).

There are many classification systems which have been used for EEG signals classification for different tasks such as clinical diagnosis. Among these approaches, several studies have been focused on ERP assessment in a P300-based GKT. These studies from independent laboratories applied different methods to achieve high classification performance. Farwell and Donchin obtained 87.5% classification accuracy using Bootstrapped Correlation Difference (BCD) method (Farwell and Smith, 1991). Rosenfeld *et al.* had reached to a detection rate of 80-95% by using Bootstrapped Amplitude Difference (BAD) and BCD methods (Rosenfeld *et al*., 2004). Abootalebi *et al.* obtained 86% classification accuracy using Linear Discriminant Analysis (LDA) classifier after optimizing features by Genetic Algorithm (GA) (Abootalebi *et al*., 2009).

Our study is a continue of previous works including P300 GKT and classification of wavelet features based on LDA and GA reported by Abootalebi *et al*. Abootalebi *et al*. (2006, 2009). Indeed, data collection and feature extraction have been more focused on previous works; however, our major focus was the improvement of pattern recognition part using AIS. We investigated the classification capability of AIS and compared it with other classifiers.

In this study, a new hybrid method was proposed for ERP assessment in a P300-based GKT problem. This report introduces CAIS algorithm to produce several optimized classifier systems in the first stage. Then, we used different approaches for parallel combination of multiple immune based classifiers to get a more accurate classifier. Indeed, the purpose of the present study was assessment of CAIS as a classifier and then, combination the decision of designed classifiers to achieve improved classification accuracy.

In this study, we have used the modified version of the data collected by Abootalebi *et al*. Abootalebi *et al*. (2006, 2009). The original database comprises 2552 samples including 1371 single sweeps for guilty subjects and 1181 sweeps for innocent subjects. Since the training phase of our proposed classifier (CAIS) was very time consuming, we had to reduce the size of data. For this reason, we calculated the average of all single sweeps of each subject and then, wavelet features form averaged data were extracted. In this way, the number of samples was decreased from 2552 to 110. To compare the effectiveness of CAIS to other classifiers, we also applied three well-known classifiers (K-Nearest Neighbourhood (KNN), Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM)) on the same dataset. The results reported in this study proved that CAIS is an efficient and competitive classifier.

BACKGROUND INFORMATION

Application of the biological metaphors to solve the computational problems is a successful idea. Similar to other artificial intelligence techniques, AIS has been emerged to solve the designed problems in different fields with high performance. This section introduces the natural and artificial immune system for better understanding of CAIS algorithm.

Natural immune system: The natural immune system as the most complex functional systems is composed of diverse molecules, cells and organs that work together to protect the body from infectious agents known as antigens (Timmis *et al*.,2008). There are two types of immune response: innate and adaptive. Innate immunity responds against general pathogens that enter to the body but is not directed towards specific infectious agents. Adaptive immunity allows the immune system to repel the Antigens (Ag) that innate system cannot remove. The adaptive immune system mainly consists of two lymphocytes known as T- and B-cells (Igawa and Ohashi, 2005). The majority of immunological researches have been focused on the adaptive immune response which is named antigenic specific response.

The clonal selection theory explains how the adaptive system recognizes and eliminates specific Ags via B-cells (Castro and Timmis, 2002). When B-cell's receptors which are named Antibodies (Ab) recognize an Ag, the B-cell is selected to proliferate. The number of generated B-cell's clone is proportional to the affinity of the selected B-cell and the Ag. Therefore, the highest affinity cells proliferate and the B-cell clones undergo somatic hypermutation process to produce B-cells with more affinity with the presented Ag. In addition, the best B-cells which their Abs present high affinity with the Ag are considered to remain as memory cells. Memory B-cells are kept for secondary responses to the same (or similar) antigenic patterns. Figure 1 illustrates the clonal selection principles as a biological inspired model which was performed the classification task in our proposed method.

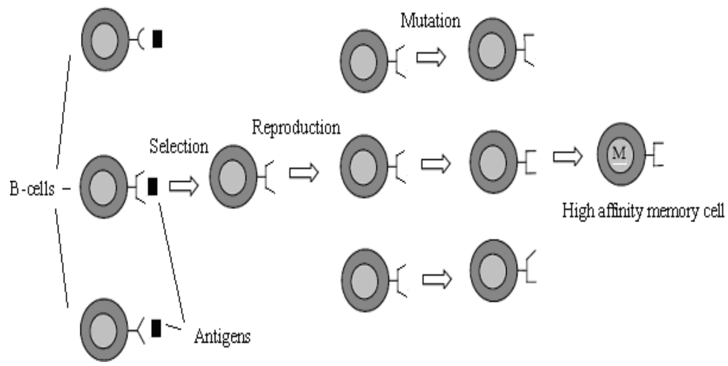

Fig. 1: Clonal selection principle

Artificial immune system: AISs inspired from biological immune system proposed in 1990s as a new computational research area (Omkar *et al*., 2008). AIS has been applied successfully to a variety complex engineering problems such as classification. Like Artificial Neural Network (ANN), AIS is capable of learning new information, save this information at its memory, recall the learned information and then perform the pattern recognition task.

Representation type for modelling of immune cells is one of the most important issues in the AIS researches. Among different representation methods that have been proposed, we applied the most commonly used model named shape-space representation introduced by Perelson and Ostar (1979). This model quantitatively describes the interactions between cells and antigens (Ozsen *et al*., 2007).

USED DATA SOURCE

The method applied for production of lie-detection dataset was as follows (Abootalebi *et al*., 2006, 2009):

Data acquisition: The EEG signals were recorded with Ag/AgCl electrodes placed frontal, central and parietal sites of 63 subjects (60 male, 3 female) in the modified GKT experiment. The recorded signals having information of brain electrical activities were amplified and then digitized at a rate of 256 samples per second and also filtered in 0.3-30 Hz range to prepare for analysing stage.

Stimulation and recording procedure: In designed modified GKT experiment, after guidance of the subject about the protocol, a box containing a jewel was given to him/her and the subject was asked to perform protocol without presentation of examiner. At this moment, the subject could choose and play one of two possible roles: guilty or innocent. When the subject acted in guilty role, he/she was expected to open the box, see the jewel precisely and memorize the details of it. While in the second case, the subject played the innocent role and could not open the box and therefore had no information about the object.

After that, examiner returned to the examination room and started to perform protocol. The subject sat in front of a monitor and then, brain signals recording was started with attachment of electrodes. During the recording, pictures of five pieces of different jewels (each one with 30 iterations) containing one target, one probe and three irrelevents were showed successively and randomly on monitor. The probe was the object in the box and target had been previously presented to the subject before the starting of the examination.

The subject was given one push button in each hand, right hand click as "YES" and left hand click as "NO" and then, he/she was asked to reply "YES" to the items saw them previously an "NO" for unknowns. All subjects (innocents and guilties) answered "YES" for targets and "NO" for both probes and irrelevants. Therefore, innocents and guilties, both replied honestly to targets and irrelevants, but the innocents replied honestly to probes while guilties answered them falsely.

In the designed protocol, each subject was participated two times in the experiment which the boxes and all jewels were different. The subjects were supposed to choose a guilty role in one experiment and innocent role in another. Therefore, for 63 subjects, totally 126 tests were performed, which 33 subjects chose the innocent role and 30 subjects chose guilty role in the first experiment. The brain signals recorded from these two experiments were analyzed independently. At the end of experiments, a few test results were removed because of misconducting the protocol with subjects or examiner and inappropriate quality of the recorded signals. Finally, 59 recorded of guilty cases and 51 recorded from innocent were used for our following investigation.

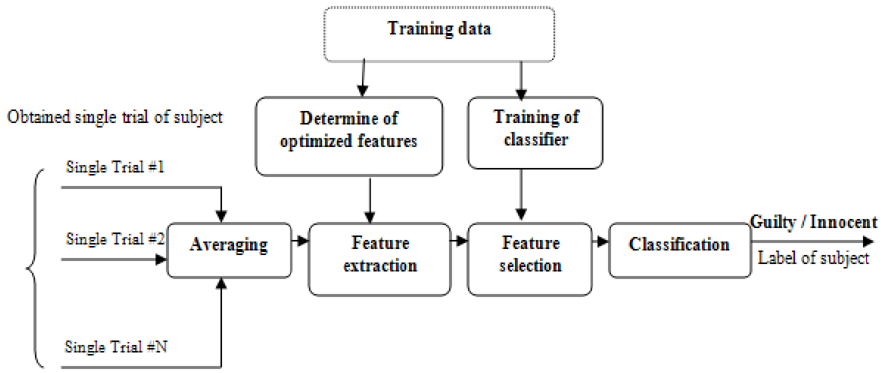

Fig. 2: Block diagram of the propose system for analysing of lie-detection dataset

Data analysis: In this study, we used classification based method for analyzing of the recorded signals. Our processing method included feature extraction, feature selection and classification. Figure 2 shows the different stages of our methods to analysis of brain lie-detection dataset. The first step is extraction of wavelet features (32 features) from the raw data which was averaged for each subject (Abootalebi *et al*., 2006). Second step is selection the best features by GA and finally classification of data by CAIS is the last step.

METHODOLOGY

Our proposed method involved two stages: designing of immune based classifiers in first stage and combining the classifier results in second stage. The block diagram of proposed method is shown in Fig. 3.

Compact artificial immune system: This report used a version of AIS classifier algorithm which is different from conventional AIS classifier (Leung *et al*., 2007) . There are two main problems in conventional immune based classifiers. The first is corresponding to population control mechanism. On the other hand, when some B-cells match to an antigen, their population increases trough cloning and mutation. Therefore, the number of produced B-cells become more than initial B-cell population. The second problem is that in most AIS classifiers which are designed based on population of B-cells, there is an optimization problem of one B-cell as a part of the classifier. In our used AIS classifier system, two mentioned traditional problems were solved. This approach did not need any population control mechanism and used global optimization of the whole system.

The constructive units of designed system have been shown in Fig. 4. As it can be observed, each B-cell represents a perfect classifier where each row represents an object category and each column represents a feature. It should be noted that this structure is designed for binary classification problem and for multi-class dataset the number of rows should be reformed.

Notations used in the algorithm follow as:

Ag:	Input sample
N:	Number of *Ag*s in training phase
L:	Number of features of each *Ag*
C:	Number of categories (2 is selected for lie-detection dataset)
Clonal_Rate:	Number of clones created for each cell
Prob_Mut:	Probability of mutation for each clone
current_Bcell:	Representation of perfect classifier (size:(C, L))
clon_Bcell:	Proliferated B-cells population
mut_Bcell:	Mutated B-cells population
max_Itr:	Maximum number of iterations
Bcell_num:	Number of produced classifiers

CAIS algorithm: The training phase of CAIS algorithm was designed in seven steps:

1. **Initializing:** The first step of the algorithm is determination of the initial values of the parameters and vectors. In this step, the initial memory B-cells that each of them represents a perfect classifier system, are randomly formed. For each memory B-cell known as *current_Bcell*, steps 2-6 are iterated until termination condition is met (In the current implementation, the stopping criteria is adapted for a given number of iterations).
2. **Evaluation:** The training *Ag*s are loaded and *current_Bcell* is evaluated by determination of the classification accuracy.
3. **Cloning:** The *current_Bcell* proliferates and produced clones are saved in *clon_Bcell* matrix. The number of clones is determined by *clonal_rate* factor.

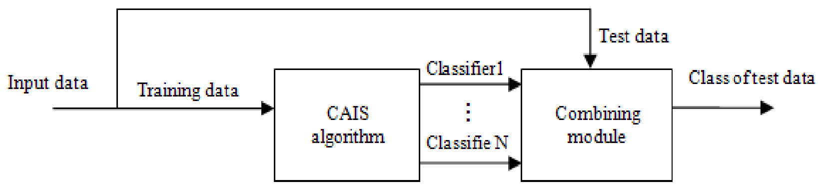

Fig. 3: Block diagram of the propose system

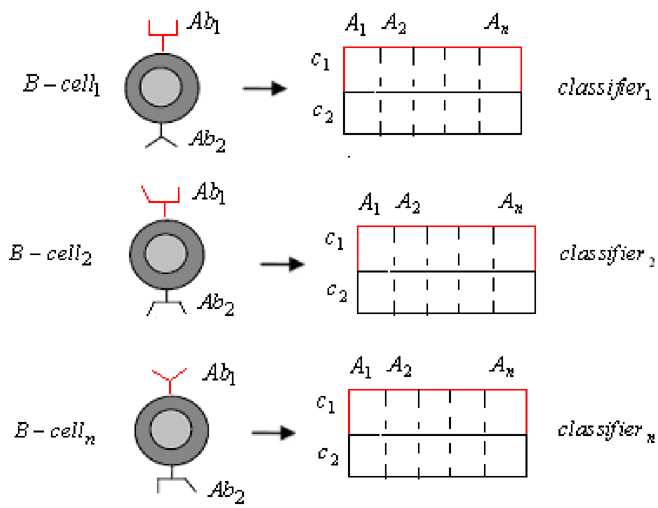

Fig. 4: Structure of classifiers used in CAIS algorithm

4. **Mutation:** Each clone of the *current_Bcell* undergoes a mutation process by randomly mutating the attributes of each clone. Then the mutated clones saved in *mut_Bcell* population.
5. **Evaluation and selection:** The behavior of all mutated B-cells is evaluated. On the other hand, all training *Ag*s are presented to each mutated B-cell to be recognized and classified. Then, after evaluation of mutated B-cells, the best B-cell with highest classification accuracy is selected as *Best_Bcell*.
6. **Comparison:** In this step, the behavior of *Best_Bcell* is compared with *current_Bcell*. If it performs better than *current_Bcell* in term of recognizing the training samples, It will be chosen as *current_Bcell*.
7. **Save:** The *current_Bcell* represented a perfect classifier is saved in the system.

The proposed method for mutation of B-cells is as follows (Leung *et al*., 2007):

1- for each clone of each B-cell
  1-1- for each antibody
    1-1-1- for each feature
      1-1-1-1- select a random number between 0 and 1.
      1-1-1-2- If the selected number is higher than *Prob_mut*, replace a random number in the interval (0 1) as *mut_Value* instead of feature.
    1-1-2- Set *mut_Value* to the clone.

The flowchart of the CAIS algorithm is shown in Fig. 5.

At the end of training phase, there are several CAIS classifiers that each one is able to discriminant guilties and innocents with an error rate. It is obvious that the classification results of different B-cells produced by CAIS algorithm are different. On the other hand, some subjects who are recognized incorrectly by a B-cell, can be detected by another B-cell appropriately. Therefore, combination the decision of different classifiers was proposed to improve the results.

Fusion techniques: In pattern recognition fields, one of the two combination approaches has been usually used: feature- and decision-fusion. In this work, we used the decision fusion model which all classifiers present their own result in parallel form and then, the final decision is given with combination of results. In this section, some non-trainable (fixed) combiners applied in our framework are introduced (Tin Kam *et al*., 1994).

Assume that a classifier *cl* is any mapping $d:U\rightarrow[01]^C$, C is the number of pattern classes and *d(X)* is a *C*-dimensional response vector. i^{th} component of *d(X)*

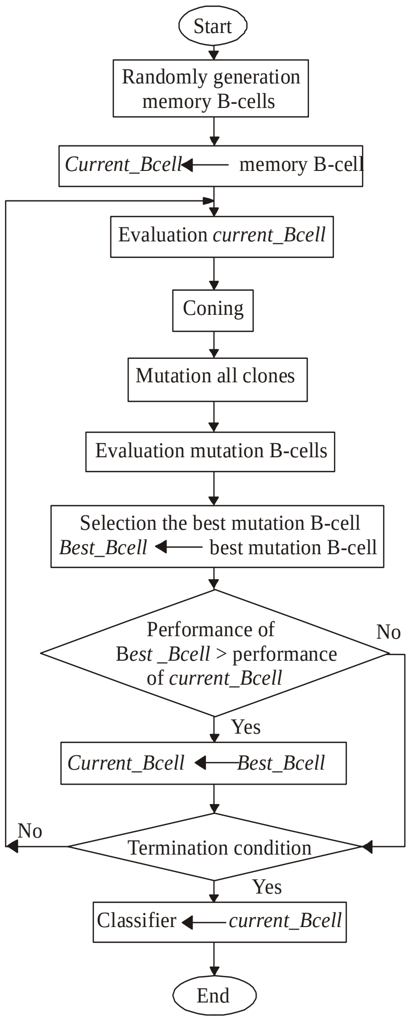

Fig. 5: Flowchart of the CAIS algorithm

denotes how much the input *X* is close to class *i*. for *C* classes and *L* base experts:

$$d_{cl}(X) = (d_{cl}^{1}(x), d_{cl}^{2}(x), \ldots, d_{cl}^{C}(x)) \qquad (1)$$
$$d_{cl}^{i}(x) \in [0,1]$$

These components whether crisp or continuous were produced by experts. Response vector provided by a classifier is known as the soft class labels. The decision of a classifier can be hardened to a crisp class label *c*, where $c \in \{1, 2, \ldots, C\}$. Combination strategies give the final decision by fusing the response vectors from *L* classifiers as follow:

$$DF(x) = F(D1(x), \ldots, DL(x)) = F(DP(x)). \qquad (2)$$

where *F* denotes an aggregation rule.

The outputs of classifiers are organized in a decision profile as a matrix *DP(x)* as follow (Kuncheva *et al*., 2001) :

$$DP(x) = \begin{bmatrix} d_{1,1}(x) & \cdots & d_{1,j}(x) & \cdots & d_{1,c}(x) \\ d_{i,1}(x) & \cdots & d_{i,j}(x) & \cdots & d_{i,c}(x) \\ d_{L,1}(x) & \ldots & d_{L,j}(x) & \ldots & d_{L,c}(x) \end{bmatrix} \qquad (3)$$

Some fusion approaches that use the *DP* regarding the classes are called class-conscious techniques. Indeed, these techniques apply a column-wise operation on *DP(x)* matrix to obtain *DF(x)*. Examples of this type of fusion techniques are: minimum, maximum, mean, sum and product (Kittler *et al*., 1998).

The voting methods are another form of non-trainable techniques (Van *et al*., 2002). In these methods, the classifiers are the voters and the classes are the candidates while a winner is introduced as a result of classification. There are different types of voting methods such as un-weighted and weighted voting techniques.

In un-weighted voting techniques, each vote carries equal weight and voters cannot express the degree of preference of a candidate. Therefore, the differentiation between the candidates is only the number of votes. Majority voting as one of the well-known rules of combination approaches was used in this study (Lam and Suen, 1997) .

In weighted voting methods, the voters give different weight to any candidate while different criterions are used for weighting.

PERFORMANCE EVALUATION METHODS

Three methods were used for performance evaluation of lie-detection signals classification in this report. These methods are explained in the following subsections.

Classification accuracy: The classification accuracy of the proposed system was measured as following:

$$accuracy = \frac{\sum_{i=1}^{N} assess\,(i)}{N} \qquad (4)$$
$$assess(i) = \begin{cases} 1 & if\ \ classify(i)\ is\ true \\ 0 & otherwise \end{cases}$$

where, *N* is the number of subjects and *classify(i)* returns the predicted label of i^{th} subject by immune based classifier.

Sensitivity and specificity: For sensitivity and specificity analysis, the following expressions were used:

$$\text{Specificity} = TP/(TP+FN) \tag{5}$$

$$\text{Specificity} = TN/(FP+TN) \tag{6}$$

where, *TP* denotes true positive that represents the number of correct predictions of innocents, TN is true negative which indicates the number of correct predictions of guilties, FP represents false positive which is the number of incorrect predictions of innocents and FN denotes false negative that means the number of incorrect predictions of guilties.

Leave one out cross-validation: For testing the results to be more valid, we used Leave-One-Out (LOO) cross validation. In this method, the classification algorithm was trained and tested *K* times (*K* is the number of subjects). In each case, one of the sample represented average signals of a subject was taken as a test data and remaining *K*-1 samples were kept to form the training data. Therefore, *K* different test results existed that the average of these results was the final classification accuracy.

EXPERIMENTAL RESULTS

To evaluate our proposed approach, we used lie-detection dataset consisting of 110 samples, 32 wavelet features and two categories (guilty and innocent) which was collected by Abootalebi *et al*. at Amirkabir University of Technology (Abootalebi *et al*., 2006, 2009) .

The initial assessment of the results has shown that the total number of wavelet features was high compared to the number of training samples and this caused the over fitting of the CAIS algorithm in training phase and lower ability of generalization in testing phase. Therefore, Genetic Algorithm (GA) was applied to select the optimized features. Since the training phase of our proposed classifier (CAIS) was very time consuming, feature selection for our classifier by GA needed so much time to run. Indeed, we applied GA to LDA classifier for feature selection. There are some reasons why LDA has been selected as a classifier for selection of the best wavelet features such as simple structure of this classifier, simplify in simulation, good processing rate and existence of no parameters for simulation.

In this study, the binary coding was used for representation of GA's chromosomes for feature selection, where a bit with value '1' represented the selected feature and '0' represented unselected feature. Also, the classification accuracy was used as the fitness function.

Table 1: GA parameters for feature selection

Used parameters	Value
Population size	20
No. of the genes	32
Crossover rate	0.5
Mutation rate	0.01

Table 2: Number and name of features which are selected by GA

Feature no.	Feature name
1	D (250-375)
2	D (375-500)
3	D (500-625)
4	D (875-1000)
5	T (375-500)
6	T (500-625)
7	T (875-1000)
8	A (63-125)
9	A (250-312)
10	A (313-375)
11	A (438-500)
12	A (500-562)
13	A (625-687)
14	A (875-937)
15	A (938-1000)

Table 3: Used parameters in CAIS algorithm

Used parameters	Value
Pro_mut	0.5
Clonal _Rate	20
Bcell_num	4
Max_Itr	100

Table 4: Obtained results of different classifiers designed by CAIS

Method	Accuracy	Sensitivity	Specificity
CAIS1	79.09	75.00	83.33
CAIS2	80.00	73.77	87.75
CAIS3	76.36	69.84	85.11
CAIS4	76.36	70.49	83.67

Table 1 gives the GA parameters which were used in our experiment and then, the number and name of 15 features selected by GA is given in Table 2.

The details of parameter setting for CAIS algorithm in our experiment, is shown in Table 3. These parameters were selected by trial and error. The parameter *Bcell_num* which determine the number of classifiers designed in CAIS algorithm was set 4.

In test stage of CAIS algorithm, each antigen was presented to the B-cells produced in training phase and recognized by an affinity factor and then classified. The results of classification by these B-cells are shown in Table 4. The maximum accuracy reported in this Table is 80% and minimum accuracy is 76.36%.

The combination approaches of multiple classifiers were applied in order to improve the recognition results. In non-trainable techniques mentioned in fusion techniques section, the affinity between the antibodies of each B-cell and current antigen can be defined as membership degree of that antigen to different classes. It is obvious that the B-cell which has high affinity with the antigen has to have more contribution in recognition of the antigen. Table 5 shows the classification performances

Table 5: Performance of different strategies of combination the decision of CAIS classifiers

Combination method	Accuracy	Sensitivity	Specificity
Maximum	77.27	71.67	84.00
Minimum	77.27	71.67	84.00
Mean	80.91	76.78	85.18
Product	80.91	76.78	85.18
Sum	76.36	70.49	83.67
Majority voting	79.09	69.84	85.11
Weighted voting	77.27	71.87	89.13

Table 6: Comparison the performance between CAIS and other classifiers

Method	Accuracy	Sensitivity	Specificity
KNN	75.45	73.08	77.59
LDA	76.36	73.58	78.95
SVM	79.09	75.92	82.14
CAIS	80.91	76.78	85.18

of different combination methods. The attraction of this result is based on the premise that combination of CAIS classifiers is more accurate than an individual CAIS classifier. It was found that the maximum accuracy (80.91%) was obtained by mean and product approaches of combination while the minimum accuracy (76.36%) was belonged to the sum method.

Table 6 shows the classification performance of CAIS when compared to some other classifiers applied to our used data. We have used three well-known classifiers for comparison of the results: KNN, LDA and SVM.

KNN as our first selection of different classifiers is very simple to use and has a parameter K which should be set by the user (Polat *et al*., 2007). We selected it in the range of (1-15) from odd numbers (because of binary classification problem) while the best mean result corresponding to $k = 1$ was reported.

LDA has very low computational requirement which is suitable for pattern recognition problems. This classifier has been used successfully in a great number of ERP processing researches (Bostanov, 2004). LDA is also applied to our data to compare its performance to our proposed method SVM as one of the well-known techniques for classification can use different kernel function such as sigmoid, polynomial and Radial Basis Function (RBF) (Cortes and Vapnik, 1995; Çomak and Arslan, 2008). In this study, RBF kernel function that is an effective option for classifying binary data was applied. In SVM classifier with RBF kernel, two parameters C and γ must be selected appropriately. We optimized these two parameters with trial and error.

It should be noted that, while different decision methods were applied to combine the multiple CAIS classifiers, only the best classification performance is shown in Table 6. The results show that the performance of CAIS classifier is more accurate than KNN, LDA and SVM.

CONCLUSION

The main purpose of this study was to evaluate the performance of a new classification method in a P300-based GKT. Previous studies of GKT by P300 for psycho physiological detection of concealed information indicated that P300 amplitude in guilty subjects is larger than innocents (Farwell and Smith, 1991) .

In our presented method, at the first part, a feature set consisting of 15 wavelet features was extracted from the raw data. This selected feature set was not optimized for our implemented classifier. Training phase of proposed classifier (CAIS) was very time consuming, therefore, feature selection for this classifier was impossible. Indeed, we used different feature sets to assess our proposed approach, but in this report, only the best result which is associated with optimized wavelet feature set was reported. Our studies on different feature sets proved the effectiveness of CAIS classifier. The classification accuracies of our applied methods are higher than what some other groups have reported and also lower than some others (Farwell and Smith, 1991; Rosenfeld *et al*., 2004; Abootalebi *et al*., 2009). It is notable that comparison between implemented methods with different input datasets is impossible. The detection accuracies obtained by different groups in addition of processing algorithms depend on some other factors like subject numbers, subject type and used protocol (Farwell and Smith, 1991; Rosenfeld *et al*., 2004). In fact our processing methods cannot be compared with previous works because the input dataset is not exactly similar. Therefore, to illustrate the advantages of implemented processing methods (CAIS), we applied three well-known classifiers on the same dataset. The results achieved in this work proved that CAIS is a competitive classifier.

In fact, our purpose of this study was to assess CAIS as a classifier and then, improve the recognition results by combining the decision of designed classifiers.

We tested several immune based classifiers designed by CAIS algorithm on lie-detection dataset for ERP assessment in a P300-based GKT and found that CAISs are competitive classifiers. Also, in the experiments, it was observed that using the decision fusion techniques for multiple classifier combination leads to better recognition results.

Future work lies in improving the classification performance of CAIS by tuning the parameters of CAIS algorithm. In this study, we set these parameters by trial and error, while optimizing some parameters such as *Bcell_num*, *max_Itr* and *Clonal_Rate* can improve the results. Also, the selected feature set in this study was not optimized for CAIS classifier. Further study to select the best features will be effective to improve the results.

The fusion techniques implemented for combination the results of CAIS classifiers were very simple while there are various methodologies to combine decision of multiple classifiers which can be considered as a future work.

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