Detection of P300 based on Artficial Bee Colony

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Keywords: P300, Artificial Bee Colony, Brain-Computer Interface.

Abstract: A Brain-Computer Interface (BCI) is a system that allows users to communicate with their environment through cerebral activity. P300 signal, which is used widely in BCI applications, is produced as a response to a stimulus and can be measured in the parietal lobe of the brain. In this paper, an approach which is a swarm intelligence technique, called Artificial Bee Colony (ABC) together with Multilayer Perceptron (MLP) is used for the detection of P300 signals to achieve high accuracy. The system is based on the P300 evoked potential and is tested on four healthy subjects. It has two main blocks, feature extraction and classification. In the feature extraction block, Power Spectrum Density (PSD) is used whereas ABC was employed to train Multi Layer Perceptron (MLP) in the classification part. This method is compared to other methods such as Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). The best result that is achieved in this work is 99.8%.

1 INTRODUCTION

A BCI is a system that allows a person to control or communicate with a computer by using brain signals. In various BCI systems, electroencephalography (EEG) is still the most common method because of being non-invasive. By analyzing the EEG activities recorded from the scalp, a computer can recognize the signal and translate it to specific commands for output devices such as a computer application or neuroprothesis in order to accomplish user's desired activity (Wolpaw et al., 2002).

Infrequent or particularly significant visual stimuli, when interspersed with frequent or routine stimuli, evoke a positive peak at about 300 ms in the EEG over parietal cortex. Donchin and et all have used this 'p300' or 'oddball' response in a BCI (Farwell and Donchin, 1988). Oddball paradigm states that: "Rare expected stimuli produce a positive deflection in the EEG after about 300 ms". This P300 component is present in nearly every human (Rakotomamonjy and Guigue, 2008). P300 signal can be seen in Figure 1. (Wolpaw et al., 2002).

They proposed a speller system based on P300, which subjects were able to spell words by sequentially choosing letters from the alphabet (Serby et al., 2005). A 6x6 matrix containing the letters of the alphabet and other symbols was displayed on a computer screen. Rows and columns of the matrix were flashed in random order. In order to select a symbol, subjects count how often it was flashed. Flashes of the row or column containing the desired symbol evoked P300-like EEG signals, while flashes of other rows and columns corresponded to neutral EEG signals.

The target symbol could be inferred with a simple algorithm that searched for the row and column which evoked the largest P300 amplitude.

Since the work of Farwell and Donchin, many researchers in the area of P300 based BCI systems has concentrated on developing new application scenarios (Polikof et al., 1995, Bayliss, 2003) and on developing new algorithms for the detection of the

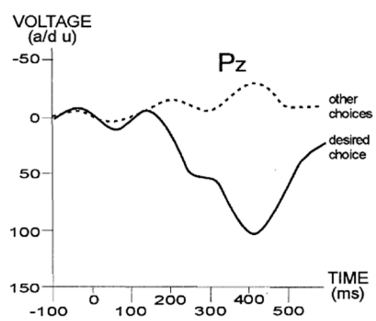

Figure 1: P300 signal (Wolpaw et al., 2002).

Aytekin, S. and Kiyan, T.
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DOI: 10.5220/0005696001830189
In *Proceedings of the 9th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2016) - Volume 4: BIOSIGNALS*, pages 183-189
ISBN: 978-989-758-170-0

P300 signal from noisy data (Hoffmann et al., 2005, Kaper et al.,, 2004, Rakotomamonjy et al., 2005; Thulasidas et al., 2006, Xu et al., 2004).

In this paper, a pattern recognition system is used for the detection of P300 signals. A five-choice P300 paradigm is tested. Five different images were flashed in random order with a stimulus interval of 400 ms.

The MLP – ABC model is proposed for the detection of P300 signals and compared to MLP, Linear Discriminant Analysis (LDA) and Support Vector Machine (SVM). Classification accuracies were obtained for four healthy subjects. MLP trained with the standard BP algorithm normally utilizes computationally intensive training algorithms.

2 MATERIALS AND METHODS

A BCI takes EEG signal as input and delivers device commands as output like any typical communication system. Between input and output, there are components that translate input into output. Proposed BCI system with its elements and their principal interactions is shown in Fig. 2 and each element is described in this section in detail. Signal processing and classification algorithms were implemented by using MATLAB.

2.1 Data Acquisition

Four subjects are utilized in this study and they are healthy college students whose ages are between 20 and 26. Three of them are male and the fourth subject is female. Subjects were facing a screen on which five images were displayed. The images are a window shutter, a telephone, a lamp, a door, and a television (see Fig. 3). The images were selected according to an application scenario in which users can control electrical appliances via a BCI system. The images were flashed in random sequences, one image at a time. Each flash of an image lasted for 100 ms and no images were shown during the following 300 ms. One stimulus time is 400 ms.

Figure 2: Design and operation of the BCI system.

Figure 3: The display used for evoking the p300.

Total record time for each subject is five minutes. So total flashes are 150 times and each image flashed 30 times in total record.

The EEG was recorded at 250 Hz sampling rate from 64 electrodes which are placed at the standard positions of the 10-20 international system. EGI Geodesic EEG System 300 was used for amplification and analog to digital conversion of the EEG signals.

2.2 Preprocessing

In this step, in order to eliminate high and low frequency noise, the signal is passed through a high pass filter which has a cut off frequency of 0.1 Hz and a low pass filter which has a cut off frequency of 40 Hz.

Another critical issue is to choose appropriate channels. In order to avoid large number of channels used for data recording and to avoid complicated calculations, eight channels were used including CFz, CP1, CP2, Fz, Pz, POz, P7 and P8 in this work (Figure 4).

2.3 Feature Extraction

Before the classification, suitable features are extracted from the raw signal. The goal of the feature extraction is to remove noise and other unnecessary information from the input signals. In this paper, Power Spectral Density (PSD) method is utilized which is generally used for characterizing random processes. It can be calculated with the help of Fourier Transform (Howard, 2002).

Discrete Fourier Transforms (DFTs) of filtered EEG are calculated using Equation 1.

$$X(k) = x(n).e^{-j2\pi kn/N} \quad k=0,1,\ldots N-1 \tag{1}$$

In Equation 1, x(n) represents the discrete samples of EEG data and N is the length of the EEG data. After calculation of DFT (X(k)) of EEG samples, periodogram of EEG is calculated by using Equation 2. Periodogram may express as a basic of PSD.

$$P(k) = |X(k)|^2 \quad k=0,1,\ldots,N-1 \tag{2}$$

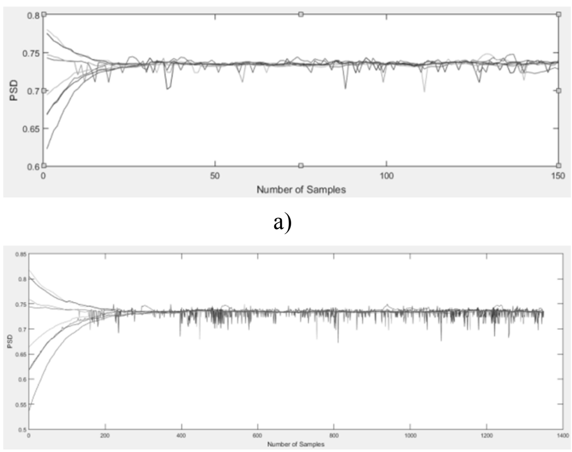
For each subject, the EEG signals are recorded for five minutes. So, there are 75000 samples in five minutes. We observed P300 signal presence between 200-400 ms after a stimulus is incident on the computer screen. This interval expresses 50 data instances. Data separated 1500 segments and each segment have 50 data instances. Each segment of PSD is average of own instances of periodograms and it is calculated Equation 3.

$$P'(k) = \frac{1}{K}\sum_{i=1}^{K-1} P_i(k) \quad k=0,1,..,N-1 \quad K=50 \qquad (3)$$

As a result, data sample size is reduced from 75000 to 1500 by PSD method. PSD of target samples and non-target samples for eight channels are shown in Fig. 4.

2.4 Classification

MLP-ABC scheme was proposed in this study for classifying P300 and non-P300 signals. The optimal weights of MLP were obtained by ABC algorithm which is an optimization algorithm.
(ANN) model that maps sets of input data onto a set of appropriate outputs. It was first introduced for the non-linear XOR, and was then successfully applied to different combinatorial problems.
In classification, we used MLP which has an input layer, an output layer, and a hidden layer. Input layer represents EEG channels which are defined according to international 10-20 system. The most commonly used three brain regions (frontal, vertex and parietal) in the literature is considered for selecting channels. There are eight neurons (CFz, CP1, CP2, Fz, Pz, Poz, P7 and P8 channels) in the input layer of MLP which are shown in Fig. 5 in the order of 4, 21, 41,6, 34, 36, 30



a)

b)

Figure 4: a) PSD of target b) PSD of non – target samples.

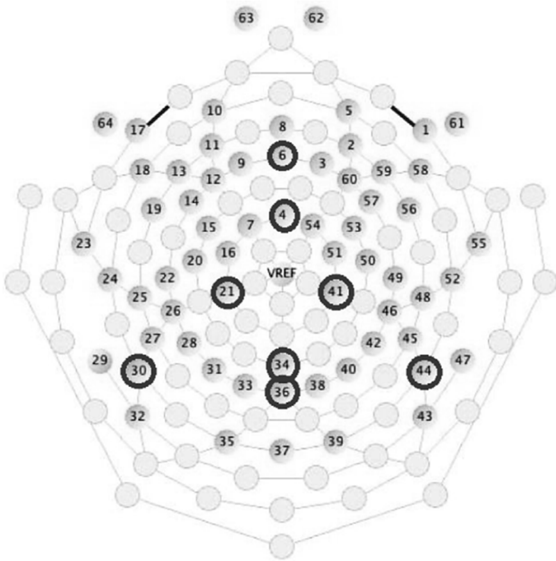


Figure 5: Electrode placement.

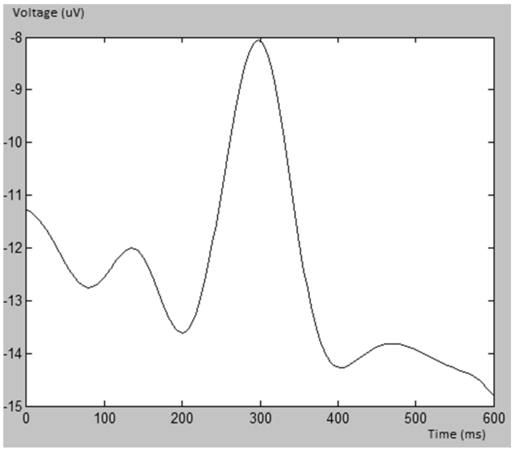
and 44. Each channel represent The output layer represents presence of P300.
So, there are two possible outputs: P300 or non-P300 (see Fig. 6). In this study, activation function is defined as a log-sigmoid function and it is calculated by using Equation 4.

$$f_a(x) = \frac{1}{1+e^{-x}} \qquad (4)$$

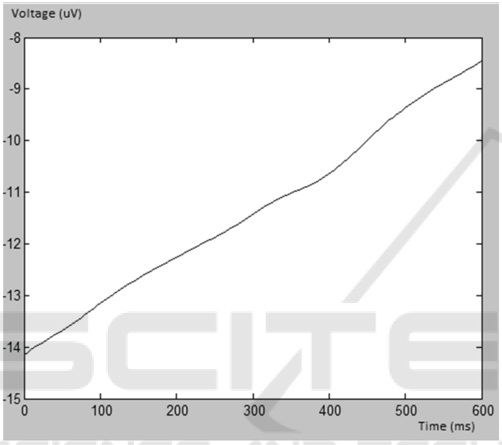
where x represents the sum of input and weights multiplication.
MLP is generally trained by back-propagation (BP) algorithm. The training of a BP neural network is carried out by the minimization of an error function. The error function is defined as the difference between the actual output and the desired output of the ANN over a set of training patterns. The weights assigned to the connections between the neurons within the ANN are updated at each cycle to minimize the error function. Training an ANN is an optimization task since the objective is to find the optimal set of weights of a neural network which minimizes the error function.

On the other hand, there are some drawbacks of using BP algorithm. If the multidimensional search space has many local optima, BP may not reach the global minimum successfully. Since, ABC algorithm has the capability of searching the different unidentified sections in the solution space to find out the global minimum, it is used in this study to train MLP (Shah and Gazali, 2011).

The main idea of using ABC algorithm is to employ bees to search the best combination of weights of the MLP network. The optimization task



(a)



(b)

Figure 6: Voltage versus time graphs for a) Target (P300) and b) Non – target (non – P300) signals.

by the ABC algorithm will involve the “bees” searching for the optimal values of the weights. Weights of the MLP structure are expressed as food sources in ABC algorithm. The detailed pseudocode of ABC algorithm is given in Section III.

3 ARTIFICIAL BEE COLONY ALGORİTHM

Artificial Bee Colony algorithm (ABC) is an optimization algorithm and it simulates the intelligent foraging behaviour of honey bee colonies. ABC is more successful and most robust on multimodal functions included in the set with respect to Differential Evolution (DE) algorithm (Yu and He, 2006) and Particle Swarm Optimization (PSO) (Eberhart et al., 2001).

In ABC algorithm (Karaboga and Akay, 2007, Karaboga, 2005, Basturk and Karaboga, 2006, Karaboga and Akay, 2009), the colony of artificial bees consists of three groups: employed bees, onlookers and scouts. The number of employed bees is equal to the number of food sources.

The possible solution of the optimization problem in ABC corresponds to the position of a food source and the nectar amount of it is related to the quality of the possible solution. At the first step, the ABC generates a randomly distributed initial population of SN solutions (food source positions), where SN denotes the size of population. Each solution xi (i = 1, 2, ..., SN) is a D-dimensional vector where D is the number of optimization parameters. After that, the employed bees, the onlooker bees and scout bees search the space for solutions in repeated cycles C = 1, 2, ..., MCN During the search process, an employed bee finds a new food source (new solution) and checks its nectar amount (fitness value). If it has a higher nectar amount than that of the previous one, the bee memorizes the new position and erases the old one. If not, the position of the previous one is retained in her memory. After all employed bees complete the search process; they share the information of the solution positions with the onlooker bees. An onlooker bee evaluates the nectar information taken from all employed bees and selects a food source with a probability related to its fitness value. Each onlooker bee chooses a food source with the probability as given in (5).

$$p_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{5}$$

where SN is the population size and fit_i is the fitness value of the solution x_{ij} (6).

$$fit_i = \begin{cases} \frac{1}{1+f_i} & f_i >= 0 \\ 1+abs(f_i) & f_i < 0 \end{cases} \tag{6}$$

A new food source is produced by an employed bee as given in (7).

$$v_{ij} = x_{ij} + \phi_{ij}(x_{ij} - x_{kj}) \tag{7}$$

where ϕ_{ij} is a random number within [-1,1]. After v_{ij} is produced, it is compared to x_{ij} solution. As can be seen from (5), as the difference between the parameters of the $x_{i,j}$ and $x_{k,j}$ gets smaller, the perturbation on the position $x_{i,j}$ gets decrease, too. Thus, as the search approaches to the optima in the search space, the step length is adaptively reduced.

If the solutions can not be improved by employed bees, they abandon the food source and it is replaced with a new food source. Employed bees become scouts. Scouts make random search in search space by (8)

$$x_i^j = x_{min}^j + rand(0,1)(x_{max}^j - x_{min}^j) \qquad (8)$$

After each candidate source position $v_{i,j}$ is produced and evaluated by the artificial bee, it is compared with the old one. If the new food has equal or better nectar than the old source, it is replaced with the old one in the memory.
Detailed pseudo-code of the ABC algorithm is given below:

1: Initialize the population of solutions xi,j , i = 1 ...SN,j = 1 ...D

2: Evaluate the population

3: cycle=1

4: **repeat**

5: Produce new solutions υi,j for the employed bees by using (2) and evaluate them

6: Apply the greedy selection process

7: Calculate the probability values Pi,j for the solutions xi,j by (1)

8: Produce the new solutions υi,j for the onlookers from the solutions xi,j selected depending on Pi,j and evaluate them

9: Apply the greedy selection process

10: Determine the abandoned solution for the scout, if exists, and replace it with a new randomly produced solution xi,jby (3)

11: Memorize the best solution achieved so far

12: cycle=cycle+1

13: until cycle=MCN

The aim of the bees is to discover the places of food sources with high nectar amount and finally the one with the highest nectar. Artificial bees explore the multidimensional space for food sources depending on each bee's experience and adjust their positions. Every bee produces new solution area for the network and the Greedy Selection decides the best food source position. The food area is limited in the range of [-20, 20]. If the new food source has equal or better nectar than the old food source, it is replaced with the new food source. Otherwise, the old food source is kept in the memory. Employed bees and onlooker bees continue searching until the last cycle to find optimum weights. SN parameter is selected 50 and MCN parameter is selected 100 in this work.

4 ABC – MLP COMBINATION

The proposed ABC – MLP algorithm used to optimize weights for training NN. The bees (employee, onlooker) search until the last cycle for finding best weights values for network training. The food source of which the nectar is neglected by the bees is replacaed by the scout bees. Every bee (employee, onlooker) produce new solution for the network and the greedy selection decide the best foods source position. The food area is limited in range apply the randomly and is initialized for evaluation. This operation is defined by the equation (7). Every bee produce new evaluated solution area for the network training. The food contains three parameters such as range, foods number and dimension which shown in equation 9, 10 and 11 (Shah and Gazali, 2011).

Foods Area = rand(FN,D).* Range + Lower (9)

$$R = \begin{pmatrix} a_{11} & \cdots & a_{1n} \\ . & & . \\ a_{m1} & & a_{mn} \end{pmatrix} \qquad (10)$$

$$L = \begin{pmatrix} l_{11} & \cdots\cdots & l_{1n} \\ . & & . \\ . & & . \\ . & & . \\ . & & . \\ l_{m1} & L & l_{mn} \end{pmatrix} \qquad (11)$$

where a_{m*n} shows the range of colony which is equal to upper bound minus lower bound, FN shows the number of food source equals the half of the colony size, L shows the lower bound for the foods area. The upper and lower bounds are optional while the most commonly used range is [10, -10], D shows dimension of foods. The agent of ABC select the value from foods and is assigned to network. The bees select the weight from the foods area and evaluate for fitting to input (Shah and Gazali, 2011).
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5 RESULTS

In this study, data instances are reduced from 75000 to 1500 using PSD as mentioned in Section II. Then, samples are separated as target (150x8) and non-target (1350x8). Before classification, training (1000x8) and test (500x8) datasets are created. Training dataset includes 100 target and 900 non-target instances whereas test dataset include 50 target 450 non-target instances. The learning and momentum rate for MLP are chosen to be 0.5. There are five neurons in the hidden layer. Some parameters of the MLP network are shown in Table I. The performance of the proposed BCI system is demonstrated in Table II. MLP-ABC method is compared with other classification algorithms such as MLP-BP, LDA and SVM in order to demonstrate its performance. Discriminant type of LDA is

Table 1: Architecture of the MLP Network.

Parameters	
Neurons in the input layer	8
Neurons in the hidden layer	5
Neurons in the output layer	1
Transfer function in the hidden layers	Logsig

Table 2: Classification results.

Methods	Subjects			
	Subject 1	Subject 2	Subject 3	Subject 4
ABC + MLP	99.85	99.06	99.59	99.84
MLP	92.75	92.83	92.83	92.83
LDA	93.19	91.27	91.58	91.74
SVM	92.6	92.83	92.83	92.83

'linear' which estimates one covariance matrix for all classes. Kernel function of SVM is 'polynominal' which default order is 3.

For all subjects, ABC+MLP approach gives a better result than other methods.

6 CONCLUSION

The aim of this study is to detect P300 signals by employing PSD for feature extraction and MLP-ABC scheme as a classifier. BP is a common approach for training MLP. The ABC algorithm combines the exploration and exploitation processes successfully, which proves the high performance of training MLP for P300 classification. It has the powerful ability of searching global optimal solution. The simulation results show that the proposed MLP-ABC algorithm can successfully classify P300 data comparing with the traditional BP algorithm and some classification algorithms that include LDA and SVM. It was shown that MLP-ABC approach shows significantly higher accuracy in classification than the other methods.

ACKNOWLEDGEMENTS

This research has been supported by Yildiz Technical University Scientific Research Projects Coordination Department. Project Number is 2014-04-03-KAP01.

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