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Dynamic Classification Based Brain Emotional Learning for EEG Signal Processing in P300-based Brain and Computer Interface

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Abstract

Aims/ objectives: Today, the interest in brain and computer interfaces has rapidly grown owing to the possibility of providing disabled subjects with new communication channels. Despite these interests, there are some obstacles in providing applicable BCIs. One of these obstacles is the non-stationary nature of brain signals varying from trial-to-trial and subject-to-subject. To overcome this problem, we need to design dynamic systems to adapt them to this data.
Methodology: In this paper, we propose a dynamic classifier-based brain emotional learning (DCBEL) for P300 based BCIs. This algorithm, by inspiration of brain emotional learning system, provides a dynamic system which is able to deal with non-stationary nature of brain signals.

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The application of the proposed method in P300 based BCIs is done for the first time. We test this system, on 4 able-bodied and 4 disabled subjects.
Results: The results showed classification accuracy of 95.39 for disabled and 93.27 for able-bodied.
Conclusion: The comparison of our results with two other algorithms multilayer perceptron and fuzzy inference system proves the superiority of our proposed algorithm.

Keywords: Brain and Computer Interface, P300, Disabled subjects, Classification, Brain emotional learning, EEG signals

1 Introduction

Since the discovery of the electrical nature of the brain, the idea of the possibility to communicate persons with external devices only through the use of brain signals, was formed [1, 2].

Brain and computer interfaces (BCIs) enable subjects to send commands to an electronic device through brain signals. Such systems can be considered as suitable tools of communication for people by severe physical impairment such as neurological diseases [3].

Recently, the interest in brain and computer interfaces has rapidly grown. The possibility to assist disabled subjects with new communication channels (such as BCI spellers) and new mobility channels (such as BCI driven wheel chairs or BCI controlled mechanical prostheses) makes this a very attractive research field [4].

Despite the applicability of current BCI systems, it is still limited by a number of obstacles. One of these obstacles is the presence of non-stationarities in the data [5]. These non-stationarities cause the patterns associated with each task during the training of the BCI to be distinct in the test phase, leading to poor performance.

Different approaches have been suggested to overcome this problem [4, 5, 6, 7]. Some of these approaches belong to the preprocessing methods and some others are machine learning, signal processing and classifier techniques. In this paper, we propose a new dynamic classifier for EEG signal processing in P300-based brain and computer interface.

The P300 event-related potential is a positive deflection in the EEG signals, appearing approximately 300ms after the presentation of rare or surprising, task-relevant stimuli [8]. The P300 were employed as a control signal by Farwell and Donchin for the first time [9]. They presented the P300 speller system, with which subjects were able to spell words by sequentially choosing letters from the alphabet. After the Farwell's work, much of the research in the area of P300-based BCI systems has concentrated on development of new application scenarios (see for example [10, 11]), and on the development of new algorithms for the detection of P300 of noisy data (see for example [12, 13, 14, 15, 16, 17, 18, 19].

Furdea and his colleagues [20] used two different scenarios in their experiment, visual and auditory speller. Their visual speller was like the Farwell's, but the matrix size was smaller in order to reduce the experiment time. Fifteen healthy participants were present in the experiment, and they used sixteen electrodes to record the EEG signals. They also applied SWLDA as classifier. Two participants were excluded from the study since the algorithm was unable to detect the P300 peak properly. Finally their average classification accuracy in visual scenario was 94.6 percent and 65 percent in auditory scenarios. Note that the amplitude of this accuracy was among 75- 100 percent in visual scenario and 0100 percent in auditory,which is a deterrent for real-world application.

Rivet and his colleagues [15] offered another developed P300 speller. Their experiment had 20 healthy participants, and they used thirty two electrodes to record the EEG signals. After recording EEG signals, xDAWN algorithm was used for filtering and BLDA for classification. They also used an adaptive training method. At the end their average classification accuracy was approximately 86 percent.

Recently, several studies have been published in which P300 based BCI systems were tested with disabled subjects (see for example [21, 22, 23, 24].

Spuler and his colleagues [16]applied a developed P300 speller by a different scenario. Their experiment included three groups of participants: First group consists of nine healthy participants, the second group consists of eight elderly subjects with motor impairments, and the third group consists of six disabled participants. The EEG signals were recorded through 16 electrodes and SWLDA were used in the first training part. In this study, the average classification accuracy for the first group was 81 per cent, and 79 per cent and 74 per cent for the second and third group, respectively.

In another study in 2014 [25], the P300 speller that was developed and tested on 25 disable participants. 16 electrodes were used to record EEG signals, and the SWLDA was used as classifier. Finally, the classification accuracy results were divided into two groups: The first group consisted of eight participants, which had classification accuracy of less than 40 per cent. The second group was the rest, who had classification accuracy of higher 70 per cent. In this case the average classification of these 17 participants was 93 per cent by application of 8 electrodes and 95 per cent for 16 electrodes.

In this research, we also present a novel classification algorithm for detection of P300 signals. Our algorithm is based on brain emotional learning, which provides a dynamic classifier for EEG data with non-stationary nature. This algorithm can perform classification with high accuracy even with low volume of data (by application of just 4 electrodes). It is also able to perform classification by high accuracy for each participant. Our algorithm has been tested both on disabled and healthy subjects.

After this introduction, a brief review of the brain emotional learning literature will come in section 2. Section 3, fully describes the data, preprocessing steps, and the proposed algorithm. Section 4 and 5 introduce two other classification algorithms: multilayer perceptron neural network and fuzzy inference system. Section 6 provides the results.

2 Brain Emotional Learning

Recently, there has been a great trend toward behavioral approaches in decision making problems. Behavioral architecture has been widely used and admired in the fields such as soft computing and artificial intelligence[26, 27, 28].

Emotions are thought to be concerned with activity in brain areas that manage our attention, motivate our behavior, and specify the significance of what is occurring around us. Papez [29] and MacLean [24] stated that emotion is related to the limbic system, a group of structures in the center of the brain. The limbic system plays significant role in the emotional reaction. It includes several main parts, such as orbitofrontal cortex, thalamus, and amygdala. The amygdala is the center of the limbic system, a small area like almond, which is responsible for making emotional response [30]. There is abundant evidence that learning does occur in the amygdala[31]. The assumption here is that the amygdala reacts to stimuli that are either emotionally charged or to the stimuli that are novel, i.e. that have not been encountered before and that have not been associated with a charged stimuli. When such a stimulus occurs, a charged stimuli or a primary reward will be learned.

Orbitofrontal is another important part of the limbic system that reacts to improper responses. In fact, it evaluates the activity of the amygdala. The orbitofrontal cortex is a region of association cortex of the human brain involved in cognitive processes such as decision making. This part of a brain is among the least understood regions of the human brain but has been proposed to be involved in sensory integration, in demonstrating the effective value of reinforcers, and in decision making and setting expectation[28]. Particularly, the human orbitofrontal is believed to govern planning behavior associated with sensitivity to reward and punishment. In the event of an omitted reward or punishment, it will inhibit areas of the amygdala, as well as other areas [32], thereby inhibiting the associations responsible for the expectation of a reward or punishment [33, 34].

3 Materials and Methods

In this research, we used the EEG data of Hoffman's work [21] which was downloaded in 2013 [35]. The data include a six-choice P300 paradigm, which was tested on a population of four healthy and five disabled subjects. Six distinct images were flashed randomly with a stimulus interval of 400ms. Electrode configuration was composed of four electrodes. Multilayer perceptron, fuzzy inference system and DCBEL were tested for classification.

3.1 EEG data acquisition

During the test, each user was facing a laptop screen on which six images were displayed. The images consisted of a television, a lamp, a telephone, a door, a window, and a radio. The images were flashed in random sequences according to an application scenario. Each flash of an image lasted for 100ms and during the 300ms that followed none of the images were flashed. The EEG signals were registered at 2048Hz sampling rate from 32 electrodes placed in the standard positions of the 10-20 international system. Signal processing and machine learning algorithms were implemented in MATLAB software. The participants were five disabled and four able-bodied subjects. The disabled participants were all wheelchair-bound but had varying communication and limb muscle control abilities. The characteristics of disabled subjects were described in Hoffman's paper[18]. These subjects were numbered from 1 to 5. Subjects 6 to 9 were Ph.D. students of the laboratory. They were all men, and their average age was 30 years. Each subject was tested during four sessions. The first two sessions were performed on one day and the rest of the two sessions on another day. For all subjects, the time between the first and the last session was less than two weeks. Each session consisted of six sub-sessions, one run for each of six images. The following protocol was used in each of the runs.

I Participants were asked to count how often a defined image was flashed.

II The six images were displayed on the screen and a warning tone was sounded.

III A random sequence of flashes was started 4 seconds after the warning tone, and the EEG was registered. The sequence of flashes was arranged by the application scenario in the way that after six flashes each image was flashed once, after twelve flashes each image was flashed twice, etc.. The number of blocks was chosen randomly between 20 to 25. Each block consisted of six different images. The counting image was called target and the others non-target image.

IV By the means of a classifier the target image was inferred from the EEG signals in the second, third and the fourth session.

V After each run, participants were asked what their counting result was.

The execution time of one run was approximately one minute [21]. The aim of this research is detection of the target image from a sequence of EEG trails based on the difference between the waveform of the target and non-target trials by means of an efficient classifier. In other words, we are going to predict the picture, which the participant is counting.

In fact, subjects show a P300 peak in the target condition which is not present in the non-target condition. Figure 1 shows the P300 peak of a healthy and a disabled person. The picture at the top of Figure 1 belongs to a disabled subject, and the picture at the bottom belongs to a healthy one. The latency of the P300 is higher for the disabled subject when compared with the one from able-bodied subject. The amplitude at the P300 peak is smaller for the disabled subject than for the healthy one.

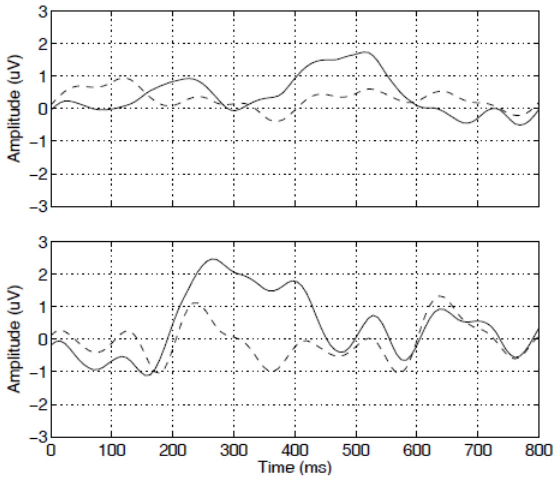

Figure 1. Top: Waveforms at electrode Pz for a disabled subject. Bottom: Waveforms at electrode Pz for an able-bodied subject. Solid lines show the responses to target stimuli and the dashed lines show the responses to non-target stimuli.

Figure 2 presents the four electrodes configuration which were used for EEG acquisition.

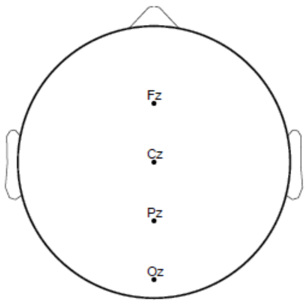

Figure2. 4 electrodes Configuration used in the experiments.

3.2 Signal preprocessing

Before applying a classifier, several preprocessing steps were applied to the data. These steps were as follows.

I Referencing

The average EEG signal of the two electrodes was used for referencing.

II Filtering

For filtering the data, a 6th order forward-backward Butterworth band pass filter was used. Cutoff frequencies were set to 1 Hz to 12 Hz. The MATLAB function butter was applied in computing the filter coefficients and the function filtfilt was applied for filtering.

III Downsampling

The EEG signals were downsampled from 2048 Hz to 32 Hz by selecting each 64th sample from the band pass-filtered data.

IV Single trial extraction
Single trials of 1000ms duration were extracted from the data. Single trials started at the beginning of the intensification of an image and ended 1000ms later. Because of the ISI of 400ms, the last 600ms of each trial were overlapping with the first 600ms of the next trial.

V Windsorizing
Subject movement, muscle activity, eye blinks, and eye movements can cause large amplitude outliers in the EEG signals. To decrease the effects of such outliers, the data from each electrode was windsorized. To do so, the 10th percentile and the 90th percentile of each sample were computed. Then the amplitude values lying below the 10th percentile or above the 90th percentile were then replaced by the 10th and the 90th percentile, respectively.

VI Scaling
The samples of each electrode were scaled to the interval of -1 to 1.

3.3 Proposed algorithm

In this paper, we provided a computational model as a dynamic classifier for P300-based brain and computer interface. This model was inspired from brain emotional learning system. The proposed model is a new version of Morens computational model [36]. The model structure consists of three main modules which try to accomplish their tasks to provide the correct answer. The name of modules is like the name of limbic system parts. Figure 3 illustrates the input, output, and connections between modules.

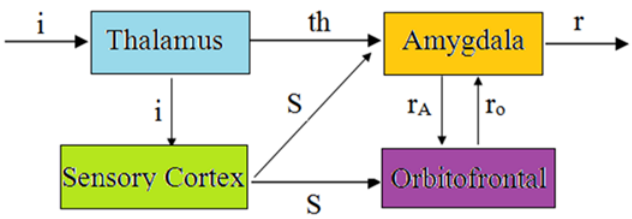

Figure 3. The DCBEL architecture

The DCBEL works in two phases: the amygdala learns to react and predict a given reinforcer. This part will never unlearn a connection; once learned, it is stable, giving the system an ability to retain emotional connections for as long as necessary. The orbitofrontal system tracks mismatches between prediction and actual reinforcement signals and inhibits the output in proportion to the mismatch.

These subsystems take different inputs. The amygdala receives the stimuli coming from thalamus and sensory cortex and an abstract reinforcer. The orbitofrontal takes the same inputs; but in addition, it receives a prediction from the amygdala. The amygdala is then inhibited by the orbitofrontal as proper in the current state. Here, the power of the model comes not from the learning system within each component, but from the way they are interconnected.

The function of different parts of DCBEL is described as follows:

- Thalamus: It receives the initial inputs, I, and prepares the desired inputs of sensory cortex and amygdala. Some simple preprocessing such as noise reduction or filtering could be done on the initial inputs. In fact, it extracts the strongest emotional stimuli as the input of the amygdala. Although, this structure is a simple model of real thalamus.

$$Th = max(I)$$

- Sensory cortex: This module provides the input of the amygdala and orbitofrontal. The inputs of our system are EEG signals which enter the thalamus as raw data. This raw data, I, will turn to information, S, after the preprocessing steps in thalamus and sensory cortex. Then it is transferred to amygdala and orbitofrontal; after passing training processes, it inverts to our desired knowledge to recognize among target and non-target stimuli.
- Amygdala: It receives the outputs of thalamus and sensory cortex. Then it provides two different outputs, first it does its initial prediction and prepares the initial response of the input,E_a and sends it to orbitofrontal. Second, it receives the orbitofrontal correction and provides the final response,E. $E_a(n)$ is the amygdala output in the nth iteration for orbitofrontal, and V is the weight vector.

  $$A_n = S.V$$
  $$E_a(n) = E_a(n-1) + \Sigma_i A_n(i)$$

  Our input after doing preprocessing steps is matrix S. This matrix includes the EEG data of a session, which consists of six runs and is applicable as a training session. S is a three dimensional matrix, which is as follow:

  $$S = a \times b \times c$$

  Here, a represents the number of electrodes, which is equal to 4 in our experiment. b is related to the data samples and is equal to 32 according to the downsampling part in preprocessing, and c is the number of pictures that were shown in 6 runs. Furthermore, v and w are the weight vectors by length of a b . Finally, A and O are our prediction vectors and have length c. These vectors indicate the results of the problem under consideration. Each entry of these vectors is related to the response of a participant to a special image. The value of each entry is between -1 to 1. The value of -1 to 0 represents the response to non-target image and the value of 0 to 1 represents the response to target image.
  The weight of the amygdala is updated by the following formula:

  $$\Delta v_n = \alpha(S.max(R_n E_a(n), 0))$$
  $$R_n = \Sigma_j w_j r_j$$

  The learning procedure is based on a reinforcement signal, presented by R. Where r_j are the factors of the reinforcement agent, and w_j are the related weights. Here α is the learning rate of amygdala and is in the interval of 0 to 1. This parameter is usually set at low value.
- Orbitofrontal: it receives the amygdala and sensory cortex and provides its correction for the amygdala.

  $$O_n = S.W$$
  $$E_o(n) = E_o(n-1) + \Sigma_j O_n(j)$$

  The weight of W is updated in proportion to the sensory cortex output and internal reinforcement signal of orbitofrontal, R_o:

  $$\Delta W_n = \beta.S.R_o$$

  β is the learning rate of orbitofrontal.

  $$R_o = \begin{cases} \max(E_a(n) - R_n, 0) - E_o(n) & \text{if } R_n \neq 0 \\ \max(E_a(n) - E_o(n), 0) & \text{otherwise} \end{cases}$$

The internal reinforcer of orbitofrontal does a bit more work than the one in the amygdala. The above expression says: If there is reinforcing signal $(R_O \neq 0)$, then the reinforcer is calculated to be the difference between the amygdala output and reinforcer R, minus the orbitofrontal output. Thus, the orbitofrontal output is adjusted to minimize the difference of amygdala output and the reinforcer.

When the reinforcer R is not present, then R_o becomes the difference between the amygdala output and the orbitofrontal output, if it is positive.

- The final output: eventually, the output is provided by the following formula:

$$E(n) = E_a(n) - E_o(n)$$

The value of E is between -1 to 1. such that the negative values represent the response to non-target image and positive ones represent the response to target image.

4 Multilayered Perceptron Neural Networks

After Rosenblatt presentation of single layer perceptron and perceptron learning rule [37], Minsky and Papert pointed out that many problems of our world do not fall into this simple framework [38]. They showed that while this was not possible with a perceptron network, it can be done with a multilayer perceptron.

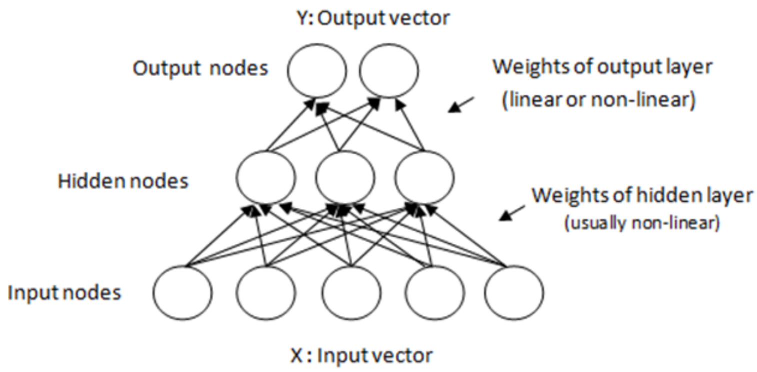

Figure4. The multilayer perceptron architecture

Figure 4 shows the structure of two-layer perceptron. It consists of a set of source nodes forming the input layer, one hidden layer, and an output layer of nodes. The computational formula of this network is as follows:

$$Y = F(X) = Bf(AX + a) + b$$

Where Y is a vector of outputs and X a vector of inputs. A is the matrix of weight of first layer and a is the bias vector of this layer. Similarly, B is the matrix of weight of the second layer and b is the bias vector of this layer. is the activation function and can be any non-linear function.

In this paper, we applied the generalized back-propagation algorithm with variable learning rate and momentum as training procedure. Our network was a two-layer neural network with 15 nodes in the hidden layer. The activation function of hidden layer was tansig and the output layer was purelin. We also used the mean squared error for measuring the misclassification.

5 Fuzzy Inference System

Fuzzy inference is the process of formulating the mapping from a given input to an output using fuzzy logic. A fuzzy inference system is composed of five functional parts: a rule base, a database, a decision-making unita fuzzification interface, and a defuzzification interface [39].

Several types of fuzzy reasoning have been offered in the literature [40]. Accordingly, there are several types of fuzzy inference system. Mamdani and Sugeno are the most common among them. In this paper, we applied the Sugeno fuzzy inference system [41]. In this model the output of each rule is a linear combination of input variables plus a constant term. The final output is the weighted average of each rules output. The main formula of the Sugeno fuzzy inference system is as follows:

$$\hat{y} = \sum_{i=1}^{M} f_i \phi_i(u)$$

Where

$$f_i = w_{i0} + w_{i1}u_1 + w_{i2}u_2 + \ + w_{ip}u_p$$

Where u_i is the jth element in the data vector, hence representing the value of the jth channel. The f_i values are consequent functions of m rules.

$$\phi_i(u) = \frac{\mu_i(u)}{\sum_{i=1}^{M} \mu_i(u)}$$

The ϕ_i values are called basis functions, which normalize the degrees of rule fulfillment by application of product t-norm, i.e.

$$\mu_i(u) = \prod_{j=1}^{p} \mu_{ij}(u_j)$$

The membership degree of u_j to the fuzzy set, μ_{ij} describes the jth part of the ith rule.

6 Results

The research data were obtained from 9 participants during 4 sessions. The data from three recording sessions was used to train the classifier and the data from the last session was used for the test. We also repeated the algorithm for four iterations, to use a distinct session as the test session. Table 1 shows Minimum, Maximum and average of classification accuracy of Multilayered perceptron, Fuzzy inference system, and DCBEL among for iteration for all participants.

Table 1. Minimum, Maximum and average of classification accuracy of Multilayered perceptron, Fuzzy inference system and DCBEL among for iteration for all participants

Classifier	MLP			FIS			RMPBEL		
Subjects	Min	Max	Avg	Min	Max	Avg	Min	Max	Avg
S1	81.11	85.02	83.08	83.45	84.30	83.86	93.23	94.95	93.89
S2	81.46	84.42	82.75	83.09	83.83	83.38	92.90	95.63	93.78
S3	84.84	90.44	87.19	86.23	89.21	87.63	94.11	96.07	95.39
S4	82.04	83.83	82.90	82.85	84.65	83.72	93.78	95.02	94.57
S6	80.14	86.23	83.93	81.98	85.49	84.34	92.64	94.23	93.27
S7	82.86	85.74	84.23	84.54	85.78	85.19	92.09	92.95	92.47
S8	84.93	88.40	86.54	87.28	89.85	88.11	92.02	93.56	93.17
S9	81.03	85.57	83.28	82.85	85.57	84.02	91.57	93.01	92.35

The data for 5 subjects is not included in our results. This is because it was not clear whether the subjects understood the instructions given before the experiments. Furthermore the level of alertness of the subjects fluctuated strongly and rapidly during the experiments. As we see in table 1, MLP and FIS show similar results in different cases, but the results of DCBEL were greatly better than the others. The reinforcing structure of the DCBEL algorithm was one of the crucial factors in its success. The difference of average classification accuracy of three algorithms can be seen in figure 5.

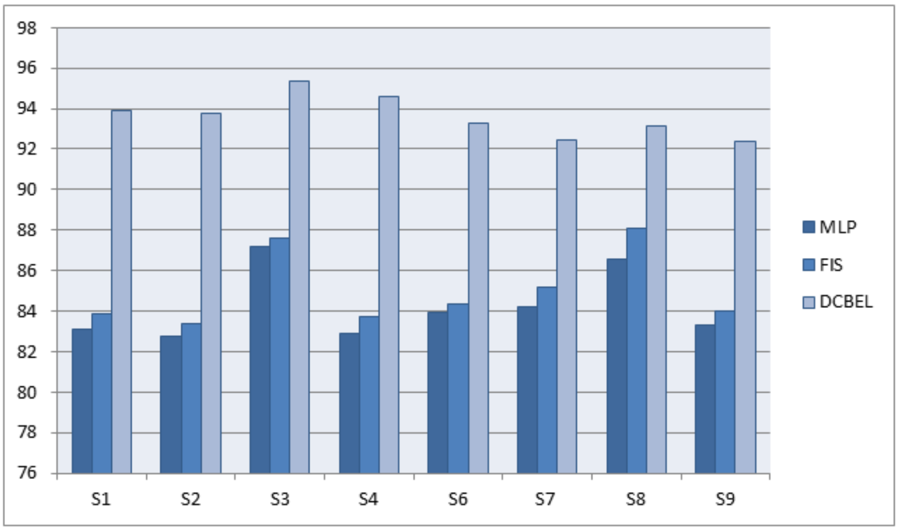

Figure 5. Average classification accuracy of Multilayered perceptron, Fuzzy inference system and DCBEL among for iteration for all participants

Table 2 shows the average of classification accuracy for abled-bodied and disabled subjects by each algorithm.

Table 2. The average of classification accuracy for abled-bodied and disabled subjects by each algorithm

Subjects	MLP	FIS	DCBEL
S1-S4	83.98	84.64	94.41
S6-S9	84.50	85.42	92.81

In this research, we applied the methods, both on able-bodied and disabled subjects. According to the results of tables 1 and 2, DCBEL could gain not only the highest classification accuracy in all subjects but also higher classification accuracy improvement of disabled subjects than the healthy ones. This improvement in classification accuracy of disabled subjects will be an important factor in implementation of BCI systems for disabled.

7 Conclusions

The selection of an appropriate classifier for a BCI is a crucial factor in its success due to the non-stationary nature of brain signals. To cope with such complex data, we proposed dynamic classifiers to adapt themselves to this data structure. This model is based on brain emotional learning for P300-based brain and computer interface was presented. After the acquisition of EEG data, we performed several preprocessing steps, and then the proposed classifier, DCBEL, was applied. We tested the method for healthy as well as disabled subjects. Finally, the results were compared with two other algorithms, multilayer perceptron and fuzzy inference system. The comparison proves the efficiency of the proposed algorithm with higher accuracy.
Future works will deal with the use of this method in another kind of BCI systems or BCI scenarios. Moreover, it might be useful to apply this method in online BCIs.

Competing Interests

The authors declare that no competing interests exist.

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