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Binary particle swarm optimization (BPSO) based channel selection in the EEG signals and its application to speller systems

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Abstract

Social participation of people with disabilities is tried to be increased with state-supported projects recently. However, even in neuromuscular diseases such as Motor Neurone Disease (MND), Full Sliding Status (TSD), even the communication skills of individuals are interrupted. Brain-Computer Interfaces (BBA), which have a few decades of history and an increasing number of studies with exponential momentum, are being developed to enable individuals with such disorders to communicate with their environment. Spelling systems are BBA systems that detect the letters that the person focuses on the matrix of letters and numbers on a screen and convert them into text through the application. In this context, with the random flashing of the letters on the screen, it aims to detect the electrical changes occurring in the brain as a result of the stimulus given to the person. Research reveals that the stimulus that the individual encounters cause an amplitude in the EEG signal called P300, between 250 and 500 ms. Brain-computer interfaces are used through EEG signals to provide environmental interactions for individuals with restricted movements due to stroke or neurodegenerative diseases. The multi-channel structure of EEG signals both increases system cost and reduces processing speed. For this reason, reducing the system cost by detecting more active electrodes during the process increases the accessibility of people. In this context, the use of optimization techniques in electrode selection is used to determine the most effective channels by a random selection method. In the study, particle herd optimization algorithm, one of the herd-based optimization techniques, was used with two classifiers, SVM and Boosted Tree, and the eight most frequently selected channels were determined to improve system performance in terms of speed and accuracy.

Keywords

brain-computer interface, optimization, BPSO

1. Introduction

In physical obstacles that completely immobilize the individual, such as motor neuron disease (MND) or complete exile (TSD), the individual has difficulties in moving and communicating with his environment. Brain-computer interfaces (BCI) have started to be used with the development of computer technology in order to enable individuals who are in this situation to move or communicate with their environment.

BBAs are transforming the brain activities taken from the individual into movement or writing through this application. For this purpose, it uses electroencephalogram (EEG) signals, one of the methods that visualize brain activities. The EEG signals obtained are turned into meaningful information by using machine learning methods through computers. EEG signal acquisition is carried out through electrodes, and a large number of electrodes are used for this process [1].

The excess in the number of electrodes increases the required capacity of the electronic and computer equipment used. This situation causes both the material burden and the transaction burden to increase. Therefore, the physical dimensions of the systems used increase and their cost exceeds the values that everyone can reach.

The number of electrodes used to reduce physical dimensions and cost can be reduced. At this stage, the main problem is determining which electrode is more effective. In a recording with 64 electrodes, if we try to select the active electrode by trial and error method, more than 10^{19} possibilities must be tested one by one. However, this is not possible under today's conditions [1].

The nervous system consists of sections that work in coordination on a network. Neurons are the basis of this system. There are about 100 billion nerve cells in a person's brain. Neurons in the entire nervous system are responsible for delivering the message they receive to the next neuron. Transmission begins with the displacement of ions inside and outside the neuron. This change causes the formation of an electrical potential along the axon. The electrical activity called nerve current or axon potential continues along the neuron [2]. The electrical signals formed during the activities of these nerve cells in the brain were recorded for the first time with the Electroencephalograph developed by [3, 4, 22, 26, 28]. These recorded signs are called EEG and can be obtained over a very large surface of the cerebral cortex.

The main purpose of BCI systems is to provide communication capability to seriously disabled people who are completely paralyzed or "locked" with neurological neuromuscular disorders such as MNH, brainstem stroke or spinal cord injury. Figure 1 shows the Brain-computer interface basic block diagram.

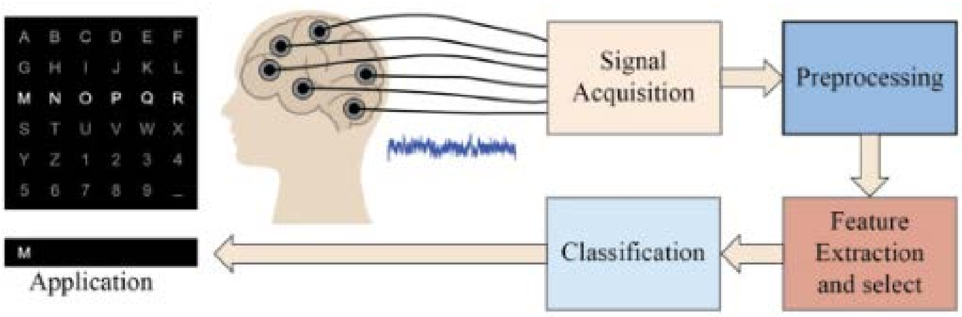

Figure 1. Brain-computer interface basic block diagram [1]

In BCI systems, applications that require the lowest level of individual capacity and enable individuals with disabilities to communicate with their environment are spelling systems. Spelling systems are based on the P300 wave, one of the event-related potentials. The aim is to determine the letter that the user focuses on within the letter table presented to the user. In spelling systems, the screen presented to the user is named as paradigm [1]. Figure 2 denotes the P300 signal.

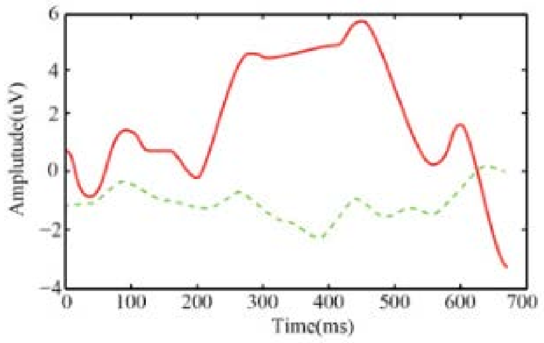

Figure 2. P300 signal (Red: Target character - Green: Non-target character) [1]

Today, modern computers are used with environmental input tools such as mouse and keyboard. As an alternative to this situation, BBAs are designed to work with tactile senses, sound or vision. The purpose of BBAs is to use disabled people with EEG signals without using any muscle or peripheral nerve groups. In this way, individuals who are completely paralyzed can control a system with cognitive activities [5]. The complex structure of EEG signals can only be resolved using powerful computers and machine learning methods. However, the multi-channel structure of EEG signals increases the cost of systems used during data recording and instantly generated data. The effectiveness of electrodes in the system differs according to regions and people. Detecting effective electrodes using traditional methods requires a lot of trial and time due to a large number of channels. In these and similar situations, instead of finding the result exactly, finding the closest result to the truth based on randomness is used as a method. Although there are many different optimization methods in the literature, particle swarm optimization (PSO) algorithm, which is one of the herd-based optimization algorithms that are among the heuristic methods, is used. Although the starting point of the standard PSO method is to detect continuous variables, since electrode selection is a binary variable, it can be used as binary PSO (Binary PSO - BPSO) with sigmoid transformation [6, 7, 24, 25, 26, 27].

In the study, it is aimed to determine the most effective electrodes to be used on a person basis, to decrease the processing load by reducing the data size obtained and to increase the classification performance.

2. Material and Method

2.1. Dataset

Wadsworth BCI Dataset, also known as BCI Competition III Challenge 2004 - Dataset II, was used in the study. It was recorded using a 6x6 row-column paradigm. Registration was taken over 2 separate users. It was carried out with a bandpass filter with 240 Hz sampling frequency and 0.1 Hz - 60 Hz lower and uppercut frequencies. 85 letters from the users were recorded as education and 100 letters as a subset of the test. The experiment steps shown in Figure 1 were followed 15 times for each letter. On the screen, each row and column is polished 100 ms once and 75 ms darkened [8]. Using the row-column paradigm with a 6 * 6 matrix structure, 85 different characters for training from two separate users and 100 different characters for the test were recorded with 15 repetitions. The recordings were realized as 64 channels with 240 Hz sampling frequency. During recording, a filter band passing between 0.1 Hz - 60 Hz was applied. Published dataset; it consists of training and test data for each user. In both education and test datasets; There are “Signal”, which includes 64 channel EEG signals, “Flashing” on the paradigm, “Flashing” which indicates the moment of shining of the letter and “StimulusCode” indicating which character shines by giving the row and column number. There are also “StimulusType” variables that label target characters and “TargetChar” variables that indicate the target character in the training data set [9, 10, 11, 12]. Table 1 shows the Status of variables in a single glow for the target character M in the Data Set.

Table 1. The Status of variables in a single glow for the target character M in the Data Set [1, 9].

Data Point	1-24	25-42	43-66	67-84	85-108	109-126	127-150	151-168
Flashing	1	0	1	0	1	0	1	0
Stimulus Code	2	0	9	0	10	0	5	0
Stimulus Type	0	0	1	0	0	0	0	0
Data Point	169-192	193-210	211-234	235-252	253-276	277-294	295-318	319-336
Flashing	1	0	1	0	1	0	1	0

Stimulus Code	3	0	8	0	12	0	4	0
Stimulus Type	0	0	0	0	0	0	0	0
Data Point	337-360	361-378	379-402	403-420	421-444	445-462	463-486	487-504
Flashing	1	0	1	0	1	0	1	0
Stimulus Code	6	0	11	0	7	0	1	0
Stimulus Type	0	0	0	0	0	0	1	0

2.2. The Proposed Method

In this paper, we have proposed a hybrid method for the speller system based on EEG signals. Figure 3 demonstrates the pre-processing stage of the proposed method. The signal is segmented by the start of the flashing moment of each row or column. As partition time, 667 ms was preferred in order to include the P300 wave, which may occur between 250-500 ms. Then, a 0.1-20 Hz bandpass filter was used to filter the P300 wave, which is a low-frequency wave. Finally, in order to make the P300 wave more prominent, every signal in 15 repetitions was collected arithmetically. Thus, while the P300 at the target character moment becomes evident, signals at the moment of the non-target character are damped.

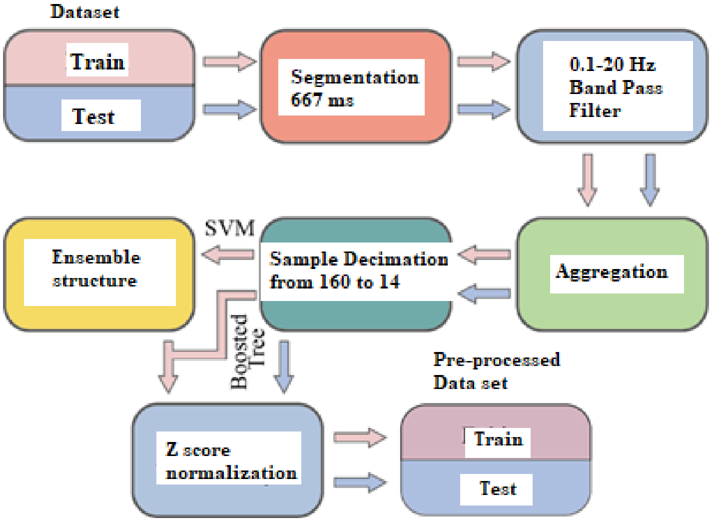

Figure 3. The pre-processing stage of the proposed method in the speller system design

No feature extraction was performed over EEG signals, sample reduction was applied to represent the signal. With this method, each segment with 160 data points is processed with 14 data points. Community structure that contributes to classification performance is used. The 85-letter educational data set is divided into 17 separate letter groups. This process was applied only to the training dataset. During the testing phase, each letter was applied to the classifier one by one.

2.2.1. The channel selection by BPSO

In the study, BPSO (Binary particle swarm optimization), which is one of the metaheuristic optimization methods, was used for electrode selection. The algorithm is built entirely on randomness. Here, Peni represents the goal function result of each individual in the herd, while Genis represents the individual with the best goal function and the goal function value in all iterations [13, 24]. Figure 4 shows the Electrode selection phase block diagram.

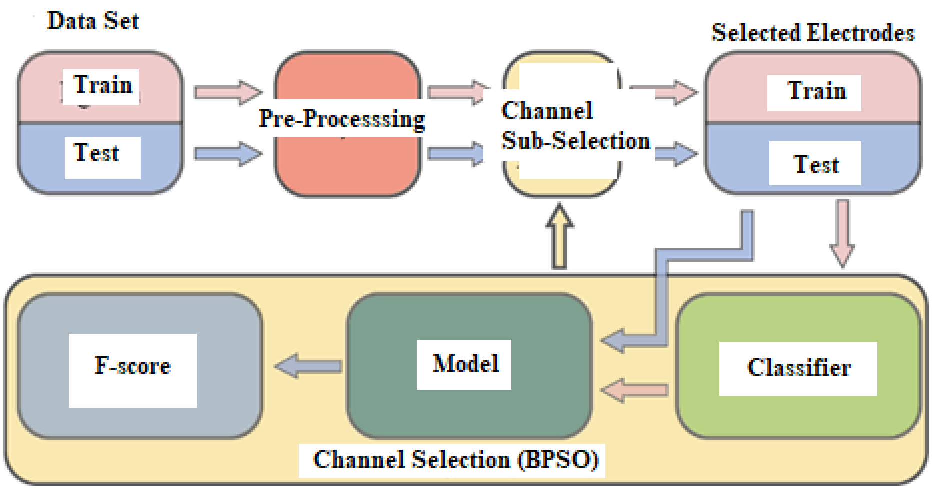

Figure 4. The Electrode selection phase block diagram.

The herd matrix is created with the function given in Equation (1).

$$X_{mi} = round(random[0,1]) \qquad (1)$$

$$V_i^{(t+1)} = \omega V_i^t + C_1\varphi_1(P_{best} - X_i^t) + C_2\varphi_2(G_{best} - X_i^t) \qquad (2)$$

In equation (2), $\omega_{min} = 0{,}4$ and $\omega_{maks} = 0{,}9$ are taken in our experiment. In Eq. 3, $(c_1 = c_2)$ is taken in the experiments.

$$w_i = \omega_{min} + (\omega_{maks} - \omega_{min}) * \left(1 - \frac{Again_i}{Again}\right) \qquad (3)$$

$$1 > w_i > \frac{(c_1 + c_2)}{2} - 1 > 0 \qquad (4)$$

where $\boldsymbol{m = 1, 2, 3, \ldots, N\ ve\ i = 1, 2, 3, \ldots, B}$. In the study, f score was used as the objective function. Information on complexity matrix and measurement metrics is provided in the classification section. The F score function is a better indicator of classification performance by accuracy in unbalanced datasets. Its highest value is 1.Table 2 shows the BPSO initial values for our problem.

Table 2. The BPSO initial values for our problem

Variable	**Values**
Number of harnesses	20
The number of repetitions	20
Dimension (D)	64
Number of solutions (N)	20
ω, c_1 and c_2	Equation 4

2.2.2. The classification stage

Support Vector Machine (SVM) and Boosted Tree classifier were used in the study to see the effect of electrode selection on classification performance. The system block diagram of the classification process is given in Figure 5. Detailed information about the classifiers used can be found in the relevant references [14, 15].

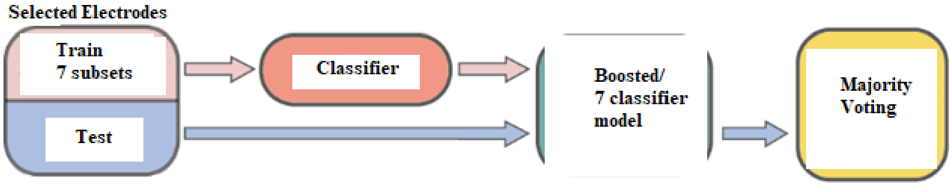

Figure 5. The Classification algorithm block diagram for our problem

4. The Results and Discussion

Classifier performances are given by using the accuracy given in Equation (5) and F score given in Equation (2). In these equations; true value (TP) if the true value and the estimated value is 1, true negative (TN) if the true value and the estimated value is 0, the false negative (FN) when the true value is 1, and the estimated value when the true value is 0- 1 indicates false positives (FP) [16].

True positive (TP): Prediction is +ve and X is non-target, we want that

True negative (TN): Prediction is -ve and X is target, we want that too

False-positive (FP): Prediction is +ve and X is target, false alarm, bad

False-negative (FN): Prediction is -ve and X is non-target, the worst

$$\text{Accuracy} = (TP+TN)/(TP+FP+FN+TN) \tag{5}$$

$$\text{Precision (specificity)} = TP/(TP+FP) \tag{6}$$

$$\text{Recall} = TP/(TP+FN) \tag{7}$$

$$\text{F1 Score} = 2*(\text{Recall} * \text{Precision}) / (\text{Recall} + \text{Precision}) \tag{8}$$

The channels selected with the PSO algorithm are arranged according to the classification algorithm used. In Table 3, the names and selection numbers of the 8 channels selected most frequently according to the purpose function calculated with SVM and Boosted Tree for User A and User B, while the density of the channels selected with SVM in Figure 6, the channels selected with Boosted Tree and the selection in Figure 7. numbers are given for both users. Electrode selection intensities are proportioned from blue to red, blue corresponds to zero, and red corresponds to twenty selections.

Also, "FZ, CZ, PZ, OZ, P3, P4, PO7, PO8" electrodes defined by Krusienski et al. [17] are used for comparison purposes.

Table 3. Channels selected with BPSO for our problem

Number	SVM				Boosted Tree			
	User A		User B		User A		User B	
1	P8	20	CZ	20	CZ	19	PO8	20
2	O1	20	PO8	20	PO7	18	P4	16
3	C5	19	C2	17	P5	16	C4	15
4	T8	19	CP5	17	O1	16	PO7	15
5	P5	19	P6	17	CP2	15	FC3	14
6	PZ	19	CPZ	16	CP4	15	CZ	14
7	PO7	19	P8	16	T8	15	FPZ	14
8	P7	18	PO4	16	C2	14	F8	14

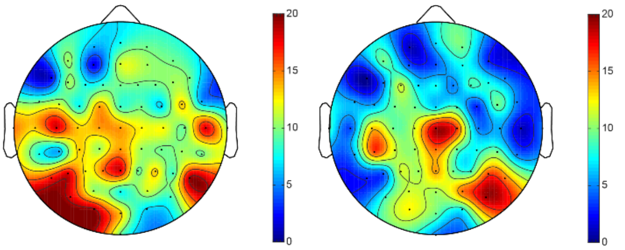

Figure 6. The Density of electrodes selected with BPSO with SVM classifier

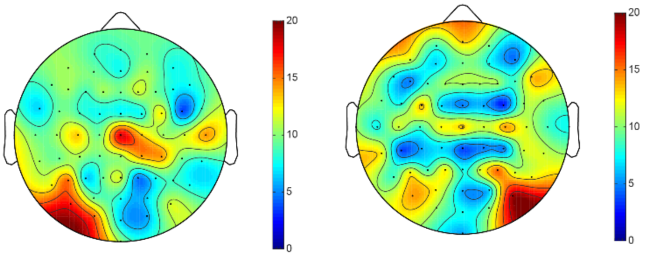

Figure 7. The Density of electrodes selected with BPSO with Boosted Tree classifier

The comparison of the classifications performed with the subset of data obtained with BPSO with 64 electrodes and 8 electrodes defined as standard is given in Table 4.

Table 4. Classifier performance measurements

	Channel Selection	User A		User B	
		Accuracy	F score	Accuracy	F score
SVM	**64**	83.916	0.641	42.833	0.323
	8	90.166	0.745	67.000	0.463

	8 (BPSO)	83.000	0.619	**72.416**	**0.526**
Boosted Tree	**64**	90.392	0.654	88.921	0.560
	8	90.294	0.683	90.196	0.632
	8 (BPSO)	90.000	0.664	89.803	0.611

4. Conclusions

When figures 6 and 7 are analyzed, it is seen that there are piles of temporal, occipital and central regions. Again, there are changes in the figures in the active areas of the person. When the results given in Table 4 are analyzed, it is seen that the performance increases with the selection of electrodes according to 64 channel SVM classification belonging to User B, where the performance is low. In the literature [18–21], the improvement was achieved in studies similar to our study results in electrode selection. The classifiers used in the study were inadequate in solving the problem. The change in the classifier selection may increase the classification performance to higher levels.

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Conflicts of Interest

There is no conflict of interest

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