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Original Article

A New method for Improvement of the Accuracy of Character Recognition in P300 Speller System: Optimization of Channel Selection by Using Recursive Channel Elimination Algorithm Based on Deep Learning

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Abstract
Introduction: P300 speller is a kind of Brain-Computer Interface (BCI) system in which the user may type words by using the responses obtained from human focus on different characters. The high sensitivity of brain signals against noise in parallel with the similarity of responses obtained from the user focus on different characters makes it difficult to classify the characters based on their respective P300 wave. On the other hand, all areas of the brain does not carry useful P300 information.
Methods: In this study, a new method is proposed to improve the performance of speller system which is based on selecting optimal P300 channels. In the proposed method, recursive elimination algorithm is presented for channel optimization, which utilizes deep learning concept (e.g. Convolutional Neural Network) as its cost function. The proposed method is examined on a data set from EEG signals recorded in a P300 speller system, including 64 different channels of responses to 29 characters. Then, its performance is compared with some existing methods.
Results: The obtained results showed the ability of the proposed method in recognizing the characters in such way that it could accurately (i.e. 97.34%) detect 29 characters by using only 24 out of all 64 electrodes.
Conclusion: Applying the proposed method in speller systems led to considerable improvement in classification of characters compared to its alternatives. Several experiments proved that utilizing the proposed scheme may increases the accuracy almost 12.9 percent compared to non-optimized case in parallel with reduction of the number of involved channels by approximately 1/3. Based on these results, the proposed method may be considered as an effective choice for application in P300 speller systems, thanks to reduction of the complexity of the system which is caused by the reduced number of channels and, on the other hand, due to its potential in increasing the accuracy of character recognition.
Keywords: P300 speller, Brain-Computer Interface, Channel Selection, Optimization, Deep Learning, Recursive Channel Elimination, Convolutional Neural Network.

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Introduction

The brain-computer interface is a kind of technology that makes a communication channel between the signals produced by the human brain and the outside world (1, 2). The P300 speller paradigm is one of the most commonly used applications of such systems, in which the user may type words without muscle activity on the screen, by using the received responses from focusing on the characters of the specific matrix (3).

The P300 wave is an unstable positive pattern in the form of human brain Electroencephalogram (EEG) signal that occurs approximately 300 ms after the stimulation in response to the external stimulus (4). There are different methods for recording the brain signal, but the use of surface electrodes is the most appropriate option for practical applications. Safety, being non-invasive, and low cost are the main benefits of surface electrodes. Therefore, such electrodes are frequently used for recording EEG signals compared to other brain signals recording methods (5). In the process of recording the above signal, a certain number of surface electrodes is installed according to the standard model on the user's skin; then, the user is asked to focus on a character that may contain numbers, letters or symbols during a short time (6).

Unfortunately, brain signals have low SNR. Furthermore, many internal and external factors influence the formation of the P300 wave. Furthermore, the P300 signal is highly unstable; therefore, its responses obtained from focusing on the same character may be different. Therefore, recognizing characters by using P300 waveform become a challenging problem (7). Consequently, applying an appropriate classification method to recognize characters from recorded brain signals has become one of the important subjects in this field (8, 9).

In several researches, various feature-based or non-feature-based methods have been used to address the problem of character recognition by using P300 signals (10). The approaches in this domain may be mainly divided into two categories: linear and non-linear algorithms. The main objective of all these schemes is to obtain higher recognition accuracy when the character diversity increases (11, 12). In some studies, the Support Vector Machine (SVM) (13) has been used as a classifier which has made use of Gaussian kernels. The use of the Gaussian kernel results in more flexibility in decision boundaries, thereby ultimately increasing the accuracy of the classification. However, in the above method, the selection of SVM parameters is very challenging because the obtained accuracy is highly dependent on these parameters. In an improved idea, the combination of several SVMs is investigated (14); the results of various SVMs are used to decide about recognition of more characters, ultimately, based on the score obtained by each character in several classifiers.

The concept of machine learning based on gradient boosting was firstly introduced in (15). The main imperfection of this method is its dependence on the number of repetition of the algorithm. In another study, the ideas of Learning Vector Quantization (LVQ) and its improved version, Multichannel learning Vector Quantization (MLVQ) have been performed (16). The statistical methods such as Linear Discriminant Analysis (LDA) and Kernel Fisher Discriminant (KFD) have also been examined in some researches (16, 17). The performance of these methods is also highly sensitive to extracted features of EEG signal. Neural networks are another commonly used solution to address P300 detection problem (17). The disadvantages of this method are a) dependence of results on the extracted features from the signal, b) dependence of results on the network structure, and c) time consuming procedure of neural network.

Apart from the classification problem, another important challenge in the P300 speller system is that the recordings of electrodes are seriously different. In other words, some regions of the brain make the P300 signal more suitable than others. Therefore, it may be said that rejecting those electrodes which carry weaker P300 signals (i.e. electrode selection) is so effective in improving the efficiency of character classification.

So far, extensive researches have been conducted on electrode selection. The use of the Particle Swarm Optimization algorithm was proposed in (18). Despite the success of this method in improving the performance of speller system, but its performance in clinical applications is hampered because of its time consuming nature.

Some other methods make use of mutual information concept as a way for channel selection (19). Such algorithms are based on the frequent selection of new electrodes and, accordingly, electrodes should be ranked. Furthermore, the mutual information of electrodes is considered to achieve more accurate ranking, which leads to much improved results.

In (19), sequential reverse selection, which makes use of Signal-to-Noise Ratio (SNR) as its cost function in order to optimize the channels, has been introduced. Unfortunately, by using this approach, the early removal of some channels leads to a loss of classification accuracy.

This study presents a new approach which is based on the optimized selection of P300 registered channels to address the complexity and accuracy problems in P300 speller systems. For this purpose, the optimization algorithm which is based on recursive channel elimination is applied on the recorded data set, and the deep learning P300 speller is utilized as cost function of the above optimizer. Most of the current methods which are used to construct speller systems require the extraction of features from the raw data. However, extracting the proper features is so difficult; additionally, it is possible that the extracted features are not suitable for a variety of recorded samples. To overcome these limitations, we used the convolutional neural network (CNN) as our learning scheme in which the extraction and classification steps are performed simultaneously and automatically. Automatically learning from raw data is better for achieving acceptable results in such a way that they are independent from different test subjects (20). As a result, at each stage, the high-level features of the network are extracted from the data and finally classification is performed according to them. Hereupon, in the proposed method, by selecting the optimal channels in parallel with applying the concept of deep learning, the separation of characters in the P300 speller will be achieved more accurately than the existing schemes.

In the second part of this study, the proposed algorithm is described which performs based on channel optimization and deep learning. In the third part of the study, the performance of the proposed method is evaluated on the P300 speller data set and its improvement is investigated. The final part of the study is dedicated to the conclusion.

Methods

Currently, neural networks are being used as the most efficient classification tool in speller systems. Although the accuracy of this tool is relatively better than previous methods, the involvement of all recording EEG channels hampers the performance of such methods. In this section, the proposed scheme of this study is illustrated in which the optimization algorithm is applied on the recorded data set. The proposed method is based on optimizing the channel selection by using the recursive channel elimination concept. Since the aforementioned optimizer uses convolutional neural network as its cost function, in subsection bellow (2-1. Convolutional Neural Network), this kind of deep neural network is firstly studied. Then, in the latter subsection (2-2. Recursive channel elimination), our proposed optimizer algorithm will be described.

Convolutional Neural Network

One of the most effective deep learning classifiers is the convolutional neural network. This family of deep learning schemes makes use of numerous layers to incorporate more abstract features in classification procedure (21, 22).

The extraction of the feature in CNN is hierarchical, which means as layers become deeper, the extracted features become higher level and more non-linear. The basic structure of the convolutional neural network is presented in Figure 1.

The convolution layer contains a collection of filters bank that, by applying to the raw input, extracts various features. If the input size is assumed N × N and ω is a convolution filter with dimensions of m × m, then the convolution relationship between these two items may be described in the form of equation (1).

$$x_{ij}^{l} = \sum_{a=0}^{m-1}\sum_{b=0}^{m-1} \omega_{ab}\, y_{(i+a)(j+b)}^{l-1} \qquad (1)$$

In the above equation, x_{ij}^{l} represents the output of layer, *l* shows the layer number, and the pair of *(i,j)* demonstrates the location of the above output cell in the active map. Finally, the output size of the layer is equal to (N-m+1)×(N-m+1). At this step, the size of the data decreases slightly due to the convolution operation compared to its initial state. Convolving in each layer is followed by a non-linear activation function. For example, in ReLU activation function, all negative values are considered zero and the resultant value (i.e. y_{ij}^{l}) is fed into the next layer, as described in equation (2).

$$y_{ij}^{l} = \max\left(0, x_{ij}^{l}\right) \qquad (2)$$

Due to the heavy and complex calculations carried out in the convolutional layer, the numbers of parameters (weights and bias) are increased. Therefore, the pooling layer is used to simplify the calculations. Max pooling is one of the methods used in this layer. In Max pooling strategy, a k×k window slide on the output of the previous layer and due to the size of the window looks for the neuron with the maximum value. Ultimately, the size of the output is reduced to $\frac{(N-m+1)}{k} \times \frac{(N-m+1)}{k}$.

After extracting the features, they should be fed to a classification layer. The part of CNN which performs this task is called fully connected layer in

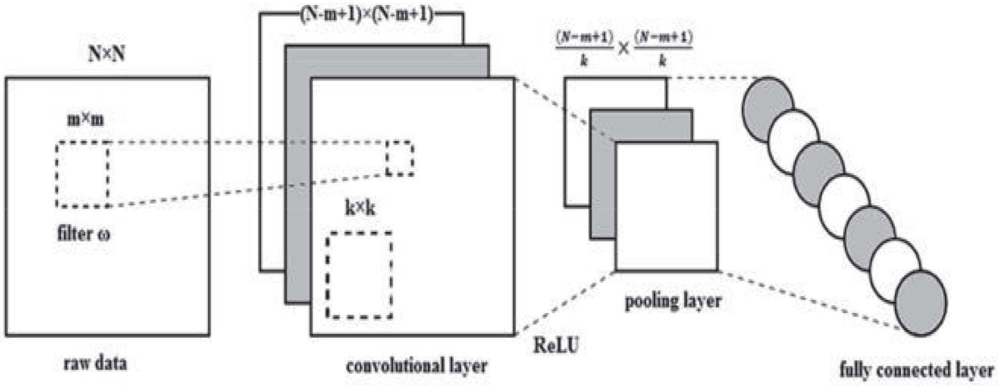

Figure 1: A type of convolutional neural network structure

which a complete connection exists between all the neurons and those of the previous layer. In addition, in the previous layers, the outputs were expressed in mass form, but in this layer, because the results of the classification should be expressed, the output is shown in the form of the vector.

Recursive Channel Elimination

Most of the recorded brain signals are based on 64 electrodes, which are installed on the user's scalp according to the 10-20 standard (23). It should be noted that each region of the brain carries a type of information. For example, in some regions of the human brain, such as the central and occipital lobes, P300 wave is formed stronger; on the contrary, weaker wave of the P300 is produced in the temporal and frontal lobes. On the other hand, the place of production of the best signals is not necessarily adjacent, and choosing the best electrodes individually and placing their signals together does not lead to the best results (24). Accordingly, in most BCI systems, the use of these 64 electrodes is not necessary and optimization of electrodes is a challenge (25).

In this method, first, using all 64 channels, the CNN method is performed, and then each of the 64 electrodes are separately and temporarily removed. In each deletion, the fitness function is produced for the remaining 63 electrodes (i.e. electrode set with 63 members), based on trained CNN. Finally, we have 64 responses that were obtained from 64 electrode sets (each of them comes from all electrodes, except one). Now the best result is selected among the above 64 responses and the neglected electrode in this result is completely removed from the electrodes set. Similarly, in 63 new electrodes, along with increased accuracy, the number of channels using the recursive channel removal method is reduced. Eventually, a set of electrodes is obtained which gives the highest accuracy. It should be noted that performing the above method by single electrode neglecting strategy is very time consuming. Therefore, in order to compromise between time and accuracy, it is possible to remove an arbitrary multiplex set of electrodes in each step rather than single electrode. In Figure 2, a pseudo-code is presented for the proposed method. In this paper, each eight-member set of electrodes is removed at each step, and finally only those electrodes which led to the most accuracy in distinguishing several characters remained.

Results

The proposed method was implemented by using Matlab 2016a on a PC with a seven-core CPU with 2.10GHz processor, 64 GB RAM and Windows 8.1 operating system. Then, the proposed method was tested on a set of recorded brain signals (26) in which the subjects were exposed to a 6×6 matrix, as depicted in Figure 3, which contains the letters [A- Z], numbers [1-9] and [-].

Loading data

Remove one of a electrode from set of channels temporarily

SET OF CHANNELS= [1, …. , number of channels]

while SET OF CHANNELS not empty

for all electrodes in SET OF CHANNELS

for number of epoch=1: n

Set the train data

Set the target

Create a neural network

a) Set the parameters (input size, filter size , pooling size, pooling step, ….)
b) Convlayer: $x_{ij}^{l} = \sum_{a=0}^{m-1} \sum_{b=0}^{m-1} \omega_{ab}\, y_{(i+a)(j+b)}^{l-1}$
c) ReLU layer: $y_{ij}^{l} = \max(0, x_{ij}^{l})$
d) Maxpooling layer: Dimensionality reduction
e) fully connected layer: for classification of data
f) operations error back propagation
g) update weights in convolutional layer & fully connected layer:
$$(w)_{new} = (w)_{old} + \alpha\, e_n$$

train stage

end for

give the test data to the net

calculate of accuracy

end for

Remove the electrode from set of channels permanently

the SET OF CHANNLES are selected to have highest accuracy

end while

Figure 2: Convolutional neural network algorithm pseudo-code along with Recursive channel elimination algorithm

Figure 3: A 6×6 matrix containing the letters [A-Z], numbers [1-9] and [-] [23]

This matrix had been organized in 6 rows and 6 columns; each of them was randomly and continuously blinking. Then, the user is asked to focus on one of the characters. Each character is obtained from the intersection of a given row and column. For each focusing period on a specific character, the rows and columns of the matrix are turned on and off 15 times and eventually averaging is performed. Thus, focusing on a character would result in a different P300. The complete specifications of the dataset are summarized in Table 1. This Table shows the basic parameters of the signals used in this research. These signals are utilized to evaluate the performance of the proposed method in two scenarios, which are fully embedded in the following sections (e.g. 3-1 and 3-2). Therefore, the reader must first understand the nature of the applied data.

In order to evaluate the effectiveness of the proposed method, two other state-of-art methods have been implemented along with it. The alternative methods include: a) classical multi-layer neural network with error back propagation training and b) deep learning based on convolutional neural network without channel optimization. The tests were performed in two different scenarios as follows.

First Scenario: Deep Learning without Optimization

In the first scenario, the ability of deep learning paradigm is evaluated to address the mentioned character recognition problem. For this purpose, the data set which was described in previous section was presented in parallel manner to the convolutional and the multilayer perceptron neural networks (i.e. CNN and MLP). The structure and some parameters of the neural networks in this scenario are described in Table 2.

In the first scenario, different modes of the classic neural network were implemented in order to classify the characters. In the first step, a neural network was created for the classification of 2 different classes and gradually, the number of classes (and therefore inputs) increased. Table 3 shows that MLP network separates two characters from each other with accuracy of 96.67%, while the accuracy of the convolutional neural network was one percent lower in a same test. By increasing the diversity of characters, the performance of the MLP was significantly reduced compared to the CNN. Increasing the characters' diversity up to 4, the

Table 1: Specification of the raw data which were subjected in all performance evaluations

Data specification	Description
Experienced people	2 subjects, healthy
Number of record sessions	5 sessions
Number of electrodes	64, according to standard 10-20
The duration of the rows or columns is ON	100 ms
The duration of the rows or columns is OFF	75 ms
Sampling frequency	240 Hz
Blinking rate	5.7 Hz
Number of characters for each subject	85
Preprocessing	Bandpass Filter: 0.1-60 Hz

Table 2: The structure and parameters of MLP and CNN

Network	Learning rate	Activity function	Layers
MLP	0.01	Logsig	Variable between 1 to 4 hidden layers
CNN	0.01	ReLU	A convolutional layer & a pooling layer

*MLP: Multilayer Perceptron, CNN: Convolutional Neural Network

Table 3: Results obtained from two MLP and CNN networks

Variety of number of characters	2	3	4	5	10	15	20	25	29
Number of training data	770	1001	1694	2097	3542	4697	5390	6006	6545
Number of testing data	510	663	1122	1377	2346	3111	3570	3978	4335
Accuracy of CNN (%)	95.58	94.38	91.87	88.89	85.46	84.80	84.71	84.62	84.41
Accuracy of MLP (%)	96.67	86.12	54.81	....	....	....	....	....	....

*MLP: Multilayer Perceptron, CNN: Convolutional Neural Network

MLP leads to unacceptable accuracy to the extent of 54.18%. Therefore, the MLP was not used more. The performance of CNN in the same situation (i.e. 4 types of characters) has still been satisfactory (91.87%).

Thus, this test showed that CNN had a significant gain compared to the MLP in distinguishing several types of characters. According to Table 3, in parallel with gradual increase in the variety of characters, the CNN still has a satisfactory performance in such way that with a variety of 29 characters its accuracy has been almost 84.4%.

As observed in the above table by using 770 training patterns and 510 test patterns, the MLP was able to separate the two characters with an accuracy of 96.67%. However, CNN achieved an accuracy of 95.58% by using the same patterns, which indicated that the CNN performed slightly weaker than MLP. In the next step, the MLP achieved the accuracy of 86.12% in recognizing three characters, but the CNN was able to achieve 94.38% accuracy, which was a bit strong than MLP. For identifying four characters, although MLP network became much more complex than previously examined MLPs, it reached the unacceptable accuracy of 54/81 percent. In contrast, the CNN reached the accuracy of 91.87%, which showed a difference of 37.06% compared to MLP. The results show that MLP neural network does not work well for separating more than three types of characters. Therefore, only CNN was used to continue the test procedure. The CNN was able to separate 5 characters with 2097 training data and 1377 test data with an accuracy of 88.89%. The number of characters increased step by step; as a result, CNN achieved the accuracy of 84.41% in separation of 29 characters. In the latter case, 6545 train patterns in parallel with 4335 test patterns were utilized which had been obtained by using 64 electrodes.

Second scenario: Deep Learning with Electrode Selection Optimization

As mentioned, an important challenge in BCI speller character recognition is selecting those channels whose P300 signals are more effective in improving the performance of the system. In the second scenario, the recursive channel elimination method was used to improve the above selection. Then, the optimal selected channels are used as deep learning input data. Finally, the results of such optimization are compared with those of the results of deep learning method without optimization; therefore, the improvement created by the proposed method is indicated.

Several researches in neuroscience (27) mentioned that the strongest P300 signals maight be obtained in the regions Fz, Pz, and Cz; on the other hand, because of visual stimulation, occipital areas carry useful features in connection with the P300 signal (28). Based on this information, it may be understood that some brain regions, especially temporal regions, produce weak signals.

To perform recursive channel elimination, at each step, an arbitrary set (containing 8 electrodes) was temporarily removed, so that each electrode was at least once removed from the electrodes set.

Table 4 clearly explains how the proposed method may improve the accuracy of the speller system by means of removing ineffective electrodes during a step-by-step procedure. For instance in the first step, a considerable accuracy improvement was obtained (e.g. increasing accuracy from 84.41 to 90.61 percent) due to the removal of Fpz, F8, F7, T7, T9, T10, P7, P6 electrodes (see the first and second rows of Table 4). Therefore, the process continued without the presence of these electrodes.

In the next step, among 56 remaining electrodes, the recursive channel elimination was performed. In this generation, the elimination of electrodes FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3 improved the accuracy of the speller system up to 95.36%. To show that only removing those electrodes which have been indicated by our algorithm may improve the results, in a separate test we removed another

Table 4: Results obtained by applying recursive channel elimination in step-by-step sense

Generation number	Electrodes removed up to this generation	Accuracy %
1	-------------------	84.41
2	Fpz, F8, F7, T7, T9, T10, P7, P6	90.61
3	FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3, Fpz, F8, F7, T7, T9, T10, P7, P6	95.36
4	FC5, FC6, FP1, AF4, CP5, CP6, P8, Iz, FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3 Fpz, F8, F7, T7, T9, T10, P7, P6	95.48
5	FP2, AFz, F5, F6, C5, C6, P5, PO4, FC5, FC6, FP1, AF4, CP5, CP6, P8, Iz, FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3, Fpz, F8, F7, T7, T9, T10, P7, P6	96.52
6	AF3, F4, FCz, C4, P1, PO3, FC4, CP2, FP2, AFz, F5, F6, C5, C6, P5, PO4, FC5, FC6, FP1, AF4, CP5, CP6, P8, Iz, FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3, Fpz, F8, F7, T7, T9, T10, P7, P6	97.34

set of electrodes. The obtained results of this test showed if we mistakenly remove, for example, the set of electrodes "FP2, F4, FC5, C2, TP7, CP4, P1, O1", the accuracy of the results not only did not improve, but also decreased to 49.48% percent. This example may show the effectiveness of rejecting valid weak electrodes which are indicated by recursive channel elimination.

The results of two previous steps showed that removing 16 among 64 electrodes caused impressive increase of accuracy to the extent of 10.95%, compared to the absence of channel optimization. This fact shows that this area produces the least valuable P300 wave. In the next generation, rejecting set of electrodes FC5, FC6, FP1, AF4, CP5, CP6, P8, and caused a slight increase in accuracy (e.g. 0.12% between the third and fourth rows of Table 4).

Subsequently in the next step, the other 8 high electrodes were removed from the 40 remaining electrodes. As shown in Table 4 (row 5), removing these electrodes increased accuracy a bit (i.e. approximately one percent), compared to the last previous state.

In the fifth step of applying the recursive channel elimination method, the CNN achieved an accuracy of 97.34%, by removing the 8 other worse electrodes from the above remaining set. In the next step, the mentioned method was continued in order to increase the accuracy and also reduce the number of the remaining electrodes. However, the obtained accuracy in this step was 91.31%, which not only was not better than the fifth step, but also showed a significant loss about 6.3%. Therefore, it may be concluded that the continuation of this process is no longer effective in promotion of the speller performance. Thus, the optimal result was stabilized as 97.34%, which had been obtained by removing 40 electrodes, as summarized in Table 4.

Discussion

The 6*6 matrix was used as the pattern to stimulate the test objects, and as a result to obtain the P300 signal including 36 different characters. The routine of the tests was that each test object was asked to focus on a character which is indicated as the junction of the specified rows and columns (e.g. corresponding to the desired character). Each row or column was on and off for 100 and 75 milliseconds, respectively. In total, the brain signal was recorded in 5 sessions which led to 85 characters per person. The signals were recorded by utilizing 64 electrodes mounted on the skull. Figure 4 clearly shows the arrangement of the removed electrodes at each step of running of recursive channel elimination algorithm, depending on their location on the patient's head. Therefore, this figure may help us to analyze how well the performance of the proposed method is compatible with biological facts. As a result, Figure 4 and its sub-figures (a-f) play an important role in all analyses of this section of the study. Because not all regions of

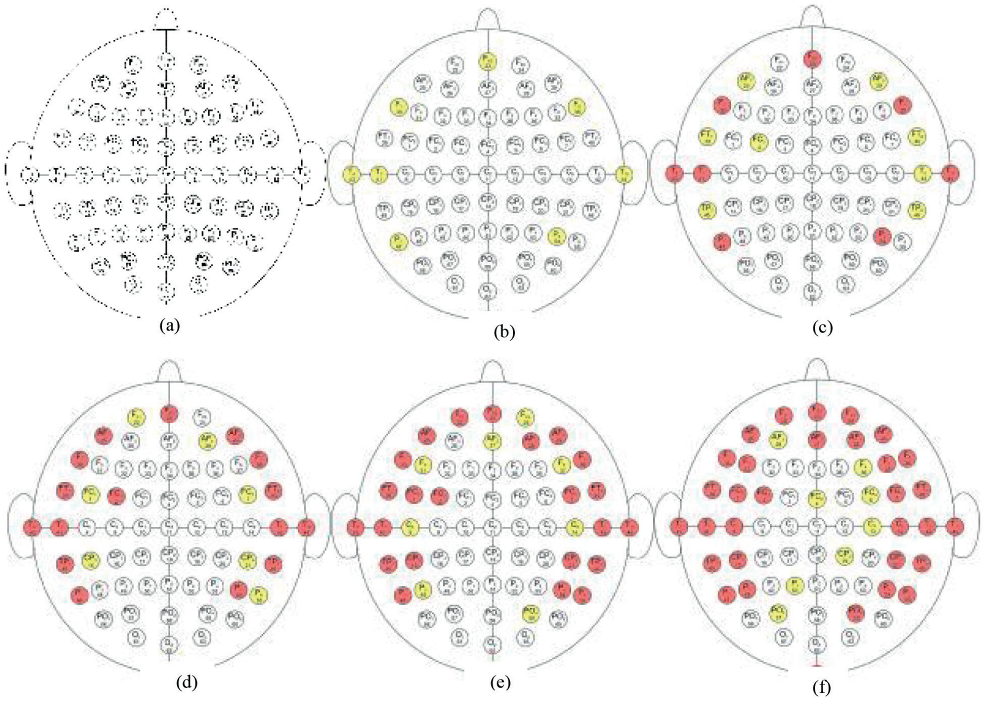

Figure 4: The images above show the removed electrodes in each step. The white electrodes represent the active channels, the yellow electrodes represent the electrodes removed at each step, which caused an increase in accuracy, and the red electrodes are the channels that were permanently removed from the network in previous stages and continued to be processed without their presence.

the brain produce strong P300 signal, the intensity of the signal recorded from different electrodes varied. Therefore, poor signals may have a negative effect on character recognition (e.g. accuracy reduction). We made use of recursive channel elimination algorithm as an optimizer concept for reinforcement of deep neural networks to better recognize the characters in P300 speller. This algorithm detects and subsequently eliminates the electrodes whose signal has a negative effect on the accuracy of the step-by-step method. The above algorithm identified and removed eight electrodes (i.e. Fpz, F8, F7, T7, T9, T10, P7, P6) in its first step, which resulted in considerable improvement of accuracy about 6.2 percent (which was described in Table 4). The considerable thing that makes us rightly hopeful is that the above electrodes were mainly located in the head margin as well as near the ears (see Figure 4-b). These areas contain those regions of the brain that have the least chance of producing P300 signal in biological point of view. Consequently, the results of this step of our optimization method were overall in a good agreement with biological facts. The second batch of electrodes removed by the optimizer algorithm also increased the accuracy by about 5%. The second level of electrodes may be illustrated as a set of FT7, FT8, AF7, AF8, T8, TP7, TP8, FC3, as described before in Table 4. These electrodes were mainly placed in the head margins (as shown in Figure 4-c) and, therefore, we can conclude that in the mentioned steps most of the electrodes which had been located in the temporal regions of the brain have been removed, which increased the performance of the system by almost 11 percent. The only unexpected coincidence in these results was the removal of the electrode FC3. This electrode is located in a region of the brain that is predominantly known as imagine motion area (see Figure 4-c). Thus, although this area of the brain is not directly related to the type of activates which we were looking for, but it was not initially considered a good candidate for elimination. It seems that the mutual effects of the adjacent regions on the electrode were the reason of this undesirable phenomenon. However, this may be an interesting topic for future research. Removing the next three levels of electrode (e.g. last three rows of Table 4) clearly indicated a serious difference between the importance of non-temporal and temporal electrodes (e.g. regions) in the optimization process. As shown in the section results, the removal of temporal electrodes led to 11 percent improvement in speller accuracy. However, the rejection of non-temporal set electrodes in the next three cycles resulted in only almost 2% improvement in the final result (see last three rows of Table 4 in parallel with Figure 4-e to 4-f). However, after five optimization levels that resulted in only 24 most effective set of electrodes remaining, it was found that removing much more electrodes did not improve the results. Accordingly, the final 24 electrodes were fixed with the accuracy of more than 97% as the final result. The most important drawback of this method is that the mutual effects of their respective regions on each other were not considered in optimizing the procedure. As described in the preceding lines for one of these electrodes, if we can obtain the appropriate mathematical relationships to model this effect, we can reach the same results with even fewer electrodes. This may be the subject of our future research in this domain.

Conclusion

In this study, an optimization scheme was proposed in order to improve character recognition accuracy in BCI speller. The proposed technique was based on recursive channel elimination which used a trained CNN as its cost function. The aim of the proposed method is to achieve the highest accuracy in the presence of the lowest number of recording channels. To achieve this goal, it tries to neglect less effective recording channels in the procedure of P300 speller.

To evaluate the performance of the proposed solution, firstly the performance of classic and deep neural networks in P300 based character recognition was compared. The comparisons indicated that along with the increase of varieties of characters, the performance of the deep neural network become significantly better than the traditional structure of neural networks in such way that in four-character recognition mode, the deep learning method reached an accuracy of almost 40 percent more than traditional neural networks. In this way, deep learning was fixed as the cost function block for our proposed optimization scheme. In the second scenario, the channel optimization algorithm was performed by using the above-mentioned cost function. The obtained results showed that the proposed method was able to delete the channels (i.e. recorded signals) which contained lower P300 information than others. This method improved the accuracy for distinguishing 29 characters from 84.41 percent (e.g. employing of all 64 channels) to 97.34 percent (e.g. in presence of only 24 optimal channels). The obtained results suggest that the use of the proposed method in P300 speller technology may significantly improve the accuracy of the system in parallel with the reduction of the number of channels.

Conflict of Interest: None declared.

References

1. Hassanien AE, Azar A. Brain-computer interfaces. *Switzerland: Springer*. 2015. doi: 10.1007/978-3-319-10978-7 .
2. Bansal D, Mahajan R. EEG-Based Brain-Computer Interfaces: Cognitive Analysis and Control Applications. Germany: Academic Press; 2019..
3. Colwell KA, Ryan DB, Throckmorton CS, Sellers EW, Collins LM. Channel selection methods for the P300 Speller. *J Neurosci Methods*. 2014;232:6-15. doi: 10.1016/j.jneumeth.2014.04.009.
4. Sanei S, Chambers J. EEG Signal Processing, Centre of Digital Signal Processing, Cardiff University, UK. *Publicação acadêmica, 1ª Edição, Elsevier*. 2007;16.
5. Magee JC, Winhusen T. The coupling of nicotine and stimulant craving during treatment for stimulant dependence. *J Consult Clin Psychol*. 2016;84(3):230-7. doi: 10.1037/ccp0000054.
6. Shahriari Y, Erfanian A, editors. A mutual information based channel selection scheme for P300-based brain computer interface. 2011 5th International IEEE/EMBS Conference on Neural Engineering; 2011: p. 434–7.
7. Rosas-Cholula G, Ramirez-Cortes JM, Alarcon-Aquino V, Martinez-Carballido J, Gomez-Gil P, editors. On signal P-300 detection for BCI applications based on wavelet analysis and ICA preprocessing. 2010 IEEE Electronics, Robotics and Automotive Mechanics Conference; 2010: IEEE. 10.1109/cerma.2010.48.
8. Selim AE, Wahed MA, Kadah YM, editors. Machine learning methodologies in P300 speller Brain-Computer Interface systems. 2009 National Radio Science Conference; 2009: IEEE.
9. Manyakov NV, Chumerin N, Combaz A, Van Hulle MM. Comparison of classification methods for P300 brain-computer interface on disabled subjects. *Comput Intell Neurosci*. 2011;2011:519868. doi: 10.1155/2011/519868.
10. Santamaria-Vazquez E, Martinez-Cagigal V, Gomez-Pilar J, Hornero R. Asynchronous Control of ERP-Based BCI Spellers Using Steady-State Visual Evoked Potentials Elicited by Peripheral Stimuli. *IEEE Trans Neural Syst Rehabil Eng*. 2019;27(9):1883-92. doi: 10.1109/TNSRE.2019.2934645.
11. Kübler A, Botrel L, editors. Imagining the P300 Speller: Good idea or nonsense? 2019 7th International Winter Conference on Brain-Computer Interface (BCI); 2019.
12. Gu Z, Chen Z, Zhang J, Zhang X, Yu ZL. An Online Interactive Paradigm for P300 Brain-Computer Interface Speller. *IEEE Trans Neural Syst Rehabil Eng*. 2019;27(2):152-61. doi: 10.1109/TNSRE.2019.2892967.
13. Kaper M, Meinicke P, Grossekathoefer U, Lingner T, Ritter H. BCI Competition 2003--Data set IIb: support vector machines for the P300 speller paradigm. *IEEE Trans Biomed Eng*. 2004;51(6):1073-6. doi: 10.1109/TBME.2004.826698.
14. Rakotomamonjy A, Guigue V. BCI competition III: dataset II- ensemble of SVMs for BCI P300 speller. *IEEE Trans Biomed Eng*. 2008;55(3):1147-54. doi: 10.1109/TBME.2008.915728.
15. Hoffmann U, Garcia G, Vesin J-M, Diserens K, Ebrahimi T, editors. A boosting approach to P300 detection with application to brain-computer interfaces. Conference Proceedings 2nd International IEEE EMBS Conference on Neural Engineering, 2005; 2005: IEEE. doi: 10.1109/cne.2005.1419562.
16. Liang N, Bougrain L, editors. Averaging techniques for single-trial analysis of oddball event-related potentials2008.
17. Mirghasemi H, Fazel-Rezai R, Shamsollahi MB. Analysis of p300 classifiers in brain computer interface speller. *Conf Proc IEEE Eng Med Biol Soc*. 2006;2006:6205-8. doi: 10.1109/IEMBS.2006.259521.
18. Ang KK, Chin ZY, Zhang H, Guan C. Mutual information-based selection of optimal spatial–temporal patterns for single-trial EEG-based BCIs. *Pattern Recognition*. 2012;45(6):2137-44. doi: 10.1016/j.patcog.2011.04.018.
19. Cecotti H, Rivet B, Congedo M, Jutten C, Bertrand O, Maby E, et al. A robust sensor-selection method for P300 brain-computer interfaces. *J Neural Eng*. 2011;8(1):016001. doi: 10.1088/1741-2560/8/1/016001.
20. Shan H, Liu Y, Stefanov TP, editors. A Simple Convolutional Neural Network for Accurate P300 Detection and Character Spelling in Brain Computer Interface. IJCAI; 2018.doi: 10.24963/ijcai.2018/222.
21. Zhang X, Yao L, Wang X, Monaghan J, Mcalpine D, Zhang Y. A Survey on Deep Learning based Brain Computer Interface: Recent Advances and New Frontiers. arXiv 2019. *arXiv preprint arXiv:190504149*.
22. Kundu S, Ari S. MsCNN: A Deep Learning Framework for P300 Based Brain-Computer

Interface Speller. *IEEE Transactions on Medical Robotics and Bionics*. 2019.

23. American Electroencephalographic Society guidelines for standard electrode position nomenclature. *J Clin Neurophysiol*. 1991;8(2):200-2.
24. Kee C-Y, Ponnambalam SG, Loo C-K. Multi-objective genetic algorithm as channel selection method for P300 and motor imagery data set. *Neurocomputing*. 2015;161:120-31. doi: 10.1016/j.neucom.2015.02.057.
25. Xu M, Qi H, Ma L, Sun C, Zhang L, Wan B, et al. Channel selection based on phase measurement in P300-based brain-computer interface. *PLoS One*. 2013;8(4):e60608. doi: 10.1371/journal.pone.0060608.
26. Krusienski D, Schalk G. Wadsworth BCI dataset (P300 evoked potentials). *BCI Competition III Challenge*. 2004.
27. Cecotti H, Graser A. Convolutional neural networks for P300 detection with application to brain-computer interfaces. *IEEE Trans Pattern Anal Mach Intell*. 2011;33(3):433-45. doi: 10.1109/TPAMI.2010.125.
28. Hillyard SA, Kutas M. Electrophysiology of cognitive processing. *Annu Rev Psychol*. 1983;34:33-61. doi: 10.1146/annurev.ps.34.020183.000341.