Towards Adaptive Brain-Computer Interfaces: Improving Accuracy of Detection of Event-Related Potentials

Robert Moro, Patrik Berger and Maria Bielikova
Faculty of Informatics and Information Technologies
Slovak University of Technology in Bratislava
Ilkovičova 2, 842 16 Bratislava, Slovakia
Email: {robert.moro, xbergerp, maria.bielikova}@stuba.sk

***Abstract*—Electroencefalography (EEG) has a wide range of applications in human-computer interaction and in adaptation and personalization of the interfaces. It can be used either as a sensor, e.g., for emotion detection, or as an input device that allows to take actions based on the brain's response to the presented stimuli. For the latter, it is crucial to be able to reliably detect event-related potentials (ERPs), which can be a hard task because of the noise in the signal, especially when using affordable consumer-oriented devices, such as Emotiv Epoc. In the paper, we present a method of EEG signal processing and classification for detection of ERP P300 wave. We particularly focus on the adaptive channel selection and propose to use genetic algorithm combined with linear discriminant analysis to determine the optimal subset of electrodes for signal processing for each individual user. We evaluated our proposed method on a standard data set outperforming the existing approaches even with decreasing size of a training set. In addition, we conducted a user study with Emotiv Epoc device on a standard P300 Speller task in order to compare the results of our method and to find out, whether this device is suitable for P300 detection.**

Keywords*—*EEG, event-related potentials, P300, Emotiv Epoc, genetic algorithm, adaptation

I. Introduction

In order to have truly intelligent and personalized interfaces, they have to acquire various information on the users that interact with them, such as their interests, tasks, goals as well as individual traits and affective states [1]. In addition, they should provide the user with the means of intuitive, effective, and efficient control. Both aspects are increasingly addressed with the use of various sensors, such as eye trackers [2] or EEG devices [3]. The latter are used in BCIs (Brain-Computer Interfaces), on which we focus in this work. These devices are usually much simpler than the ones used for medical purposes; they use smaller amount of electrodes, are portable and quite affordable. Examples include Emotiv Epoc[1] or NeuroSky[2].

One of the major BCI tasks is to correctly interpret the brain signal, which is the result of a very complex brain activity that is not fully understood yet. Furthermore, the acquiring ability of an EEG device is limited and the signal contains noise created by the electric potentials from different parts of the body, such as eye blinks, muscle activity, or heart beats [4].

It is still not possible to recognize a specific thought in general; however, there are three mental activities that can be presently identified with BCI applications [3]: concentration, stimulus response, and imagined movement. Most of the research in this area and also our work is focused on the stimulus response. There is a technique called *oddball paradigm* commonly used in the stimulus response based applications [5]. It uses target and non-target elements shown to a subject in a random order with about 80% probability of the non-target and 20% for the target element. A participant is instructed to do a mental activity such as counting occurrences every time the target element appears. That creates event-related potential (ERP) wave called P300, since it occurs approximately $300\,\mathrm{ms}$ after the event.

In this paper, we propose an EEG signal processing method in order to recognize P300 that adapts to a specific user. We mainly focus on the step of channel selection, where we propose a genetic algorithm combined with LDA (Linear Discriminant Analysis) to select the best subset of the channels for a specific user. We examine the following research questions:

1) Can our proposed method of channel selection outperform the existing methods?
2) Is it possible to use our method to recognize P300 event even with a low-cost EEG device, such as Emotiv Epoc with sufficient accuracy?

Addressing these questions, we formulated these hypotheses that we evaluate in the paper:

- H1: Using a subset of channels selected by our proposed method will be better than using all channels.
- H2: The channel subset selected by our method will outperform the fixed subset of channels based on the domain knowledge (knowing, where the P300 event is usually measured).
- H3: The channel subset selected by our method will outperform the recursive channel elimination.
- H4: Using a low-cost EEG device Emotiv Epoc, we will be able to detect P300 event with above-random probability.

[1] https://emotiv.com/epoc.php
[2] http://neurosky.com/

II. Related Work

As already mentioned, BCI applications can be used for different tasks, such as emotions detection [6] or detection of a users' reaction to the presented stimuli. In [7], the latter was used to create a practical application called NeuroPhone. It connects iPhone with the low-cost EEG device Emotiv Epoc. The application flashes six contacts from address book of the phone to a user for $500\,\mathrm{ms}$ each, until the P300 response is recognized, then the contact is automatically dialed. The authors used a subset of channels based on a domain knowledge and a lightweight Bayesian classifier to differentiate between P300 events and blinks. They achieved a reasonable accuracy up to 88.9% for a $100\,\mathrm{s}$ window, while the guess chance for six contacts is $1/6 \approx 16.67\%$.

The Emotiv Epoc was also used in [8] specifically for the P300 Speller task. They proposed a classifier ensemble; first, they performed PCA (Principal Component Analysis) projection on each channel separately and combined corresponding dimensions into M feature vectors, where M equalled the number of dimensions used in PCA. They trained M classifiers on these feature vectors using both LDA (Latent Discriminant Analysis) as well as FDA (Fisher Discriminant Analysis). Their best achieved accuracy was $73.3\% \pm 23.2\%$ averaged over three users when using $300\,\mathrm{ms}$ intensification interval.

The spatial occurrence of P300 is differs for every person like a fingerprint. This results in a need for selection of an optimal electrodes subset. In [9], a genetic algorithm was used to select the optimal subset. An individual was defined by four genes representing the numbers of used channels and its fitness value. The fitness value of an individual was computed as the sum of the peak values of the variance between conditions with a target present and a target absent across its channels. The total population size was set to 10 individuals. The authors showed that a minimal number of electrodes (four) can be used in a P300 based BCI system without any significant accuracy changes. That means less time needed for the signal processing as well as less preparation needed to set up an EEG device.

A recursive channel elimination (RCE) was examined in [10]. It finds optimal channels subset without any prior knowledge about the subjects or a type of the task. The authors focused on the cross-person differences in the optimal subset, especially whether the subset chosen by RCE from multiple person data will be equally accurate for a new user as the subset found by RCE with his or her data only. They found out that although the accuracy from multiple person data is lower, the maximum error rate did not reach 17%. Nevertheless, they conclude that the individual channel ranking is still preferable over cross-person ranking, thus further motivating the need for a user-adaptive channel selection method.

III. Method of EEG Signal Processing Using Genetic Algorithm

In this paper, we propose a method for EEG signal processing and further classification of P300 occurrence in response to a presented stimulus. It consists of two phases:

1) A *training* phase, during which a classifier is trained for a specific user and an optimal set of channels (electrodes) is determined for that user; this presents an *adaptation step* of the method.

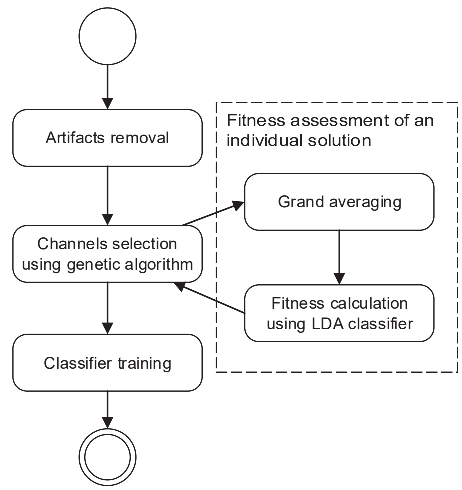


Fig. 1. An overview of the proposed method depicting the training phase.

2) A *classification* (or *deployment*) phase, in which the classifier trained during the first phase is used to identify P300 occurrences in the EEG signal. Only a subset of electrodes adaptively selected in the previous phase is used as an input to the classifier.

The first phase consists of the following steps (see Fig. 1):

1) Artifacts removal based on ICA (Independent Component Analysis) and a defined set of heuristics identifying artifacts, such as blinks or muscle activity.
2) Channel selection using a combination of genetic algorithm and LDA classifier.
3) Dimensionality reduction using grand averaging.
4) Classification of P300 using LDA classifier.

The second phase follows the same set of steps using the selected set of channels and a classifier trained in the first phase. Our contribution lies in the proposed method of channel selection that combines optimization based on a genetic algorithm with LDA classification and cross-validation that are used for fitness calculation. Other steps can be found also in the related works analysed in the previous section.

Before applying the method, we pre-process the EEG data. We center the signal around zero by subtracting the average value of signal based on the first two seconds of the recording when no actvity occurs. This is applied to each channel for the whole length of the recording. Next, we filter the signal using the 2$^{\text{nd}}$ order Butterworth filter leaving frequencies between $0.1\,\mathrm{Hz}$ and $30\,\mathrm{Hz}$, where P300 can be detected. Lastly, we undersample the signal by a factor of 12 (a number that is also used in the related works), i.e., we represent each 12 samples by their mean. This serves as an input to our method.

A. Artifacts Removal

We use ICA (Independent Component Analysis) for removal of noisy artifacts. These include different eye movements, such as blinks, muscle activity or heart beats [4]. It is computationally more demanding than PCA (Principal Component Analysis), but it is more robust and achieves in general better results. It aims to reconstruct the original signals in case that only their mixture is available; it is analogous to the "coctail-party" problem, in which we record several people speaking at once using several microphones [11]. In case of EEG, the sources of signal are the centers in the brain as well as the sources of the noise; the microphones are electrodes.

We have to decide, which of the identified components represent the actual signal, and which can be attributed to the sources of noise. We use heuristics defined in [12]:

- The eye movements are usually recorded in the frontal part of the brain and have low frequencies.
- The eye blinks are also recorded in the frontal part; typical are quick large amplitudes.
- The muscle activity is recorded mainly in the temporal part of the brain (bottom part in the back) and its frequency is higher than 20 Hz.

After removing the components representing the noise, the signal is reconstructed and repaired.

B. Channel Selection

The spacial location of the P300 causes that it does not manifest equally in all the electrodes (channels). Additionally, this location can differ between individuals, which motives the adaptive selection of the optimal subset of channels. In our method, we use genetic algorithm for this purpose. In each iteration, we have a population of individual solutions that represent channel subsets. Each individual is represented as a sequence of numbers that denote the selected electrodes; e.g., sequence (15, 5, 9, 10) represents a subset of channels 15, 5, 9, and 10. The length of an individual, i.e., the number of genes, determines the size of the channel subset.

The value of the fitness function is computed as a classification accuracy obtained by a 5-fold cross-validation of the LDA classifier trained on the training EEG data taking into account only the subset of electrodes represented by the individual, the fitness of which is being assessed. The values from the considered subset of electrodes are averaged (in the grand averaging step) and in this form they serve as an input to the classifier (our fitness function in this case). The advantage of our approach over the one proposed in [9] is that we do not consider just the importance of the individual channels, but we test their performance in their combination.

Each generation consists of P individuals. The first one is generated randomly, the following ones are created using $P-k$ one-point cross-overs of the parents. The position of a cross-over point is randomly chosen from interval $[2, 6]$ (i.e., at least two genes are transmitted from a parent). As a result of a cross-over, it is possible that the new individual will have multiple genes coding the same channel. When computing the fitness, these multiple occurrences are taken into account, i.e., it serves as a weight of a gene (of the corresponding channel). The best k individuals are preserved for the next generation, thus ensuring that the maximal fitness monotonically increases between the generations. For selecting the individuals for cross-over, we use a weighted roulette; the fitness function is modified to spread the values of fitness so that its higher values increase the probability of the selection of an individual:

$$f = f + f_{max} - 2f_{min} + 1 \quad (1)$$

Our proposed genetic algorithm also uses mutations; the probability of a mutation during a cross-over is 0.4%. The use of mutations prevents getting stuck at a local optimum and helps find novel solutions by allowing to introduce genes that were previously not present in the population. The algorithm stops if the increase in the average fitness in 25 generations is lower than the defined threshold ϵ (stopping criterion).

Overall, the proposed method of channel selection using genetic algorithm has six parameters that are summarized in Tab. I together with the used values. In some cases (e.g., the number of genes or population size), we tested multiple settings of the parameters; the results are presented in sec. IV.

TABLE I. THE PARAMETERS OF THE PROPOSED METHOD OF CHANNEL SELECTION.

parameter	value
number of genes N	{2, 4, 6, 8, 12}
population size P	{25, 50}
number k of individuals preserved for the next generation	3
stopping criterion ϵ	0.5
frequency f_{Stop} of testing the stopping criterion	once in 25 generations
mutation probability p	0.4%

C. Classification

We use LDA (Linear Discriminant Analysis) classifier in the step of fitness assessment of an individual during the search for the optimal channel subset as well as for detecting the P300 pattern in the EEG signal. The former is performed with the training data, which are also used for training the final model. This model is then used to classify the P300 occurrences on the test or unknown data using the averaged values of EEG signal from the selected subset of channels.

Because we use the oddball paradigm, i.e., we measure the user's reaction to the presented stimuli, we know when the events of interest occurred. Then, it is sufficient to look whether we detected P300 event, which should occur (if it occurs) 100–700 ms after the stimulus.

IV. EVALUATION

The evaluation of our method consists of two parts: First, we evaluated it on a standard data set from a BCI Competition II[3] [13]. We used data set IIb[4] provided by the Wadsworth Center, New York State Department of Health that contains data collected using a P300 Speller. Second, we carried out our own experiment using our implementation of a P300 Speller (see Fig. 2) and the low-cost EEG device Emotiv Epoc.

The P300 Speller is a commonly used experiment to evaluate a BCI system originally proposed in [14]. It is built on the idea of the oddball paradigm. The user is instructed to choose a character and then rows and columns in a typically 6×6 matrix of characters are randomly highlighted (see Fig. 2), while the user is supposed to count the occurrences of his or her chosen character. An occurrence means that a row or a column containing the target character was highlighted. That evokes P300 response in the acquired EEG signal.

[3]http://www.bbci.de/competition/ii
[4]http://www.bbci.de/competition/ii/albany_desc/albany_desc_ii.html

Fig. 2. Our implementation of P300 Speller. A row or a column are alternately highlighted. In this case, the user is supposed to count the number of times the character *A* is highlighted.

The task of a BCI system is in this case to correctly identify a row and a column, the highlighting of which evoked a P300 response. The correct character is then determined as an intersection of the two. Typically, several blocks of trials are used for the system to determine a correct character (in each trial, each row and column is highlighted exactly once, only the order is varied). The number of required trials needed for a system to reliably determine the character can be used to compare the competing BCI systems.

In case of a Wadsworth BCI data set, the rows and columns were highlighted for $100\,\mathrm{ms}$ with $75\,\mathrm{ms}$ blank intervals between them. The data were collected from 64 channels, using $240\,\mathrm{Hz}$ sampling rate. It contains 42 target characters (11 in the training set and 31 in the testing set). For each target character, the data set contains 15 sets of 12 intensifications (highlighting of a row or column) organized in a block in the randomized order. That means 180 intensifications for a target character.

In case of our experiment with the P300 Speller and Emotiv Epoc, we collected data from 10 participants in the User Experience and Interaction Research Center[5] at our university. The device has 14 electrodes (channels). We used 5 randomly chosen words consisting of 20 characters in the training phase and two words consisting 8 characters in the testing phase minimizing the number of repeating characters in the collected sets. We slightly modified the time during which a row or a column was highlighted (we used $93.75\,\mathrm{ms}$) as well as the time of blank intervals (using $78.125\,\mathrm{ms}$). The reason for this was a different sampling rate of Emotiv Epoc ($128\,\mathrm{Hz}$); we wanted to have uninterrupted samples within the chosen window.

A. Results on the Standard Data Set

First, we removed artifacts from the EEG signal using ICA (Independent Component Analysis) and a set of heuristics described in sec. III-A. Our goal was to identify two components of P300, namely P3a and P3b [15]. The former manifests at the frontal part of the brain, while the latter at the posterior part. Fig. 3a depicts the P3a component identified in the signal. It is contrasted with the noise in the form of blinks that we aim to remove from the signal (see Fig. 3b). Fig. 4 shows the reconstructed signal after removing the noise components.

Next, we tested the influence of population size P (25 vs. 50 individuals) on the performance of the genetic algorithm. We can see in Fig. 5 that in both cases the search for the optimal solution progresses with approximately the same speed; the risk with a smaller population is in initialization of the first generation that—in case of insufficient variety in the gene pool—can negatively influence the capability of the algorithm to find the optimal solution.

As to the number of genes N, we tested different values when decreasing the number of intensification blocks used for determining the character, the user thinks of. We can see that we can achieve 100% accuracy of determining the correct character in the test test when using the maximum number of 15 blocks with as few as two genes (representing the EEG channels); see Tab. II. The accuracy drops to 90.32% when using 10 blocks and to 83.87% when using only five blocks and the number of four genes. Since this setting (i.e., having four genes) achieved the best results, we used it in the rest of the experiments presented in this section.

TABLE II. THE COMPARISON OF THE RESULTS OF THE PROPOSED GENETIC ALGORITHM W.R.T. THE NUMBER OF GENES N AND THE NUMBER OF INTENSIFICATION BLOCKS.

#Blocks	GA (2)	GA (4)	GA (6)	GA (8)	GA (12)
15	100%	100%	100%	100%	100%
10	90.32%	90.32%	90.32%	90.32%	90.32%
5	80.64%	83.87%	80.64%	80.64%	80.64%

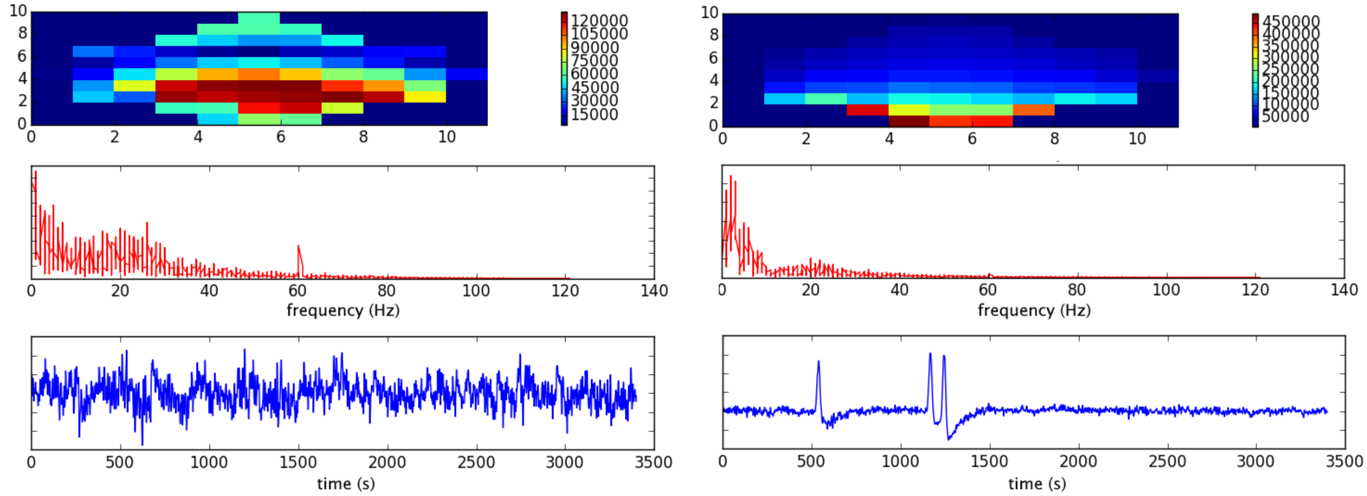
We compared our proposed method of channel selection using a genetic algorithm with three existing methods: using all channels, using a subset of channels selected based on the domain knowledge, and with the method of recursive elimination that in each step eliminates electrode which has the least contribution to the solution. Since we tested two different subsets of channels based on the domain knowledge (channels $\{CP_5, CP_3, CP_1, CP_Z, CP_2, P_3, P_1, P_Z\}$ and channels $\{CP_5, CP_1, CP_2, PO_7, PO_Z, F_5, F_2, C_1\}$ based on the standard channel coding), we had altogether four solutions to compare with our method. The results are shown in Tab. III.

We can see that our proposed algorithm outperformed all the compared variants, thus confirming hypotheses H1–H3. The advantage over recursive elimination showed to be in the fact that our algorithm can consider some of the channels multiple times as well as that it in each step evaluates the solution as a whole, while the recursive elimination uses the greedy approach that can prevent it to find the optimal solution.

B. Results on the Collected Data Set

The data collected with Emotiv Epoc contained more noise that the standard data set used in the previous section. We had to filter out the noise components from the signal manually based on the spatial distribution of active electrodes, since the proposed heuristics turned out to be difficult to apply automatically. We also halved the number of samples used

[5]http://uxi.sk



(a) P3a Component

(b) Blinks component

Fig. 3. The spatial distribution of the signal, its representation in the time dimension and in the frequency spectrum for: (a) P3a component, (b) blinks component. We can see that the P3a is present in the frontal electrodes (shown facing the bottom part of the plot), but not in the foremost ones, where—on the other hand—the blinks are present. There is also a clear difference between the two components in the time dimension; the blinks are characterized by quick large amplitudes.

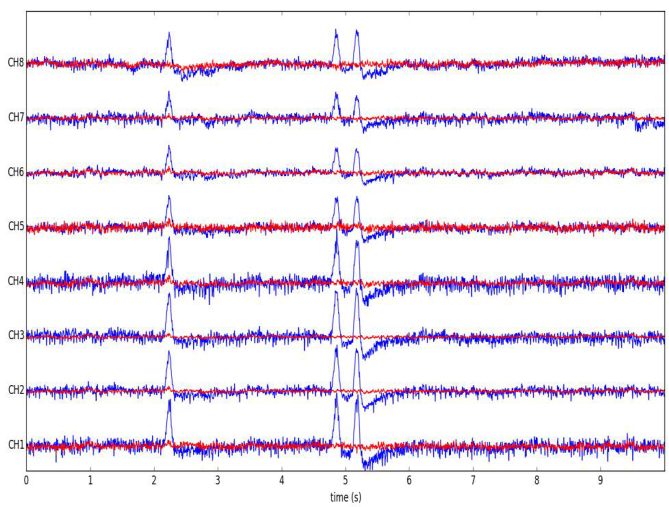


Fig. 4. The difference between the reconstructed (cleaned) signal (in red) and the original one (in blue) shown for the set of eight frontal electrodes.

TABLE III. THE COMPARISON OF THE RESULTS OF THE PROPOSED GENETIC ALGORITHM WITH FOUR GENES (GA) WITH ALL CHANNELS (ALL), THE SELECTED SUBSETS OF CHANNELS (S1 AND S2), AND WITH THE RECURSIVE CHANNEL ELIMINATION (RCE) W.R.T. THE NUMBER OF INTENSIFICATION BLOCKS.

#Blocks	GA	All	S1	S2	RCE
15	100%	96.77%	64.51%	96.77%	100%
10	90.32%	80.64%	51.61%	80.64%	87.09%
5	83.87%	61.29%	41.93%	61.29%	77.41%

for undersampling, i.e., we used factor of 6 instead of 12 (see sec. III).

We evaluated not only the accuracy of determining the correct character, but also the accuracy of determining the correct highlighted row or a column. The collected data set contains 8 characters in the training set, to which corresponds 16 highlighted rows and columns. The results for all channels are shown in Tab. IV. We can see that the accuracies are rather low, although better than random (which is 2.78% for determining a correct character out of 36); therefore, we can confirm also the last hypothesis H4.

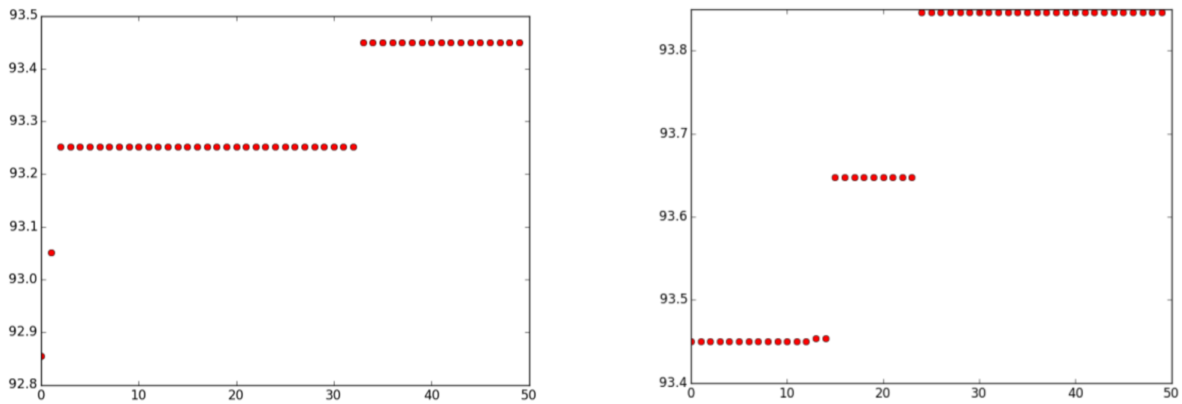
We also tried to select a subset of electrodes using our and other methods, but this has generally worsened the results. We attribute the poor results to the quality of the signal obtained from the Emotiv Epoc device and also to the fact that the arrangement of the electrodes on the scalp does not sufficiently cover locations, in which the P300 manifests the most strongly. The reason might be also a lower number of training samples and a shorter intensification interval than usually used when working with Emotiv Epoc [7], [8].

TABLE IV. THE RESULTS OF DETERMINING THE CORRECT CHARACTER OR ITS CORRESPONDING ROW OR COLUMN ON THE DATA COLLECTED USING EMOTIV EPOC.

Accuracy	Mean	Std. deviation
Character	19.44%	11.02%
Row or a column	37.52%	13.26%

V. CONCLUSION

In the paper, we proposed a method of EEG signal processing focusing on the user-adaptive channel selection. Our contribution lies in the combination of a genetic algorithm with LDA classifier that is used for assessing the fitness of an individual solution. The selected representation of an individual allows to select a channel multiple times, which serves as a simple weighting mechanism. We demonstrated on a standard data set that our method outperforms the existing solutions based on the recursive elimination or the domain expertise. We also achieved better results than in [9]; however, since their approach was evaluated on a different data set, it cannot be directly compared and further evaluation is needed.



(a) $P = 25$

(b) $P = 50$

Fig. 5. The progress of the search for the optimal solution (represented by the maximal fitness value in each generation) by the proposed genetic algorithm for the population size P of (a) 25 individuals and (b) 50 individuals.

Although we evaluated our approach on a P300 Speller problem, it could be also used for other classification problems pertinent to the intelligent user interfaces domain that can benefit from selecting an optimal set of electrodes, such as emotions detection or reading analysis. However, the evaluation of the applicability of the proposed approach on a wider range of problems remains a future work.

Additionally, we evaluated the suitability of the low-cost EEG device Emotiv Epoc for detection of the event-related potentials. The results were not very satisfactory; although the achieved accuracy was above random, the noise in the signal and the arrangement of electrodes resulted in a high variation rendering the classification far from reliable. Although we could have enlarged the training set and the intensification time interval, the practical applicability of such a solution is questionable. This suggest that a more reliable device should be used in the future; Open BCI[6] initiative seems promising in this regard.

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