STUDIA INFORMATICA 2016
Volume 37 Number 1 (123)

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PERFORMANCE ANALYSIS AND OPTIMAL PARAMETER SELECTION FOR 300-BASED BRAIN-COMPUTER INTERFACE

Summary. The paper is dedicated to parameter adjustment and performance analysis of the brain-computer interface based on P300 paradigm. The aim of the paper is to present the construction of the brain-computer interface and the study of optimal parameter selection as well as the data analysis process. The BCI with different parameters was run and tested under the case study. The aim of the study was to find the most suitable parameter of P300-based BCI.

Keywords: EEG, P300 paradigm, Brain-Computer Interface

ANALIZA DOBORU PARAMETRÓW INTERFEJSU MÓZG-KOMPUTER OPARTEGO NA PARADYGMACIE P300

Streszczenie. Artykuł poświęcony jest dostosowaniu parametrów oraz analizie wydajności interfejsu mózg-komputer opartego na paradygmacie P300. Opisano konstrukcję interfejsu oraz proces doboru jego parametrów, a także cały proces analizy. Interfejs BCI z różnymi zestawami parametrów został uruchomiony i przetestowany. Przedstawiono studium przypadku poświęcone analizie danych oraz analizie wydajnościowej danych pochodzących z interfejsu BCI.

Słowa kluczowe: EEG, paradygmat P300, interfejs mózg-komputer

1. Introduction

Electroencephalography (EEG) is an electrophysiological monitoring method dedicated to record electrical activity of the brain. This non-invasive method measures specific waveforms emitted by the brain [19]. It can be applied repeatedly to patients and healthy donors. The signal is gathered directly from human scalp by special electrodes. EEG signal depends on the age of the patient, actually performed activity and psychological aspects [15, 10].

EEG signal analysis have a wide range of applications [22]. Routine EEG is typically used in such clinical circumstances as monitoring patients in coma or suffering from epilepsy or sleep disorders [6]. EEG studies are also applied in diagnosis or in functional brain activity analysis [3]. Nowadays EEG analysis are becoming increasingly popular in construction of brain-computer interfaces (BCI) [8, 21]. BCI might be applied in rehabilitation of people with disabilities [7] or used to control robotic devices performing different functions such as transporting or manipulating [12, 17, 18]. BCI is a direct communication pathway between brain and an external device without using physical capabilities of the body [16, 17].

However, building an efficient BCI is a challenging task. The paper describes the construction process of BCI based on the P300 paradigm. Although the BCI concept is well known, the specificity of P300 makes it still a challenging task to build high-performance BCI [11, 13]. In contrast to such paradigms as SSVEP, P300 might occur to be hard to detect and the latency might differ between examined persons, what which undermines the universality of the P300. The P300-based BCI presented in the paper was constructed in a process of the parameter set selection including different classification methods. The first BCI run attempts failed, so the analysis was perform over the series of parameters, which occur to have a major impact on the results. The aim of the paper is to present the result of the study of optimal parameter selection for 300-based brain-computer interface. The BCI with different parameters was run and tested under the case study. The aim of the study was to find the most suitable parameter of P300-based BCI. The second chapter is about P300 paradigm. The third chapter is divided into four parts. The first and the second part are dedicated to the construction of the BCI experiment. The third part presents the description of parameters and parameter adjustment process and the last one is dedicated to the data analysis procedure. The fourth chapter presents obtained results. The last chapter is dedicated to conclusion.

2. P300 paradigm

P300 paradigm is one of the basic BCI paradigms. It is directly related to evoked-related potentials phenomenon which is the electrical potential detected in the brain activity. Such potential appears as a reaction to a specific stimulus. It was proven that it might be visual, auditory or sensory stimulus [3]. Among other evoked potential P300 is the strongest potential indicating a conscious conditional response. In the averaged signal [20] it should be detected as a peak received as a brain response to the previously expected stimulus [1]. However in practice the signal might occur between 300 and 600 ms after the expected stimulus [5]. It depends on the individual user characteristics, the level of user concentration and other issues related to both, performed experiment and individual user variation.

P300 paradigm is correlated to the event-related potential occurred in the human nervous system which might be detected during multiple presence of oddball stimuli. Such stimulus needs to be presented to a user repeatedly in a sequence. However, such sequence is optimal only if the target stimulus is rare and occur among other, non-target stimuli.

3. Applied classification algorithms

Two classification algorithms were applied in the study. The first one is Linear Discriminant Analysis (LDA) – popular classifier successfully applied to the BCI problem. This method might be applied to both feature reduction and classification and it implements allocation of feature space [1]. The method consists in derivation of new data coordinates to present them in different way and to make it easier to distinguish class membership. The new coordinates should maximise scatter between classes and minimise the scatter within classes. In the classification task associated with the division of the feature space, it is assumed that each category is represented in the feature space by a certain subset of standard features [24].

Another classification algorithm applied in the study is the common special pattern (CSP). It is widely applied to two- and multi-class problem [9]. For two class problem the algorithm consists in finding directions (spatial filters) to maximize variance of one class and minimize variance for the other class. What is more, CSP algorithm calculates the dual filter focusing on the interesting area. To reduce data dimensionality, small Laplacian spatial filter was also applied. Such filters are used to remove the average value of the potential, which exists on each electrode and does not bring useful information. Although the use of a spatial filter results in obtaining a new signal, it is constructed using other electrodes and can improve the signal quality. Assuming a symmetrical electrode placement, Laplacian filter is determined by subtracting the weighted average of the potential of the adjacent electrodes.

4. The BCI case study

4.1. Experiment description

Construction of BCI applied in the study was based on P300 event. The BCI was designed in OpenVibe environment connected with 21 channel EEG amplifier – Mitsar EEG 201.

There are two systems of placement electrodes. In the first scheme the signal was gathered from eight electrodes: C_3, C_z, C_4, P_3, P_z, P_4, O_1, O_2 placed in a special EEG cap to keep electrodes in right position.

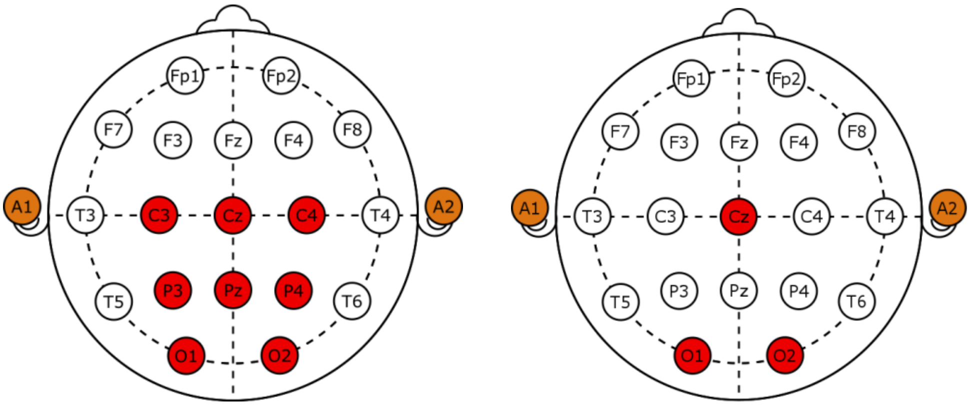


Fig. 1. The scheme of eight (left) and three (right) electrodes placement
Rys. 1. Schemat rozmieszczenia ośmiu (z lewej) i trzech (z prawej) elektrod

In the other the signal was gathered only from three electrodes: C_z,O_1,O_2. In addition, the ground electrode was placed in the centre of the frontal lobe and two reference electrodes (A_1, A_2), were placed on ears. Electrodes used in the experiment were located according the 10-20. The Fig. 1 presents the scheme of electrodes placement.

The samples were recorded with the 360 Hz frequency and transferred to a computer and processed in real time. The experiment was based on twelve figures displayed to a user sequentially. In a single experiment several series were run. In a single series only one of these twelve figures were treated as the target figure whereas the rest figures were treated as non-target values. There were eight targets out of twelve images (figures), but it was only one target image at time. Users were asked to concentrate on the target image. The classifier results were presented to a user during the simulation.

The signal was gathered with the 21 channel Mitsar 201 amplifier using cup-shaped electrodes attached to the cap located on the head. EEG amplifier transmitted data to computer with the native software (EEG Studio) installed. EEG Studio application received the signal and used dedicated API for Mitsar to transmit it to the OpenVive application in two ways. The first one was based on the Matlab environment. The signal was transmitted from Matlab to the OpenVibe application using the LabStreamingLayer (LSL) library. The second way was based on EEG Studio with LSL library implemented. In the second way it was possible to transfer EEG signal directly to OpenVibe acquisition module without the intermediary Matlab.

4.2. BCI construction

The BCI scenario was prepared and realized in OpenVibe application. Implementation of the experiment was based on four scenarios:

1. Online calibration scenario enabling to adapt the parameters of the BCI interface to the particular user. The simulation was displayed and user was asked to concentrate on the target figure. The steps carried out in this scenario include online signal acquisition, channel selection, signal filtering with Butterworth Band pass filter in the frequency range between 1 and 20 Hz. Signal was decimated to reduce the sampling.
2. Offline training scenario was applied to learn classifier and adjust its parameters. Offline training scenario was performed on data read from a file saved during online calibration scenario. The scenario had implemented also channel selection, filtering, decimation. Signal was also epoched based on simulation data taken from the file saved in calibration scenario. The signal was averaged among all epochs and feature vectors were generated based on this result. The classifier was trained and its parameters were estimated. The classifier was adjusted to separate two classes: Target and Non-target figure. K-fold cross based validation test was applied to check the classifier performance.
3. Online testing scenario processing of EEG signals in real time. The signal was filtered, epoched and averaged and it was processed by the classifier learned in the training scenario. The simulation presents user response online. The scenario implements the same procedure as offline training scenario. The feature vectors are classified and the result (the figure found as target figure) is displayed to a user online, after the series completion. To implement this scenario the same procedure as in the scenario 2 was carried out and then generated feature vectors were classified based on classifier setting obtained in scenario 2.

4.3. Parameters description and adjustment

The case study covered parameters adjustment phase to find the proper value of parameters charactering experiment scenario, data analysis and data transfer. Some of mentioned parameters were adjusted jointly as they were interdependent, some could be treated as independent. Some settings could had been adjusted offline, but most of considered parameters had to be analysed in online case study with test users. The research showed that both, the figure displaying duration and the break period after the figure displaying are important parameters. The important aspect is also the number of displayed stimulus – including target and non-targets figures and the appropriate proportion between them.

Two different classification algorithms were tested including spatial filter for different settings. What is more, hardware limitation resulting from the process of transfer of data and analysis on-line was included in the analysis. It occurred to be a difficult task due to the delays and difficulties in the data transmission.

In the aspect of experiment scenario the following parameters were adjusted:

- *Total number of displayed images* – the scenario is adjusted to display images in the form of matrix. The number of images needs to be large enough to receive the effect of rare target image displaying among non-target images. It was assumed that twelve is sufficient number of images. They were displayed in the form of 3x4 matrix.
- *Number of images displayed in a single series* – this number is related to the total number of displayed images. As the total number of displayed images was set to twelve, the number of images displayed in a single series was also set to twelve to assure that in each series target image is displayed.
- *Number of series repetitions* – this parameter is related to duration time of image and break display. The number of repetitions needs to be large enough to gather sufficient number of signal pieces which are averaged in the further analyse to get the P300 potential. On the other side, the number of series repetitions together with duration times of single image display and break between images display determine the length of the experiment. The time of single scenario should not exceed the 15 minutes because of the concentration ability of test users. This parameter was tested in online scenario. Its range was between 4 and 12.
- *Duration time of single image display* – the parameter determines the time of flash displayed for each single image in the series. This duration time is equal for all images in the single scenario and its length needs to be adjusted regarding both, the brain response on the stimulus and delays related to the EEG signal passing. This parameter was tested in online scenario. As the typical P300 response is in the range of 200-600ms after the stimulus, the total time of the duration time of single image display and duration time of break between images display should not exceed 1s. Its range was between 0.2s and 0.8s.
- *Duration time of break between images display* - analogously to duration time of single image display, the duration time of break between images display is related to all no-flash periods between images in the single series. It should be smaller than the flash time. It is enough to set this parameter as a hath of duration time of single image display. This parameter was tested in online scenario. Its range was between 0.1s and 0.4s.

In the aspect of data analysis the following parameters were adjusted:

- *Number of EEG channels* – in the case study several EEG electrodes were used. As the P300 signal is the strongest at the parietal lobe, C_x, P_x and O_x electrodes from the 10-20 system were applied. In the study two sets of electrodes were applied. The first one covered eight electrodes (C_3, C_z, C_4, P_3, P_z, P_4, O_1, O_2) and the second set was reduced to three electrodes (C_z,O_1,O_2) as shown in Fig. 1.

- *Signal decimation parameter* – this value is applied to reduce and smooth the data. By default, the decimation factor was set to 4, but tests covered also two more options: factor set to 2 and no decimation.
- *Classifier algorithm* – the basic version of the BCI was based on LDA method and CSP algorithm. However, in several tests also Laplacian filter was applied in order to reduce dimensionality and strengthen the signal coming from 8 electrodes.

In the aspect of data transfer the following parameters were adjusted:

- *Applied software environment* – EEG Studio and OpenVibe were applied in the case study. However, there are two ways to transfer to signal from EEG Studio to the OpenVibe acquisition server - the first one is by applying dedicated Matlab library and the second one is based on Lab Streaming Layer. Both methods were tested online.
- *Frequency of transferred signal* – this parameter needs to be specified while the EEG signal is transferred. It is directly related to the time window for data buffering. These values set mistakenly might results in large data latencies and drifts as well as in data samples loss. The offline analysis were performed for frequency range of 300 to 500 Hz. The best results (99% of transferred samples) were obtained for 340 Hz and this value was applied in the study.
- *Time window for data buffering* – this parameter determines the size of the transferred EEG data buffer. The offline analysis were performed for time window range between 0.02s to 0.4s. The best results (99% of transferred samples) were obtained for 0.2s and this value was applied in the study. In the case of direct EEG Studio-OpenVibe communication (without Matlab) 64 sample count per block was applied.

4.4. Data analysis process

The BCI was run online so that the efficiency of the interface was estimated at once. Detailed data analysis, however, was performed offline. The analysis was done separately for each test user, because individual differences between particular persons make it pointless to analyse all data as a one uniform dataset.

Detailed procedure of the analysis was divided into three parts: data epoching, data interpolation and data averaging. Data epoching involves several steps:

1. The first step is separation of single data files of particular test user. Each gathered signal set is analysed separately. For single experiment two separate data sets were obtained: learning data and online test data. Both data sets could be analysed separately and inde-

pendently. Single data set contain three files: simulation file with displayed figure labels complemented by related display times, simulation file with displayed only first figure labels indicating target figure complemented by related display times and gathered EEG signal divided into eight channels.

2. The next step involves obtaining times and labels of all target images and dividing signal into time blocks according these times.
3. The procedure involves also channels separation in each EEG signal file.
4. In the further analysis times of stimulus were found according times of images displaying. These times were impose on the signal. If it was necessary, linear interpolation was also applied to align the times.
5. The next step is to cut signal into time epochs to obtain fragments between stimulus.
6. Next, the cut signal is aligned and each epoch is treated as it start with the same time.
7. After that the signal is divided into epochs into two groups based on the type of displayed figure and classified as target or non-target event related.
8. The last step is averaging the signal in each of two groups (target/non-target)

The second part of the analysis, data interpolation, is optional. If needed, interpolation in all generated signal epochs is performed. Single X axes should be generated. The last step is averaging. If all signal epochs are prepared, averaging in groups might be applied.

This procedure was applied several times for the each analysed parameter set. The process of parameters adjustment is presented in Fig. 2.

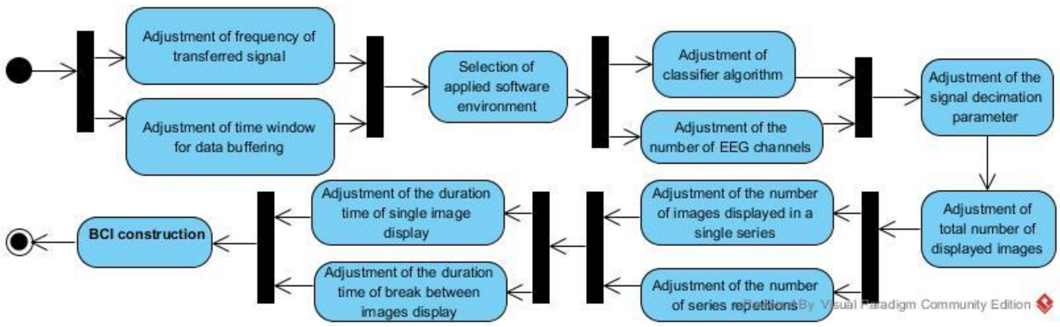


Fig. 2. The procedure of parameters adjustment
Rys. 2. Procedura doboru parametrów

5. Results

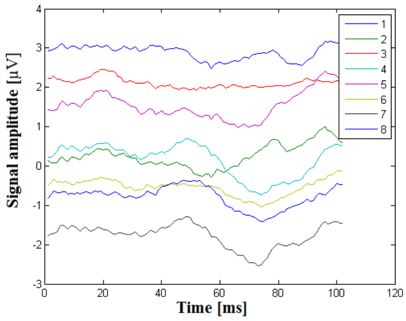
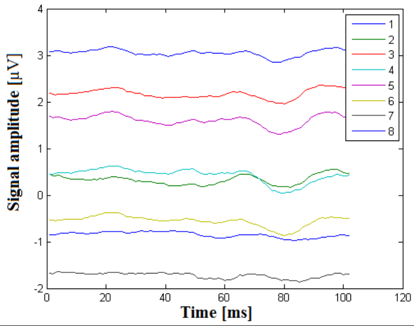
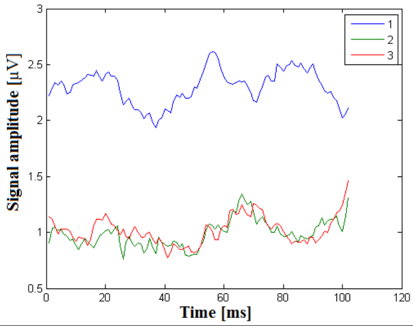
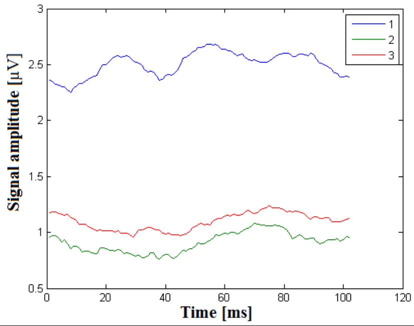
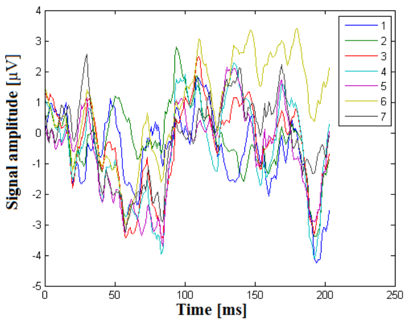
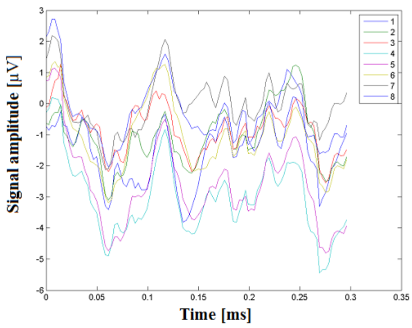
Results were obtained separately for each single test user, exam, target figure and channel. Results were also obtained separately for target and non-target figure.

Table 1 presents the results obtained in the case study. It contain the performance of the BCI and the mean results for target and non-target image. The results cover the following test cases in the table designated as *param. set no.*:

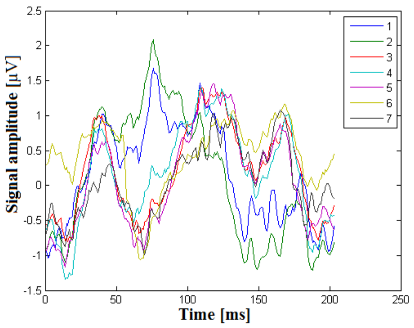
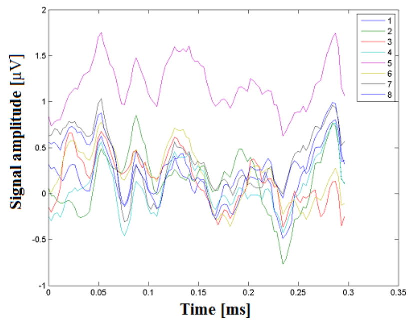
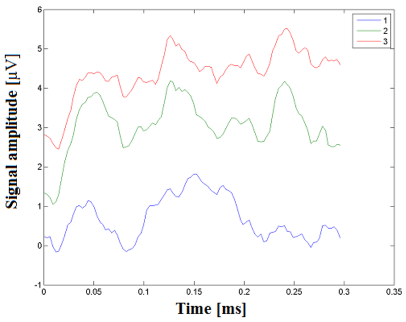
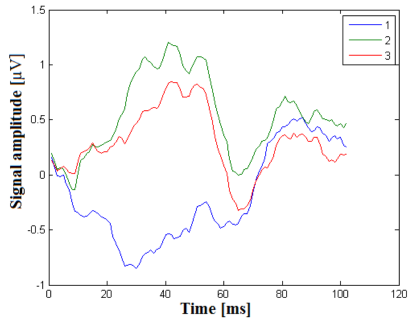
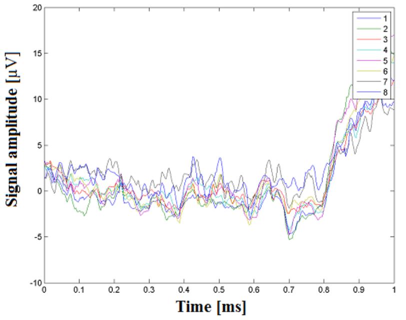
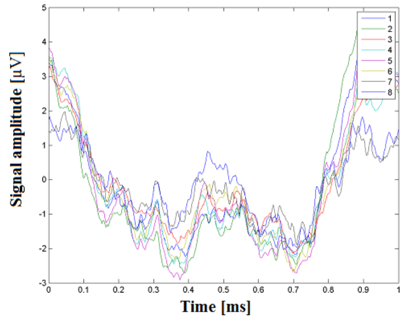
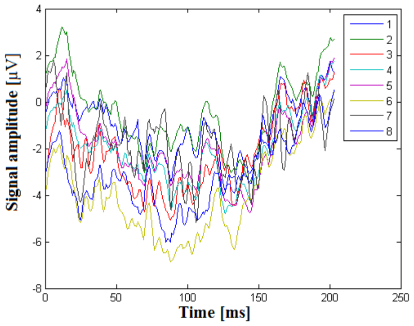
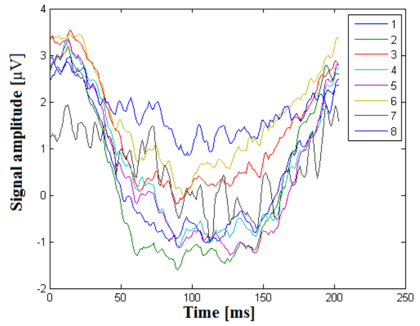
1. 8 channels, no Matlab, *image display time*: 0.2, *break time*: 0.1, *number of repetitions*: 10
2. 3 channels, no Matlab, *image display time*: 0.2, *break time*: 0.1, *number of repetitions*: 10
3. 8 channels, Matlab, *image display time*: 0.2, *break time*: 0.1, *number of repetitions*: 10
4. 8 channels, Matlab, *image display time*: 0.4, *break time*: 0.2, *number of repetitions*: 8
5. 3 channels, Matlab, *image display time*: 0.4, *break time*: 0.2, *number of repetitions*: 8
6. 8 channels, Matlab, *image display time*: 0.6, *break time*: 0.4, *number of repetitions*: 5
7. 8 channels, Matlab, CSP, *image display time*: 0.4, *break time*: 0.2, *number repetitions*: 8

Table 1

Example results of P300-based BCI for different set of parameters

Param. set no.	BCI perf.	Results for target image	Results for non-target image
1	83%		
2	79%		
3	81%		

con. table 1

Param. set no.	BCI perf.	Results for target image	Results for non-target image
4	80%		
5	78%		
6	77%		
7	77%		

6. Discussion and conclusions

The paper discusses the performance of the brain-computer interface based on P300 paradigm. The case study was performed on a group of 10 test users – men of a similar age (22-24 year old), each of which was took part in few sessions. Jointly 30 independent results were obtained for different set of parameters. Among different results seven chosen were presented.

Performed analysis showed that there are differences between particular results. The best detectable P300 potential might be noticed for parameter set no 3 and 4, obtained for data transferred though Matlab, where the time of single image is displayed through, respectively 0.2 and 0.4s and the number of repetitions is 10 and 8, both obtained with 8 electrodes. Good results were obtained also for direct EEG Studio-OpenVibe communication. The performance of BCI was the best for the case of direct EEG Studio-OpenVibe communication.

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Omówienie

Artykuł poświęcony jest dostosowaniu parametrów oraz analizie wydajności interfejsu mózg-komputer opartego na paradygmacie P300. Interfejsy mózg-komputer (ang. *Brain Computer Interface,* BCI) oparte są na sygnałach elektroencefalograficznych (EEG). Elektroencefalografia (EEG) to metoda, która służy do rejestracji aktywności elektrycznej mózgu. Aktywność ta odczytywana jest za pomocą elektroencefalografu – urządzenia umożliwiającego nieinwazyjny pomiar aktywności elektrycznej mózgu. Pomiar ten realizowany jest z zastosowaniem elektrod umieszczanych na powierzchni głowy lub kory mózgowej badanego, zwykle w sposób zgodny z międzynarodowymi standardami, takimi jak standard 10-20.

Interfejsy mózg-komputer umożliwiają sterowanie aplikacjami komputerowymi oraz urządzeniami elektronicznymi bez wykorzystania mięśni, za pomocą aktywności umysłowej użytkownika. Interfejsy mózg-komputer oparte na paradygmacie P300 wykorzystują zjawisko potencjałów wywołanych (ang. *event-related potential*), które są potencjałami skorelowanymi ze zdarzeniem. Jednak wykrycie potencjałów wywołanych wymaga wielokrotnej prezencji bodźców, a otrzymany sygnał musi być uśredniony. P300 to komponent uwidaczniający świadomą reakcję na oczekiwany bodziec i wykrywalny na elektrodach umieszczonych nad centralno-ciemieniowym obszarem czaszki. Artykuł poświęcony jest dostosowaniu parametrów oraz analizie wydajności interfejsu mózg-komputer opartego na paradygmacie P300. Opisano konstrukcję interfejsu oraz proces doboru jego parametrów, a także cały proces analizy. Interfejs BCI z różnymi zestawami parametrów został uruchomiony i przetestowany. Przedstawiono studium przypadku poświęcone analizie danych oraz analizie wydajnościowej danych pochodzących z interfejsu BCI.

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