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Analysis of the application of brain-computer interfaces of a selected paradigm in everyday life

Analiza zastosowania interfejsów mózg-komputer o wybranym paradygmacie w życiu codziennym

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Abstract

The main objective of this paper is to carry out a research on the analysis of the use of brain-computer interface in everyday life. The article presents the method of recording brain activity, electroencephalography, which was used in the study. The brain activity used in the brain-computer interface and the general principle of brain-computer interface design are also described. The performed study allowed to develop an analysis of the obtained results in the matter of evaluating the usability of brain-computer interfaces using motor imagery. As a result of the process of analyzing the results obtained during the research, it was found that each subsequent experiment allowed for obtaining more favourable results than the previous one. The reason for this was the use of an additional training session for the next test person. In the final stage, it was possible to evaluate the usability of the brain-computer interface in everyday life.

Keywords: brain-computer interface; electroencephalography; motor imagery

Streszczenie

Głównym celem artykułu jest przeprowadzenie badania nad analizą wykorzystania interfejsu mózg-komputer w życiu codziennym. W artykule przedstawiono metodę rejestrowania aktywności mózgu, elektroencefalografię, która została wykorzystana w badaniu. Opisano również aktywność mózgu wykorzystywaną w interfejsie mózg-komputer oraz ogólną zasadę projektowania interfejsu mózg-komputer. Przeprowadzone badanie pozwoliło na opracowanie analizy uzyskanych wyników w zakresie oceny użyteczności interfejsów mózg-komputer z wykorzystaniem obrazowania motorycznego. W wyniku procesu analizy wyników uzyskanych podczas przeprowadzania badań ustalono, iż każdy następnie zrealizowany eksperyment pozwalał na uzyskanie korzystniejszych wyników od poprzedniego. Powodem tego było zastosowanie dodatkowej sesji treningowej dla kolejnych badanych osób. W końcowym etapie można było ocenić przydatność interfejsu mózg-komputer w życiu codziennym.

Słowa kluczowe: interfejs mózg-komputer; elektroencefalografia; wyobrażenia ruchowe

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1. Introduction

The brain-computer interface is a variant of the human-machine interface, which is a direct communication path between the human brain and an external device without the involvement of the peripheral nervous system and muscles [1,2]. Brain-computer interface requires a combination of knowledge from several sciences: artificial intelligence, biomedical engineering, neuroscience and electronics. The continuous development of these fields of science has resulted in an increase in research and publications on the issue of the brain-computer interface. The brain-computer interface is defined as interdisciplinary, therefore the article covers only its individual fragments related to processing, analysis and classification [3].

Brain-computer interfaces are systems with practical use in everyday activities, communication, entertainment, rehabilitation and prosthetics. For people with disabilities, they offer the possibility to control the device that performs the movement for them, and for people for whom communication with the environment is impossible, they offer the ability to write only from the activity of the nervous system, without the involvement of muscles [4]. In the research carried out for the purposes of this article, the potential related to the image of movement was used. In order to apply it correctly, the user had to learn to visualize the movement, and it was also necessary to construct the experiment requiring many repetitions to ensure that the signal-to-noise ratio of the synchronization and desynchronization of the signal was low. This potential is related to the ERD/ERS stimulus, ERD means a decrease, while ERS means an increase in the average signal strength in a given frequency band. The occurrence of desynchronization and synchronization takes place within the motor cortex of the brain.

2. Purpose of the work

The main purpose of this article was to process, analyze and classify EEG signals in terms of the use of the brain-computer interface. The obtained results allowed for the assessment of the usefulness of brain-computer interfaces in general human life. For the purposes of the study, a thesis was formulated: Adequate training before using the brain-computer interface and its subsequent use allows for a significant improvement in the quality of human life. In order to achieve the aim of the work, a selected paradigm of the motor imagery was used, the operation of which was preceded by the analysis of its data, extraction and selection of features.

3. Materials and methods

3.1. Electroencephalography (EEG)

During the research, the method of electroencephalography was used. It is a non-invasive method of recording the brain's bioelectric signals with the use of electrodes placed on the subject's scalp. EEG is characterized by the highest time resolution, safety and low cost of carrying out a brain activity test [7].

3.2. Preparation for the EEG examination

The preparation of the EEG cap is very important steps. This is due to the fact that the electrodes collect potentials from the head of the examined person, so the EEG cap must be perfectly fitted to it. Therefore, the head surface at the electrode site should be cleaned of the secreted sebum and exfoliating epidermis. Then, using a tailor's tape measure is the distance between the point of the seeds (nose bridge) and the inion (place of the bulge in the center line of the skull base). Then the circumference of the head is measured in order to select the appropriate size of the EEG cap to the tested person's head based on the measurement result.

3.3. The 10-20 system of EEG electrode placement

The 10-20 assembly system, which is the arrangement of the arrangement of 21 electrodes on the surface of the subject's head. The 10-20 system is characterized by the necessity to divide the head into uniform sections in relation to the following places on the skull: right and left ear section, external occipital tumor, nose bridge. The name of the assembly system 10-20 indicates equal distances, expressed as a percentage, between individual points such as: the base of the nose (seeds), the occipital tumor on the antero-posterior plane (inion), right and left segment of the ear on the dorso-abdominal plane. The reference point is defined as 10% of the total distance measured in cm from the root of the nose. Figure 1 shows the 10-20 assembly system in theory [3,8].

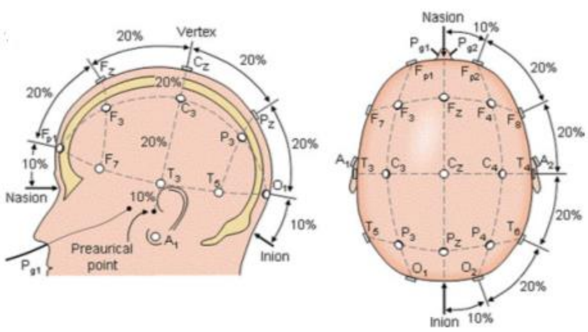

Figure 1: Ideal electrode placement in a 10-20 system [12].

3.4. Brain-computer interface

BCI can be defined as a computer system that obtains signals from the human brain, analyzes them and translates into commands. An important aspect of BCI is the conversion of a signal from human brain activity into a digital signal that is passed to an output device that performs the desired action. Hence, the relationship between humans and computers, especially in terms of communication, takes on a new meaning [2].

3.5. The stages of the brain-computer interface

The brain-computer interface works by measuring the activity of the user's brain. The detected brain activity through the BCI system does not provide many perspectives because it is impossible to read human thoughts. The only use of the resulting models of brain activity is to classify them with certain events. Therefore, during the study, the participant had to focus to generate the appropriate brain activity using a specific event or stimulus. The user uses the so-called mental strategies of focusing on a certain event or image in order to generate useful EEG waves.

The first stage of the brain-computer interfaces is the training session. This is an action taken by the user prior to the application of the brain-computer interface. Training is an element that is often required from the user along with learning about the mental strategy. It consists in learning to consciously manipulate a given feature with the use of simulators [8]. When learning the system, it is sometimes necessary to carry out even several training sessions. This is required in many cases due to the easy possibility of making a mistake during the human-device communication process. During training, the user performs a specific task, e.g. imagining the movement of the right hand.

After completing this mental task, the signal parameters needed at a later stage called classification are obtained. The training stage is followed by teaching, more precisely training the classifier. The brain-computer interface used during the research worked online, thanks to which a threshold classifier was used. Its operation is based on the fact that after reaching a certain value of a certain parameter, the signal will remain qualified to a certain class [4,9].

After training the classifier, the system is ready for further tests. The next stage consists of training sessions repeated several times. The test person tries to generate perfect signals by observing the results appearing on the computer monitor. This action is called user training based on feedback [6]. This process allows the test subject to receive real-time information on how to classify his or her reactions. It is a facility that allows the user to influence his or her next reactions and obtain the best possible results of the study [5,10].

The last stage consists in appropriate use of the interface, to control devices or communicate with the environment by people with disabilities. The person using the interface does not need additional help from another person, and if there is such a need, it is usually a small help. a person with a disability, e.g. paralyzed, is able to: control the movement of his own wheelchair, guide the cursor on a monitor screen, use a whiteboard with letter symbols to communicate his thoughts, control an artificial prosthesis [10,13].

3.6. Motor imagery (MI)

During the study, the motor imagination paradigm was used. The sensation of movement is a cognitive-perceptual process consisting in the mental performance of movement without the use of muscle activity [8]. It is an experience that suggests that the subject feels, the performance of which he imagines. Motor imagery require the conscious activation of certain areas of the brain that are directly related to the exercise and preparation for movement. It is used in the neurological rehabilitation of patients who have suffered a stroke and have paresis in moving certain parts of the body.

4. Experiment description

During the experiment, the subjects were presented with an interface consisting of a board with an arrow on it. Right and left arrows were displayed randomly during the presentation. Depending on the stage of research, the commands and requirements for the user of the brain-computer interface changed. During one stage, the participant was asked to focus on the monitor screen and imagine the bend of the right or left hand, depending on the appearance of arrows on the monitor. Alternatively, the participant had to physically bend the individual hands. The main stage of the study was preceded by registration with eyes closed and open while the subject was resting. During the experiment, the accuracy and additional parameters of the algorithm, such as efficiency, were tested [9,11].

The electroencephalography study was carried out using 21 measuring electrodes connected according to the 10-20 assembly system. The 10-20 system is characterized by the necessity to divide the head into uniform sections in relation to the following places on the skull: right and left ear section, external occipital tumor, nose bridge. The actual arrangement of the electrodes in the 10-20 system is shown in Figure 2.

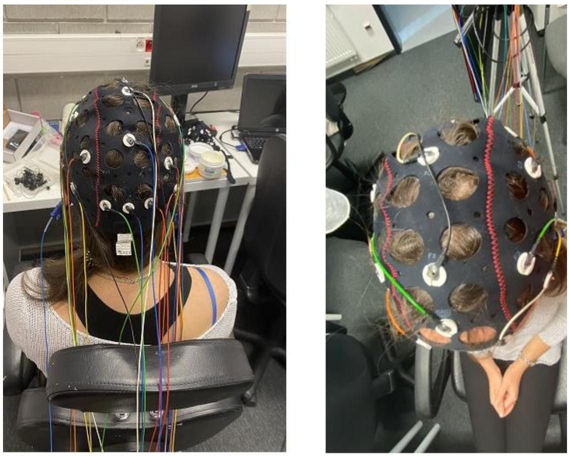

Figure 2: Placement of electrodes during the test.

The Mitsar amplifier shown in Figure 3 was used to transmit the signals from the electrodes to the computer. The procedure of recording the brain activity was repeated twice for each person: the first study for the hand flexion with the use of muscles, and the second one exclusively with the use of the hand movement image paradigm [7,8,12].

Figure 3: Test stand.

4.1. Data analysis process

The data analysis process involves the processing of EEG signals, which is the main component of the brain-computer interface system. As a result, EEG signal processing is very often the subject of research, and the general structure of a typical BCI solution is shown in stages which include: pre-processing, extraction and feature selection. Data from EEG channels are considered input. After the signal pre-processing stage, feature extraction begins. This step is to provide the most important set of values representing the characteristics of the signals. After that, the collected data are subjected to a selection of features, so that they can be classified [7].

4.2. Research scenario

The "Motor imagery" scenario available in the OpenViBE program was used to achieve the research goal. The scenario consists of six stages: signal monitoring, acquisition, interface training, classifier training, online testing, replay. For each test subject, two trials of the research experiment were used. The first attempt consisted in training the participant in which he squeezed rubber balls using the muscular activity of his right and left hands. However, during the second attempt, balls were not used and the user imagined the movement of his hands. The second attempt was based on the use of the motor imagination paradigm [8].

The "Motor imagery" scenario uses a linear discriminant analysis classifier with a k-fold cross-validation algorithm to classify data. The LDA classifier is used to reduce the number of features for easier value management before classification. On the other hand, the algorithm of k-fold cross-validation ensures that the full data set is used both for model validation and its training. In addition, while training the model, it determines its quality to prevent the problem of overfitting.

One of the Motor imagery scenarios written in the graphic language is shown in Figure 4.

An interface is required to gather the necessary information along with the events that have occurred while running the experiment. Its operation is presented below through the visualization presented to the respondents in Figure 5.

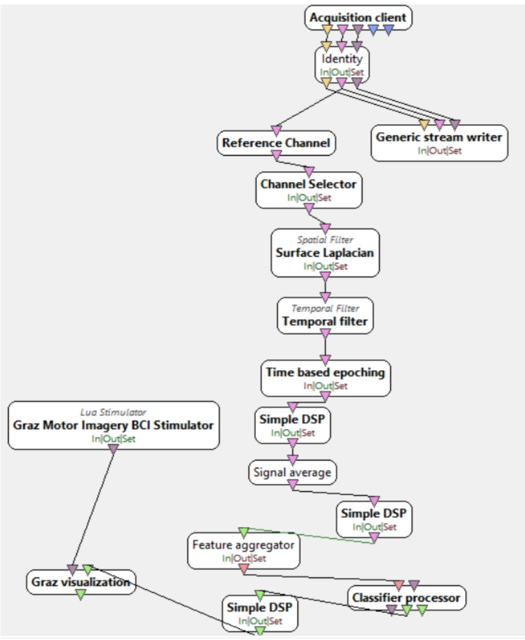

Figure 4: Motor imagery – online.

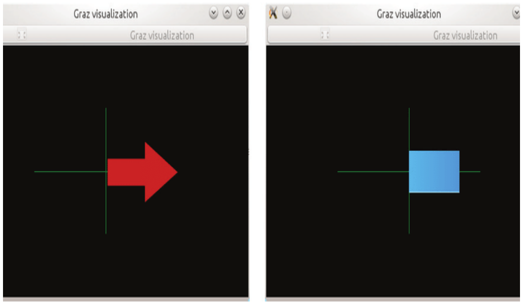

Figure 5: Motor imagery scenario in OpenViBE.

5. Results

During the experiment described in point 3, each of the tested algorithms went through the stages of learning and testing twice. Its parameters were recorded at each stage. This was for the paradigm of imagining the movement and flexing of the arms with the use of muscle activity. The data obtained during the learning of the classifier with the use of the k-fold cross-validation algorithm were extracted was recorded during each session of individual users. All results were averaged and displayed in this section.

5.1. Accuracy results

Accuracy results are the results of a trained classifier running online against guessed user intent. The task of the learned classifier was to cause an impulse in the form of an arrow in relation to the defined stimulus, which means determining the side of triggering the arrow on which the subject imagines the bending movement of his hand. At the end of the training, a matrix was obtained, its results are presented in Table one.

The obtained results for both the accuracy and the value of correct forecasts per class were favorable. High accuracy values mean the precision of the feature vectors classification and the effectiveness of the online classifier method. For the first person tested, in trial 1, who obtained the following results: 70.6% and 29.4%. This meant that 70.6% of the feature vector for Objective 1 was actually intended as Objective 1, the right hand flexion. For sample 2, which obtained the following results: 39.4% and 60.6%. This meant that 60.6% of the feature vector for Objective 2 was actually envisioned as Objective 2, the left hand flexion. For the next respondents, the obtained results are much higher, which was caused by the use of an additional training session.

Table 1: Class accuracy results by class

Person	cls vs cls [%]					
	Input 1		Input 2		Average [%]	Accuracy [%]
	1	2	1	2		
1	70,6	29,4	39,4	60,6	65,61	50
2	77,6	22,4	24,9	75,1	76,33	85
3	80,4	19,6	14,7	85,3	82,86	75

Performance results

Based on the k-fold cross-validation, an analysis of the LDA classifier performance was developed. The results of learning the LDA classifier using k-fold cross-validation against the training algorithm, in which the subjects used the motor image paradigm, are presented in Table two. The value of k is 7 according to the assumptions of k-fold cross-validation where k is the number of patterns of the data set that they are learning.

Table 2: Results of k-fold cross-validation

Person	k-fold cross validation [%]								Sigma [%]
	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Average	
1	63,92	79,64	79,64	63,21	82,14	80,35	68,21	73,87	7,76
2	70	80,35	56,42	66,78	79,28	83,57	44,28	68,67	13,20
3	95	86,78	97,5	99,28	97,5	78,57	86,42	91,58	7,17

The obtained results of seven sets show the efficiency of the training algorithm, which can be understood as the level of acquiring knowledge during the learning stage. The achieved results for the LDA classifier are very good. The mean value of the k-fold cross-validation for all interface users is greater than 60%.

The results of learning the LDA classifier with the use of k-fold cross-validation against the training algorithm, in which the subjects used their muscle activity and bent their hands alternately, are presented in Table three.

The achieved results are much worse than the previous ones, from Table 2, despite the fact that the obtained data came from the same users and the same classification procedure was used. The mean k-fold cross-validation for two interface users is greater than 40%. The reason for such poor results is that it was user training, consisting in the actual bend of the hand, and above all, it was the first approach of the respondents with BCI.

Table 3: Results of k-fold cross-validation

	k-fold cross-validation [%]								
Person	Stage 1	Stage 2	Stage 3	Stage 4	Stage 5	Stage 6	Stage 7	Average	Sigma [%]
2	50,71	37,85	34,28	35,35	68,21	17,14	42,14	40,81	14,59
3	44,28	63,57	47,5	52,85	48,92	72,5	52,85	54,64	9,22

6. Conclusions

At the beginning of the article it was mentioned that the aim of the experiment was to analyze the use of brain-computer interfaces in everyday life. As a result of the process of analyzing the results obtained during the research, it was found that each subsequent experiment allowed for obtaining more favorable results than the previous one. The reason for this was the use of an additional training session for subsequent test persons, as well as the use of new cosmetics to prepare the head surface for examination. The results for the first test person may be burdened with technical and physiological artifacts. They result from the subject's thick hair, so that the electrodes may not be connected precisely during the test. Nevertheless, the results obtained during the classifier learning process and the main study with the use of the motor imagination paradigm were satisfactory for all the subjects.

The collected data allowed to state that the LDA classifier is very effective and equivalent to the feature vectors on which it carries out the classification process. The LDA classifier perfectly guessed the users' intentions, which were based on the motion image paradigm, which in effect contributed to the display of arrows on the monitor according to the image of hand movement. This means the effective learning of the classifier and the correctness of the data obtained during the EEG test. Thus, the designed brain-computer interface successfully accomplished its task.

Currently, BCI systems are no longer perceived as advanced projects implemented only in a scientific laboratory, but are gaining importance as opportunities to improve the quality of human life. The main aspect is improving the performance of the central nervous system in people suffering from neurological diseases. However, the implementation of BCI systems for use is associated with some challenges, such as: numerous training sessions, observation of feedback, the presence of a trained person during the test, access to research equipment and appropriate cosmetics to prepare for the test. Research on BCI technology gives hope for promising innovations that will surely have a huge impact on all of us.

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