Brain-Computer Interface System Based on Electroencephalography

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***Abstract*— The article describes the approach to the design of brain-computer interface system based on electroencephalography that was implemented during students' research work at the Department of Computer Systems and Networks of Bauman Moscow State Technical University. The system is based on P300 technique; signals are classified by artificial neural network. The hardware and software structure of the interface system is shown. The results of students' projects based on the brain-computer interface system are presented. Prospects of the project's further development are pointed out.**

Keywords*— *brain-computer interface; electroencephalography; neural network; P300 technique

I. Introduction

The brain-computer interface (BCI) systems represent one of the promising areas in modern science. They are intended not only to simplify interaction between human and computer, but also to make this interaction possible for disabled people whose diseases forbid the usage of common manipulators like keyboards, mice, and touchscreens.

Presently there are two main research directions in this area: invasive interface systems that involve implanted electrodes and technical devices for duplex information exchange with human neural system, and non-invasive ones that capture external manifestations of brain activity ([1]). The first way is hard to design and implement due to the need for surgical interventions, and it is also limited by ethical issues. The non-invasive approach is devoid of these shortcomings, but it provides satisfactory resolution for many practical purposes. This approach became the basis of the BCI system described in this article.

The BCI system based on electroencephalography (BCIS hereinafter) has been designed by the students of the Department of Computer Systems and Network of Bauman Moscow State Technical University with applying the electroencephalograph by Bruk IECM (Institute of Electronic Control Machines) in accordance with improved educational program [2, 3, 4]. The BCIS became the core for a variety of students' Internet of Things projects developed during thematic hackathon [5, 6]. This article gives main principles of BCIS and the results of its learning and usage.

II. The P300 Technique

Electroencephalography is a non-invasive method of brain activity exploration based on registration of bioelectric activity. It provides millisecond time resolution that allows capturing instantly the induced potentials that are reflections of human's cognitive activities and reactions to external stimuli. There are visual, auditory, somatosensory, event- (including cognitive) and motor-related induced potentials. The event-related potentials are exploited by the P300 technique ([7]).

P300 is an event-related potential induced during the decision making process. This component appears as a reaction to an unexpected and rarely (e.g., with probability rate 0,2) presented stimulus when it emerges amidst frequently presented insignificant stimuli ([8]). According to [1], the P300 potential appears approximately in 300 milliseconds after appearance of significant stimulus; its duration amounts to 300-400 msec, its amplitude makes up to 5–15 uV and grows with the decrease of target image's presentation probability. The parameters of the stimulus do not matter, for P300's features depend only on the subject's mental focus.

The basic experiment for P300's detection involves the so-called oddball-paradigm ([1]). The subject is presented with target and non-target significant stimuli, and the target stimuli make up a small share in the whole amount. The retrieved electroencephalogram is divided into periods from the moment of presentation of target stimulus. The data within these time intervals is added up, and the induced potentials are being identified. Amongst them the P300 wave emerges with latency about 300 msec (Fig. 1).

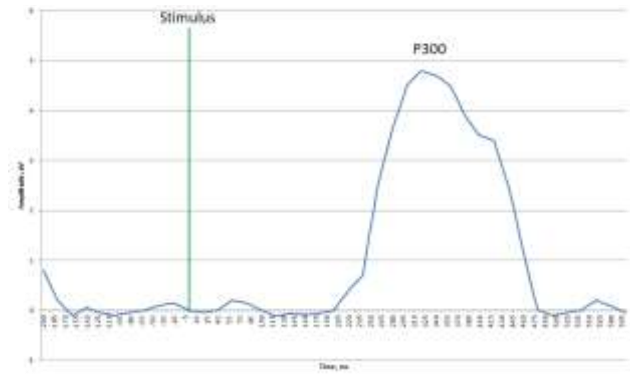

Fig. 1. The P300 induced potential

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Originally the P300 technique was actively used in medical practice for detection and measurement of dementia, cognitive impairments, and also for examination of medications' spillover effects, psychological testing and professional selection. With the development of BCI concept the technique became widely spread in this area. There is a variety of interface systems for disabled people based on the P300 method, and also prospective projects by Facebook, Neurable and other IT corporations.

III. IECM Electroencephalograph

The electroencephalograph designed by Bruk IECM is a multichannel recording device with eight identical amplifying-recording blocks that allow simultaneous capturing of electrical activity from corresponding number of dry electrode pairs. The electrodes' signals is transformed into digital representation and captured by means of STM32 microcontroller.

The data is captured continuously and transmitted according to MODICON MODIBUS RTU protocol implemented on physical interface lines RS232 via FTDI chip that translates RS232 packets to USB format. The appearance of the device is shown in the Fig. 2.

IV. The BCIS's Structure

The BCIS's block diagram is represented in the Fig. 3.

In addition to the encephalograph, the BCIS's hardware also includes a Raspberry Pi microcomputer that performs real-time processing of captured signals. The processing consists of the primal preprocessing (filtration and normalization), recognition, and fetching the proper instruction according to identified user reaction. Hardware features of Raspberry Pi allow carrying out such processing without large latencies; on the other hand, the device's size makes it possible to design a portable BCI system.

Apart from making up the control action for the terminal device, the recognized signal is used for statistics collection and data analysis. For these purposes, the IBM Cloud services are applied.

Fig. 2. The BCIS based on IECM's electroencephalograph

The IBM Cloud platform provides a wide variety of tools for quick prototyping and deployment of web-applications in a cloud server [9]. Regarding BCIS, the data collection services and analytical tools are applicable. The analytical tools are needed for data consolidation and finding different patterns. Also the visualization services are used for data representation as diagrams.

The computational core of the BCIS is represented by a classifier capable of identifying the P300 wave in common signal flow. Applying the deterministic algorithms as a classifier does not promise acceptable results due to considerable variation of input data's amplitude and pulse shapes. Also the encephalogram is prone to noises and distortions of both electrical and physiological nature. For these reasons it was decided to apply a trainable artificial neural network for P300 identification. Not only does this approach allow solving the problem of input data variability, but also makes the BCIS an agile interface system capable to be adjusted for certain user.

The schema of artificial neural network applied in the BCIS is represented in the Fig. 4.

The network has a fully connected structure. The input and output layers' neurons have a linear activation function; they are labeled as L on the scheme. The inner layers' neurons have sigmoid (logistic) activation function; these ones are labeled as S.

Since only 3 of 8 encephalograph's channels were used in the experiments, each one transmitting 64 bytes of data, each packet includes 192 bytes. The number of input neurons corresponds to this count.

Generally, a classifying artificial neural network has as many output neurons as it can recognize classes. For P300 identification only one output neuron is required; its activation means the P300 component detection.

The number of neural network's hidden layers and the number of neurons in each of them is usually determined experimentally. With increase of neurons' count the computing time and load grow4; on the other hand, it was experimentally found that two hidden layers sufficed for satisfactory P300 recognition.

The number of neurons in hidden layers was calculated by heuristic formulae (1) – (3).

$$r = \sqrt[3]{\frac{i}{o}} \tag{1}$$

$$k_1 = \lceil o \cdot r^2 \rceil \tag{2}$$

$$k_2 = \lceil o \cdot r \rceil \tag{3}$$

In formulae (1) – (3): i – number of neurons in input layer; o – number of neurons in output layer; k_i – number of neurons in i^{th} hidden layers, r – characteristic coefficient.

Thus, the first hidden layer contains of 34 neurons, the second one – of 6 neurons.

The training of neural network is carried out according to oddball-paradigm. The subject is asked to mentally mark the target image amongst presented ones. With every new image weights in neural network's hidden layers are corrected according to the back propagation algorithm.

As soon as the difference between real and expected parameters reaches acceptable values the training is over.

According to the aforesaid decisions the prototype of BCIS was created and used by students during thematical hackathon. Teams of developers were to train a neural network on their own and to try to use the BCIS for P300 identification. Their results are considered in the next section.

V. Outcome of Experiments

The practical tests for BCIS were held as a contest of students' projects based on the developed prototype. The teams offered and developed their own ideas of BCIS usage; there can be followed several trends:

- The recognition of physiological and emotional state of human.
- Capture and processing of meaningful motor signals emitted by brain.
- Remote control.
- Measuring subject's focus degree.

In the Table 1 the most successful teams' results are presented. These participants managed to carry out neural network training and trial operation of their projects.

TABLE I. Results of Neural Networks Training

Periods of training	**Number of subjects**	**Normalization**	**Number of target images, order**	**Recognition accuracy**
20	1	Yes	1000	40%
50	4	Yes	10	80%
10	1	No	10	38%
30	1	Yes	1	73%
10	1	Yes	10	67%

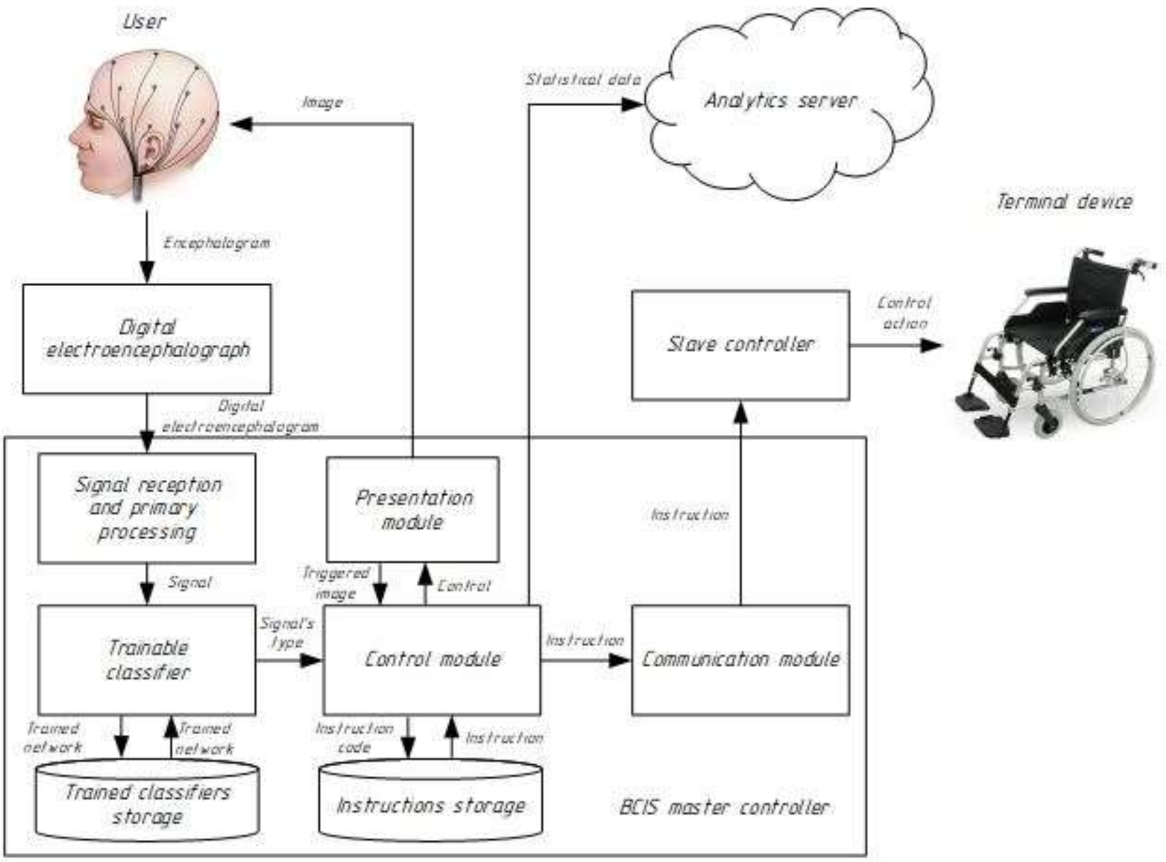

Fig. 3. BCIS's Block Diagram

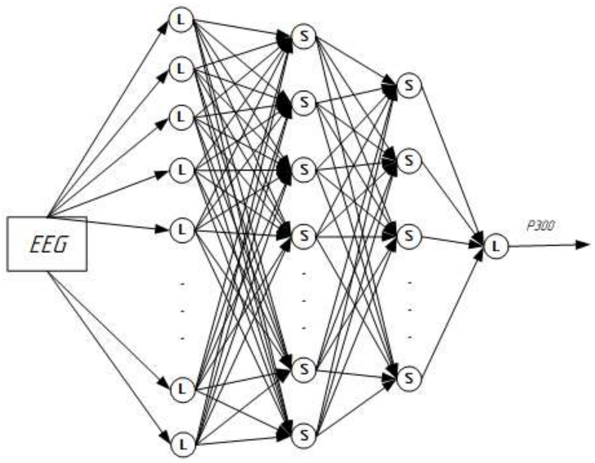

Fig. 4. Artificial Neural Network Scheme

It can be seen that the results are generally better with more periods of training (overfitting was not reached by any of participants). But it is not the only factor affecting the classifier's accuracy. E.g., the team that used four subjects for training instead of one had managed to reach an average accuracy more than 80%.

It must also be noted that without data normalization the accuracy falls dramatically. The absence of normalization negatively affects the neural network's operation quality: instead of mapping from [-1; 1] to [0;1] the network is forced to map wide ranged numbers, so the accuracy drops.

Strong impact on the accuracy is caused by number of target images. The team that used only 3 images managed to achieve rather high accuracy while using only one subject.

Thus, most of the teams succeeded in inventing an idea of BCIS's practical usage, develop a concept, adjust the system for their needs, train the neural network and hold several experiments. The contest's results showed that BCIS has a plenty of potential usage areas and that it can be also successfully implemented.

VI. The Conclusion and Further Prospects

The total outcome of the work was rational principles of BCIS's design, and also a working prototype based on these principles.

The experiments have shown that proper training of neural network for BCIS is a laborious task and requires a large set of training examples. Nevertheless, the students managed to get the signals recognized more or less and to present the results of their projects.

The width of the scope of proposed ideas demonstrates large prospects for BCIS's application in different areas, from medicine to social networks.

Among the further directions of this project's development is improvement of P300 identification accuracy, including following modifications:

- Improving quality of income signals by filtering artifacts like electromagnetic noises, electrodes displacement, muscle tension, movements, blinking etc.
- Improvement of normalization method.
- Shrinking the time interval for capturing P300.
- Experimental determination of optimal frequency of target image presenting.
- Alteration of number and structure of neural network's inner layers, neurons' types, connectivity, algorithm and training method.
- Adaptive regulation of classification criteria.
- Exploration of other algorithms for classifying signals.

References

[1] A.A. Frolov, V.Ju. Roschin. "Brain-computer interface. Reality and future," №16, Neural Networks, 2017.

[2] Shakhnov V.A., Zinchenko L.A., Rezchikova E.V., Verstov V.A. Distinctions of a learning content for education in the field of nanotechnology. International Journal of Nanotechnology, 2017, Vol. 14, Issue 7-8, pp. 690-697.

[3] Vlasov A.I., Yudin A.V., Salmina M.A., Shakhnov V.A., Usov K.A. Design Methods of Teaching the Development of Internet of Things Components with Considering Predictive Maintenance on the Basis of Mechatronic Devices. International Journal of Applied Engineering Research, 2017, Vol. 12, Issue 20, pp. 9390-9396.

[4] Titov I., Smirnova E. Network architectures of remote laboratories proposal of a new solution and comparative analysis with existing one. International Journal of Online Engineering, 2013, Vol. 9, Issue 6, pp. 41-44.

[5] Titov I., Glotov A.N., Andrey Y., Petrov V. Standartization use case of solid-state laser lab and RF & Microwave Amplifier Remote and virtual laboratories at Labicom, International Journal of Online Engineering, 2016, Vol. 12, Issue 9, pp. 47-51.

[6] Titov I., Glotov A., Vlasov I., Mikolnikov J. Labicom labs 2015: Remote laser virtual and remote lab, global navigation satellite systems virtual and remote lab, microwave amplifier remote lab. International Journal of Online Engineering, 2016, Vol. 12, Issue 4, pp.17-19.

[7] S.J. Luck, "Introduction to the Event-Related Potential Technique," Massachussetts Institute of Technology, 2005.

[8] Sutton S., Braren M., Zubin J., John E. R. Evoked correlates of stimulus uncertainty. Science 1965;150:1187–1188.

[9] Popov A., Belov S., Sorokin A. Cloud Based IT Learning Infrastructure to Support New Generation of Services. Programmnaya Ingeneria, 2018, Vol. 9, No 6, pp. 281–286.