



Hardware-Software Complex of the Mobile Brain-Computer Interface for Technical Means of Rehabilitation

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Abstract—Brain-computer interfaces, which are systems for the exchange of information between the brain and an electronic device, are the subject of unabated scientific interest in many laboratories in the world. Today, the practical application of brain-computer interfaces is found mainly in the field of rehabilitation. Research conducted in the 1970s at the University of California at Los Angeles showed the fundamental possibility of restoring the damaged functions of hearing and vision, as well as lost motor skills due to biological feedback. In this paper, the hardware-software complex of a mobile sensorimotor brain-computer interface based on electroencephalography for controlling modern technical means of rehabilitation is considered. Software implementation of the technology of localization of sources of electrical activity of the brain allows designing a device with the number and location of electrodes that is optimal for a particular patient according to the signal to noise ratio. The basis of the device is a wearable platform for enhancing biopotentials, providing mobility and ease of use in combination with technical means of rehabilitation.

Keywords— *brain-computer interface, EEG, rehabilitation, cyber-physical systems*

I. INTRODUCTION

According to a World Health Organization study, more than 100 million people are suffering severe forms of diseases of the nervous system, disorders of sensory functions, vegetative states [1]. The task of rehabilitation is the restoration of physical, psychological and social functions, as well as improving the quality of life of patients. Studies conducted in Russia [2, 10, 11, 12] and abroad [3, 7, 9, 13] showed that the brain-computer interface (BCI) can improve the results of rehabilitation processes through the formation of links between intact brain regions and auxiliary devices that are able to compensate for missing or damaged motor or sensory functions [2]. At the same time, the effect of a BCI is not only in assisting the movement, but also in facilitating the restoration of damaged functions due to the mechanisms of neuronal plasticity [5, 6, 13].

In the face of the challenges of the fourth technological revolution, involving the massive introduction of cyber-

physical systems, the tasks of creating and improving BCIs are relevant and practically significant. However, the creation of an effective BCI is a complex problem, requiring the selection of appropriate methods for recording neuronal activity, digital signal processing in order to get rid of noises and artifacts of various nature, feature extraction and selection, classification and finally conversion of the resulting data into a useful signal, readable by technical means of rehabilitation. Furthermore, the medical BCI must meet stringent requirements for all the methods used. In this paper, authors propose their views and technical decisions for this problem.

In the following sections the structural diagram and technical requirements for the medical BCI are considered, the hardware platform and the software complex for EEG processing satisfying these requirements are described. The results are presented in Results and Discussion section.

II. GENERAL TECHNICAL REQUIREMENTS AND POSSIBLE STRUCTURAL DIAGRAM FOR MEDICAL BCI

Unlike BCIs developed in laboratories for research purposes, medical devices must meet a number of special requirements. Among them are the following demands:

- Ability to work both "offline" and in real time.
- Independence of blocks and components. This requirement assumes that each of the blocks can be replaced by a block that performs the same functions in a different way, without the need to replace the other blocks. For this purpose, standard inter-unit communication protocols should be used.
- Scalability. The BCI design should not impose restrictions on the number of channels for receiving information, the sampling rate, the number of system parameters or event markers.
- Satisfactory weight and size parameters, device mobility.

- High information transfer rate (ITR).

To meet these requirements, taking into account the stochastic nature of the EEG, which can change not only from patient to patient, but also within one patient during different recording sessions, the configuration of the BCI for a specific patient was chosen, deliberately sacrificing generalization of the device in favor of its accuracy and speed.

At the stage of the configuration, a personal computer (PC) with an electroencephalograph connected to it with the maximum possible number of electrodes is used. The code of program blocks for a PC is written in the *Python* programming language, which is currently the main language for implementing machine learning and data processing algorithms. For data processing, *scikit-learn*, *NumPy* and *SciPy* libraries were used, as well as a specialized *MNE* library for processing and visualizing biopotentials [19].

After recording the encephalograph signals and files containing system parameters and event markers, the received signals are subjected to filtering and artifact removal, feature extraction and classification in accordance with the task of restoring motor functions. After the implementation of algorithms for localization of sources of neuronal activity, the selection of meaningful channels for a particular patient is carried out and the BCI is assembled on the basis of a specially designed wearable high-resolution platform with the optimal number of channels. For programming the platform, the *C* language is used, the method of low-voltage loop programming of microcontrollers according to the *IEEE Std 1149.1* standard with the possibility of debugging *JTAG* (Joint Test Action Group)/*SWD* (serial wire debugging).

The following modules (Fig. 1) can represent the structure of the developed BCI.

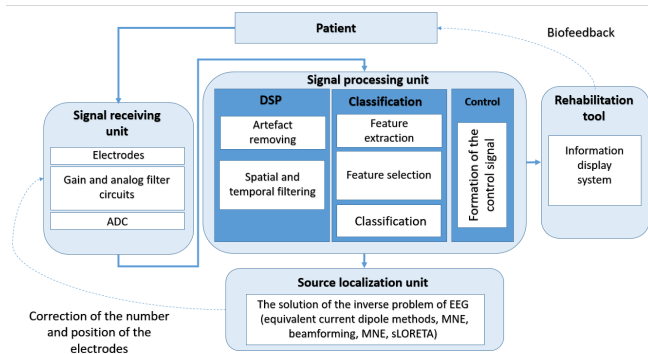


Fig. 1. Mobile BCI structural diagram

The signal receiving unit implements recording, amplification, analog filtering, analog-to-digital conversion, as well as the storage of EEG signal files together with specialized files of system parameters and event markers. It also monitors the quality of the contact of the electrodes with the scalp and the quality of the received signal.

The of source localization unit allows solving the inverse problem of EEG and determining the location of sources of neuronal activity. According to data coming from the unit, fine configuration of the BCI is carried out. As a result of finding the localization of sources of neuronal activity, it is possible to reduce the number of electrodes and correct their location, which is necessary for the operation of the motor

BCI for individual patient, and makes it possible to improve the accuracy and usability of the BCI, as well as reduce its weight and size parameters.

The signal processing unit includes software blocks that implement digital signal processing (DSP) and the classification of the received signals, on the basis of which a control signal is generated that arrives at a rehabilitation tool. If possible and appropriate, a rehabilitation tool is better to provide with a display system for the formation of sensory feedback.

III. HARDWARE COMPLEX OF THE MOBILE BCI

The wearable platform for mobile BCI is based on a specialized high-performance microprocessor core, a number of amplifiers and analog filters, a 16-bit multichannel ADC module, high-speed data interfaces, and a convenient user interface with the ability to control, record and output information. The operating frequency of the newest STM32 microcontroller on the *Cortex M7* core is 216 MHz. The sampling frequency of the signal is 1024 Hz, which will avoid aliasing when high-frequency interference occurs, and also allow to use the platform for recording of the electrical activity of the muscles and eyes, the signals of which lie in areas of higher frequencies than the EEG.

The signal of each channel is recorded using two electrodes. The third channel electrode is used as a common-mode input [15]. The signal from a pair of electrodes is fed to the radio frequency filter, then to the input of the protection circuit, and then to the instrumentation amplifier INA128P, which amplifies the differential signal approximately 13 times (Fig. 2).

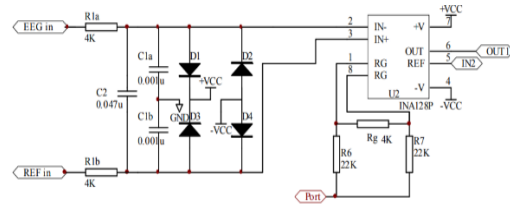


Fig. 2. Radio frequency filter, protection circuit, and the instrumentation amplifier

Next, the signal is passed through a high-pass filter with a cut-off frequency of 0.5 Hz (Fig. 3, a) and amplified approximately 50 times by the main amplifier. This is followed by a bandpass filter consisting of high- and low-pass filters, acting as an anti-aliasing filter and preventing the baseline signal from drifting (Fig. 3, b). Finally, a matching amplifier with an adjustable gain allows to coordinate among the analog input and the ADC, because different ADCs have different gains (Fig. 3, c). The presence of a matching amplifier is a prerequisite for the implementation of the above-described requirements for the independence of units and components. In addition, it is known that different people have different levels of the EEG signal, and the matching amplifier is able to adjust the amplitude range in case of a too weak signal. The gain is adjusted using the potentiometer VR1.

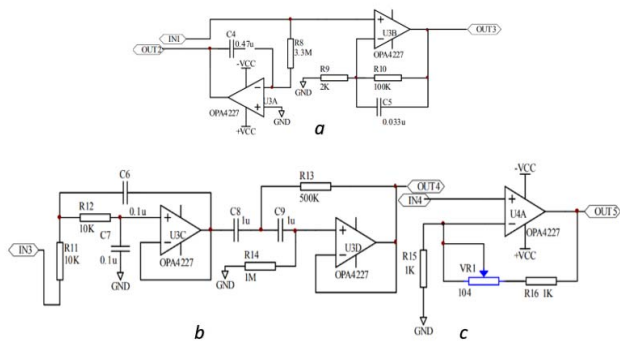


Fig. 3. High-pass filter and main amplifier (a), bandpass filter (b), and matching amplifier (c)

The common-mode signal circuit is represented by two OPA2227 operational amplifiers, which carry out inverting at the common-mode input in order to suppress, through feedback, the possible interference of the useful signal (Fig. 4).

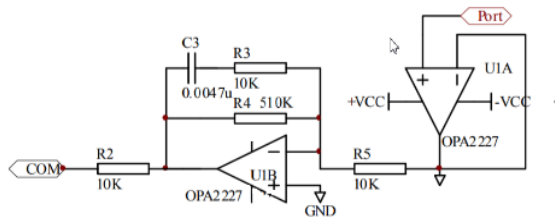


Fig. 4. Common-mode signal circuit

It was decided to abandon the hardware network interference filtering, implementing it in software, which also contributes to reducing the mass of the device.

IV. SOFTWARE COMPLEX OF THE MOBILE BCI

For the initial testing of the proposed concepts, the publicly accessible EEG Motor Movement/Imagery Dataset database was used, available at <https://physionet.org> [15]. Three experiments were chosen in which the subject, simultaneously with the appearance of a visual stimulator in the appropriate place of the screen, imagined the clenching of both fists (T1 mark), and then the fingers of both legs (T2 mark), alternating periods of movement imagination with relaxation (T0 mark).

A. Filtering and artifact removal

A 1-30 Hz bandpass filter with a finite impulse response (FIR) was applied to the database. Such filters have a linear phase response in the passband, which ensures the same group delay at different frequencies [20].

Two groups of methods are usually used to remove physiological artifacts:

- Recalculation of the values of the EEG signal relative to the new reference potential (Fig. 5).
- Methods based on the linear decomposition of the EEG signal into its components, the selection of the artifact and the restoration of the EEG without the artifact component. Methods of this type include principal component

analysis (PCA) and Independent Component Analysis (ICA).

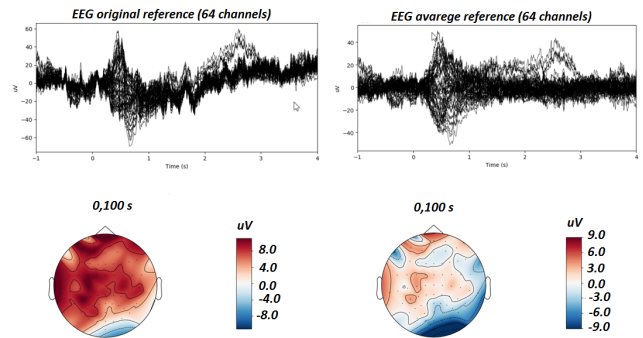


Fig. 5. Original and average reference of EEG signal

Software complex allows to implement both groups of methods. Recalculation of the values of EEG signals relative to the total average referent proved to be the simplest, i.e. providing minimal computational cost, although the ICA method (Fig. 6) in general allows more accurate artifact removal. In this study the ICA method was used.

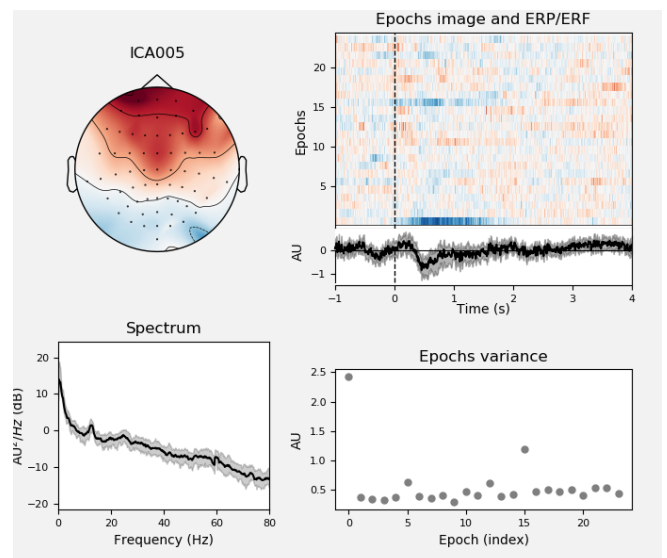
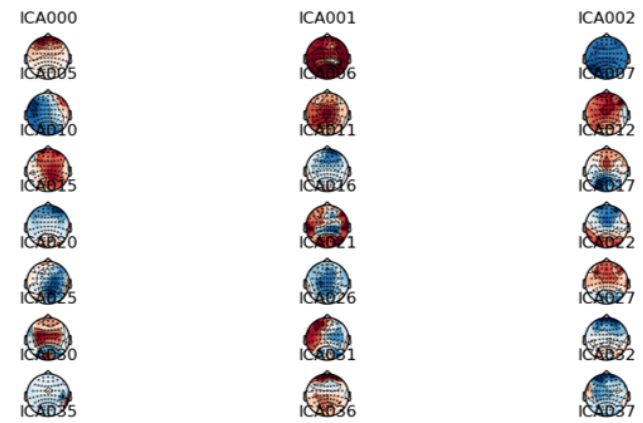


Fig. 6. ICA components of the signal and the EOG artifact (its topomap, spectrum and variance)

B. Feature extraction

Feature extraction was carried out using the common spatial pattern (CSP), which implements a signal decomposition method based on precedent training. Namely, each of the multichannel EEG records is assigned to one of two classes with labels 1 and 2. The initial signal X is decomposed into such components for which the following conditions are fulfilled [23]:

- the first k components of the decomposition have the maximum variance if X belongs to the class labeled “1”, and the minimum variance if X belongs to the class labeled “2”;
- the last k components of the decomposition have the maximum variance if X belongs to the class with the label “2”, and the minimum variance if X belongs to the class with the label “1”.

As a result, a signal decomposition matrix is formed.

As a result of applying the method, the maximum dispersion values for the decomposed signal will be observed in the first n channels, therefore, the remaining channels can be ignored. To solve the problems of EEG classification, it is customary to use the value $n = 3$ [24].

From Fig. 7, which represents the results of applying a common spatial filter, it can be seen that the features are linearly separable. Thus, the linear classifier is optimal from the point of view of accuracy and machine time. In addition, the method used does not require a large number of training samples to obtain reliable results [17, 18, 25].

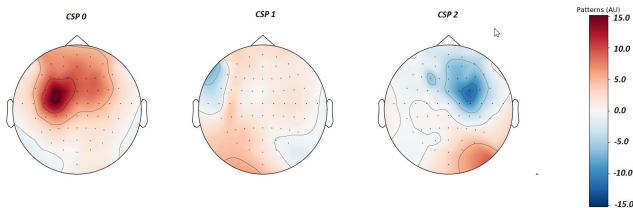


Fig. 7. Topomaps of first 3 CSP components of the signal

C. Classification

Among different classifiers used for BCI Linear Discriminant Analysis (LDA) was preferred due to its simplicity for the binary classification task and low computational cost.

To assess the capabilities of the selected model, a cross-validation based on the Monte Carlo method was used. The average accuracy of the algorithm was 95% for the selected patient.

The performance of classifier over time is presented on the Fig. 8.

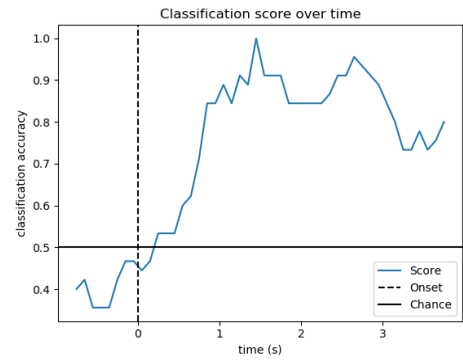


Fig. 8. Topomaps of first 3 CSP components of the signal

It can be seen that the satisfactory classification accuracy (well beyond the chance level) is reached in 1 second.

D. Localization of sources of neuronal activity

It is known that the EEG taken from the scalp is a superposition of potentials from a variety of sources located in the inner regions of the human brain. Among the most accurate methods of localization of these sources, i.e. EEG inverse problem solutions, the most widely used methods are MNE, beamforming, dSPD and sLORETA. However, it should be noted that the exact localization of sources of brain activity is a complex problem that often requires a large amount of additional research, such as CT and MRI of the brain, MEG, etc.

A simpler method for localizations of sources of neuronal activity is the use of an analysis of independent components in conjunction with the method of equivalent current dipoles. The essence of the method is that the original signal is decomposed into M maximally independent components, the number of which is equal to the number of electrodes. For greater accuracy of the method, the analysis of independent components is performed by three different methods: FastICA, Infomax and Extended Infomax. Components whose degree of difference from method to method exceeds the specified threshold are discarded. Components that stand out in all three methods are then represented as equivalent current dipoles [27].

The first ten components of the signal, composed of epochs corresponding to the movement of the feet, are shown in Fig. 9. Components, the degree of dispersion of which is acceptable for further analysis, are selected visually (highlighted in yellow), although later a search for the optimal algorithm for selecting significant components is planned.

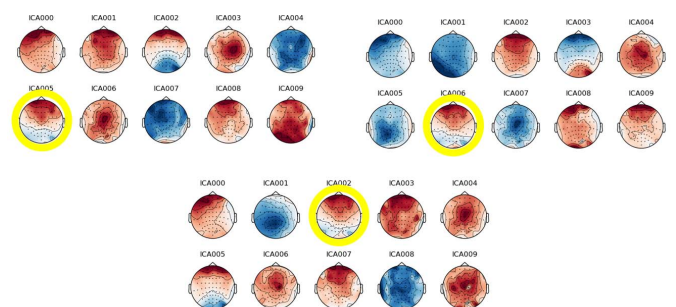


Fig. 9. Independent components, selected for the localization search

As a head model, the boundary element model (BEM) is used. This method allows to solve the direct problem of EEG in the assumption of constant conductivity within each of the three distinguished layers, which include the skin, skull and cerebral cortex. The chosen model as a whole is more accurate than spherical, despite the fact that it is numerical, while the spherical model is analytical.

For the selected component, marked in Fig. 9 and representing the symmetric activity of the right and left lobes, a model consisting of two dipole sources was chosen, the localization and direction of which are shown in Fig. 10.

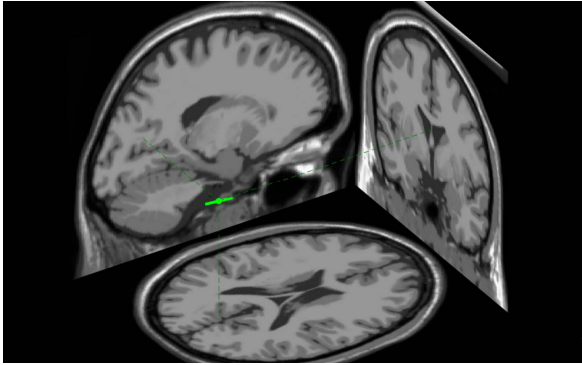


Fig. 10. Localization of the equivalent current dipole for one of the independent components

At this stage, the configuration of the BCI ends. Based on the calculations performed, the required number of electrodes is selected, the parameters of the calculated models are transferred to the wearable platform based on the embedded system.

V. RESULTS AND DISCUSSION

To verify the correctness of the calculations, as well as the quality of the BCI, a continuous supply of signals from the database using a specialized real-time data flow simulator *MNE Real-time server* was implemented.

A microcontroller device based on the *Atmega 328P-PU*, equipped with display devices (Fig. 11), was connected to the PC COM port.

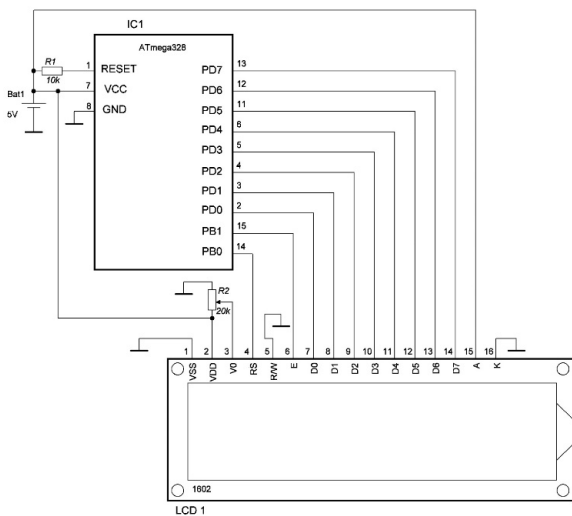


Fig. 11. Microcontroller device for modeling of the rehabilitation tool

The linear classifier, working in the “online” mode, distinguished epochs corresponding to the movement with arms and legs and transmitted appropriate command to the COM port of the PC. The command is read by the microcontroller device, which, in accordance with the program, controlled the display facilities. Normalized confusion matrix for signals issued by microcontroller device is shown in Fig. 12.

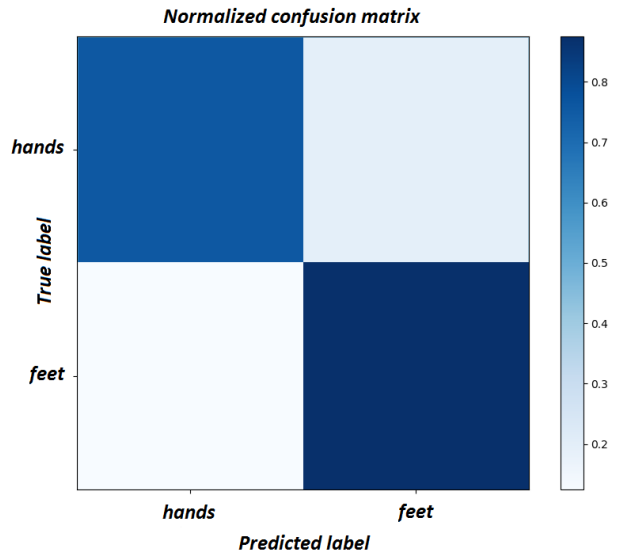


Fig. 12. Normalized confusion matrix for signals issued by microcontroller device

According to the results of the experiment, it was concluded that the correct operation of the program blocks and the classifier is satisfactory for the tasks of designing an BCI for managing modern technical means of rehabilitation.

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