CENTRAL ASIAN JOURNAL OF MATHEMATICAL THEORY AND COMPUTER SCIENCES
https://cajmtcs.centralasianstudies.org/index.php/CAJMTCS
Volume: 06 Issue: 02 | April 2025 ISSN: 2660-5309

Article

Brain-Computer Interface and Neurointerface Technologies for Control with Robotic Devices

Duhaidahawi Murtadha Ahmed Luti*[1], Dheyab Salman Ibrahim[2], Tomashevsky Yuliy Boleslavovich[3]

1. Postgraduate, Saratov State Technical University named after Gagarin Yu.A
2. Professor of Operations Research Diyala University
3. Professor of Technical Sciences, Saratov State Technical University named after Yu.A.

* Correspondence: murtazalute7@gmail.com

Abstract: The object of the study is the neural interfaces that control ro- botic devices using signals of brain origin recorded by electroencephalography. The subject of the study is the methods and algorithms for recognizing EEG patterns corresponding to the image of an imaginary motor team subject. The aim of the work is to develop a software and hardware complex for controlling robotic mechanisms, which allows to recognize EEG patterns of motor activity and adapt to a specific operator. Materials and methods.To solve the tasks in the work, methods of processing time series and creating artificial neural networks were used. Results. A device is proposed that is implemented on the platform of an analog-to-digital recorder such as Arduino uno. The device allows you to recognize EEG signals of brain activity and generate signals for controlling robotic mechanisms such as bionic prostheses, robotic wheelchairs, exoskeletons. Conclusions. Using the proposed device will allow people suffering from serious disorders of the motor system to improve their quality of life.

Keywords: Robotic Mechanisms, Electroencephalogram (EEG) Pattern Recognition, Brain Rhythms, Artificial Neural Networks, Neurointerface

Citation: Luti, D. M. A., Ibrahim, D. S., Boleslavovich, T. Y. Brain-Computer Interface and Neurointerface Technologies for Control with Robotic Devices. Central Asian Journal of Mathematical Theory and Computer Sciences 2025, 6(2), 219-224.

Received: 12th Mar 2025
Revised: 15th Mar 2025
Accepted: 18st Mar 2025
Published: 25th Mar 2025

1. Introduction

The last decade of the twentieth century has signified by the rapid development of information technologies, which provide high-speed computers with large memory. Advances in digital signal processing, statistical analysis and promoted theoretical knowledge of neural networks have opened the prospect of practical implementation of various kinds of neural interfaces [1]. The neurointerface or brain-computer Interface (BCI) has found its application in various fields: neurological treatment, neurological training, neurological rehabilitation, etc., [2], [3]. For instance, there are many developments and open data in neurological rehabilitation that provide a system for controlling a computer or connected devices with brain-derived signals. Currently, the BCI is becoming a popular device widely used in modern robotics [4], [5], which allows a person to influence the environment with the effort of thought through decoding mental commands from signals in the electroencephalogram (EEG) or other methods of recording brain activity [6], [7]. Most of the work on the modern BCI aimed to improve the quality of life of people suffering from serious disorders of the motor system. Extensive work is underway to integrate BCI into robotic wheelchairs, robotic prostheses, and exoskeletons. However, BCI can be also used by healthy people in such areas as controlling robotic devices such unmanned aerial vehicles, virtual reality games and simulators [8].

The current research intends to develop an integrated hardware and software complex designed to control robotic mechanisms. The advanced system emphases on identifying electroencephalogram (EEG) patterns associated with motor activity, which enables it to get used to to the specific needs and purposes of the operator. By leveraging real-time EEG data, the complex intends to improve the interaction between humans and robots, helping more intuitive and responsive control of robotic systems. This research grasps the prospective to improve applications in fields such as rehabilitation.

Assistive technology, and human-robot collaboration, eventually enhancing the efficiency and usability of robotic mechanisms in different settings.

2. Materials and Methods

EEG rhythm is an electrical activity type of a constant frequency, which corresponds to a particular state of the brain and links to certain cerebral mechanisms. In this regard, the amplitude and its characteristic features can be changed over time with changing the functional activity of the brain [9]. As depicted in Fig. 1, the operation and the BCI architecture can be stated as follows; if the user intends to perform-an action, the electrical activity of the corresponding brain areas increases. These signals are record, amplify, digitize, and sent as digital data to a computer, where the signal features characteristic of a particular mental desire are calculated. Further, the set of features is divided into types, and the computer generates a command that controls the executive device (computer program, wheelchair, prosthesis, etc.). The user monitors the system's response to his mental action in real time, see Figure 1.

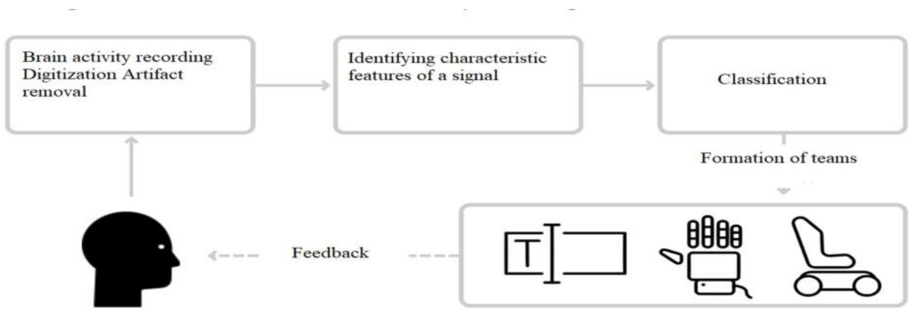

Figure 1. The architecture of the BCI.

Brain activity signals can be recorded in both invasive and non -invasive ways [10]. If bio potentials are removed from the surface of the head, then BCI is call non -invasive. When recording bio potentials from the cerebral cortex (ECoG) or from individual neurons in deep structures, BCI are known as invasive, as shown Figure 2. Despite the fact that invasive methods of BCI have greater recognition accuracy, their use strongly limited by the need for a complex surgery, as well as problems associated with the gradual overgrowth of electrodes with connective tissues. This leads over time to a significant deterioration in electrical contact with the brain, with its complete violation later. Due to these circumstances, non -invasive BCI has been the most developed. In most studies on encephalography, the EEG signal for all subjects are analyzed in classical frequency ranges borrowed from clinical practice: Gamma rhythm (γ-rhythm) is an oscillation frequency above 30 Hz, sometimes reaching 90 Hz, the amplitude usually does not exceed 15 μV. It is recorded in the precentral, frontal, temporal and parietal zones of the cerebral cortex. Alpha-rhythm-regular, sinusoidal, with a frequency of 8-13 Hz (fluctuations in 1 s) and an amplitude of 20-80 MV (microvolts). The alpha rhythm is recorded when bio potentials are diverted from all areas of the cerebral cortex, but more constantly — from the occipital and parietal regions. Alpha rhythm is recorded in a person in conditions of physical and mental rest, always with the eyes closed and the absence of external stimuli. The beta rhythm has an oscillation frequency of 1435 Hz. The amplitude is 10-30 MV. It can be registered in any area of the brain, but it more pronounced in the frontal lobes. When opening your eyes, doing mental work, and other stimuli, the alpha rhythm quickly changes to the beta rhythm.

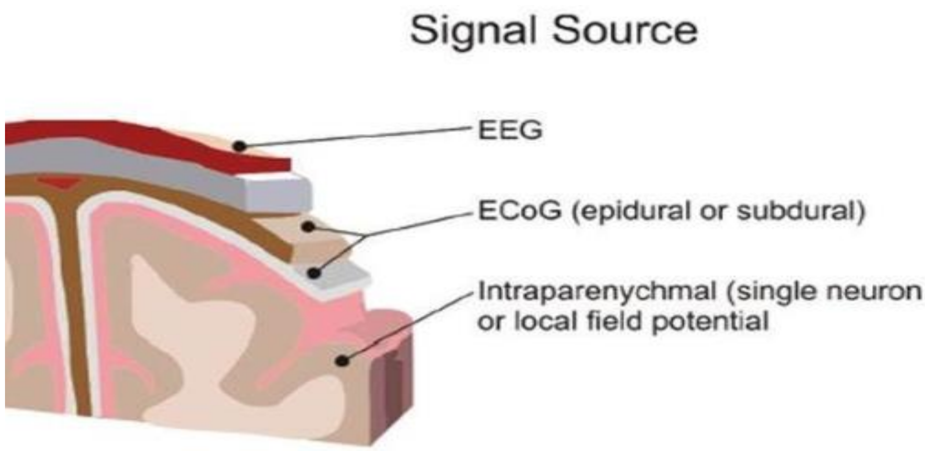

Figure 2. Invasive and non-invasive methods of recording brain activity

This phenomenon of changing is rare rhythm to a more frequent one called the activation reaction (or desynchronization). The theta rhythm has a frequency of 4-7 Hz and an amplitude of 100-150 MV. It is observing in a state of shallow sleep, with oxygen starvation of the brain, anesthesia. The delta rhythm is characterizing by slow oscillations with a frequency of 0.5-3 Hz, a high amplitude of 250- 300 MV, up to 1000 MV. This is specifically found in all areas of the brain, during deep sleep, as well as during anesthesia.

Significant images can be extracted from EEG patterns using various classifiers (linear discrimination methods, support vectors, Bayesian classifiers, artificial neural networks, etc. [11]). As a rule, several characteristic features are associated with each channel (lead) in the EEG recording. Moreover, the greater the total number of features, the more examples are required for correct training of the classifier. However, in practice, obtaining large samples of training data can be difficult. In this regard, the selection of informative features is an important operation that allows us to extract features that do not carry "noise", but information useful for a given task [12].

3. Results and Discussion

The current research has conducted investigations of brain activity by using EEG methods. When registering the EEG, "10-20%" was used – a standard system for placing electrodes on the surface of the head, which is recommended by the International Federation of Electroencephalography and Clinical Neurophysiology. According to this scheme, 21 electrodes were applied to the surface of the head as represented in Fig. 3. It was found that the main brain activity associated with major motor skills (arm and leg movement) is in the range between 7 to 30 Hz, while the signal amplitude has not exceeded 80 MV. The main disturbances were identified, which included disturbances caused by eye, electrode, and muscle movement. They were located in the region of lower frequencies - between 0.1 to 6 Hz. Therefore, it is necessary to filter the signals. It was decided to use signals from only eight active (AE1–AE8) and one passive electrode (PE), and monopolar lead was used, with the active electrodes located in the areas responsible for motor activity (central and parietal brain regions), and the passive electrode was attached to the subject's earlobe, as shown Figure 3. The electrodes are highlighted in dark color) [13]. The amount of information received from these electrodes was quite enough to recognize most significant images: turning devices on/off, controlling the cursor, the model of the car, and the prosthetic arm.

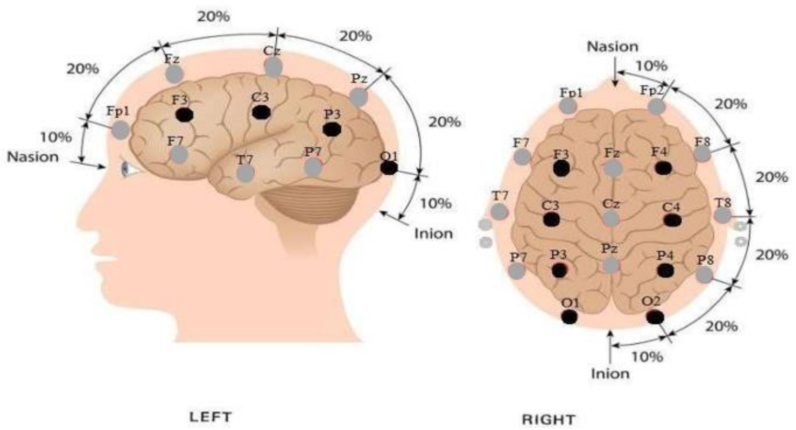

Figure 3. Electrode arrangement diagram.

The block diagram of the developed device is shown in Figure 4. The device consists of two blocks-a block for processing analog and digital signals, respectively.

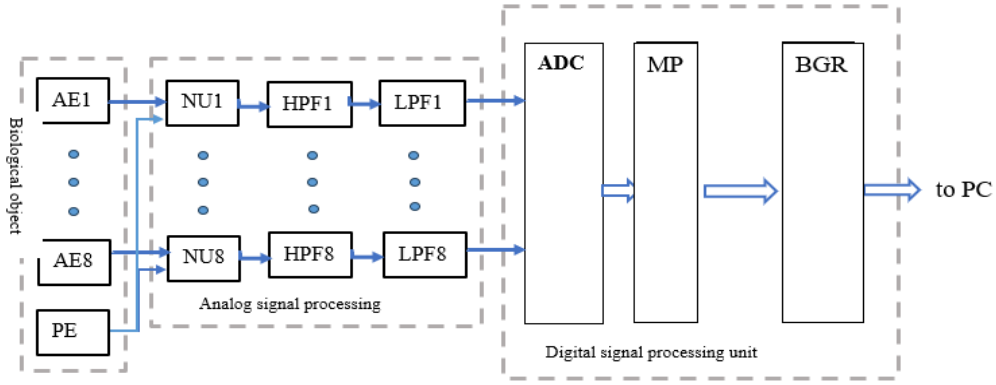

Figure 4. Block diagram of a device for monitoring brain activity parameters.

EEG signals are fed to the analog signal processing unit, where they are amplified by normalizing amplifiers (NU1–NU8), filtered using high-pass (HPF1–HPF8) and low-pass (LPF1–LPF8) filters. The normalizing amplifiers are assembled on instrumental amplifiers of the INA321 type. The filters are implemented on multichannel amplifiers of the MCP 6004 type, the passband of the filters lies in the range from 6 to 30 Hz. The output signals of the analog signal processing unit are fed to the digital signal processing unit, implemented on the basis of an analog-to-digital recorder of the Arduino type [14]. The choice of this type of recorder is dictated by the presence of nodes for controlling robotic mechanisms and the accuracy of recording analog signals up to 0.1 %, which is sufficient to solve the task of recognizing EEG signals. The main node of the logger is an 8-bit microcontroller of the AVR – ATmega328 family with a clock frequency of 16MHz. It includes everything necessary for convenient operation with the microcontroller: 14 digital inputs/outputs (6 of them can be used as PWM outputs), 6 analog inputs, which can work with both internal and external reference voltage [15]. Figure 5 shows the results of experimental data obtained using the EEG electrodes used.

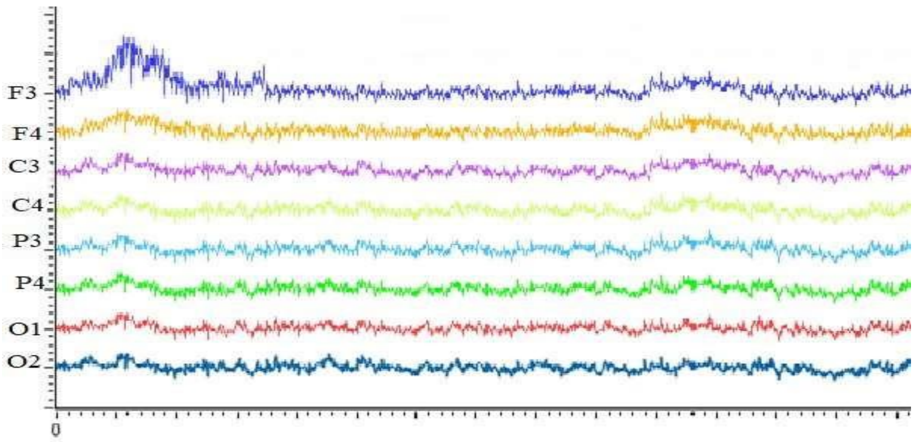

Figure 5. Experimental EEG data.

The digitized data from the recorder were fed to a laptop with specialized software (SW), installed on it, using the Korhonen artificial neural network to recognize EEG patterns. The choice of the network type is due to the fact that it is designed to search for patterns in large arrays of data, thereby allowing the classification of the user's mental commands. The sample of EEG signals was formed based on the readings of five people. For analysis, a fragment of the EEG signal recording with a duration of 30 s was selected. When forming the input of the neural network, a matrix was made up of the number of rows equal to the number of signals 8 and the number of columns equal to the number of samples in accordance with the selected sampling frequency (500 Hz) and recording time (30 s). To identify the EEG pattern, the matrix rows were divided into time segments with a duration of 2 s. Since the sampling frequency is 500 Hz, the length of each segment was 1000 elements, therefore, the total number of segments was 15. In each time segment, the presence of an EEG pattern was checked using the fast Fourier transform algorithm. The value of the maximum amplitude was compared with the threshold value, if the amplitude value exceeded the threshold, then the EEG pattern was present, and 1 was written to the new matrix of information features, otherwise - 0.

After processing all the data using a neural network, a vector of 15 values was created for each patient. The set of obtained vectors represented a training set for the neural network [16], [17]. The neural network, having trained on a set of patterns for each class of images of the user's mental commands, will be able to correctly distinguish them from each other. The BMC will perform recognition of EEG signals using a classifier trained on patterns, after which it will generate control actions for the robotic device.

4. Conclusion

The current research presented the general structure of brain-computer interfaces based on the recognition of types of movements that mentally provided to subjects. The main attention was paid to the methods of identifying the characteristic features of the EEG signal. Accordingly, the possibility of implementing neural interfaces based on an analog to digital recorder of the Arduino, widely used in robotics, were presented. Also, the use of the selected artificial neural network made it possible to recognize the EEG pattern of a user's mental command with a sufficient degree of reliability.

REFERENCES

[1] H. K. S. A. Salih, S. K. Gharghan, J. F. Mahdi, and I. J. Kadhim, "Lung Diseases Diagnosis-Based Deep Learning Methods: A Review," *Journal of Techniques*, vol. 5, no. 3, pp. 158-173, 2023.

[2] M. F. Mridha, S. C. Das, M. M. Kabir, A. A. Lima, M. R. Islam, and Y. Watanobe, "Brain-Computer Interface: Advancement and Challenges," *Sensors*, vol. 21, no. 5746, 2021.

[3] A. Mora-Cortes, N. V. Manyakov, N. Chumerin, and M. M. Van Hulle, "Language Model Applications to Spelling with Brain-Computer Interfaces," *Sensors*, vol. 14, pp. 5967–5993, 2014.

[4] R. A. Miranda, W. D. Casebeer, A. M. Hein, J. W. Judy, E. P. Krotkov, T. L. Laabs, J. E. Manzo, K. G. Pankratz, G. A. Pratt, J. C. Sanchez, D. J. Weber, T. L. Wheeler, and G. S. Ling, "DARPA-funded efforts in the development of novel brain–computer interface technologies," *J. Neurosci. Methods*, vol. 244, pp. 52–67, 2015, doi: 10.1016/j.jneumeth.2014.07.019.

[5] H. Kumano, H. Horie, T. Shidara, T. Kuboki, H. Suematsu, and M. Yasushi, "Treatment of a depressive disorder patient with EEG-driven photic stimulation," *Biofeedback Self Regul*, vol. 21, no. 4, pp. 323–334, 1996, doi: 10.1007/bf02214432.

[6] K. Belwafi, S. Gannouni, and H. Aboalsamh, "Embedded Brain Computer Interface: State-of-the-Art in Research," *Sensors*, vol. 21, p. 4293, 2021.

[7] N. Siribunyaphat and Y. Punsawad, "Brain–Computer Interface Based on Steady-State Visual Evoked Potential Using Quick-Response Code Pattern for Wheelchair Control," *Sensors*, vol. 23, p. 2069, 2023.

[8] Z. He, Z. Li, F. Yang, L. Wang, J. Li, C. Zhou, and J. Pan, "Advances in Multimodal Emotion Recognition Based on Brain–Computer Interfaces," *Brain Sci.*, vol. 10, p. 687, 2020.

[9] S. P. Singh, S. Mishra, S. Gupta, P. Padmanabhan, L. Jia, T. K. A. Colin, Y. T. Tsai, K. T. Kejia, P. Sankarapillai, A. Mohan, et al., "Functional Mapping of the Brain for Brain–Computer Interfacing: A Review," *Electronics*, vol. 12, p. 604, 2023.

[10] M. Orban, M. Elsamanty, K. Guo, S. Zhang, and H. Yang, "A Review of Brain Activity and EEG-Based Brain–Computer Interfaces for Rehabilitation Application," *Bioengineering*, vol. 9, p. 768, 2022.

[11] J. Park, J. Park, D. Shin, and Y. Choi, "A BCI Based Alerting System for Attention Recovery of UAV Operators," *Sensors*, vol. 21, p. 2447, 2021.

[12] G. Amprimo, I. Rechichi, C. Ferraris, and G. Olmo, "Measuring Brain Activation Patterns from Raw Single-Channel EEG during Exergaming: A Pilot Study," *Electronics*, vol. 12, p. 623, 2023.

[13] K. Glavas, G. Prapas, K. D. Tzimourta, N. Giannakeas, and M. G. Tsipouras, "Evaluation of the User Adaptation in a BCI Game Environment," *Appl. Sci.*, vol. 12, p. 12722, 2022.

[14] D. Chang, Y. Xiang, J. Zhao, Y. Qian, F. Li, "Exploration of Brain-Computer Interaction for Supporting Children’s Attention Training: A Multimodal Design Based on Attention Network and Gamification Design," *Int. J. Environ. Res. Public Health*, vol. 19, p. 15046, 2022.

[15] M. T. Knierim, M. G. Bleichner, and P. Reali, "A Systematic Comparison of High-End and Low-Cost EEG Amplifiers for Concealed, Around-the-Ear EEG Recordings," *Sensors*, vol. 23, p. 4559, 2023.

[16] C. G. Lim, C. P. Soh, S. S. Y. Lim, D. S. S. Fung, C. Guan, and T. S. Lee, "Home-based brain–computer interface attention training program for attention deficit hyperactivity disorder: A feasibility trial," *Child Adolesc. Psychiatry Ment. Health*, vol. 17, p. 15, 2023.

[17] Z. Jia, X. Cai, and Z. Jiao, "Multi-Modal Physiological Signals Based Squeeze-and-Excitation Network with Domain Adversarial Learning for Sleep Staging," *IEEE Sens. J.*, vol. 22, pp. 3464–3471, 2022.