ITM Web of Conferences **59**, 04001 (2024) https://doi.org/10.1051/itmconf/20245904001
HMMOCS-II 2023

Application of an effective neural network architecture based on deep learning algorithms for the development of a noninvasive neurocomputer interface

Denis Karandeev[1*], *Irina* Karandeeva[1], *Irina* Bychkova[1], and *Ruslan* Bazhenov[2]

[1]Katanov Khakass State University, 92, Lenina ave., Abakan, 655017, Russia
[2]Sholom-Aleichem Priamursky State University, 70A Shirokaya street, Birobidzhan, 679015, Russia

Abstract. The article highlights the relevance of the development of modern noninvasive neurocomputer interfaces and identifies a problem in their development, which is the low accuracy of decoding human brain activity using modern noninvasive bidirectional neurocomputer interfaces, which makes it difficult to develop fully functioning noninvasive neuroprostheses. This problem is associated with a small number of domestic research in this area, as well as with an insufficient number of necessary tools for the development of this kind of neuroprostheses. The paper presents the principle of operation of this kind of interfaces, as well as varieties of neural interfaces. The scope of application of neurointerfaces and possible prospects for the development of this field are considered. The need to develop an artificial neural network using fuzzy logic aimed at improving the efficiency of isolating and filtering subtle signal patterns and structures of the human brain from the general signal background is justified.

1 Introduction

To date, an increasing amount of research is being conducted in the field of the development of innovative neurocomputer interfaces (Brain–computer interface (BCI)). This type of interfaces is aimed at solving problems of establishing a direct connection between the human brain and various external devices by researching, transforming, improving or restoring cognitive or sensorimotor functions of the human nervous system. Such devices can be any gadgets like moving robotic spiders or balls, in which case we are talking more about neural gadgets aimed at entertainment. It can be noted that to a greater extent this kind of interfaces are aimed at helping people with disabilities, including people with limb paralysis. It is relevant to adapt the developed tools for use, in particular, in the lives of paralyzed patients or people with motor disorders, which becomes even more relevant in the current realities. This is due to an increase in the number of people, who have needs for the use of this kind of tools to improve their quality of life. Another promising area of application of the proposed solution can be the "Smart Home" system. The practical significance lies in the possibility of

* Corresponding author: DenisKhsu@bk.ru

implementing the developed adaptive neural network, which solves the problem of effectively isolating and filtering subtle signal patterns and structures of the human brain from the general signal background, both in the field of neuroprosthetics, by introducing this neural network into the work of neuroprostheses developed on the basis of a noninvasive neurointerface, and in the future into the "Smart Home" system. The problem of developing neuroprostheses based on invasive and semi-invasive neurocomputer interfaces has been widely studied in the scientific literature, but the issue of developing domestic neuroprostheses based on noninvasive neurointerfaces is still open [1, 2].

2 The principle of operation of the neurocomputer interface

The basic principle of operation of the neurocomputer interface is to read the signals of the human brain, then process these signals and output decoded commands to the executing device.

The signals that the neurocomputer interface reads are most often received in the form of electroencephalography (EEG), which in turn visually reflects the activity of the human brain in the form of frequency graphs [3].

It is important to understand that these graphs differ in amplitudes and frequency. Speaking of frequency, we can distinguish 4 main "rhythms" of the human brain: δ delta (0.1-4 Hz), θ theta (4-7.5 Hz), α alpha (7.5-12 Hz), β beta (12-30 Hz) and γ gamma (over 30 Hz).

The higher the frequency, the more complex the mental task the human brain is trying to solve. It is also important to distinguish the so-called μ, mu-rhythm, or sensorimotor rhythm (SMR), which has a frequency similar to the alpha rhythm of 8-13 Hz and is recorded over the motor area of the cerebral cortex located in the posterior part of the precentral gyrus. Only the shape of the waves distinguishes these rhythms, the mu-rhythm waves have rounded tops. It is at this frequency that neurointerfaces are most often developed. This is due to the fact that this frequency of brain activity is fixed when a person makes a movement, and also carries out any simple thought processes, in particular, imagines how he performs any movement with his hand, foot or, for example, head. Through this kind of training, a person can train a neurocomputer interface.

3 Types of neurointerfaces

According to the method of receiving a signal from the brain or according to the so-called degree of invasiveness, neurointerfaces are divided into:

- invasive neurointerfaces that require direct implantation of introcortical microelectrodes into the human brain, it is worth noting that this type of neurointerfaces is the most effective, but also the most dangerous;
- noninvasive neurointerfaces, analysis of brain activity for these neurointerfaces is carried out without implanting electrodes into the human brain, reading occurs from the surface of the head by using electroencephalography (EEG), magnetoencephalography or functional magnetic resonance imaging;
- semi-invasive neurointerface, in this case the electrodes are not implanted into the brain itself, but are located under the skull bone and are located on the surface of the brain, an example of this type of neurointerface can be called electrocorticography (ECoG).

Noninvasive neurointerfaces are on average at a distance of 1.5 cm. from the brain. This is one of the main problems when using noninvasive neural interfaces, due to the occurrence of a large amount of noise and distortion when receiving electroencephalograms. It is worth noting that the smaller the distance between the electrode and the brain, the higher the accuracy of the received signals.

In addition, neural interfaces are divided by the type of direction of action: unidirectional and bidirectional. In the first case, they either receive signals from the brain, or vice versa, they only send them to it. In the second case, the flow of information in both directions is provided, which allows the brain to control external devices.

This kind of devices at the moment, if we talk about invasive and semi-invasive neurointerface, are used mostly in medicine, improving the quality of life for people with disabilities, but they can also be used later for the correction and prevention of diseases of various kinds. If we talk about noninvasive neural interfaces, they are becoming more and more popular in the gaming field [4], there are more and more different kinds of neural gadgets. At the current pace of development of this industry, a kind of revolution in this area may occur in the future, since a large amount of research is being conducted in this direction [5, 6].

4 Possibilities of using deep convolutional neural networks to solve the described problem

At the same time, it can be highlighted that one of the promising directions in this area is the use of deep convolutional neural networks aimed at decoding the kinematic parameters of movement of various parts of the body [7].

In the future, with the help of these neural interfaces, it will be possible to control any bionic limbs of a person [8]. However, it is important to remember in this case about information security, since any system can be subject to hacking, but hacking a system of this kind can be even more dangerous, because here we are talking about human life [9].

The scientific significance of this problem lies in the fact that with the use of artificial neural networks, it will be possible to increase the efficiency of isolating and filtering subtle signal patterns and structures of the human brain from the general signal background obtained through a noninvasive method of studying the functional state of the brain by registering its bioelectric activity in the form of electroencephalograms. The filtered signal structures can subsequently be identified and classified using artificial neural networks based on deep learning algorithms. As a practical application of the hypothesis, the creation of an adaptive convolutional neural network is proposed. It is relevant to adapt the developed tools for use, in particular, in the lives of paralyzed patients or people with motor disorders, which becomes even more relevant in the current realities. This is due to an increase in the number of people, who have needs for the use of this kind of tools to improve their quality of life. Another promising area of application of the proposed solution can be the "Smart Home" system. In addition, the need to develop this toolkit is due to the country's transition to the so-called "Industry 4.0", based on the mass introduction of cyber-physical systems into production and other areas of activity, including the development of the "Smart Home" system, the resulting tools will contribute to solving this problem [10].

There is a lot of research in this area, but the optimal architecture of a convolutional neural network has not yet been developed, the authors of the article are engaged in solving this problem [11-17]. As a toolkit for the development of this network, the authors use the Python programming language with connected libraries OpenBCI, fuzzyTECH, pyfuzzy, SciPy, TensorFlow. An example of the data captured by an electroencephalograph is shown in Figure 1.

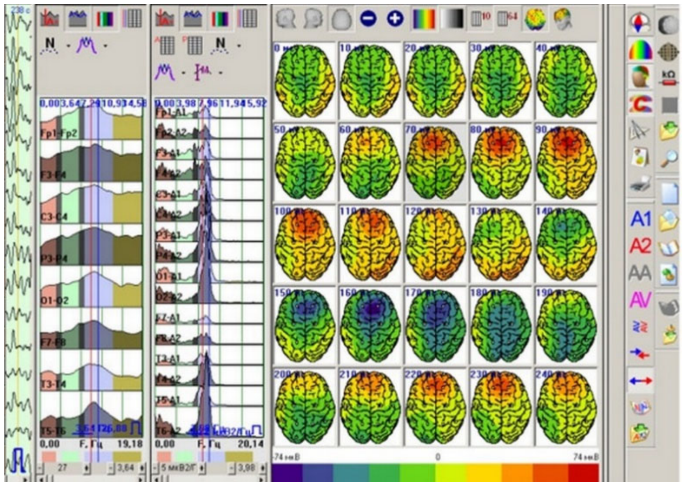

Fig. 1. Data captured by an electroencephalograph.

In the future, it is planned to purchase a 64-channel instrument for collecting electroencephalograms with a shell and hardware for OpenBCI. Now, the authors have formed the architecture of a convolutional neural network aimed at effective filtering of subtle signal patterns of the brain, this architecture is being finalized and it is planned to be tested on specific examples.

5 Conclusion

The use of artificial neural networks, as well as fuzzy logic, can make it possible to increase the efficiency of isolating and filtering subtle signal patterns and structures of the human brain from the general signal background obtained through a noninvasive method of studying the functional state of the brain by registering its bioelectric activity in the form of electroencephalograms. The filtered signal structures can subsequently be identified and classified also using artificial neural networks based on deep learning algorithms. As a practical application, the development of an adaptive convolutional neural network is proposed, on the basis of which it will be possible to develop more functional noninvasive neuroprostheses. The need for these developments is due to the country's transition to the so-called "Industry 4.0", based on the mass introduction of cyber-physical systems into production and other areas of activity, including the development of the "Smart Home" system, the resulting tools will contribute to solving this problem. The practical significance lies in the development of tools that can be implemented in the rehabilitation system for people with disabilities, as well as in the "Smart Home" system. In the future, with the help of these neural interfaces, it will be possible to control any bionic limbs of a person.

References

1. G. Bieker, G. Noethe, M. Fried-Oken, *Brain-Computer Interface: Locked-in and Reaching New Heights*, SpeakUP, 3-6 (2011)
2. A. Rezeika, Brain Sci **8(4),** 57 (2018). https://www.doi.org/10.3390/brainsci8040057
3. F. Lotte, L. Bougrain, A. Cichocki, M. Clerc, M. Congedo, A. Rakotomamonjy, F. Yger, Journal of Neural Engineering **15,** 031005 (2018). https://doi.org/10.1088/1741-2552/aab2f2

4. H.J. Kang, D.H. Kim, B.M. Kim, D. Oh, S.B. Jang, International Journal of Advanced Science and Technology **95,** 73-88 (2016)
5. L. Acqualagnav, M.S. Treder, M. Schreuder, B.A. Blankertz, *Novel brain-computer interface based on the rapid serial visual presentation paradigm*, Engineering in Medicine and Biology Society (EMBC), Annual International Conference of the IEEE, 2686-2689 (2010)
6. P.A. Yuan, Journal of Neural Engineering **10**, 026014 (2013). https://www.doi.org/10.1088/1741-2560/10/2/026014
7. J.H. Jeong, K.H. Shim, D.J. Kim, S.W. Lee, IEEE Trans. Neural Syst. Rehabil. Eng **28**, 1226-1238 (2020). https://www.doi.org/10.1109/TNSRE.2020.2981659
8. S.N. Abdulkader, A. Atia, M.M. Mostafa, Egyptian Informatics Journal **16,** 213-230 (2015)
9. M. Ienca, P. Haselager, Ethics and Information Technology **18**, 117-129 (2016)
10. L. Angrisani, P. Arpaia, N. Moccaldi, A. Esposito, *Wearable augmented reality and brain computer interface to improve human-robot interactions in smart industry: a feasibility study for SSVEP signals*, IEEE 4th International Forum on Research and Technology for Society and Industry (RTSI), IEEE, Piscataway, 1-5 (2018)
11. X. Chen, Proc Natl Acad Sci USA **112**, 6058-6067 (2015). https://www.doi.org/10.1073/pnas.1508080112
12. J.R. Stieger, S.A. Engel, D. Suma, B. He, Journal of Neural Engineering **18,** 046082 (2021). https://www.doi.org/10.1088/1741-2552/ac0584
13. B. He, B. Baxter, B.J. Edelman, C.C. Cline, W.W. Ye, IEEE **103,** 907-925 (2015). https://www.doi.org/10.1109/JPROC.2015.2407272
14. D.J. Karandeev, A.S. Dulesov, R.I. Bazhenov, I.J. Karandeeva, IOP Conference Series: Materials Science and Engineering **862,** 062026 (2020). https://www.doi.org/10.1088/1757-899X/862/6/062026
15. M. Akcakaya, B. Peters, M. Moghadamfalahi, A. Mooney, U. Orhan, B. Oken, D. Erdogmus, M. Fried-Oken, IEEE Rev Biomed Eng **7**, 31-49 (2014). https://www.doi.org/10.1109/RBME.2013.2295097A
16. A. Materka, P. Poryzala, High-speed noninvasive brain-computer interfaces, 6th International Conference on Human System Interactions (HSI), Sopot, Poland, 7-12 (2013). https://www.doi.org/10.1109/HSI.2013.6577795
17. A.I. Renton, J.B. Mattingley, D.R. Painter, Scientific Reports **9**, 18705 (2019). https://www.doi.org/10.1038/s41598-019-55166-y