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Application of deep neural networks for EEG signal processing in brain-controlled wheeled robotic platform

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***Abstract* — The article describes the essence of functioning of the neural computer interface, as well as provides the prototype of the custom neural computer control system, which includes the helmet with the Open BCI Cyton platform, BCI-server on the basis of the personal computer and, the wheeled robot itself with the on-board computer Raspberry Pi. Transmission of the recorded 16-channel EEG-records onto the BCI-server is performed using the Bluetooth protocol, and the Wi-Fi standard is applied for the communication between the robot and the BCI-server. The main task was to create and research the possibility of application of the deep learning technologies to classification of the filtered signals (frequency band of the EEG Alpha-waves) under relatively low data volume scenario. Program architecture and system functioning algorithm are presented, convolutional neural network and the multi-layer perceptron are researched as the neural classifiers. EEG-signals filtering and their classification are performed on the BCI-server. Neuroclassifier on the basis of the convolutional neural network showed higher accuracy, however it demands bigger calculating resources for its realization.**

Keywords — EEG-signals, 'brain-computer' interface, deep learning, convolutional neural networks, multilayer perceptron.

I. INTRODUCTION

Human computer interaction systems may have different structures and application. During the last years the researchers' attention has been attracted by the systems based on the 'brain – computer' interface (BCI). The main idea of such systems lies in the selection and processing of encephalogram signals in order to interpret patterns (emotions, thoughts, commands, etc.). 'Brain-computer' interface or the other name - neural computer interface (NCI) is a unique communication channel between the human brain and the outer world, which in contrast with the traditional technologies of the message communication has a number of peculiarities, advantages and limitations [1,2].

Control systems on the basis of the 'brain-computer' interface may find and have already found the wide application in different domain from games and entertainment to neurorehabilitation [3,4]. The key aspect in work with NCI is the intellectual analysis of encephalograms. For such a purpose different machine learning algorithms are used [5].

Cerebral activity including the mental processing of the person is accompanied with spread of the electric biopotentials on the surface of the head. Extraction of these biopotentials using the electrodes, their intensification and recording with the help of the corresponding equipment makes the essence of the electroencephalography method [6]. During the substantial time this method was applied in medical diagnostics, where the physician 'decoded' the multi-channel EEG-records to define the correspondence of the encephalogram with or deviations from the norm.

The situation drastically changed with the development of the information technologies. Not only the systems to support the decision making in medical diagnostics are created on the basis of the machine learning algorithms, but also the range of tasks connected with the intellectual analysis of the encephalograms. The significant part of such tasks is based on the usage of the 'brain-computer' interface [1,3,7]. Creation of the computer interface with the help of the brain signals met a lot of challenges both with technical nature and the ones raised by the usability comfort under the real-life conditions.

Difficulty in EEG-signals processing is conditioned by their intermittent nature, weak intensity, exposure to influence of outer destabilizing factors such as changes of the electrodes location, interference of the other electric signals, caused by the electric activity of the heart (electrocardiogram) and skeletal muscles (electromyogram), as well as due to eye movements (electrooculogram). To decrease the influence of artifacts a number of digital signal conditioning methods is being applied, which are based on the formal methods of frequency and spatial filtering, time-frequency transformations, statistical and correlational analysis, etc. [3,8,9]. Certain companies, e.g., Texas Instruments, manufacture special hardware modules (Front-End) for registration and conditioning of EEG-signals [10,11].

While applying the formal methods there exists a problem of oppressing the influence of artifacts, frequency band of which is overlapped with useful components of EEG. Due to this the application of the informal machine learning models for detection and removal of the anomalies from the biosignals looks rather promising [12].

The other serious barrier standing before the NCI is the natural variability of the electrophysiological signals of brain [6,13]. Mental and emotional conditions, level of exhaustion and concentration are the factors creating unpredictable changes and deviations in the EEG signals, received during the recording sessions. These factors mask the main structure of the EEG-signals, making it difficult to differentiate and select the weak useful components. Here arises the necessity to use the informal models of EEG-signals processing, based on the machine learning algorithms.

Notwithstanding that the machine learning domain itself is rather young, during the last years the novel direction – deep learning – has appeared in this domain and it has been rapidly developing. Due to this deep learning technology the revolutionary breakthrough was achieved in issues of the computer image recognition, natural language processing, human genome mapping [14,15,16]. Different architectures of neural networks (e.g., convolutional networks), are applied to realize the deep learning [17].

Application fields of the deep learning technology is constantly growing. Deep learning is expedient to be used for solving complicated tasks [18]. Here definitely belongs intellectual analysis of EEG-signals in the 'human-brain' interface.

Thus, the aim of current research is to research and validate the design approach suitable for building miniaturized BCI system designed under very low data volume scenario using recent advanced in the field of machine learning and neural networks.

II. STRUCTURE AND FUNCTIONING OF NEURAL COMPUTER INTERFACE

The typical structure of 'brain-computer' interface is composed of five structural components:

- EEG-signal extraction unit is responsible for multichannel recording of bio potentials using the electrodes on the head surface and formation of the 'raw' digital EEG-signals;
- unit for conditioning the 'raw' EEG-signals by their intensification and noise filtering;
- unit for extracting the characteristic features forms the descriptive features (descriptors) from the relevant EEG-signals, decreasing the size of data received by the classifier
- classification unit built by one of the machine learning methods allocates EEG-signals to one of classes by analyzing the descriptors' vector;
- transmission unit forms the output data, which format depends on the designated use of the 'brain-computer' interface. For example, these can be commands for operation of the technical objects, cursor movement or writing letters on the display.

To record the EEG-signals the special helmets are used. Currently helmets of different companies are present on the market, the most popular of them are Emotiv, OpenEEG, OpenBCI, Muse, MindWave [9]. Extraction systems differ by type and number of electrodes (recording channels), their location, quality of the registered EEG-signals.

Intensity of EEG-signals is more than two orders lower than the same in electrocardiogram signals and does not exceed 100 microV. This means the extremely high exposure of EEG-signals to influence of different destabilizing factors with the inner biological nature, such as eye and muscles movements heart beating, as well as technical origin, first of all power supply network, artifacts conditioned by the changes of 'skin-electrode' impedance. To suppress the networks obstacles the barrier filters (Power-Line Notch Filter) are being used. To improve the correlation of the signal to the noise different types of the bandpass filters are traditionally being used, which are designed for the frequency interval of the informative EEG-signal parts. Out of different mental activity waves the most appropriate are the Alpha-waves located in the band between 7 Hz and 13 Hz.

Traditional approaches of the electrocardiograms intellectual analysis foresee the stage of the characteristic feature extraction, due to which the classifier may unambiguously differentiate EEG-signals to secure the next stage – classification. To extract such features different methods of transformations are being used both in time and in frequency aspects, for example auto-regression analysis, canonical correlation analysis - CCA), short-time Fourier transform (STFT), wave transformation, smoothing filter [3,9,19]. Extracted features receive the descriptors vector which comprises the input date for the classifier, which realizes one of the machine learning algorithms.

III. PROGRAM ARCHITECTURE AND SYSTEM FUNCTIONING ALGORITHM

To conduct a real experiment the authors built a system consisting of three separate physical components:

- helmet with the Open BCI Cyton platform [20];
- personal computer executing the function of the BCI-server;
- wheeled robot with the mounted Raspberry Pi board.

The helmet with the installed Open platform BCI Cyton provides 16-channel extraction of the encephalograms using sampling rate of 125Hz with further data transmission via the Bluetooth protocol onto the personal computer. Program conditioning of the EEG-signals is performed on the PC.

The authors applied the deep learning paradigm for the intellectual analysis of EEG signals, according to which the descriptor receives as an input data not the descriptors, but the filtered EEG-signals. To perform the research, we developed two types of classifiers – on the basis of the convolutional neural network and the multilayer perceptron.

The classification results from the BCI-server via the Wi-Fi standard are transmitted onto the single board computer Raspberry Pi, which is mounted on the wheeled robot. The main advantages of Raspberry Pi include compact dimensions (85x56x17 mm), availability of the specialized operation system Raspbian (written on the basis of the Linux core), support of the wireless data exchange protocols Wi-Fi and Bluetooth. One should also separately highlight the availability of the GPIO type digital output which allows to form the control signals to operate the engines via the special driver plate.

The authors developed their own variant of the EEG-signals processing intellectual system, which consists of three main units:

- Data collection unit (COLLECT DATA)
- Model training unit (TRAIN MODEL)
- Prediction unit (PREDICT).

Each of these units is responsible for the separate working mode of the system, which is set by defining the corresponding parameter in the configuration file before starting the main program (MAIN).

In the COLLECT DATA mode using the OpenBCISerial and DataOrganizer modules the selection and recording of the registered EEG-signals take place. Meanwhile the object OpenBCISerial reads data from the helmet via the Bluetooth protocol. When the data selection starts the separate thread is created from the Open BCI Cyton board, and the data from it is recorded into the buffer of the BCI-server in parallel with the program work. When the buffer is full the data is transferred to the DataOrganizer module, and the buffer is being cleaned. DataOrganizer module is responsible for storing the data batches received from the buffer in the .cvs files and organization of the files on the disc according to the defined structure.

During the TRAIN MODEL mode, the neural networks are being trained with the help of the NNModel module. The model of the neural network is being created in this unit with the help of training on the data collected in COLLECT DATA mode. The data read from files is aggregated into the input matrix or tensor and is provided in such a form as an input for the computing graph, where the iterative process of the optimal weight coefficients in the layers of the neural network takes place. After the training is finished the neural network model is saved into two separate files – a .json file with the structure of the computing graph and a .h5 file with weighted coefficients.

Via OpenBCISerial, Predictor and NNModel modules the PREDICT unit recognizes the registered EEG-signals with the help of the neural network trained in the TRAIN MODEL mode. Module OpenBCISerial sends in batches the new processed EEG-data for the intellectual analysis onto the Predictor module, where the signals are cut into segments of the corresponding length and are transferred onto the NNModel module, where the classification procedure itself takes place. From the Predictor module the classification results are transmitted onto the board computer of the wheeled platform, where the corresponding control commands are formed on their basis.

IV. EXPERIMENT METHODOLOGY AND RESULTS

Two types of deep neural networks – multilayer perceptron (hereinafter – MLP) and convolutional neural network (hereinafter – CNN) were developed and verified as classifiers of EEG signals. Program implementation of the algorithm was executed in the programming language Python3 using the specialized frameworks for building deep neural networks: Tensorflow v1, Keras, NumPy.

Neural network on the basis of the multilayer perceptron is composed of 4 blocks on the basis of the dense layers. Total number of layers in MLP model – 9, out of them – 4 layers with the weight coefficients due to which the training itself is performed. Sizes of the stated layers are the following: Dense1 - 32, Dense2 - 64, Dense3 - 32, Dense4 - 5. For MPL input layer, data vectors from each EEG channel (256x1) are concatenated to create a 4096x1 vector (256*16=4096). For CNN input layer, EEG data is represented spatially, where each row represents a channel, which creates a matrix of shape 16x256. Function ReLU is used in all the activation layers except for the output one, and in the output layer – softmax function.

Training of the MLP network is performed with the following parameters:

• loss function (loss): categorical_crossentropy;
• training algorithm (optimizer): Adadelta;
• number of training epochs (num_epoch): 100;
• learning rate (learning_rate): 0.001;
• cross-validation coefficient (correlation between the training and test data sets): 70/30.

Values of such parameters as type and regularization coefficient, initialization algorithm of weight coefficients are taken by default.

Training stage took 30 minutes on the Intel Core i7-5500 processor (operating system Ubuntu 18.04 LTS, 8 GB of RAM).

CNN network is composed of three blocks on the basis of the convolutional layers. The second and the third blocks additionally use the layers of dropout and max pooling type. After the convolutional layers in CNN-architecture two dense-layers are implemented. Total number of layers in the network – 18, out of them – 5 layers with weight coefficients due to which the CNN training itself is performed. Function ReLU is used in all the activation layers except for the output one, and in the output layer – softmax function. Stated layers have the following dimensions: Conv1 - 16x254x32, Conv2 - 16x252x32, Conv3 - 16x124x32, Dense1 - 128, Dense2 - 5. Peculiarity of data provided for the input layer of the CNN network is its matrix and not vector representation, in the format 16x256x1.

Training of CNN network was performed under the same hyper-parameters as the ones used for MLP network, however using one additional hyper-parameter – dropout coefficient, which value is defined on the 0,2 level. Training took 80 minutes on the Intel Core i7-5500 processor (operating system Ubuntu 18.04 LTS, 8 GB of RAM).

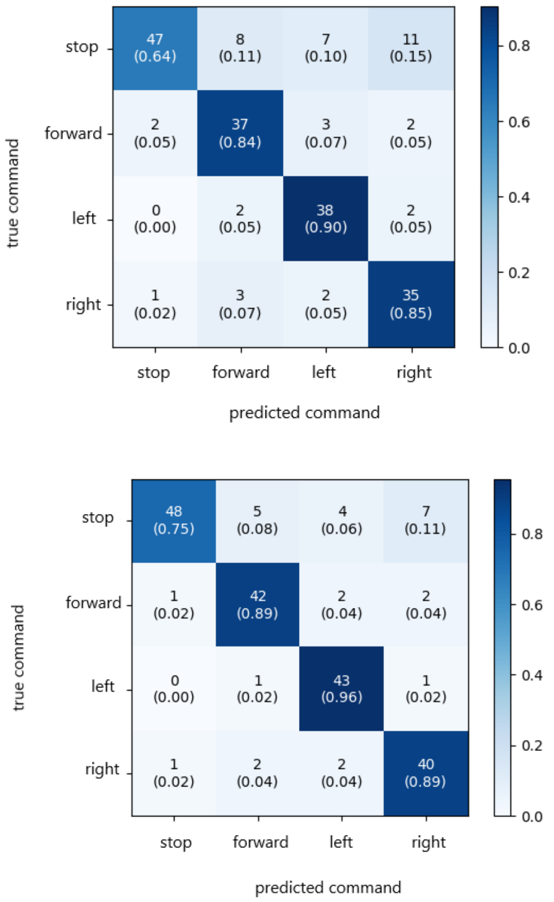

Fig. 1. Confusion matrix for MLP-model (a) and CNN-model (b)

After the training is finished the accuracy of EEG signals classification by neural network is rated on the test set. Apart from rating the network's accuracy on the test set, additional testing is executed on the real working system – in the production mode. For this purpose, the operator in the helmet executed commands forward, stop, right, left in thought, and EEG-signals corresponding to these commands were transmitted onto the BCI-server to be recognized by the neural network (first by MLP, later by CNN). Total number of commands given by the operator in the production mode was 50 for each category (forward, stop, right, left). The number of correctly and incorrectly recognized commands of the operator was calculated. Results of the experiment are provided in fig 1.

Results of system work are presented in a form of a confusion matrix: its rows correspond to the command given in thought by the human operator, and the columns – to the command recognized by the system. In such a way numbers on the diagonal elements represent the number of the correct operations, and the numbers outside of the matrix diagonal correspondingly show the number of the incorrect operations. Following the research results it was defined that the EEG-signals classifier on the basis of the convolutional network showed better results comparing to the classifier on the multilayer perceptron (accuracy on the CNN model - 86.07 %, in contrast to 78.5 % on MLP model). However, the calculating complexity of the CNN deep neural network is significantly higher both in the training mode and in the recognition mode. As far as under real conditions the CNN-model showed better result, it was used to control the wheeled platform.

As seen from the experiment results the neural computer control system demonstrates rather high accuracy, considering the complexity class of the task. In order to further increase the accuracy, the authors consider it expedient to apply autoencoder technology for detection and correction of the anomalies in filtered EEG-signals. Such an approach showed its efficiency in the biometric identification systems based on the analysis of the other type of bio signals – electrocardiograms.

V. Conclusions

Novel approach of applying deep learning paradigm to create the 'brain-computer' interface using filtered EEG signal (alpha band only) and relatively low volume dataset is presented in the article. Prototype of the custom neural computer control system was presented, which included such three components: helmet with Open BCI Cyton platform, BCI-server on the basis of the personal computer, wheeled robot with the board computer Raspberry Pi. Representation of the 16-channel EEG-records registered by means of Open BCI Cyton onto the BCI-server were performed via the Bluetooth protocol, and the Wi-Fi standard was applied for communication between the robot and the BCI-server.

The main achievement is development and research of two variants for realization of neuroclassifiers – on the basis of the multilayer perceptron and the convolutional network. Both experiments showed rather high results: decoding accuracy of the commands from EEG-signals in the test set was 90.18% for the multilayer perceptron and 93.89% for the convolutional network. Accuracy of the control commands execution somewhat decreased in the production mode (almost on 12% for the MLP model and on 8% for the CNN model). Notwithstanding that the neuroclassifier on the convolutional network provides the higher accuracy, it is more complicated in the calculation aspect, and its training time is almost three times longer.

REFERENCES

[1] Hippe Z.S., Kulikowski J.L., Mroczek T., Wtorek J. Human-Computer Systems Interaction: Backgrounds and Applications. In: Kacprzyk J. (eds) Advances in Intelligent Systems and Computing Vol. 300, Springer, Switzerland, 2014.

[2] Wolpaw, J.R.; Birbaumer, N.; McFarland, D.J.; Pfurtscheller, G.; Vaughan, T.M. Brain–computer interfaces for communication and control. Clin. Neurophysiol. 2002, 113, 767–791.

[3] Abdulkader S.N., Atia A., Mostafa M-S.M. Brain computer interfacing: Applications and challenges. Egypt. Informatics J., Vol. 16 (2), 2015, 213-230.

[4] Padmavathi, R.; Ranganathan, V. A review on EEG based brain computer interface systems. Int. J. Emerg. Technol. Adv. Eng. 2014, 4, 683-696.

[5] Kalshetti U., Goel A., Srivastava P., Ingole M., Bhide D. Human Authentication from Brain EEG Signals using Machine Learning. Int. J. Pure and App. Math., 2018, Vol. 118 (24), 1-7.

[6] Subha D.P., Joseph P.K., Acharya R., Lim C.M. EEG signal analysis: A survey. J. Med. Syst. 2010, 34,195–212.

[7] Nguyen P.T. On EEG-based Person Recognition and Human Characteristics Classification. Dr Ph. Thesis, University of Canberra, 2015, 188 p.

[8] Georgieva P., Silva F., Milanova M., Kasabov N. (2014) EEG Signal Processing for Brain–Computer Interfaces. In: Kasabov N. (eds) Springer Handbook of Bio-Neuroinformatics. Springer, Berlin, Heidelberg.

[9] Minguillona J., M. Lopez-Gordoc A., Pelayo F. Trends in EEG-BCI for daily-life: Requirements for artifact removal. Biomed. Sign. Proces. & Contr., 2017, 31, 407–418.

[10] EEG Front-End Performance Demonstration Kit. Texas Instruments. User's Guide. SLAU443B–May 2012–Revised January 2016.

[11] Uktveris T., Jusas V. Development of a Modular Board for EEG Signal Acquisition. Sensors, 2018, 18, 2140.

[12] M. Karpinski, V. Khoma, V. Dudvkevych, Y. Khoma and D. Sabodashko, "Autoencoder Neural Networks for Outlier Correction in ECG- Based Biometric Identification," 2018 IEEE 4th International Symposium on Wireless Systems within the International Conferences on Intelligent Data Acquisition and Advanced Computing Systems (IDAACS-SWS), 2018, pp. 210-215, doi: 10.1109/IDAACS-SWS.2018.8525836.

[13] American Electroencephalographic Society Guidelines for Standard Electrode Position Nomenclature. Journal of Clinical Neurophysiology. 1991. 8 (2): 200–202.

[14] Belo B., Rodrigues J., Vaz J.R., Pezarat Correia P., Gamboa H. Biosignals learning and synthesis using deep neural networks. BioMed Eng OnLine, 2017, 1-17.

[15] Babak V.P., Babak S.V., Myslovych M.V., Zaporozhets A.O., Zvaritch V.M. Methods and Models for Information Data Analysis. In: Diagnostic Systems for Energy Equipments. Syst. Decis. Control 281. – Springer, 2020. – Pp. 23-70 https://doi.org/10.1007/978-3-030-44443-3_2

[16] Babak V.P., Babak S.V., Myslovych M.V., Zaporozhets A.O., Zvaritch V.M. Simulation and Software for Diagnostic Systems. In: Diagnostic Systems for Energy Equipments. Stud. Syst. Decis. Control 281. – Springer, 2020. – Pp. 71-90 https://doi.org/10.1007/978-3-030-44443-3_3

[17] Seonwoo M., Byunghan L., Sungroh Y. Deep learning in bioinformatics. Briefings in Bioinformatics, Vol. 18(5), 2017, p. 851–869.

[18] Komar, M., Sachenko, A., Golovko, V., Dorosh, V.Compression of network traffic parameters for detecting cyber attacks based on deep learning 2018 Proceedings of 2018 IEEE 9th International Conference on Dependable Systems, Services and Technologies, DESSERT 2018, pp. 43-47

[19] Kawala-Sterniuk, A.; Podpora, M.; Pelc, M.; Blaszczyszyn, M.; Gorzelanczyk, E.J.; Martinek, R.; Ozana, S. Comparison of Smoothing Filters in Analysis of EEG Data for the Medical Diagnostics Purposes. Sensors, 2020, 20, 807.

[20] Open BCI Documentation. Cyton Board. [Electronic resource] – Access mode: https://docs.openbci.com/docs/02Cyton/CytonLanding