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doi:10.15199/48.2021.11.20

Review of solutions for the application of example of machine learning methods for Motor Imagery in correlation with Brain-Computer Interfaces

***Abstract**. Presently, numerous public databases presenting the collected EEG signals, including the ones in the scope of Motor Imagery (MI), are available. Simultaneously, machine-learning methods, which enable effective and fast discovering of information, also in the sets of biomedical data, are constantly being developed. In this paper, a set of 30 of some of the latest scientific publications from the years 2016-2021 has been analyzed. The analysis covered, among others: public data repositories in the form of EEG signals as input data; numbers and types of the analyzed tasks in the scope of MI in the above-mentioned databases; and Deep Learning (DL) architectures.*

***Streszczenie.** Obecnie dostępne są liczne ogólnodostępne bazy danych prezentujące zebrane sygnały EEG, w tym z zakresu obrazowania motorycznego (MI). Jednocześnie stale rozwijane są metody uczenia maszynowego, które umożliwiają efektywne i szybkie odkrywanie informacji, także w zbiorach danych biomedycznych. W niniejszym artyule przeanalizowano zestaw 30 spośród najnowszych publikacji naukowych z lat 2016-2021. Analizie poddano m.in.: publiczne repozytoria danych w postaci sygnałów EEG jako dane wejściowe; liczby i rodzaje analizowanych zadań z zakresu obrazowania motorycznego w ww. bazach; i architektury Deep Learning (DL). (**Przegląd rozwiązań do zastosowania metod uczenia maszynowego na potrzeby obrazowania motorycznego w korelacji z interfejsami mózg-komputer**).*

Keywords: Motor Imagery; EEG; BCI; machine learning; deep learning; deep neural networks.
Słowa kluczowe: obrazowanie motoryczne; EEG; BCI; uczenie maszynowe; głębokie uczenie, głębokie sieci neuronowe.

Introduction

In everyday medical practice, a physician, after becoming acquainted with the result of the realized data acquisition in the scope of the measurement of brain activity, most often focuses on the analysis of the *electroencelographic signal* (EEG). The analysis may be affected by an error due to overlooking some specific features in the EEG signal, which can often be attributed to tiredness of the person analyzing the result. Furthermore, it is worth noting that EEG signals are commonly used in many other branches of science apart from medicine, including automation and robotics for controlling real objects [1] as well as in the scope of neuromarketing at the stage of creating a commercial. Thus it is even more important to develop solutions, which assist proper analysis of biomedical data among people without typically medical education.

Presently, Brain-Computer Technology (BCI) develops dynamically in the scope of MI, which is caused by the application of the research results carried out in the area of both medical and technical sciences. In practice, the basic task within MI is realized through imagining the performance of a certain movement without its real performance, including, among others, a hand movement: right, left; foot: right, left. The essential problems that accompany the researchers at the stage of developing solutions within MI based on non-invasive BCI (by the measurement of the EEG signal) are the problems resulting, among others, from: EEG signal non-stationarity, both biological and technical artefacts etc. [2].

For many years, research teams used in practice traditional neural networks in the scope of solutions based on BCI technology. However, during the recent few years, a revolution in the scope of DL took place, which makes the data analysis at a large scale possible. One of the current limitations in this scope is the fact of existence of the EEG signal databases in the scope of MI which are not big enough. Therefore, their proper selection for the works carried out and their constant development are vital.

MI is presently one of the most often used paradigms in BCI technology, which may be used successfully to assist, increase sensorimotor functions of disabled patients. This is proved, among others, in the research by Z. T. Al-Qaysi, et al. in publication Review of the EEG-based wheelchair control system: Consistent taxonomy, open challenges and recommendations [3] and R. Sitaram et al. in Time classification of multichannel near-infrared spectroscopy signals for motor images for brain-computer interface development [4]. MI also finds its application in entertainment and in intelligent solutions for healthy people [5, 6]. It is worth mentioning that various ConvNet models may realize extracting various spatiotemporal features, thus the architecture of convolutional networks has impact on their efficiency and accuracy.

Brain-Computer Interface technology

The beginnings of BCI date back to year 1964. It was in that time that a British neurophysiologist William Grey Walter developed a working interface which gave a beginning for BCI. During one of the procedures he connected electrodes to the patient's cerebral cortex and based on when and how the patient switched slides on the projected with a button, he recorded his neural activity. Next, he changed the system configuration so that it would change a slide when the patient thought about it. However, Walter never announced his discovery. In 1969, Eberhard Fetz et al. presented their studies, in which the apes were the participants, for the first time. The apes mastered control on the deflection of the meter arm. When the needle passed a given point, the animal got a reward. In this way the apes learned how to control their brain activity. The first published research on BCI was presented by Jacque Vidal in 1973: "Toward Direct Brain-Computer Communication". In the system that was developed by him, he used induced visual potentials, which he recorded, from the scalp visual area to determine the direction in which the person tested wanted to move a cursor. Philip Kennedy is considered to be the constructor of the first intracranial BCI. He together with his coworkers implanted neurotropic electrode cones to the cerebral cortex of apes. Miguel Nicolelis was regarded as an advocate of using a bigger number of electrodes distributed on the whole brain area so that the signal obtained would be as good as possible and could be used to control BCI. In 1990s, he created an interface which decoded brain activity of apes and transferred the signal to the appliance which reproduced their movements on the arms of a robot. The appliance worked in real time. Summing up, it should be stressed that BCI interfaces can be divided into two types: invasive and non-invasive ones. Invasive interfaces are implanted directly into the gray matter of the brain. The advantage of this method is obtaining good quality signals. Its disadvantage is, first of all, intrusion on a human body. After some time, the implanted electrodes may film over with a scar layer – it is a natural foreign body reaction of an organism. Non-invasive interfaces do not interfere with a human body, thus they are used definitely more often than the invasive methods. The advantages of these interfaces are easiness to wear, popularity and availability. Their disadvantage is a very weak signal, which is suppressed by the skull and a big number of artefacts which can affect the quality of the emitted signal.

From the point of view of development of modern solutions within brain-computer technology, the phase of extracting features from the signal measured is vital. In practice there are a lot of techniques of feature extraction, nevertheless, as research shows, they are not as reliable as automated methods. In particular, it is important in the scope of solutions basing on MI, i.e. movement imagining. MI makes it possible, both for healthy and disabled people, to improve the work of their brain. However, from the analytical point of view, the problem lies in managing with multi-dimensional signals collected in the scope of MI. Non-linearity and non-stationarity of signals are of great significance in this case. The use of manually developed techniques of extracting features with MI data requires the process of calibration, which lasts about several dozen minutes. Therefore, the functions based on DL may be useful as the techniques of DL are not based on manually developed functions and often they do not require initial data processing – signals [7].

EEG signal

Electroencephalography is the most common non-invasive method of signal measurement of bioelectric brain activity. The electrodes distributed on the scalp register a signal which is a change of potentials caused by neural cell activity of the cerebral cortex. The EEG signal is measured based on the 10-20 system of the *International Federation of Clinical Neurophysiology* specifying the location of measuring electrodes on the scalp of the examined person (Fig. 1). The abbreviations in Fig. 1 correspond to the proper names of the electrodes according to the 10-20 standard. The EEG signal consists of a few kinds of waveforms, including: Alpha waves – they appear when relaxing and closing the eyes, and disappear when opening the eyes and activation of a light stimulus. They are most prominent in posterior leads, i.e. in the place where visual centers are located. They have a frequency between 8 and 12 Hz. Beta waves – typical for everyday activity. They also occur during mental alertness, e.g. during mathematical calculations or perception puzzles. They can be seen frontally and have a frequency between 12 and 30 Hz. Gamma waves – they accompany physical activity and motor functions. The range of this rhythm is from 30 to 100 Hz. Delta waves – they are registered during deep meditation and in stages three and four of sleep. Their frequency does not exceed 4 Hz. Theta waves – they occur during a shallow sleep and they can also be observed during hypnosis. Another kind of theta rhythm is connected with cognitive activity, memorizing and associating. It is seen in the medial section of the brain [8]. Their frequency is between 4 and 8 Hz.

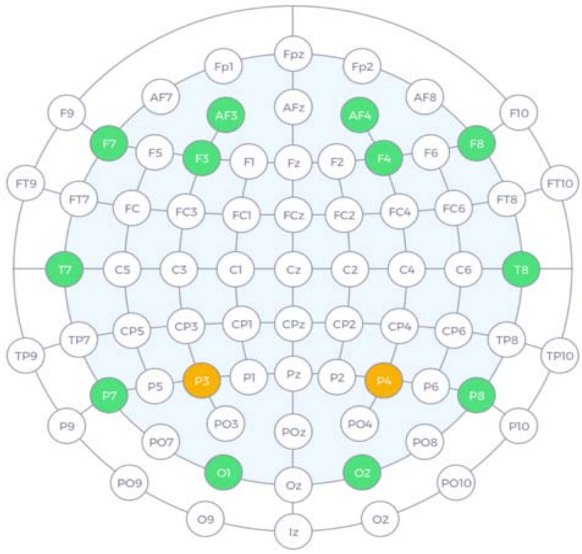

Fig. 1. System 10-20 of EEG signals measurement [2].

EEG signals are characteristic of high complexity and they strongly depend on the person tested from whom they are received. Therefore, it is vital to collect EEG signals in databases, which has a key meaning for their application in training, validation and testing of machine learning models. EEG signal databases in the scope of MI have a few key features that should be considered during their selection, including, among others: a number and a kind of tasks in the scope of MI, a number of EEG channels, a number of persons from whom the acquisition process was carried out. These aspects are analyzed in the remainder of this paper.

Deep learning (DL)

The aim of the application of machine learning in database analysis is to eliminate the defects of the neural networks implemented so far. It is worth noting that DL makes it possible to carry out the extraction process comprehensively. Raw data may be introduced directly to deep neural networks with the aim of extraction, selection and classification [9]. The application of DL makes it possible to obtain a high degree of scalability of a solution; nevertheless the trainings of deep neural networks comprise a very big number of parameters, which significantly extends their training time compared with other approaches.

The commonly used architectures in the scope of DL are, among others: CNN, recurrent neural networks (RNN), and autoencoders. CNN is a popular method used within DL which is based on specialized type of linear operation as convolution. Convolutional networks are used for processing of various types of signals, including images, audio sequences, video and specific biomedical signals, such as EEG, ECG, and EMG. CNNs most often consist of: an input layer, output layer, fully connected and pairs of convolution pooling layers. Convolution is performed through convolution of signals from several filters to extract parallel and complementary features. The process of feature extraction begins from a low-level function. While scaling a convolutional network to consecutive depths, the network bandwidth increases [10]. The pooling layer acts as a strategy of reducing the sampling process. The analysis carried out shows that both the convolution layer and the pooling layer have influence on the reduction of data complexity and the size of files.

A RNN, in which a signal received on the network output goes on its input again, is another kind of commonly used architecture within DL. A one-time activation of the structure based on the feedback loop realized may generate a whole sequence of new phenomena and signals, because in the case of RNN the signals from the network output go back to its input and thus they generate new signals to stabilize output signals. The RNN networks are most often used for the analysis of time series, including speech recognition.

Autoencoders are the simplest solution constituting an unsupervised neural network trained to code and decode data. Within this method, in the coding phase, input data are subjected to the space of smaller dimensions than the data space. During decoding, the reconstruction of real data is performed based on concealed features.

Methods

For the purposes of this study, the process of scientific databases exploration was carried out in February 2021 in the following databases: Web of Sciences, Science Direct and Scopus. It covered the period from February 2016 to February 2021. The following five key words were used for searching: deep learning, motor imagery, electroencephalography. Furthermore, the abbreviations of those names were searched, i.e.: DL, MI, EEG. The articles which were repeated during the process were eliminated so that finally only one of the repeated elaborations would be considered. The exploration process ended with 30 selected articles.

Within the DL issue the articles which did not contain classifiers other than basing only on deep neural networks were selected. Within MI, the articles representing the classification of various motor tasks were selected, including the ones in which various systems for MI realization were offered. In the scope of the articles pertaining to EEG, only the articles with EEG signals were taken into account, excluding the ones which pertained to combination of EEG with other biomedical data acquisition methods, including MRI, NIRS, and PET.

The data obtained as the result of this analysis were divided within the consecutive sections of this paper into the datasets with presentation of the kinds of tasks in the scope of MI, initial processing methods, and DL architecture.

Review of the datasets including the kinds of tasks in the scope of MI

The datasets in the papers reviewed, which were found for the purposes of this paper, are 5 publicly available repositories (listing in Table 1). The datasets differ from one another, among others, in the number of electrodes with which they were collected, the number of the people tested, and the kind of tasks in the scope of MI. Due to the fact that this paper refers to the issue of solutions for the purposes of MI, the most important variables in the datasets analyzed were the number and the kinds of tasks of MI performed by the persons tested during EEG signal registration. The number of electrodes from which the data were collected in the presented repositories is of a large span from 13 to 118 and so is the number of persons from whom the data were collected – from 1 to 109. Imagination duration is shown in the range from 2 to 10 s.

The analysis carried out shows that most datasets focus on the tasks of imagining the movement for the right or left hand/foot. A smaller number of the repositories found refer to MI in the scope of a wrist or elbow. The synthetically collected data in this scope are presented in Table 2.

Table 1. A list of public datasets used for the purposes of the publication realization in the scope of motor imagery based on EEG signal.

No.	Name of dataset – public access	Number of electrodes	Number of subjects	Imagination duration [s]	Percentage share in the publications analyzed
1	BCI Competition IV 2a	22	9	4	33.3%
2	BCI Competition IV 2b	3	9	4	50.2%
3	BCI Competition II 3	3	1	6	6.6%
4	BCI Competition III 4a	118	5	2	6.6%
5	PhysioNet EEG	64	109	10	3.3%

Table 2. A list of the number and types of the tasks analyzed in the scope of motor imagery in the datasets analyzed in relation to the publication

No.	Number of tasks in the scope of Motor Imagery	Types of movement imagining	Percentage share in the publications analyzed
1	Two	left hand, right hand	56.8%
2	Four	left hand, right hand, foot, tongue	33.3%
3	Two	right hand, right foot	6.6%
4	Five	eye, feet, fists, left fist, right fist	3.3%

Review in the scope of initial data processing

This section of the paper presents in a synthetic way the application of the initial signal processing for the purposes of further realization of DL in the MI process. Within all analyzed works, researchers used one of the three types of data formulation: time-series, calculated features and images. In the vast majority, from the methods available, the Common Spatial Pattern (CSP) algorithm was used in the feature extraction process in the publications analyzed. To a lesser degree, a Continuous Wavelet Transform (CWT) was used in practice, which results from the input data format for which it is used. Detailed data in the scope of this pre-processing are shown in Table 3.

Table 3. A list of pre-processing methods used for the purposes of motor imagery realization using DL

No.	Name of the data processing method	Percentage share in the publications analyzed
1	Raw data – without the method for time-series used	40.0%
2	Common Spatial Pattern (CSP) for calculated features	26.6%
3	Empirical mode decomposition (EMD) for calculated features	6.6%
4	Continuous wavelet transform (CWT) for images	10.0%
5	Short-time Fourier transform (STFT) for images	1.3%
6	Fast Fourier transform (FFT) for images	3.3%

It is also worth adding that, often before transferring data for further analysis, a proper data filtration from biological and technical artefacts that may occur in it, is necessary. In this scope, the Independent Component Analysis (ICA) filtration method is most often used. In order to reduce the range of the signal frequency analyzed, other filters such as bandpass, low-pass and high-pass are used.

Review in the scope of DL architectures

The most common DL architectures used in the papers analyzed were: CNNs (being most often a combination of convolutional and recurrent or autoencoders) and RNN. There is no doubt that the most often used architecture was CNN, which occurred in 66.7% of the scientific publications analyzed.

Table 4. A list of deep neural network architectures

No.	Name of deep neural network architecture	Percentage share in the publications analyzed
1	Convolutional neural network (CNN)	66.7%
2	Hybrid - Convolutional neural network (h-CNN)	20.0%
3	Recurrent neural network (RNN)	13.3%

The most used activation functions in the research carried out are: Rectified Linear Unit (ReLU) and Exponential Linear Unit (ELU). During the network training process the parameters of deep neural networks are updated by using various optimization algorithms, in most cases they were Gradient Descent (GD) and Adam. Bayesian optimization was used definitely less often.

Discussions

Based on the results obtained it is concluded that there exist a few most often used EEG signal datasets which are successfully used for MI applying DL methods. The best known and presently commonly used datasets are: BCI Competition IV 2b and BCI Competition IV 2a. A smaller number of publications presents the use of BCI Competition II 3, BCI Competition III 4a, and PhysioNet EEG. The CSP algorithm and its variations are successfully used in the case of feature extraction in the scope of input data to the neural network. And the methods based on the CWT are used in the case of data in the form of images as input files to the neural network. It should be observed that in this case STFT is slightly more often used than CWT.

CNNs are the most often used deep neural network architecture for classification of movement imagining in the research analyzed. A few of the studies analyzed proves superiority of the CNN method over h-CNN and RNN. However, there are also publications which prove that RNN are accurate enough for classification of the tasks based on movement imagining. The data collected synthetically in the scope discussed are shown in Table 5 (in Appendix).

Appendix

Table 5. Summary of the collected data from the 30 reviewed articles.

No.	Authors/Article	Deep learning architecture	Dataset	Input formulation	Activation function	Optimization strategy
1	Zhu X. et al., Separated channel convolutional neural network to realize the training free Motor Imagery BCI systems [7]	CNN	BCI C IV 2b	CSP	ReLU	Adam
2	Wu H. et al. A parallel multiscale filter bank convolutional neural networks for Motor Imagery EEG classification [8]	CNN	BCI C IV 2b	Time-series	linear	Adam
3	Li Y. et al. A channel-projection mixed-scale convolutional neural network for Motor Imagery EEG decoding [9]	CNN	BCI C IV 2a	Time-series	ELU	Adam
4	Tayeb Z. et al., Validating deep neural networks for online decoding of Motor Imagery movements from EEG signals [10]	CNN	BCI C IV 2b	Time-series	ReLU	Adam
5	Zhang D. et al., Making sense of spatio-temporal preserving representations for EEG-based human intention recognition [11]	CNN, LSTM	Physio Net	Time-series	-	Adam
7	Tang X. et al., Motor imagery EEG recognition based on conditional optimization empirical mode decomposition and multi-scale convolutional neural network [13]	CNN	BCI C IV 2b	EMD	ReLU	SGD
8	Dai G. et al., HS-CNN: a CNN with hybrid convolution scale for EEG Motor Imagery classification [14]	CNN	BCI C IV 2a BCI C IV 2b	Time-series	ELU	SGD
9	Olivas-Padilla B.E. et al., Classification of multiple Motor Imagery using deep convolutional neural networks and spatial filters [15]	CNN	BCI C IV 2a	CSP	ReLU	SGD
10	Xu G. et al., A deep transfer convolutional neural network framework for EEG signal classification [16]	CNN	BCI C IV 2b	STFT	ReLU	-
11	Li D. et al., Densely feature fusion based on convolutional neural networks for Motor Imagery EEG classification [17]	CNN	BCI C IV 2a	CSP	ReLU	Adam
12	Amin S.U. et al., Multilevel weighted feature fusion using convolutional neural networks for EEG Motor Imagery classification [18]	CNN	BCI C IV 2a	Time-series	ELU	SGD

13	Tabar Y.R., A novel DL approach for classification of EEG Motor Imagery signals [19]	CNN, SAE	BCI C II 3 BCI C IV 2b	STFT	ReLU	GD
14	Schirrmeister R.T., DL with convolutional neural networks for EEG decoding and visualization [20]	CNN	BCI C IV 2b	Time-series	ELU	SGD
15	Zhang R. et al., A novel hybrid DL scheme for four-class Motor Imagery classification [21]	CNN, LSTM	BCI C IV 2a	CSP	ReLU	Adam
16	Dai M., EEG classification of Motor Imagery using a novel DL framework [22]	CNN, VAE	BCI C IV 2b	STFT	ReLU	GD
17	Majidov I. et al., Efficient classification of Motor Imagery electroencephalography signals using DL methods [23]	CNN	BCI C IV 2a BCI C IV 2b	CSP	ReLU	Adam
18	Xu B. et al., Wavelet transform time-frequency image and convolutional network-based Motor Imagery EEG classification [24]	CNN	BCI C II 3	CWT	ReLU	GD
19	Ha K.W. et al., Motor imagery EEG classification using capsule networks [25]	CNN	BCI C IV 2b	STFT	SELU	SGD
20	Hassanpour A. et al., A novel end-to-end DL scheme for classifying multi-class Motor Imagery electroencephalography signals [26]	SAE	BCI C IV 2a	Time-series	-	-
21	Tang X.L. et al., Semisupervised deep stacking network with adaptive learning rate strategy for Motor Imagery EEG recognition [27]	DBN	BCI C IV 2b	Time-series	Sigmoid	Adadelta
22	Wang P. et al., LSTM-based EEG classification in Motor Imagery tasks [28]	LSTM	BCI C IV 2b	1d-AX	Sigmoid	Adam
23	Lu N. et al., A DL scheme for Motor Imagery classification based on restricted boltzmann machines [29]	DBN	BCI C IV 2b	FFT	Sigmoid	Conjugate gradient
24	Zhang K. et al., Adaptive transfer learning for EEG Motor Imagery classification with deep Convolutional Neural Network [30]	CNN	BCI C IV 2b	Time-series	ELU	SGD
25	Zhang R. et al., Hybrid deep neural network using transfer learning for EEG Motor Imagery decoding [31]	h-CNN	BCI C IV 2b	Time-series	ELU	SGD
26	She Q. et al., A hierarchical semi-supervised extreme learning machine method for EEG recognition [32]	ELM	BCI C IV 2b	CSP	Sigmoid	-
27	Luo T. et al., Exploring spatial-frequency-sequential relationships for Motor Imagery classification with recurrent neural network [33]	GRU	BCI C IV 2a	CSP	ReLU	SGD
28	Chaudhary S., et al., Convolutional neural network based approach towards Motor Imagery tasks EEG signals classification [34]	CNN	BCI C III 4a	CWT	ReLU	GD
29	Lawhern V., et al., EEGNet: a compact convolutional neural network for EEG-based brain-computer interfaces [35]	CNN	BCI C IV 2a	Time-series	Linear, ELU	Adam
30	Taheri S., et al., Convolutional neural network based features for Motor Imagery EEG signals classification in brain-computer interface system [36]	CNN	BCI C III 4a	EMD, CSP	ReLU	-

Conclusions

According to literature studies carried out, MI, in recent years, was more and more often used by many researchers in the world involved in the brain-computer technology development, as a source of the control signal [37]. However, we should bear in mind the fact that the signals from MI are changeable due to physiological and psychological characteristics of each person, which makes their common implementation difficult. As the analysis presented shows, many researchers had used various feature extraction and classification methods before deep neural networks were created. Nowadays, unfortunately, the classification using deep neural networks encounters a problem of small sizes of datasets available publicly, and classifiers require many examples for proper learning. It should be stated that DL based on CNN architecture with rectified linear activation function is the most effective classification function in the scope of MI. The most often used activation functions in CNN and h-CNN studies are ReLU and ELU. Machine learning has the possibility of using all input data to training networks. It is also worth mentioning that, as research shows, a too large number of concealed layers not always leads to better efficiency, but it may lead to the problem connected with neural network overfitting.

This research was funded in whole by National Science Center, [Grant number: 2021/05/X/ST7/00034, MINIATURA 5]. Project title: Pilot research on the application of a training system based on motor imagery in the field of real object control.

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