Single Trial EEG Classification of Tasks with Dominance of Mental and Sensory Attention with Deep Learning Approach

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Abstract. In this paper, we present classification algorithms based on single-trial ElectroEncephaloGraphy (EEG) during the performance of tasks with the dominance of mental and sensory attention. Statistical data analysis showed numerous significant differences of EEG wavelet spectra density during this task at the group level. We decided to use wavelet power spectral density (PSD) computed in each channel for single trial as the source of feature extraction for the classification task. To obtain a low-dimensional representation of PSD image convolutional autoencoder (CNN) was trained. With this encoded representation binary classification for each subject with multilayer perceptron (MLP) were performed. The classification error varies depending on the subject with the average true classification rate is 83.4%, and the standard deviation is 6.6%. So this approach potentially could be used in the tasks where pattern classification is used, such as a clinical decision or in Brain-Computer Interface (BCI) system.

Keywords: Mental and sensory attention
EEG single trial classification · Deep learning · Neural networks

1 Introduction

Electroencephalograms (EEG) are the multidimensional time series with the recordings of brain activity measured as electrical potential. Analysis of EEG activity is crucial in clinical diagnostics for identification pathologies, for example, epilepsies seizure. Among the many approaches to EEG analysis, one can

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distinguish time-frequency-based analysis. Through the advantages of such methods is that many results from time-frequency- based analyses can be interpreted in terms of neurophysiological mechanisms of neural oscillations. [1]. At the last time, one can observe a growing interest in EEG-based Brain-Computer Interface (BCI). Such interfaces could be considered as an additional way to communicate between people with disabilities. To control BCI, it is necessary to identify different brain activity patterns correctly. This identification based on classification algorithm that could automatically define the type of activity by EEG data. In the 2017 year big review of actual classification algorithms for that time summarized in paper [2]. Recently the same authors released updated actual review of classification algorithm [3]. As the author noted the main difference in classification approaches is that current state-of-the-art approaches based mostly on machine learning, included neural networks and deep learning techniques. Also, authors noted that deep learning methods had not shown convincing improvement over other methods.

In this article, we present a study of a combination of machine learning algorithms for the problem of classifying attention types based on the time-frequency representation of the EEG. The training data contains time-frequency features extracted from single-trial EEG records while subject performed different tasks, in our case different attention tasks.

In psychophysiological literature term attention could be divided on externally vs. internally directed attention [4,5]. We consider sensory attention as externally directed to the incoming sensory information, mental attention we consider as internally directed to operating with the information already in the brain. These two type of attention differ significantly from the neurophysiological point of view, and statistical difference of this process was found at the group level. We decided to check whether it is possible to detect differences for individual subjects based on the time-frequency features of individual trials.

To describe the time-frequency pattern of EEG signals, we used continuous wavelet transform with Morlet kernel. The power spectral density of wavelet transform could be considered as a two-dimensional image for each channel. Usually, for the implementation of EEG pattern classifiers, various statistical features are extracted, which are then used in machine learning algorithms. We used the idea of low-dimensional representation of images using convolutional autoencoders as a features for classification.

2 Experiment Description

28 healthy volunteers (average age 29, 17 women) all right-handed participated in the study. The study described herein was approved by the Ethics Committee of Institute of the Human Brain. All subjects signed written informed consent, in accordance with the ethical standards laid down in the Declaration of Helsinki (1964), prior to their participation in the study. In this paper, we used tasks in which mental attention (MA) or sensory attention (SA) dominates. Tasks were presented in blocks, each block contains 80 trials. Experimental trial overview is presented at Fig. 1.

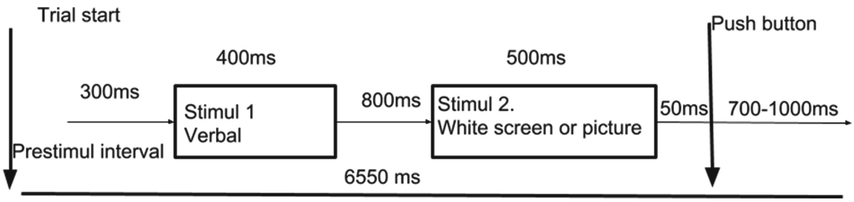

Fig. 1. Experimental trial overview.

In the block of SA task, the trials consisted of pair of stimuli: word (e.g. apple) and corresponding color image, subjects should memorize the image. Mental task consists from two different blocks: visual representation and imagination. In the block of retrieval of visual representations from memory the trials consisted of pair of stimuli: word and white screen, the words used in the previous SA task were presented. Here, the subjects were asked to recall and visualize on a white background an image, corresponding to presented word. In the block of visual imagination the trials consisted of pair of stimuli: 2 words and a white screen. Here, after simultaneous presentation of 2 words (for example: apple, machine), the subjects were asked to invent and visualize a chimera image (for example, an apple-shaped machine, seeds are pour out when the doors are opened). The duration of verbal stimulus presentation is 400 ms, the duration of second stimulus (color image or white screen) - 5 s, the interval between stimuli - 800 ms.

3 Methods

3.1 Preprocessing

19 channels of EEG were recorded using standard 10–20 electrode placement on the scalp by computer electroencephalograph "Mitsar-202" and electroencephalographic caps Electro-Cap. Monopolar montage with average reference electrode from left and right ears was used. Electrode impedances were kept below 5 kOhm. EEG recording and the subsequent removal of eye artifacts were conducted by a software package WinEEG, version 2.83 (copyright V.A. Ponomarev, J.D. Kropotov, RF2001610516, 08.05.2001). Independent Component Analysis (infomax ICA) was used in the package to correct artifacts due to vertical and horizontal eye movements and blinks. Additionally, all EEG records were inspected by operator, samples with strong movement artifacts, noise level and sudden outlets were eliminated from dataset.

Next, for each subject for each type of task, the wavelet power spectrum was calculated, according algorithms adapted for EEG analysis, described in the books [1], Khramov and our previous paper [6]. The code implemented in Python with application examples is available in the https://github.com/iknyazeva/EEGprocessing repository. The wavelet transformation was done for a grid of 20 frequencies from the 4–30 Hz range for each electrode independently, the minimum sample length in the experiment was 3480 counts or 6.96

s. Each power spectrum were normalized to the average power value during the prestimulus interval. The power spectrum for each channel was represented as an grayscale image by the dimension of the number of frequencies per time. Figure 3 shows examples of wavelet transforms for one channel and phase coherence for one pair of channels for one subject (Fig. 2).

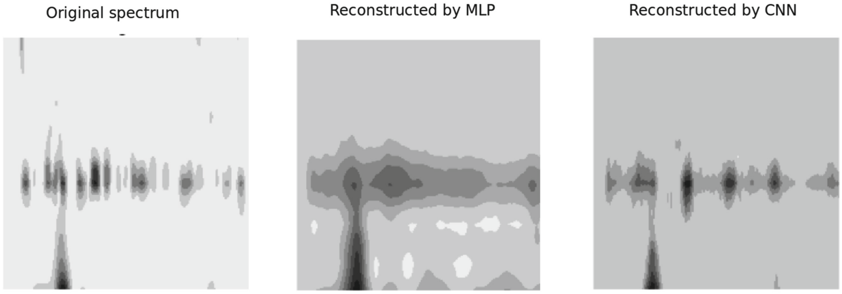

Fig. 2. Wavelet transform and phase coherence example for one subject

3.2 Computational Experiments

Computational experiments of machine learning methods application were done according to the following scheme: compression of wavelet spectra with by auto-encoders and using of low dimensional code-vectors as inputs for some model solving the classification problem. The experiment scheme and the parameters of the auto-encoder are shown in the figure. Obviously, that training neural networks with huge number of parameters (800 000 for CNN autoencoder and 380 000 for dense autoencoder) required large dataset of samples. Since the task of the encoder is the compression and reconstruction spectral patterns, we will assume that the mechanism of their compression and recovery does not depend on the channel number and it is possible to use spectra of all EEG channels independently during training. Thus, the amount of the training set was increased and consist of more than 100,000 samples. The training process was stopped by a validation set (consisted of 10% randomly selected samples with replacement): if the error, calculated on the validation set, did not decrease during 500 epochs. It should be noted, that the solution converges in less than 1000 epochs of training. The next step is solving the classification problem on compressed data. In this case spatial difference between electrodes couldn't be ignored, so the classifiers were built on own small pieces of data, corresponding each electrodes. As classification method shallow a neural network with fully connected layers was used. There were explored two approaches: training universal classifier on data of whole group of subject and training own models for each person. In second case to exclude the the effect of random splitting data to train (80%) and test (20%) sets experiments were returned 5 times: results of solving classification problem, are demonstrated at next chapter, were averaged between these 5 dataset-splits.

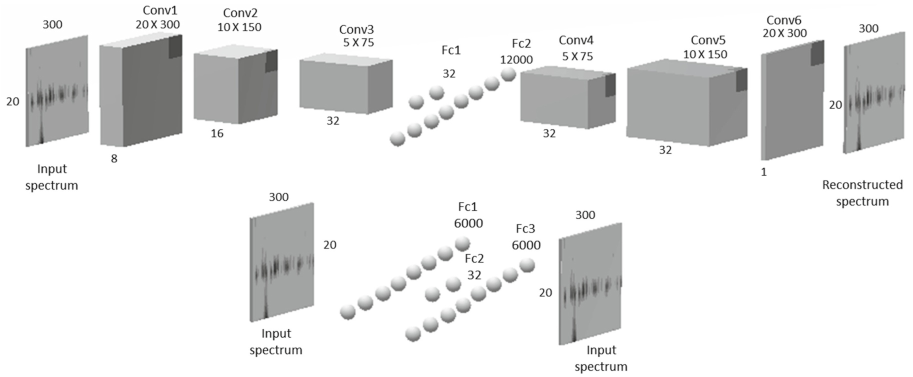

Fig. 3. Schematic representation of auto-encoders. Top: convolutional autoencoder (filter size: 3×3, maxpooling window size: 2×2, activation function: elu), bottom: dense autoencoder (activation function: elu). Loss function: mean square error, optimization algorithm: adamax.

4 Results and Discussion

During the computational experiment, the high efficiency of using convolutional networks for the coding of wavelet spectra was demonstrated. Classical neural networks with dense layers showed a much worse result. The table shows the values of the minimum error for 3 best subject and indicates 3 channels, which demonstrated the minimum error. Classification errors and corresponding channel names presented in cells. It should be noted significant differences in the results of different people: the minimum error obtained value is 1.2%, but maximum value is 31.2%. In this case, the electrodes are also different. The best results are demonstrated on wavelet spectra of the electrodes O1, O2 and T6 (Table 1).

Table 1. My caption

	Best chan1 (error)	Chan 2 (error)	Chan 3 (error)
subj_7	1.2% (O2)	1.8% (T5)	2.4% (P3)
subj_19	7.9% (Pz)	9.3% (P4, O2)	15% (Pz)
subj_16	10% (Pz)	12.5% (T6)	13.8% (F4, C3, C4, P3, P4, O2)
mean_all_subj	16.6% (Fz)	17.9% (T5)	18.6%(T6, O1, O2)

5 Conclusion

In this paper, we presented results of classification of single-trial EEG signals with using convolutional autoencoders and machine learning approach. The experiment consists of two type of tasks with the dominance of mental and sensory attention. We find clear differences not only at the group level but also could reveal them at the single-trial basis. Time-frequency features of EEG patterns, namely power spectral density of wavelet transform were used as a main discriminated factor. We used a low-dimensional representation picture of PSD image for each channel received with a convolutional autoencoder as a feature vector. The classification was carried out by data from individual channels. The quality of classification varies was from 80 to 90% for each subject. The results obtained make it possible to consider this approach as promising for both clinical classification and BCI interface creation. Within the framework of this approach, only the time-frequency features were used. Potentially, other informative features of single-trial EEG patterns, such as common spatial patterns or others [3] can be added for the model improvement.

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