Using Convolutional Neural Network to Classify 2D EEG Scalp Topograms during Visual Task

Sergey Korchagin
Department of Data Analysis and Machine Learning
Financial University under the Government of the Russian Federation
Moscow, *Russia*
sakorchaign@fa.ru

Vladimir Maksimenko
Institute of Information Technologies, Mathematics and Mechanics, Lobachevsky State University of Nizhny Novgorod
Nizhny Novgorod, Russia
Center for Neurotechnology and Machine Learning, Immanuel Kant Baltic Federal University
Kaliningrad, Russia
maximenkovl@gmail.com

Alexander Hramov
Center for Neurotechnology and Machine Learning, Immanuel Kant Baltic Federal University
Kaliningrad, Russia
hramovae@gmail.com

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***Abstract* — we developed an artificial neural network (ANN) classifier to analyze the cortical activity signals during visual information processing. We tested several ANN architectures and chose a convolutional neural network (CNN) with the Resnet50 topology. As a result, the trained CNN classifier achieved an accuracy of 74% on the data of newly recruited subjects.**

Keywords— EEG scalp topograms, convolutional neural network, CNN, ambiguous stimuli, machine learning

I. Introduction

Successful classification of EEG patterns is a step towards developing the brain-computer interfaces [1-3]. The brain-computer interface recognizes and classifies brain activity signals to form control commands for the external devices and software [4-6]. The complexity of the EEG signals classification is caused by a low spatial resolution, lack of preliminary knowledge about the exact neural mechanism generating the data. Therefore, scientists switch to using machine learning approaches to analyze brain signals [7-8]. Machine learning has advantages over traditional methods resulting in higher accuracy and enabling big data analysis with an acceptable computational power [9-10]. Currently, there is no universal tool for the classification of EEG patterns. The purpose of our work is to create an optimal classifier for dividing EEG scalp topograms into two classes, depending on the ambiguity of visual information perceived by the subjects.

II. Algorithms and Methods

A. Formulation of the problem

We used experimental data collected in the laboratory of neuroscience and cognitive technologies of the Innopolis University (Innopolis, Russia) following the Declaration of Helsinki and the local committee on research ethics. The experiment involved 16 men and 4 women aged 20-36 years. Thus, 20 subjects took part in the experiment. The subjects perceived Necker cubes repeatedly presented on a computer screen. The demonstration time varied from 1 to 1.5 seconds. Presentation times and pauses were randomized throughout the experiment. We instructed participants to identify the orientation of each stimulus and report their choice using a joystick. The left and right buttons indicated the left and right cube's orientations. With the help of noninvasive sensors, we obtained EEG signals and presented EEG power distribution in form of the scalp topograms. Our task was to create a classifier that divides the scalp topograms corresponding to the high (HA) and low (LA) ambiguity of the perceived image.

B. Algorithms and Methods

To address the classification task, we built a Convolutional Neural Network (CNN). The neural network was developed in Python using the TensorFlow library, Keras module.

We tried several CNN architectures and ran into the following problem. Simple networks were under-trained (VGG16, LeNet architectures were considered) [11-12], complex networks (such as InceptionV3, BNN-NIN, ENet) [13-14] were over-trained. The optimal architecture for our task was a CNN of the Resnet50 topology [15], consisting of 50 main layers (convolutional and fully connected). The second problem was a large amount of data. Thus, we used the Image Rescaling procedure, enabling a reduction of the image size without significant loss of information. Here we reduced the images to 224x224 pixels.

To train CNN, we utilized the backpropagation method; the activation function was ReLu. ReLu is a nonlinear function that takes less computational costs than hyperbolic tangent or sigmoid while demonstrating good approximation properties. Cross-entropy served as the loss function.

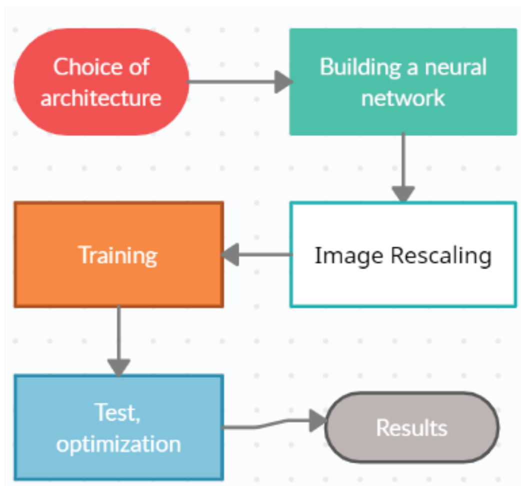

Fig. 1. Algorithm for constructing a classifier

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Each subject perceived 100 LA and 100 HA stimuli. For each stimulus, the neural activity was characterized by three images (EEG scalp topograms representing EEG spectral power in three frequency bands). Thus, participant's data included 600 images (300 LA and 300 HA tomograms). We included 11400 images of 19 subjects in the training set. The testing set consisted of 600 images belonging to one subject. Thus, CNN did not learn the data of the test subject. This procedure was repeated 20 times to test CNN for each subject. Finally, we utilized Adam's optimizer to select the optimal parameters of the neural network. To evaluate the CNN performance we analyzed the traditional metrics, accuracy, precision, and recall. The algorithm is shown schematically in Fig. 1.

III. RESULTS

Table 1 shows the classification metrics for each subject. One can see that CNN accuracy varies from 71% to 76%. The average accuracy for all subjects is 74%.

IV. CONCLUSION

We confirmed that CNN with the Resnet50 topology could classify 2D EEG scalp topograms with a mean accuracy of 74%. These topograms represented the time-frequency characteristics that we obtained earlier [17] using intra-subject statistical contrast between HA and LA classes. Thus, we hypothesized that CNN used biomarkers related to a fundamental neural process shared between subjects. We supposed that our results would be useful in the development of brain-computer interfaces. They enabled creating a pre-trained classifier whose accuracy would be improved by the particular subject during a calibration session.

TABLE I. METRICS OF THE CLASSIFIER

Table Head	***Accuracy***	***Precision***	***Recall***
test subject 1	0,735	0,7281	0,6325
test subject 2	0,761	0,7448	0,6583
test subject 3	0,7588	0,7524	0,6481
test subject 4	0,7164	0,7333	0,7018
test subject 5	0,7172	0,7061	0,7013
test subject 6	0,7594	0,7409	0,6684
test subject 7	0,7582	0,7046	0,6469
test subject 8	0,7193	0,7541	0,7093
test subject 9	0,7449	0,7164	0,6528
test subject 10	0,7388	0,7372	0,6918
test subject 11	0,7259	0,7264	0,6559
test subject 12	0,7552	0,6951	0,6848
test subject 13	0,7612	0,7223	0,6941
test subject 14	0,7307	0,7112	0,6508
test subject 15	0,7576	0,7038	0,6384
test subject 16	0,7422	0,7079	0,6929
test subject 17	0,728	0,7526	0,7035
test subject 18	0,7649	0,6987	0,6627
test subject 19	0,7512	0,7511	0,6565
test subject 20	0,735	0,7244	0,6321

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