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# Convolutional Neural Network and Adversarial Autoencoder in EEG images classification

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***Abstract*—In this paper, we consider applying computer vision algorithms for the classification problem one faces in neuroscience during EEG data analysis. Our approach is to apply a combination of computer vision and neural network methods to solve human brain activity classification problems during hand movement. We pre-processed raw EEG signals and generated 2D EEG topograms. Later, we developed supervised and semi-supervised neural networks to classify different motor cortex activities.**

***Index Terms*—EEG, Computer Vision, Neural Networks, CNN, GAN**

## I. Introduction

Brain signals classification is one of the essential problems in neuroscience [1]–[9]. The typical approach for analysis and classification of human brain motor activity collected by EEG are Linear Discriminant Analysis (LDA), Support Vector Machine (SVM), and K-Nearest Neighbors (k-NN) classifier [10]–[14]. Neural network-based classification is also widely used. It includes Artificial Neural Networks (ANN), Convolutional Neural Networks (CNN), Deep Neural Networks (DNN), and a lot more [15]–[17].

In this work, we work with data collected by EEG, using wavelet analysis techniques to generate a dataset of topograms, and implement neural network-based solutions for brain motor activity classification problems.

## II. Data collection and data structure

Fifteen healthy volunteers (age: 20-45 years, males) participated in the experiment. All of the participants were right-handed, amateur practitioners of physical exercises, and non-smokers. The subjects were conditionally healthy: no diagnosed diseases of the musculoskeletal or nervous system, no prescribed medications. Prior to the experiment, the participants were asked to maintain a healthy lifestyle for a least 48 hours, including 8-hours night rest, prohibited alcohol consumption, limited caffeine consumption, and moderate physical activity.

Before the beginning of the experiment, the volunteers were instructed about its goals and methods, along with possible inconveniences. The experimental procedure was performed following the Helsinki's Declaration and approved by the local Ethics Committee of the Innopolis University.

### *A. Task*

The experiment was performed as follows. The subject was sitting in a comfortable chair with hands placed on armrests. Each experiment began and ended with a 3-min recording of background brain activity, during which the subject was instructed to relax and make no hand movements. During the active phase of the experiment, the subject was asked to perform movements with his left or right hand according to the screen instructions. There were 40 total hand movement trials (20 for each hand).

Each hand movement trial consisted of several phases accompanied by specific commands on the monitor. The trial started with the fixation of the subject's attention: a bright cross appeared on a black screen for 2 seconds and acted as a signal for the subject to prepare for the trial. Attention fixation was followed by a visual cue: the cross stayed on the screen, and the left- or right-oriented arrow appeared on the top of it for 1.5 seconds. During this phase, the subject was informed that the left- or right-hand movement was required, correspondingly. The next phase was motor execution: the arrow disappeared from the screen, but the cross stayed for 5 seconds. During this time interval, the subject performed the required hand movement. It consisted of bending and unbending of fingers to the palm's center. The trial ended with rest: the cross disappeared, and the black screen was shown for 15 seconds. During this phase, the subject rested and waited for the next command.

### *B. EEG data acquisition and preprocessing*

EEG signals were recorded using the actiCHamp electroencephalograph manufactured by Brain Products, Germany. EEG signals were recorded with 32 channels in accordance with the 10-10 scheme. The ground was located at the site of the Fpz electrode, and the reference electrode was placed behind the right ear. For EEG registration, active Ag/AgCl electrodes ActiCAP were used, which were located on the scalp surface in the sockets of a special EasyCAP cap. To

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improve signal quality and provide better conductivity, the scalp was pretreated with NuPrep abrasive gel, and then the electrodes were positioned using SuperVisc conductive gel. During the experiment, the conductivity values were monitored at each of the EEG electrodes. Typically, the values were 25 $< k\Omega$ which is sufficient for the correct operation of active EEG electrodes. The raw EEG signals were sampled at 1000 Hz and filtered by a 50–Hz notch filter by an embedded hardware-software data acquisition complex. Additionally, raw EEG signals were filtered by the 5th-order Butterworth filter with cut-off points at 1 Hz and 100 Hz. Eyes blinking and heartbeat artifacts removal was performed by the Independent Component Analysis (ICA). Data was then inspected manually and corrected for remaining artifacts.

### C. Data processing

After the experiment, we have raw EEG data for 15 human subjects and 20 trials for each human subject.

The next step is to convert raw EEG data into 2D human scalp topographies and to choose correct samples from data trials. There is no formally verified correct way to do that. In this work, we empirically discovered the next sample selection strategy, which led to satisfying results:

- Chosen frequency is ”mu” (9-11 Hz). ”Mu” frequency was chosen because of the nature of the experiment. It is well known, that ”mu”/”alpha” frequencies are responsible for motor activity.
- To avoid edge effects, we cut the following intervals out:
  - 5.0-5.5 seconds,
  - 8.5-10.0 seconds.
- Time frame 0.0-5.0 seconds was not used. This interval corresponds to the recording of “baseline” activity.
- To extract the maximum amount of useful data we use “slicing windows” as a strategy to export EEG topographies:
  - 5.5-7.0 seconds,
  - 6.0-7.5 seconds,
  - 6.5-8.0 seconds,
  - 7.0-8.5 seconds.
- To double the exported amount of data we use two different baseline procedures:
  - “absolute”,
  - “relative”.

To generate EEG topographies Matlab’s package FieldTrip Toolbox was used [18].

### D. Finalized dataset

The final dataset consists of 939 images and two classes. The resolution of images is 840 by 630 pixels. Dataset structure is represented in Figs. 1 and 2. Approximately data was split in 80/20 proportion. 80% of images are train set, 20% of images are test set. The current data split was chosen according to Scaling Law [19] splits.

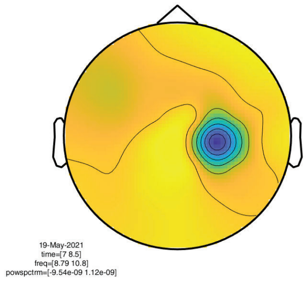


Fig. 1. Left hand-related EEG topography in Mu frequency band.

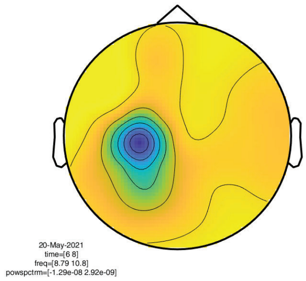


Fig. 2. Right hand-related EEG topography in Mu frequency band.

## III. Convolutional Neural Network (CNN)

Input shape for Convolutional Neural Network is 84 by 63 pixels. Reshaped images tended to better quality performance than original images with the same network structure [20]. Other parameters of the network were configured empirically during the development.

The current network uses a 5 by 5 kernel. The network contains four convolutional layers with increasing density, four pooling layers with dimensions 2 by 2, three fully connected layers with decreasing density to the number of classes we were looking for.

ReLU (Rectified Linear Unit) was chosen as an activation function. ReLU was selected for the sake of reducing computational expenses and compensating high dimensionality of other parts of the designed network. To the last fully connected layer Softmax activation function was used. ReLU activation function is defined as the positive part of its argument. Here, $x$ is a input of neuron:

$$Relu(x) = max(0, x) \tag{1}$$

SoftMax is commonly used as an activation function for the last layer of Artificial Neural Networks (ANN). SoftMax uses Luce’s choice axiom and normalizes the output of the network to a probability distribution over predicted output classes. Input of SoftMax is a vector $x$ of $K$ amount of real numbers:

$$\text{Softmax}(x_i) = \frac{\exp(x_i)}{\sum_j^K \exp(x_j)} \tag{2}$$

### A. *Results*

Convolutional Neural Network performance is satisfying for our classification problem. Supervised learning on just 10 epochs reaches an accuracy of 93,75%. Algorithm performance on a larger number of epochs is unpredictable but a bigger size train dataset may lead to better performance.

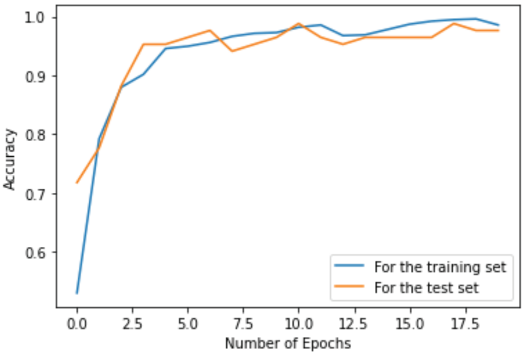


Fig. 3. The CNN's accuracy is satisfying. The network reaches accuracy over 90%even on small-scale data.

## IV. Semi-supervised Adversarial Autoencoder (AAE)

The main idea of GAN-based methods is a competition between two objects: a generator $G$ and a discriminator $D$. Generator is trying to create images that look like they belong to the original dataset $X$. The work of the discriminator is to distinguish between original data $X$ and generated images $G(X)$. In the best-case scenario, the training stops when the generator can outplay ("fool") the discriminator. So, the generalized training objective for GAN can be described as:

$$\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_{\text{data}}(x)}[\log D(x)] - \\ -\mathbb{E}_{z\sim p_z(z)}[\log D(G(z))] \tag{3}$$

In the current architecture, we use two sub-networks made up for autoencoders [21]. The training objective for the discriminator sub-network is to maximize a pixel-wise error between the reconstructed image from original dataset $X$ and generated image $G(X)$:

$$\mathcal{L}_D = \|X - D(X)\|_1 - \|G(X) - D(G(X))\|_1 \tag{4}$$

At the same time, the generator is trying to minimize the same error and "fool" the discriminator. Training objective for the generator may be represented as:

$$\mathcal{L}_G = \|X - D(X)\|_1 + \|G(X) - D(G(X))\|_1 \tag{5}$$

We chose $L_g$ (pixel-wise error) to achieve sharper results, following insights from Isola [22]. For the sake of having a more robust model, generator sub-network and discriminator sub-network are created only from fully convolutional layers.

### A. *Results*

The network was trained at 400 epochs. The training results are satisfying for our goals. Still, the results of each training are unstable. Training results are floating. The network success rate floats from 60% to 68% during different training sessions. The best-achieved result is 68%.

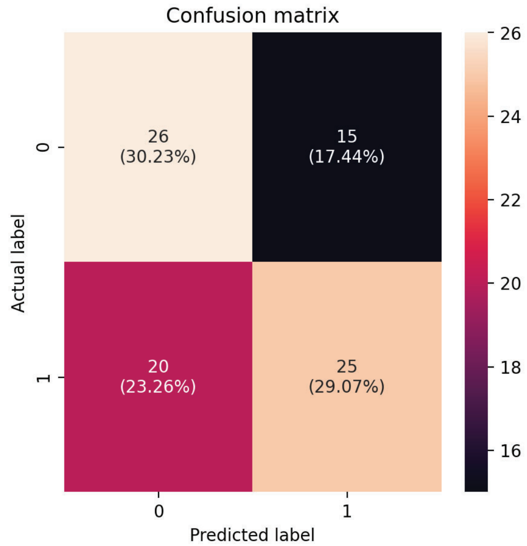


Fig. 4. The Confusion Matrix of Adversarial Autoencoder. 1 = class "left hand", 0 = class "right hand".

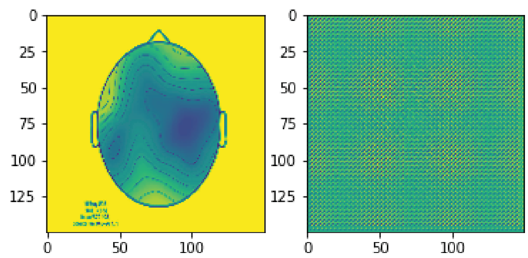

Fig. 5. Original Image after the augmentation is on a left. Generated Image is on a right. Step 0.

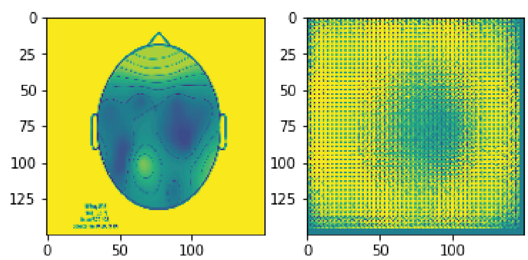

Fig. 6. Original Image after the augmentation is on a left. Generated Image is on a right. Step 150.

## V. Conclusion

In the work, we explored opportunities and capabilities of neural networks and computer vision-based techniques in the analysis and classification of human brain motor cortex activity using EEG neuroimaging. We have tested both supervised and semi-supervised approaches. As a result, motor cortex activity was successfully classified. However, the adversarial autoencoder approach requires more time and effort to achieve better results.

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