Training Artificial Neural Network to Classify Correct and Erroneous Interpretations of Visual Stimuli before Behavioral Response

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***Abstract*—We have trained an artificial neural network (ANN) to predict correct and erroneous interpretations of complex visual stimuli, Necker cubes with different levels of ambiguity. For the selected configuration of ANN, the classification accuracy was 88%. These results are prospective for developing the new-generation assistive technologies.**

***Index Terms*—Necker cube, machine learnin, cognitive task, electroencephalograms, ambiguous stimuli**

I. Introduction

In modern science, brain-computer interfaces (BCIs) occupy a special place at the intersection of neuroscience and machine learning [1]. BCIs are the devices that connect brain with the computer or an executive device. BCIs have many practical applications, including controlling prostheses or a wheelchair with commands coming directly from the brain. In addition, they can be used for the treatment of the central nervous system diseases [4], [5], post-stroke rehabilitation [3], training cognitive abilities [2] and monitoring cognitive states. Such BCIs are called passive and attract particular interest, since they can be used in the development of assistive technologies that control the cognitive state of a person while performing complex tasks that require attention and concentration. During a high cognitive load, along with a decrease in productivity in terms of response time, a person can make mistakes when responding to the external stimuli. An ultimate goal of assistive technologies is predicting and prevention of these mistakes. A promising approach for prediction is analyzing brain activity before the response and finding biomarkers prediction erroneous response. To test this possibility, we considered a decision-making task involving perception of the visual stimuli, Necker cubes and responding to their interpretation. We trained an artificial neural network to predict correct and erroneous interpretations of visual stimuli using EEG signals recorded before the behavioral response.

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II. Materials and methods

A. Experiment

To participate in the experimental sessions, we recruited a group of volunteers (26 subjects) with normal or adjusted to normal visual acuity. During the experimental sessions, we recorded electroencephalograms using the monopolar registration method and 31 electrodes arranged in accordance with the classical extended international arrangement of electrodes 10-10, with a sampling frequency of 250 Hz [7], [8]. Before starting the procedure, we placed the subjects in a chair in a comfortable position that minimizes muscle movements. On the monitor screen, the participants observed visual stimuli - Necker cubes with different levels of ambiguity [9], [10]. The subject, without any visual disturbances, interprets the 2D image of the Necker cube as a 3D object due to the specific position of the edges of the cube. The observer can perceive such an image as oriented either to the left or to the right. As a control parameter a = [0, 1] (the level of ambiguity), we used the contrast of the inner edges. This parameter was calculated as $a = g/255$, where g is the brightness of the inner edges. Thus, we had Necker cubes with parameters a = [0.15, 0.25, 0.4, 0.45, 0.55, 0.6, 0.75, 0.85]. We instructed the volunteers to report their first impression of the orientation of the visual stimulus by pressing the corresponding button on the joystick.

The whole experiment lasted about 40 minutes, including short recordings of background brain activity at the beginning and at the end of the registration. During the experimental sessions, the subjects observed Necker cubes with predefined parameters of the ambiguity level 400 times. Between each demonstration of the visual stimulus, the participants observed an abstract image on the monitor screen.

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B. Protocol

During the experimental sessions, we formed a protocol. It contained all the necessary information for working with experimental data, namely: the time of demonstration of each visual stimulus, parameter *a* of the visual stimulus, the correctness of the interpretation of the visual stimulus by the subject, as well as the time that the subject spent on the interpretation of each Necker cube.

According to the protocol, we divided the EEG recordings into 4-second trials, including 2 seconds before and 2 seconds after the demonstration of the visual stimulus.

C. Data preprocessing

We used a band-pass filter with cutoff frequencies of 1 Hz and 100 Hz and a 50 Hz notch filter for primary processing of EEG recordings. Artifacts related to blinking, heartbeat, and muscle movements were removed using the Independent Component Analysis (ICA) method [8]. This procedure was performed in Matlab software using the fieldtrip package [6]. On average, 3 components containing artifacts were removed for each EEG record. However, ICA didn't remove all the distortion of the EEG signal. We conducted a visual inspection of the processed data in order to remove trials containing high-amplitude artifacts. For this, we used the z-value threshold z $<$1.

D. ANN input

We have generated EEG recordings in the form of a matrix with a dimension of 31x375, which corresponds to a 1.5-second recording interval for each visual stimulus (TOI1) and including a 1-second prestimulus interval (TOI3) and a 0.5-second poststimulus interval (TOI2). Thus, we used three matrices as input data for the convolutional neural network: 1) TOI1 – 31x375, 2) TOI2 – 31x125, 3) TOI3 – 31x250. In this paper, we used the following hyperparameters to train a neural network: *initializer* = RandomUniform (a technique that defines the way to set the initial random weights of ANN layers), intermediate layer *activation function* = softmax (defines how the neuron transforms the weighted sum of the input into an output), Adam optimizer (an algorithm used to change the attributes of the neural network such as weights and learning rate in order to reduce the losses), *learning rate* = 1 (a hyperparameter that controls how much to change the ANN model in response to the estimated error each time the model weights are updated. A small learning rate may result in a long training process, whereas a large learning rate may result in learning a sub-optimal set of weights too fast or an unstable training process), *batch size* = 200 (defines the number of samples that will be propagated through the network. If the batch size is equal to 100, the algorithm takes the first 100 samples from the training dataset and trains the network. Next, it takes the second 100 samples (from 101st to 200th) and trains the network again. We can keep doing this procedure until we have propagated all samples through the network), *number of epochs* = 10 (defines the number of times that the learning algorithm will work through the entire training dataset. One epoch means that each sample in the training dataset has had an opportunity to update the internal model parameters. When the number of epochs is large, the ANN learns patterns that are specific to sample data to a great extent. As a result, ANN gives high accuracy on the training set but fails to achieve good accuracy on the test set).

E. Cross-validation

We implemented an artificial neural network (ANN) using the TensorFlow library in Python. We loaded experimental data into an artificial neural network, having previously converted them into a feature vector. We combined the experimental data of all 26 people and obtained as a result a data set consisting of 9534 trials, of which 8580 had a correct interpretation, and 1054 had an erroneous one. Based on these data, we trained an artificial neural network to distinguish between correct and erroneous interpretations of visual stimuli, and evaluated the effectiveness of ANN using cross-validation. Each round of cross-validation involved partitioning a dataset into two subsets, performing ANN training on the training subset (8580 trials, 90%), and validating on the testing subset (954 trials, 10%). This division was chosen because of the peculiarities of behavioral data (correct and erroneous interpretations). In each round, we estimated the model's performance using categorical accuracy (CA) as follows

$$CA = \frac{N^1_{true} + N^2_{true}}{N^1_{true} + N^2_{true} + N^1_{false} + N^2_{false}}, \tag{1}$$

where $N^{1,2}_{true}$ and $N^{1,2}_{false}$ are the numbers of true and false predictions for the class 1 and class 2, respectively. To reduce variability, we performed five rounds of cross-validation using different partitions and averaged CA over the rounds.

III. Results

The chosen configuration of the artificial neural network provided prediction of correct or erroneous interpretation of the visual stimulus to the subjects with an accuracy of 88%.

IV. Conclusion

We trained an artificial neural network to predict the correct and erroneous responses of subjects to visual stimuli with an accuracy of 88% using 31 EEG signals. However, we obtained these results using a single neural network configuration. In subsequent studies, we plan to consider various ANN configurations to select optimal parameters.

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