Artificial neural network predicts erroneous responses in the task of classifying visual stimuli

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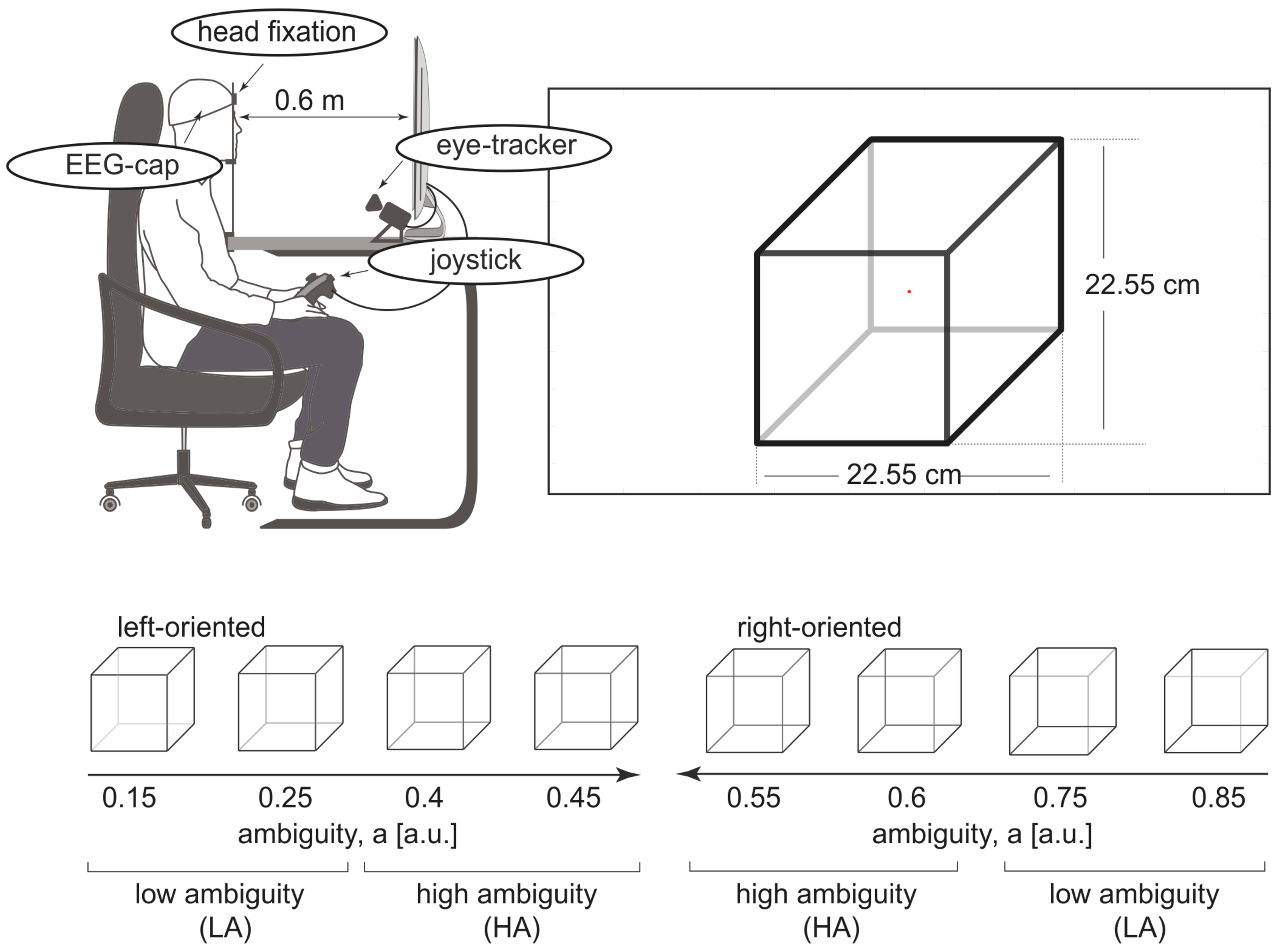
In this work, we have developed an artificial neural network (ANN) trained to distinguish between correct and erroneous behavioral reactions of the subject in the task of classifying a bistable visual image (Necker cube). We trained ANN on EEG recordings prior to the subject's behavioral response to the current visual stimulus. We examined the configuration of an artificial neural network, for which the accuracy of classification of erroneous behavioral reactions exceeded 88%.

Experimental task

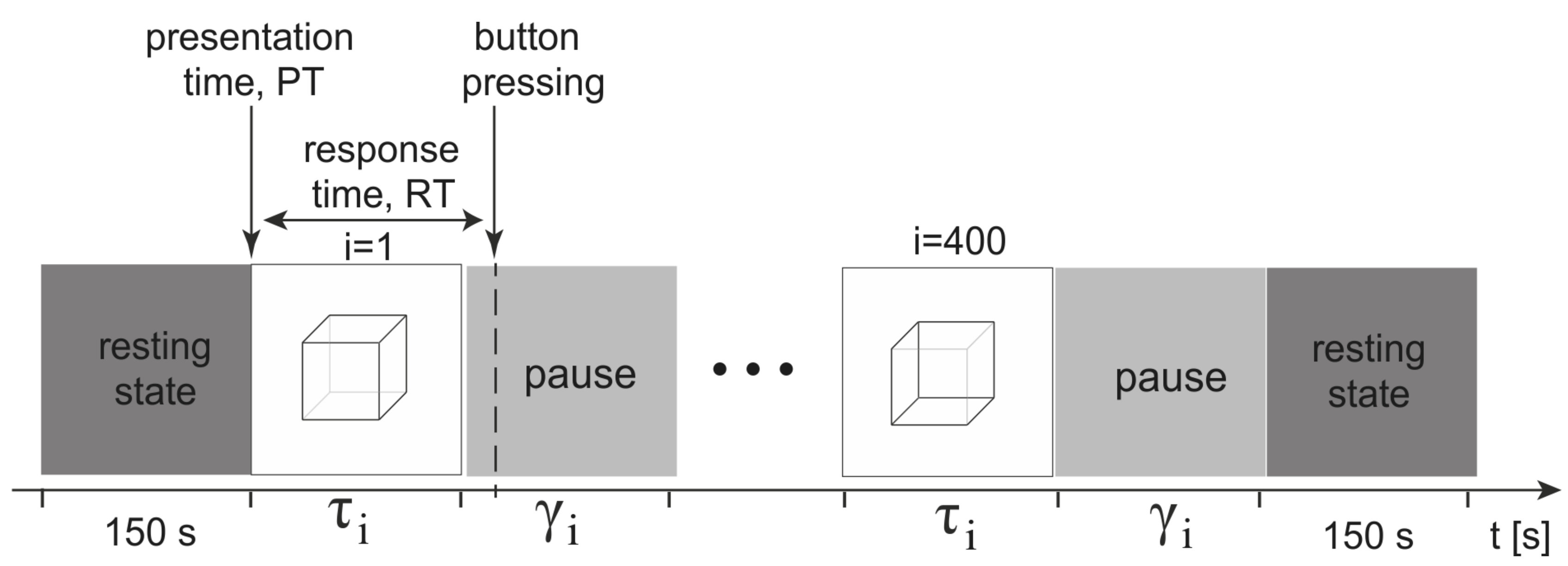


In this study, the subjects performed a cognitive task of interpreting consistently presented ambiguous images. The Necker cube was used as an ambiguous image. By changing the contrast of the inner edges, you can control the level of ambiguity of the image, as well as the orientation.

26 volunteers (age 20-36) took part in the experiment. The subjects were placed in front of the monitor screen in a comfortable position that minimizes muscle movements. The subjects were instructed to press either the left or right joystick key, depending on the first impression of the orientation of the presented visual stimulus.

During the experimental sessions, the subjects recorded the electrical activity of the brain using 32 electrodes mounted on the surface of the head.

Experimental procedure



For each participant, the entire experiment lasted about 40 minutes, including short recordings of the electrical activity of the brain at rest. After each presentation of the image of the Necker cube, the subjects observed an abstract image for 3-5 seconds to distract attention.

During the experiment, we formed a protocol that includes information about the orientation and level of ambiguity of the current visual stimulus, the time of presentation of the visual stimulus, the response time (RT) of the subject to the visual stimulus, as well as the correctness of the interpretation of the visual stimulus by the subject.

We filtered the EEG recordings with a bandpass filter with cutoff frequencies of 1 and 40 Hz, as well as a 50 Hz notch filter. We removed artifacts related to muscle movements, heartbeat, and breathing using the independent component analysis method. After that, we conducted a visual inspection to remove the high-frequency artifacts that remained after filtering the EEG recordings. Finally, we divided the received signals into 4-second segments, which included 2 seconds before the demonstration of the visual stimulus and 2 seconds after.

Results

We trained an artificial neural network using the following hyperparameters: initializer = Random Uniform, intermediate layer activation function = softmax, Adam optimizer, learning rate = 1, batch size = 200, number of epochs = 10. As input data, we used a matrix with a dimension of 31x375, which corresponds to a time interval of 1.5 seconds, including 1 second before the demonstration of the visual stimulus and 0.5 seconds after.

The training dataset consisted of 9534 tests, of which 8580 tests with the correct interpretation of the visual stimulus by the subject, and 1054 - with an erroneous one.

We evaluated the performance of the model using categorical accuracy (CA)

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

As a result, for this configuration, we obtained an accuracy of predicting the erroneous interpretation of the visual stimulus by the subject equal to 88%.

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[2] V. A. Maksimenko et al., “Neural interactions in a spatially-distributed cortical network during perceptual decision-making,” Frontiers in behavioral neuroscience, vol. 13, pp. 220, 2019.

[3] A. K. Kuc et al. “Monitoring brain state and behavioral performance during repetitive visual stimulation,” Applied Sciences, vol. 11, No. 23, p. 11544, 2021.