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Diagnostics of the Brain Neural-Ensemble States Using MEG Records and Artificial Neural-Network Concepts

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Abstract—We propose a method for the diagnostics of human brain states using MEG records and an artificial neural-network apparatus. It is shown that this approach allows various states of the human brain to be classified in the case of making decisions related to the perception of visual stimuli.

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The concept of artificial neural networks (ANNs) offers an effective mathematical tool for the analysis and interpretation of human brain activity [1]. The ANN apparatus has been widely used for studying the features of brain functioning based on data of MRT [2], EEG [3], MEG [4], and other neurophysiological methods [5].

The prospects of using the ANN approach in neural science are related primarily to the creation of a computational basis for a modern brain–computer interface (BCI) [6]. From this standpoint, ANNs have been used for the classification of motor-activity patterns and the diagnostics of psychiatric disorders and pathological brain activity [7–9]. In these applications, a properly trained ANN is capable of high-precision recognition of clearly pronounced and well reproducible patterns of oscillatory activity of the brain neural ensemble. In addition, it also of considerable interest to use ANN in cases where the brain exhibits intermittent switching between certain stable states or occurs in an intermediate state between these. This dynamics is typical of cognitive processes involved in perception of external stimuli or making decisions [10]. In this context, questions arise as to whether it is possible to teach ANN recognize various states of brain when making decisions and which peculiarities of brain functioning in these states can be revealed. Answering these questions is important for both understanding fundamental processes of cognitive human activity and employing artificial intelligence methods in developing new human–machine systems capable of increasing the efficiency of brain functioning in cognitive-activity states.

In accordance with the above considerations, this work was devoted to diagnostics of the state of a neural ensemble in the course of making decisions with the use of ANN. For this purpose, we have selected an optimum ANN architecture and processed multichannel MEG records obtained in experiments on the perception and interpretation of ambiguous visual stimulus. It should be noted that an ambiguous (multistable) visual stimulus means an image that admits several interpretations.

It this work, an ambiguous stimulus was represented by a Necker cube [11], which is frequently used in theoretical and experimental investigations of visual perception [12–14]. A Necker cube is the classical example of an ambiguous plane image comprising a superposition of projections of the left- and right-oriented volume cubes. The maximum contrast of visible wireframe ribs corresponds to almost unique identification of the cube orientation by observer, whereas a low contrast of ribs leads to ambiguous perception of the cube orientation (Fig. 1). Thus, the contrast of ribs plays the role of a control parameter that provides variation of the degree of ambiguity in interpreting image of the visual stimulus. This parameter (denoted by I) can take any value from 0 to 1, where $I = 0$ corresponds to the left-oriented cube projection, $I = 1$ corresponds to the right-oriented cube projection, and $I = 0.5$ refers to the Necker cube with the most ambiguous perception. Note that a characteristic feature of perception of the ambiguous Necker cube is frequent switching of the image interpretation. This behavior can be related to switching between the two states of activity of the brain neural network. Accordingly, it was of interest to reveal different coexisting states of human brain activity and study the switching between these states.

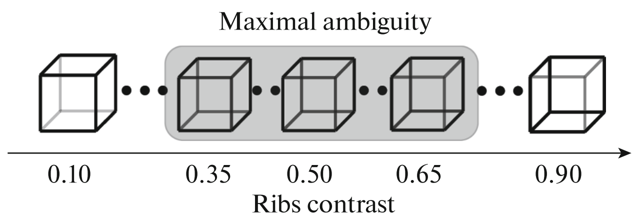

Fig. 1. Images of a bistable Necker cube presented to participants during experiments for visual perception depending on contrast I of visible ribs: images with $I < 0.5$ are usually interpreted as left-oriented; images with $I > 0.5$ are usually interpreted as right-oriented.

The investigations performed in the framework of this work were divided into two stages. The first stage was devoted to experiments on monitoring of the brain activity during perception of an ambiguous visual stimulus in a group of five healthy volunteers (males and females) aged 26–30. The activity of the neural ensemble of the cerebral cortex was monitored using a VectorVeiw 306 Channel MEG system (Elekta AB, Sweden) comprising 102 magnetometers and 204 planar gradiometers (306 channels) and capable of recording MEG signals at a discretization frequency of 1000 Hz. The experiments were performed in accordance with the Declaration of Helsinki (World Medical Association). In every experimental session, each participant was presented a set of 15 visual stimuli with parameters I randomly selected from the total set of

$$I = (0.1, 0.15, 0.3, 0.4, 0.47, 0.48, 0.49, 0.5, 0.51, 0.52, 0.53, 0.6, 0.7, 0.85, 0.9).$$

The duration of presentation of each visual stimulus was also randomly varied within 0.8–1.2 s. The total experimental cycle for each participant consisted of 15 sessions and lasted for about 25 min. Then, the initial signals were filtered in a 5–30 Hz band to remove low-frequency artifacts and high-frequency noise. The remaining undesired interferences related to heartbeats, breathing, eye movements, and blinking were removed using the temporally extended signal-space separation (tSSS) method [15].

Upon carrying out experiments and accumulating the experimental database, the second stage began that was aimed directly at the classification of states of the brain neural network using MEG data and the ANN apparatus. In this work, we applied the ANN architecture design of multilayer perceptron (MLP) [16], which is most widely used for the classification and recognition of patterns. The MLP has a relatively simple architecture representing a neural network of forward propagation, in which informative signal **X** (fed into the input layer) sequentially propagates over layers of the neural network toward the output layer, where output signal **Y** is formed.

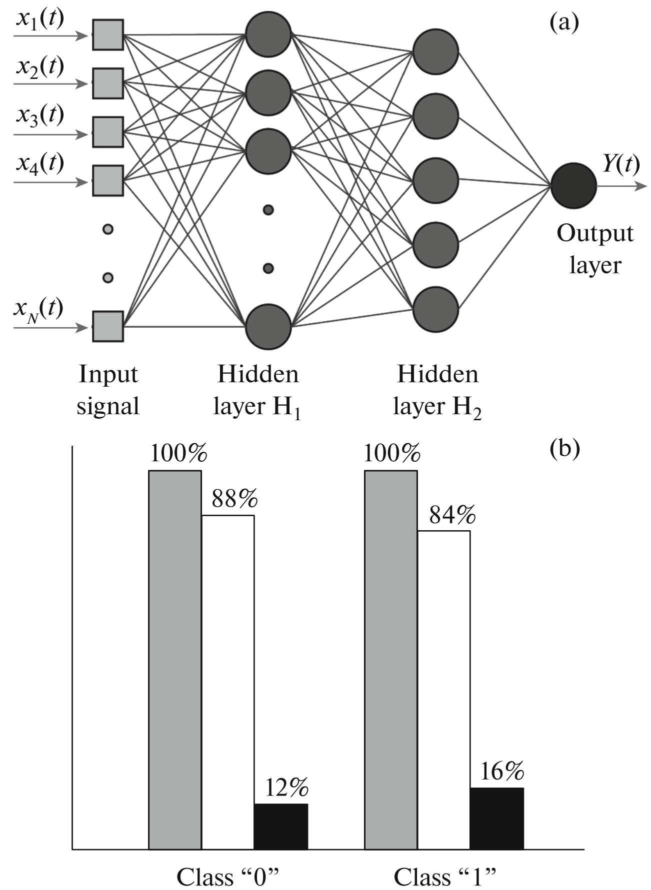

Fig. 2. (a) ANN of forward propagation with MLP design with $N = 102$ inputs (corresponding to the number of informative MEG channels), two hidden layers (with 15 and 5 neurons), and an output layer with a single neuron; (b) results of teaching and testing of the neural network: gray column shows the number of correctly classified events at the teaching stage; white and black columns correspond to the numbers of correctly and incorrectly classified events, respectively, at the testing stage. The rms error of classification at the teaching stage is on the order of 10^{-5}.

It should be noted that we are describing an instantaneous brain state (event) at time moment t_j using the N-dimensional vector

$$\mathbf{X}^j = (x_1(t_j), x_2(t_j), \ldots, x_N(t_j))^T,$$

which contains the values of signals from N MEG channels measured at this moment. Note that the vector dimensionality is $N = 102$, since the most informative signals are obtained from 102 MEG channels corresponding to magnetometers.

Figure 2a shows the neural-network architecture with MLP design used in this work. Since the problem setup stipulates the classification of only two classes of brain states, which correspond to the perception of left-oriented cube projection (class "0") and right-oriented cube projection (class "1"), the output layer consists of a single neuron forming the output signal Y.

Every layer in this ANN transforms informative input signal **x** according to the following relation:

$$\mathbf{u} = f(\mathbf{Wx} + \mathbf{b}),$$

where **u** is the output vector, **x** is the input vector, **W** is the weight matrix of links between input elements and neurons of the given layer, **b** is the vector of displacement weights, and $f(x)$ is the logistic neuron activation function defined as

$$f(x) = \frac{1}{1 + e^{-x}}.$$

The ANN was taught to classify the states of brain neural ensemble through optimization of the weights of links and displacements by means of minimization of the rms error using the Levenberg–Marquardt algorithm [16]. For this purpose, a teaching sample set was prepared in the form of 0.5-s-long segments of 20 MEG signals corresponding to the perception of Necker cubes with clearly pronounced left- and right-oriented cube projections (I = 0.1 and 0.9, respectively). The ANN testing set included the remaining ten MEG records. With allowance for the resolution of signal records on the MEG setup employed, the teaching set contained 10^4 events, while the testing set contained 5×10^3 events. The teaching session and subsequent testing of ANN showed that the classification accuracy was on the average 86% (Fig. 2b).

Figure 3 shows the results of applying the well-taught ANN to the classification of states of the brain neural ensemble for MEG records of perception of the bistable Necker cube. These data have the form of typical ANN $\mathbf{Y}(t)$ curves observed in response to the presentation of a sequence of 1-s-long MEG record segments $\mathbf{X}(t)$ after demonstrating bistable visual stimuli with various degrees of ambiguity to a participant. As can be seen, in response to the presentation of rather clear images of the Necker cube (Figs. 3a and 3c), the participant's brain neural ensemble converges to stable perception of the visual stimulus after a short transient period of 0.2–0.3 s. It is evident that this stable perception corresponds to perception of the Necker cube as associated with more contrast ribs: state "0" in case of $I = 1$ and state "1" in case of $I = 0.9$. In contrast, the presentation of a visual stimulus with the maximum degree of uncertainty leads to frequent switching between the states of the brain corresponding to alternating perception of the bistable visual stimulus.

In addition, we have also estimated the ability of participants to interpret the Necker cube orientation based on perception of the clearer ribs (Fig. 3d). For this purpose, we have introduced perception measure A defined as

$$A(I) = \begin{cases} N_0(I)/N_1(I), & I < 0.5, \\ N_1(I)/N_0(I), & I \geq 0.5, \end{cases}$$

where $N_0(I)$ is the number of brain states (events) classified by the ANN to "0" and $N_1(I)$ is the number of

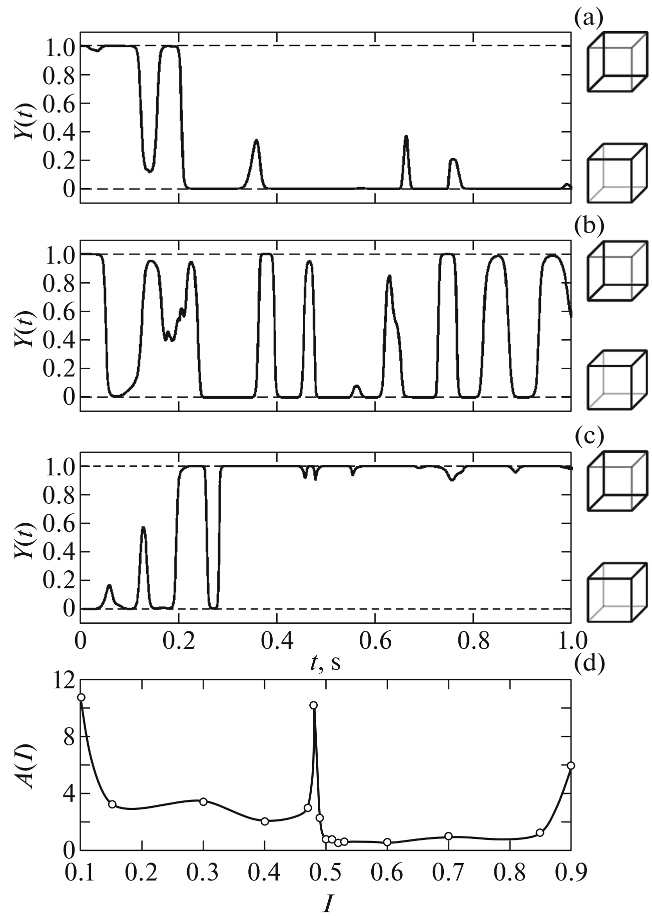

Fig. 3. Response of a taught multilayer ANN to 1-s-long MEG segments after presentation of an ambiguous Necker cube with visible rib contrast I = (a) 0.1, (b) 0.5, and (c) 0.9; (d) plot of perception measure $A(I)$ averaged over all experimental sessions.

events classified by the ANN to "1"; the $N_0(I)$ and $N_1(I)$ values are averaged over all experimental sessions. As can be seen from Fig. 3d, the participant is capable of unambiguously interpreting visual stimuli with clearly pronounced ribs, while more probably classifying the images to left-oriented cubes. It is important to notice the presence of a central peak on the $A(I)$ curve at $I = 0.48$. The peak shift to left from the middle may be related to a specific feature (habit) of perception in left-to-right reading human beings [17]. For this peculiarity of perception, a left-oriented cube sets the initial conditions and, hence, predominates. Another possible mechanism (also not excluded) of this behavior is related to the leading-eye effect [18]. Apparently, the dominating left eye can increase the probability of left-hand interpretation of ambiguous images. A final judgment as to the mechanism of this behavior requires further investigation.

In concluding, this work was devoted to ANN-based diagnostics of brain neural-ensemble states during perception of a bistable visual stimulus taking the form of a Necker cube. It is established that ANN models can be successfully used to classify the brain states corresponding to different interpretations of bistable images. In addition, the transition to a stable state of the neural ensemble was revealed after perception of the Necker-cube images with clear rib contrast, whereas the brain neural network upon the observation of ambiguous images exhibited regular switching between two states. The obtained results and proposed approaches may be of interest both for further fundamental investigations of the mechanisms of human perception and for the practical implementation of described methods in new brain–computer systems developing human cognitive properties.

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