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Calculation of the cyclic characteristics of the electroencephalogram for investigation of the electrical activity of the brain

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Abstract. The *purpose* of the study is experimental verification of the proposed EEG analysis *method* based on the construction of a connectivity graph of the analyzed signal, in which the amplitudes are displayed by vertices, and their relative position relative to each other by arcs. The display of the EEG signal in the graph structure causes the appearance of cyclic structures with the possibility of calculating their numerical characteristics. As a *result* of the study, criteria for initialization of the initial conditions of the counting algorithm have been developed. The following parameters were calculated: the number of cycles and the Euler number in the EEG recording. Coil representations of graphs are given. The proposed algorithm has a scaling parameter, the choice of which affects the final results. The second free parameter of the proposed algorithm is the degree of artificial signal coarsening. Variants of the algorithm application for multichannel EEG signals with multichannel signal processing by channel-by-channel detection of semantic units and construction of a generalized semantic connectivity graph are considered. An example of an analyzed multichannel EEG signal, which was pre-processed with reduction of all amplitudes to natural numbers in accordance with the calculated characteristics, is given. An example of an EEG of a subject with closed eyes during quiet wakefulness and an EEG of a subject with open eyes is given. In *Conclusion*, it is shown that the final indicators can vary significantly (from zero to tens of thousands or more) depending on the particular derivation of the EEG channel. Analysis of the cyclic structures of the electroencephalogram seems to be a potential way to assess various human states due to the possibility of distinguishing them using the proposed method. The study has a limited, pilot character.

Keywords: electroencephalography, electroencephalogram analysis, functional states.

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Introduction

A large number of works known to us, where the analysis of the human electroencephalogram was carried out, can be conditionally called "alpha rhythm and others". In fact, they used the approaches to analysis proposed by Gray Walter and other pioneers of such research in the middle of the 20th century. Nowadays, electroencephalography (EEG) is the most widely used in medicine and psychology, this also applies to neuroergonomics, self-regulation, games and entertainment, neuromarketing, education, security and authentication. In this regard, as well as with the expansion of computing capabilities, a set of "classical"methods for conducting and analyzing EEG data and related ideas about brain work is complemented by new research aspirations [3], among which it is necessary to highlight the use of EEG in neurointerfaces [4] and their use to assess human conditions [5, 6]. A variant of the classification of modern tasks in the analysis of EEG data includes: recognition of emotions, control of imaginary movements, assessment of mental stress, control and instrumental element of diagnosis of epilepsy, study of the structure of sleep, study of evoked potentials of the brain [3].

For the analysis of EEG data, approaches that can be described as "elements of artificial intelligence"have become widespread (for example, [3, 7]). The calculated characteristics of the signal are used, the most common methods for which are complex transformation, spatial filtering (the method of general spatial patterns), dynamic energy, fast Fourier transform, average absolute difference, spectral power density, short-term Fourier transform, singular value decomposition, swarm decomposition [3]. It should be noted that for a long time there has been an opinion that there are no obvious advantages of complex new methods of mathematical processing of EEG signals compared to "classical"spectral analysis, if there is no clear understanding of what specific contribution these new methods make to the practical work of the user.

In our opinion, the development of EEG data analysis is also associated with attempts to "formalize"various concepts of brain work, including the search for the neural foundations of consciousness, when one or another version of the analysis is developed or exploited, aimed at inductive confirmation of the authors' ideas. To some extent, this may include attempts to isolate rhythmic patterns in the human electroencephalogram and correlate them with the phenomenon of Schumann resonance (for example, [10, 11]). The development of fractal analysis, for example, can be correlated with the study of circadian rhythms, sleep [12]. In turn, it seems promising to develop ideas about the fragmentation of the processes of perception, cognitive control [13], reflected in biological rhythms — including those outlined by us [14]. There are also newer attempts to link, for example, cardiorhythm or respiration (cyclic activity) with brain activity [15, 16].

In this case, on the contrary, we believe that the general mathematical idea proposed by V.V. Aristov may be useful for the development of ideas about the work of the brain. The essence of this proposal is to search for cyclic structures of signals that can probably indicate a change in the level of general activation or regulation of functions (or, according to V. V. Aristov, the manifestation of the phenomenon of consciousness at different levels). To formalize this position, the growth of the graph tree is considered. With a certain complication, giant cycles occur at the point of the "phase transition". These ideas are based on the fact that the simpler structure of the neural network (conditionally it can be called the structure of the animal's nervous system, including the neural network of the brain) is characterized by signal transmission from the "receptor"to the "effector". Such a structure can be modeled by a graph in the form of a tree (or a pair of trees). But with the complication of the network, as was shown in [17], the so-called percolation ("phase") transition, known in kinetic statistical theory, can occur. It means the appearance of clusters, cycles that no longer have such a simple kind of trajectories in the graph system from "input"to "output"("from input to output"). The appearance of "confusing"signal trajectories in the neural network of the brain is supposed to be compared with a change in the level of general activation or regulation of functions (or even with manifestations of consciousness and self-awareness). It is the emergence of such structures that can create prerequisites, contribute to the development of some abstraction, the emergence of the opportunity to operate with signs, words, numbers, in general, elements of semiotics. However, a comprehensive development of the model is required. The identification and isolation of such autonomous formations, which was mathematically obtained and shown on models of growing graphs in [17], is a possible promising goal. In this case, the possibility of studying EEG data using a mathematical model based on graph theory is being studied. Thus, this study has limitations for reliable interpretation of the results in relation to brain conditions, but we consider it as preliminary, exploratory, aimed at developing the method. In this regard, the purpose of the work was limited to a fundamental description of a potentially useful, in our opinion, approach to a possible method of analyzing an electroencephalogram. In a broader sense, the study concerns the development of mathematical foundations for identifying cyclic signal structures based on a graph-theoretic approach with a demonstration of the capabilities of new algorithms using the example of EEG signal processing. To assess the sensitivity of the proposed approach to the assessment of functional states, various modes of operation of the psyche and the body, a significant amount of statistical data is required. In this paper, it was not intended to investigate the method being developed in relation to a specific practical task. Note that this method can be used to evaluate any biorhythms, including EEG, ECG, pulse waves, respiration, circadian rhythms and others. This method can also be used for processing and analyzing cyclic structures in signals of arbitrary nature (radio and acoustic signals, speech, solar and stellar activity in astrophysics problems), that is, wherever a quantitative assessment of hidden cyclic structures in processed signals is required. Thus, this study is narrowly focused and mainly mathematical and methodological.

1. Materials and methods

In a prospective study, previously obtained in the Laboratory of Physiology of human functional states of the P.K. Research Institute of Normal Physiology were analyzed in compliance with modern ethical standards. Anokhina records electroencephalograms of 10 conditionally healthy 20-year-old subjects. EEG registration was performed on the Neurovisor electroencephalograph (Russia), monopolarly, with the placement of electrodes according to the 10–20 system. The digitization frequency is 512,000 Hz synchronously across all channels, followed by digital filtering and thinning. The resolution is not worse than 2 MV. The dynamic range of the signal is 130 mV (22 digits of the ADC). The bandwidth is 0...70 Hz (at the level of −3 dB). Software RF filters 0.02, 0.05, 0.1, 0.25, 0.5, 1.0 Hz, 50 Hz notch. To demonstrate the proposed method of analysis, 16-second fragments of EEG recording without visually detectable artifacts were selected. Conditions — calm vertical standing with open eyes in a noise-insulated room, in daylight. The proposed method is an analysis of "cyclic structures"in the analyzed EEG recording, where, in the formal sense, by "cyclic structure"we take any reproduction of a fragment of arbitrary length (any repetition of a chain of "words") usual for signal processing in accordance with the above algorithm for analyzing EEG data based on the construction and analysis of graph parameters. The novelty of the study is related to the proposed approach and method of isolating cyclic structures, as well as the potential possibility of linking such parameters with human functional states. To search for such repeating structures, the free scaling parameter N is used here, which sets a fixed fragment length (hereinafter referred to as the length of the "word"). By changing the parameter N, it is possible to analyze the EEG at different scales, which, we believe, may be useful, in particular, to identify fractal characteristics of the signal. In this case, the scaling parameter N can be correlated with the frequency of the EEG. This line of research is borrowed from neurosemantics [18, 19] and is its further development. Note that graph theory is used to describe different methods of structural and functional communication between nerve elements [20, 21].

The proposed method includes the following steps.

1. Artificial signal coarsening (decreasing accuracy) by rounding to the L th decimal place. This is introduced to reduce the load on the calculation modules and correct the number of parameter options with the possibility of adjusting the total number of cyclic structures in the analyzed signal. This stage is optional.
2. Slicing data by N points using the maximum word overlap method.
3. Construction of a connectivity graph in which neighboring points are represented by vertices, and their direct neighborhood is represented by adjacent arcs. The uniqueness of the word representation as a vertex of the graph causes the appearance of cyclic structures in the graph, which we will call the semantic connectivity graph.
4. Estimation of graph parameters in terms of properties of cyclic structures in accordance with the research hypothesis. The parameters are the Euler number and the number of simple cycles of the semantic connectivity graph.

Let's take a closer look at these stages. Reducing the components of the information flow (EEG amplitude) to a set of natural numbers includes:

1) determining and fixing the number of decimal places and selecting the appropriate normalizing parameter L;
2) multiplication of each component of the signal (EEG amplitude) by the normalizing parameter 10^L;
3) discarding extra decimal places for each component of the signal to obtain a natural number (in further constructions — a semantic unit or its element).

The quality functional of ϕ when defining the parameter L:

1) for single-channel EEG: $\phi(L) : (E \to \max; C \to \max; T \to \max)$;
2) for multichannel EEG:
$\phi(L) : (E1 \to \min; E2 \to \max; C1 \to \min; C2 \to \max; T1 \to \min; T2 \to \max;)$, in this case, $E \in (E1, E2), C \in (C1, C2), T \in (T1, T2)$,

where E is the Euler number, C is the number of simple cycles, T is the number of simple paths of the resulting semantic graph G. The quality functional can be determined not only by the indicators E, C and T, but also other characteristics, for example, based on evaluating the effectiveness of algorithms for subsequent signal processing. The allocation of semantic units consists in determining the scaling parameter N by allocating words of length N in a sequence of length M elements with an overlap parameter K. In this case: $\exists M = n \cdot N$, $n \in N$, $K = N$. In general (for an arbitrary value of the parameter K):

$$K \in N, \quad n = 1 + \left[\frac{M - N}{K}\right],$$

where square brackets are— the procedure for taking the integer part of a number. Obviously, with $K = 1$ we get the maximum number of words of length N.

Analyzing the original signal based on different values of N generates a multiscale approach. In a multichannel stream, words can be selected according to the principle that each subsequent word is taken from the next channel. This will make it possible to build a generalized semantic graph and identify causal relationships in the structure of a multichannel stream. In Fig. 1 schematically shows this case, with an overlap of one element. In Fig. 2 provides an example of a real EEG signal and a fairly large fragment highlighted as a single word.

Note that L is the number of decimal places, and the normalizing factor is 10^L. Thus, the

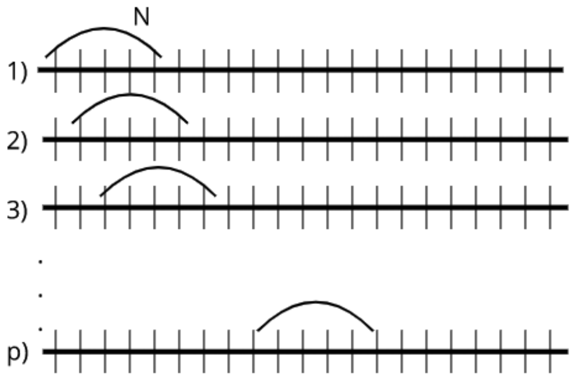

Fig. 1. An example of a generalized processing of a p-channel signal by channel-by-channel detection of words of length N at $K = 1$

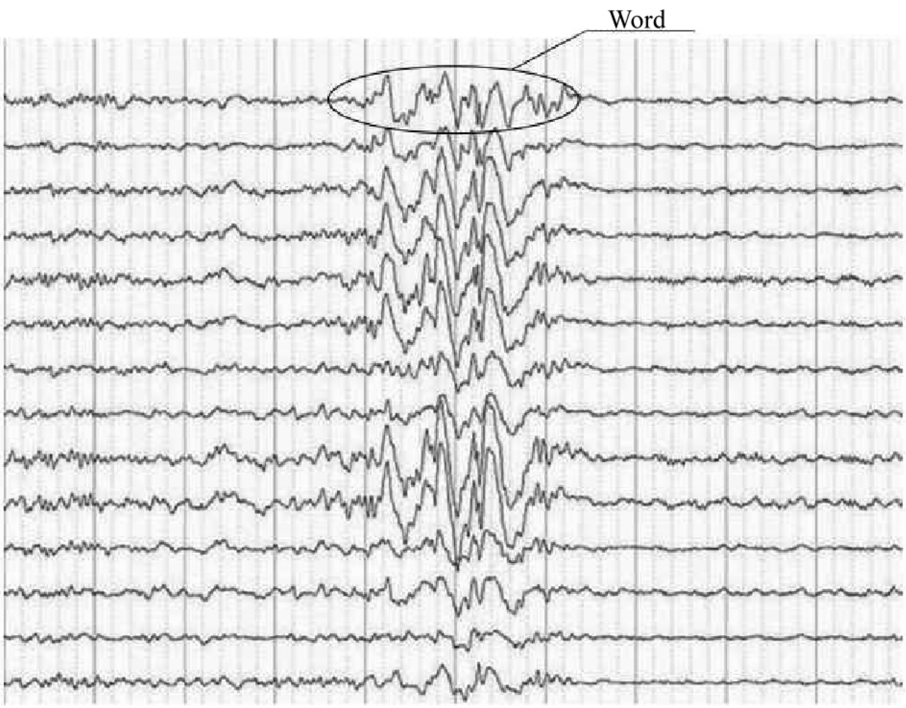

Fig. 2. An example of a word inside one of the channels of a multichannel EEG

initiating parameters of the algorithm are the parameters L, N, K.

Let's explain in more detail what the integer parameter L means. We have created a program that rounds the amplitude values to a certain number of decimal places. The choice of rounding significantly affects the result, since at this stage all semantic units are determined. You can get rid of the comma using the multiplication operation by the parameter 10^L. At the same time, the relationship between the rounded values of the amplitudes will remain. Thus, the service parameter L allows for some preprocessing, which will significantly affect the frequencies and values of all semantic units and the structure of relationships between them.

It should be noted that if the information channels are not interconnected in any way, then graph construction, including word selection, should be carried out independently in each channel.

An encephalogram is a system of channels in which each channel is correlated with the others. Therefore, it is possible to expand the scope of the algorithm in order to build a semantic graph immediately based on the results of processing all channels. In this case, each word will encode the value of the amplitudes in all channels. At the same time, it is not so important how exactly the set of amplitudes will be encoded, since regardless of the encoding (which should be functional and unambiguous), the frequencies of occurrence of certain words will be preserved. Thus, the encoding method is invariant with respect to the encoding operation. For example, to create words, you can list all amplitudes on the first channel separated by a comma or other service symbol, then all amplitudes on the second channel, etc.

The semantic graph G<X,Y> is defined by a set of vertices X and edges Y, while the set of vertices is identical to the set of words. For repeated words, we count the number of repetitions, which sets the weight, which can be displayed as the size of the corresponding vertex (Fig. 3).

When constructing the incidence matrix of the graph G<X,Y>, a sequence of words is read. The weight $\mathcal{W}$ of each vertex is $x_1....x_c \in X$ at step k is defined as $\mathcal{W}\left(x_i, x_y\right)_k = \mathcal{W}\left(x_i, x_y\right)_{k-1} + 1$ if $\exists\{x_i, x_j\}$, while the initial weights are zero and the weights of vertices and edges can only take natural values. The condition for the occurrence of a connection with an increase in the corresponding weight of the connection is the presence of a pair $\{x_i, x_j\}$ in the analyzed sequence. When constructing a directed graph, you can take into account the sequence of the elements x_i, x_j relative to each other (in this case, the incidence matrix will be asymmetric).

In the presence of a complex structure, "tangle"representations of graphs are possible (see

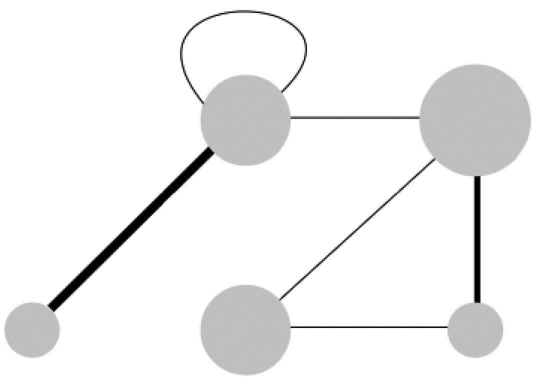

Fig. 3. An example of an undirected weighted semantic graph. The vertices and edges of the graph have different sizes to display the frequency of occurrence of the corresponding elements. The loop at the top left vertex corresponds to the cycle

below, Fig. 7). To optimize the perception of structured graph information, it is advisable to use normalization of the sizes of vertices and edges in accordance with their weights $\mathcal{W}$ based on the formula:

$$f(w) = \frac{1}{1 + e^{-\mathcal{W}}} .$$

Let's describe in more detail how the weights of vertices and edges are calculated. The initial weight of each vertex and connection is equal to one. If a certain relationship appears in the graph more than once, its weight increases by one. The same applies to vertices that display semantic units (words) — if a certain vertex or semantic unit occurs more than once, its weight also increases by one. If the sizes of vertices and edges are displayed on a semantic graph in proportion to their weights, then some vertices may turn out to be larger than the graph itself and the drawing will become completely unusable. Therefore, when constructing graphs, a nonlinear dependence is used, which smoothly displays the change in the sizes and weights of edges and vertices. A certain maximum and minimum limit of these sizes is possible. In this way, the data is non-linear normalized for more convenient display on the graph.

Characteristic maps can be any parameters of a semantic graph or a family of graphs for the corresponding initiating parameters L, N, K. Let's consider the construction of characteristic maps using the example of analyzing the cyclic characteristics of a semantic graph. To do this, the Euler number, the number of simple cycles, and the number of simple paths are calculated in the resulting graph G.

For graphs, the Euler characteristic is defined as follows:

$$E = N_{\text{links}} - N_{\text{nodes}} ,$$

that is, it is necessary to subtract the total number of nodes N_{nodes} from the total number of connections (edges) N_{links}. For any tree, $E = -1$. For a unicyclic cluster (containing a single cycle) $E = 0$. For a complex graph $E > 0$.

To obtain characteristic mappings based on semantic multiscale decomposition, it is possible to construct diagrams of the dependence of the output data on the initiating parameters of the algorithm.

In general, the method presented by us is designed to identify hidden cyclic structures at a given scale for the purpose of their subsequent mathematical evaluation. Very often, in noisy signals such as electroencephalograms, these cyclic structures are not visible to the eye. Their presence can be detected by scaling some fragments of the EEG under certain modes of brain operation. We are talking about the rhythmic activity of the cerebral cortex. Nevertheless, certain characteristics of cycles within this activity are difficult to identify by other methods due to the high noise level of signals and the extreme complexity of the nature of the electrical activity of the central nervous system and the brain, in particular. In Fig. 4 a fragment of a human electroencephalogram is presented with sufficient magnification to display some rhythmic structures.

2. Results and discussion

As a result of the conducted computational experiments, it was found that the final indicators can vary significantly. At $L = 4$ and $N = 150$, the Euler number in the multichannel EEG signal ranges from 0 to 15848, depending on the specific EEG channel lead, the number of cycles is from 1 to 411. The number of simple paths was not considered in this study. An example

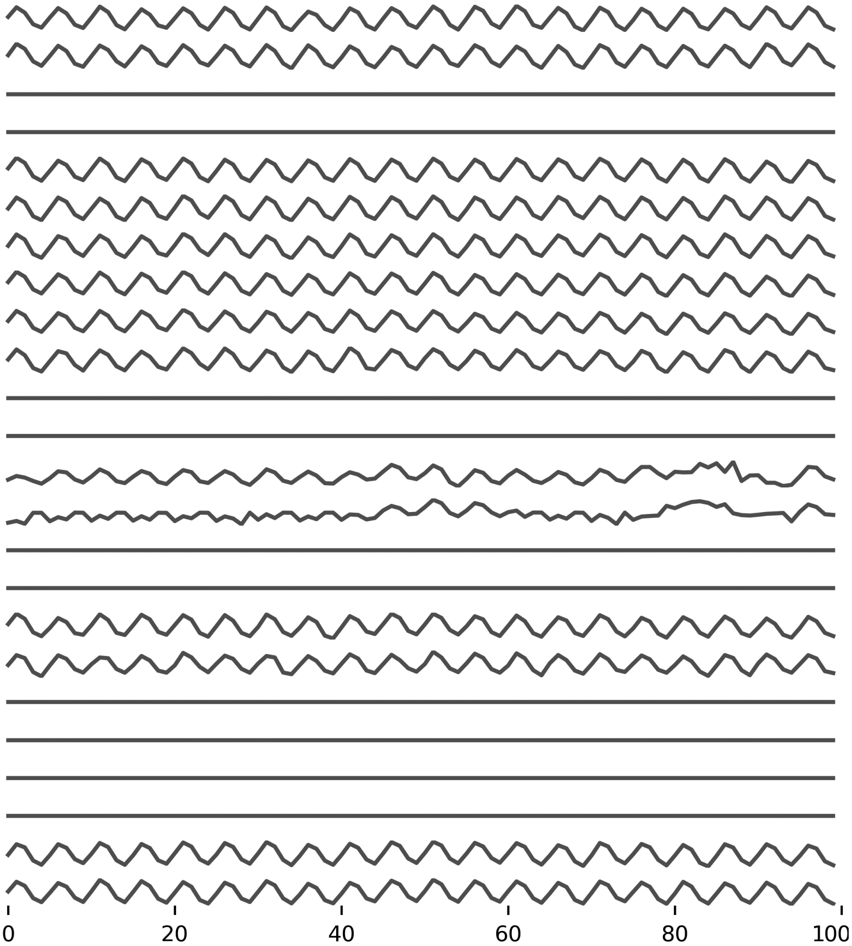

Fig. 4. An example of an enlarged fragment of a multichannel EEG, which shows cyclic structures for processing by the algorithm at the appropriate scale

of an analyzed multichannel EEG signal, which was preprocessed to reduce all amplitudes to natural numbers with calculated characteristics, is shown in Fig. 5, 6. At the same time, in Fig. 5 an example of an EEG of a subject with his eyes closed during quiet wakefulness is shown in Fig. 6— EEG of the subject with his eyes open.

We believe that the developed quality functionality was achieved by achieving a fairly wide range of changes in the recorded parameters. In our opinion, this indicates the high sensitivity of the developed mathematical apparatus and algorithms to such characteristics of the encephalogram as parameters of cyclic characteristics. In this regard, the proposed method may be a promising method for analyzing human functional states based on the results of electroencephalography, which requires further study.

It was also found that the computer calculation of the cyclic characteristics of complex graph structures (see Fig. 5) can take a wide range of time from several minutes to tens of hours on the same scale N for the same person, depending on the lead. We believe that this may reflect the diversity and complexity of processes occurring in the brain, and allows us to conclude that counting time can be an informative and significant parameter for EEG assessment.

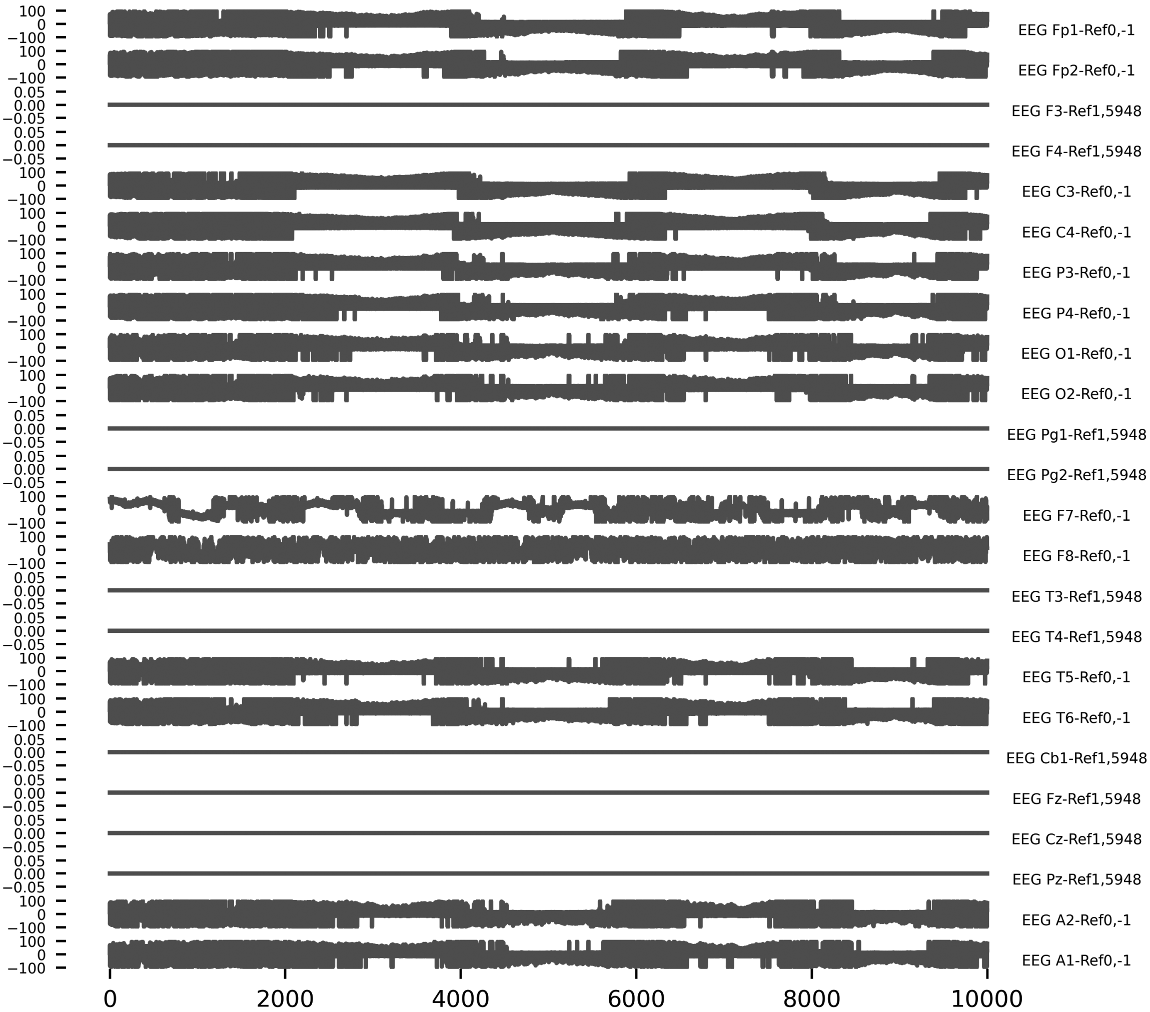

Fig. 5. An example of a multichannel EEG recording with signal coarsening in each lead ($L = 4$, with a "word" length of $N = 150$ points). To the right of each channel, its labeling and Euler number are shown. The horizontal axis is milliseconds. Quiet wakefulness of the subject with closed eyes

Conclusion

The described methodological approach substantiates and demonstrates, using the example of EEG analysis, a way to calculate quantitative characteristics associated with cyclic structures and hidden processes inside the EEG, which we can only interpret hypothetically so far. The need to use this method precisely to solve practical problems related to the processing of EEG signals has to be justified by conducting a series of experiments in accordance with the requirements of evidence-based medicine, which goes beyond the scope of our mathematical research. These studies are planned to be carried out in the future. This approach is also supposed to be developed in order to clarify the structural features of neural networks responsible for various mental manifestations. In this paper, the hypothesis proposed in [17] about modeling the elements of consciousness by studying cyclic complex structures that appear during percalation transition in tree structures on graphs was developed through the study of specific EEGS and their representations. The formalism of cyclic structures adopted in signal processing makes it

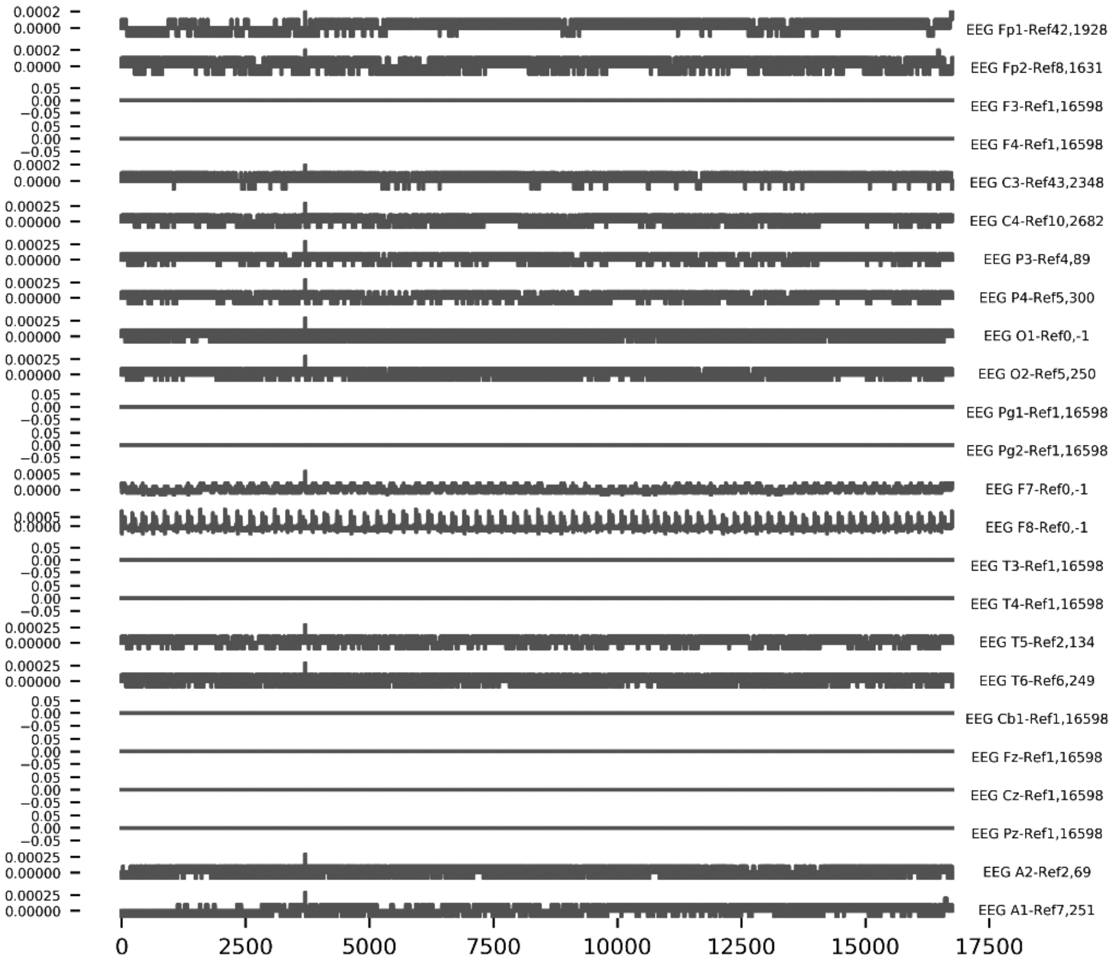

Fig. 6. An example of a multichannel EEG recording with signal coarsening in each lead ($L = 4$, with a "word" length of $N = 150$ points). To the right of each channel, its labeling and Euler number are shown. The horizontal axis is milliseconds. Subject with open eyes

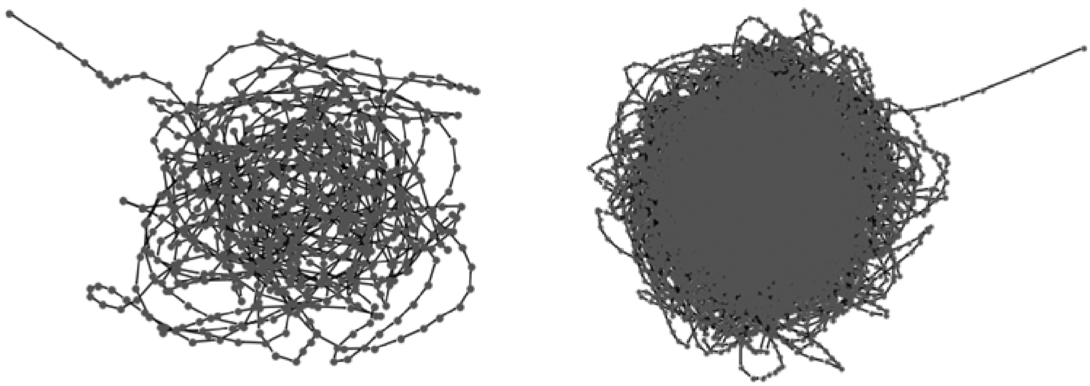

Fig. 7. EEG "tangled" representations — connectivity graphs constructed from one EEG channel of the subject. Left at $N = 4000$, $L = 2$, right at $N = 250$, $L = 4$

possible to note the reproducibility of fragments of various lengths. Structures with sufficiently large Euler numbers characterizing the nature of cyclicity have been identified. We believe that this mathematical approach to EEG analysis may be useful as a method for assessing various human conditions, which requires additional study.

Contribution of the authors

The authors are listed alphabetically. General approach and development of mathematical apparatus — V. V. Aristov. EEG data and participation in the preparation of the text — O. V. Kubryak. Development of a graph synthesis algorithm and computational implementation — I. V. Stepanyan.

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