

Multiparameter Analysis of Statistical Memory Effects in Bioelectric Signals while Performing Cognitive Tasks

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Abstract. In this research, in the framework of Memory Functions Formalism, we study statistical memory effects of electroencephalogram data for two groups of people by performing auto- and cross-correlation analysis. The first group consists of 8 professional musicians; the second group was represented by 11 people without any musical education. Bioelectrical activity signals were recorded during 2 cognitive tasks: perceiving a fragment of musical piece, and perceiving a text read aloud. During autocorrelation analysis, we identify regions of brain cortex, statistical memory effects of signals from which differ the most and use them for the following analysis. During the second stage of work, we identify differences in spectral behavior for both groups and analyze the effects of frequency-phase synchronization. Finally, it is demonstrated that our approach allows detecting differences in the cognitive abilities of people when performing various cognitive task. © 2023 Journal of Biomedical Photonics & Engineering.

Keywords: data science; living systems; biomedical data; time series analysis; autocorrelations; cross-correlations; cognition; electroencephalograms.

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1 Introduction

A complex system is a composite object, the parts of which are combined into a single whole according to certain laws or connected with each other by given relationships, because of which such a system acquires new properties that cannot be reduced to the properties of its parts. One of the examples of the most complex system is a human brain. In this work, we analyzed electroencephalogram (EEG) data – one of the methods to record bioelectric human brain activity.

Professional experience and long-term training may lead to a certain change in the activity of human brain cortex, that can be detected by analysis of bioelectric data records [1]. As a result, patterns of brain activity differ between experts and non-experts in different fields. Discrepancies between the biomedical data of professionals and non-professionals can be especially significant during the performance of expert tasks [2, 3].

This paper shows methodology to detect difference in statistical memory effects in signals of two groups of people recorded during two different cognitive tasks.

2 Literature Review

Determining the statistical features of changes in brain activity due to professional activity is not an easy task. In the study of similar data – the analysis of EEG signals when listening to musical fragments by musicians and non-musicians, the statistical parameters of the coherence of EEG signals were studied. The authors found significant changes in long-range θ -coherence in certain areas of the left hemisphere of the brain during learning [4].

In addition, at the moment, machine learning methods are widely used to classify the EEG signals of musicians and non-musicians. Thus, when analyzing the signals recorded during the task of sound perception of musical fragments, several linear and non-linear classifiers were used to classify biomedical data. As a result of a comparative analysis of the resulting models, a neural network model was developed that makes it possible to classify the initial EEG signals with an accuracy of 97.2% [5]. This indicates both the relevance of research on similar data using modern statistical methods, and their high efficiency.

Also, in some works [6] the event-related potential was studied in the framework of the original method of multivariate regression analysis using real-time biomedical data. This methodology allowed the authors to determine the degree of synchronization between the studied experimental data and the sound stimulus, presented both in the form of a melody and in the form of a single-tone sound and noise. As a result, a method for classifying EEG signals was developed, which makes it possible to determine the features of the statistical parameters of biomedical data that manifest themselves when listening to various compositions by people with and without a musical education.

In Ref. [7], when analyzing data, similar to the one studied in our work, the authors applied multivariate statistical analysis to develop a biomedical data classifier for a group of musicians and non-musicians while listening to a musical composition. The authors applied the Principal Component Analysis method and developed an original approach to signal classification when performing the studied expert task with an accuracy of 88%.

Our work is aimed at developing an original method for analyzing the autocorrelations and cross-correlations of the recording of the bioelectrical brain activity of professional musicians and people without musical education. The presented approach is based on one of the modern biomedical methods investigating the dynamics of discrete non-Markovian (idem non-Markov) random processes in complex systems: Memory Functions Formalism (MFF).

The key feature of the proposed approach is considering the high degree of “individuality” of human EEG signals, which manifests itself to an even greater extent in various cognitive and sensory processes. According to the MFF, the individual characteristics of the bioelectrical activity of the human brain, including those under external influences, can be fully considered by performing a simultaneous analysis of autocorrelations and effects of statistical memory, as well as the collective dynamics of neuron ensembles. Under the conditions of cognitive processes and sensory influences, the functioning of various parts of the human cerebral cortex must correspond to some optimal level of such interconnections.

3 The Main Features of the Memory Functions Formalism

MFF is a theoretical methodology developed by the Kazan school of statistical and computational physics as applied to the discrete dynamics of complex non-Hamiltonian systems of various nature [8, 9].

MFF is remarkable because it allows extracting a large number of significant features of the studied time series by performing auto- and cross-correlation analysis and the analysis of statistical memory effects.

In this methodology, the temporal dynamics of an experimentally recorded variable of a complex system,

can be represented as a discrete time series $\{x_j\}$ of a variable X :

$$X = \{x(T), x(T + \tau), x(T + 2\tau), \dots, x(T + (N-1)\tau)\}, \quad (1)$$

where T is the initial time of start from which the recording of experimental variable started, $(N-1)\tau$ is the signal recording time, $\tau = \Delta t$ is the sampling time step.

For a quantitative description of the dynamic properties of the living system under study (correlation dynamics), it is convenient to use the normalized time correlation function (TCF):

$$\begin{aligned} a(t) &= \frac{1}{(N-m)\sigma^2} \sum_{j=0}^{N-m-1} \delta x_j \delta x_{j+m} = \\ &= \frac{1}{(N-m)\sigma^2} \sum_{j=0}^{N-m-1} \delta x(T+j\tau) \delta x(T+(j+m)\tau), \end{aligned} \quad (2)$$

$$t = m\tau, 1 \leq m \leq N-1,$$

where x_j, x_{j+m} are the values of variable X on steps $j, j+m$ correspondingly, δx_j and δx_{j+m} are fluctuations of values x_j, x_{j+m} , σ^2 is the absolute variance of the variable X .

For greater convenience and clarity in terms of the time series' temporal dynamics, we will consider not only the TCF, but, in addition to it, the autocorrelation coefficient calculated as follows:

$$k(x) = \frac{\overline{x_T x_{T+t}} - \bar{x}_T \bar{x}_{T+t}}{\sigma_T \sigma_{T+t}}. \quad (3)$$

Zwanzig-Mori projection operators technique [8, 10] developed in nonequilibrium statistical physics allows obtaining a chain of finite difference equations of non-Markov type for the initial and higher-order memory functions $M_i(t)$ ($i=1, 2, \dots, n$):

$$\begin{aligned} \frac{\Delta a(t)}{\Delta t} &= \lambda_1 a(t) - \tau \Lambda_1 \sum_{j=0}^{m-1} M_1(j\tau) a(t-j\tau), \\ &\dots, \\ \frac{\Delta M_{n-1}(t)}{\Delta t} &= \lambda_n M_{n-1}(t) - \\ &- \tau \Lambda_n \sum_{j=0}^{m-1} M_n(j\tau) M_{n-1}(t-j\tau), \end{aligned} \quad (4)$$

where λ_n are parameters that form the spectrum of eigenvalues of the Liouville quasi-operator, Λ_n are relaxation parameters:

$$\begin{aligned} \lambda_n &= i \frac{\langle \mathbf{W}_{n-1} \hat{L} \mathbf{W}_{n-1} \rangle}{\langle |\mathbf{W}_{n-1}|^2 \rangle}, \\ \Lambda_n &= i \frac{\langle \mathbf{W}_{n-1} \hat{L} \mathbf{W}_n \rangle}{\langle |\mathbf{W}_{n-1}|^2 \rangle}. \end{aligned} \quad (5)$$

Dynamic orthogonal variables $\mathbf{W}_n$ in Eq. (5) are obtained using the Gram-Schmidt orthogonalization procedure:

$$\langle \mathbf{W}_n, \mathbf{W}_m \rangle = \delta_{n,m} \langle |\mathbf{W}_n|^2 \rangle,$$

where $\delta_{n,m}$ is the Kronecker symbol.

To quantify the effects of statistical memory, the authors proposed a frequency dependence of the non-Markov (idem non-Markovity) parameter [8, 10]:

$$\varepsilon_i(\nu) = \left(\frac{\mu_{i-1}(\nu)}{\mu_i(\nu)} \right)^{\frac{1}{2}}, \quad (6)$$

where the frequency characteristics of $\mu_i(\nu)$ power spectra are determined through the Fourier images of the memory functions $M_i(t)$:

$$\begin{aligned} \mu_0(\nu) &= \left| \Delta t \sum_{j=0}^{N-1} a(t_j) \cos 2\pi \nu t_j \right|^2, \\ \dots, \\ \mu_i(\nu) &= \left| \Delta t \sum_{j=0}^{N-1} M_i(t) \cos 2\pi \nu t_j \right|^2. \end{aligned} \quad (7)$$

Also, we use cross-correlation formalism in our work. The temporal dynamics of an experimentally recorded parameters of a complex system of living nature can be represented as a discrete time series $\{x_j\}$ and $\{y_j\}$ of a variable X , Y :

$$X = \{x(T), x(T + \tau), x(T + 2\tau), \dots, x(T + (N-1)\tau)\}, \quad (8)$$

$$Y = \{y(T), y(T + \tau), y(T + 2\tau), \dots, y(T + (N-1)\tau)\}.$$

By analogy with the autocorrelation formalism, we use cross-correlation coefficient as follows:

$$k(x, y) = \frac{\sum_{t=1}^{T-k} (x_t - \bar{x})(y_t - \bar{y})}{\sqrt{\sum_{t=1}^T (x_t - \bar{x})^2 \sum_{t=1}^T (y_t - \bar{y})^2}}. \quad (9)$$

Besides that, frequency characteristics of power spectra and non-Markov parameter are also defined for the cross-correlation case:

$$\begin{aligned} \mu_0^{XY}(\nu) &= \left| \Delta t \sum_{j=0}^{N-1} c(t_j) \cos 2\pi \nu t_j \right|^2, \\ \dots, \\ \mu_i^{XY}(\nu) &= \left| \Delta t \sum_{j=0}^{N-1} M_i^{XY}(t) \cos 2\pi \nu t_j \right|^2, \end{aligned} \quad (10)$$

$$\varepsilon_i^{XY}(\nu) = \left(\frac{\mu_{i-1}^{XY}(\nu)}{\mu_i^{XY}(\nu)} \right)^{\frac{1}{2}}.$$

In this work we develop an original method for determining the distinctive parameters of the classification of EEG signals recordings of people with different levels of cognitive abilities development. This method is based on the autocorrelation and cross-correlation analysis in the framework of MFF and the study of cross-correlation coefficients.

4 Experimental Data

Experimental data were obtained in the course of the international cooperation program (see Ref. [11], for details).

The data files were records of EEG signals recorded from the cerebral cortex during the performance of various expert tasks for two groups of men:

- 8 musicians (experts), with an average age of 25.7 years, who have been professionally involved in music for at least 5 years;

- 11 people without any musical education (non-musicians or non-experts, control group), with an average age of 25.4 years.

Biomedical data were recorded during the execution of the following tasks by the subjects:

1. The task of perceiving a fragment of a musical piece;

2. The task of perception of the text with neutral content.

The subjects' eyes were closed during all tasks. During the study, the subjects listened to an excerpt from the "French Suite No. 5" by I.S. Bach. Also, the subjects were read aloud the text of a short story in German. The duration of the recording of all time signals was 90 s.

A certain long-term cognitive activity can significantly change the dynamics of the bioelectrical activity of the human brain. Such activity includes, for example, professional activity: the statistical parameters of biomedical data can change significantly during long-term studies in the visual arts [12, 13], musical art [14, 15], etc.

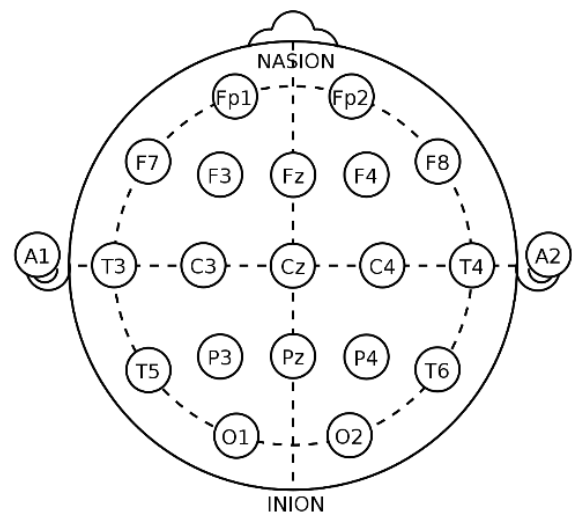


Fig. 1 International scheme of layout of electrodes "10-20%".

Table 1 Mean values and standard deviations of autocorrelation parameters for two groups of people for two tasks.

Parameter	Dataset							
	Musicians, music perception		Non-musicians, music perception		Musicians, text perception		Non-musicians, text perception	
	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation	Mean value	Standard deviation
$\varepsilon_1(0)$	7.73	1.36	9.2	2.12	12.7	2.05	8.2	1.89
$\delta_1(0)$ [8]	380	37	523	49	1158	76	580	63
$k(x)$	0.94	0.05	0.87	0.06	0.82	0.05	0.92	0.07

Recording was carried out with 19 electrodes, located according to the standard international electrode placement system “10–20%” (Fig. 1) with a sampling frequency of 128 Hz. The average signals of the lobes of both ears were used as reference.

5 Analysis of Autocorrelation and Spectral Features of Brain Activity

The analysis was carried out in two stages: in the first stage, the autocorrelation characteristics of all signals were studied. According to the results obtained during autocorrelation analysis, for each person during the performance of each task, non-Markovian parameter $\varepsilon_1(0)$, memory information measure $\delta_1(0)$, and autocorrelation coefficient $k(x)$ were calculated. Next, the average values and standard deviations of the correlation characteristics for two groups of people were calculated (Table 1).

It can be observed that for the two groups of people in both tasks' correlation features are different. In the case of the task of perceiving a piece of music, the values of the information measure of memory $\delta_1(0)$ and the non-Markov parameter $\varepsilon_1(0)$ are much lower for the representatives of the expert group, while the autocorrelation coefficient $k(x)$ is larger. Respectively, for the task of text perception, the situation is reversed: the values of the signal correlation parameters $\varepsilon_1(0)$, $\delta_1(0)$ (excluding the autocorrelation coefficient $k(x)$) are significantly higher for a group of experts.

As is known, the calculated measures of statistical memory allow dividing the considered processes into three groups: processes with strong memory ($\varepsilon_1(0)$, $\delta_1(0) \rightarrow 1$), processes with moderate (intermediate) memory ($\varepsilon_1(0) \sim 10$, $\delta_1(0) \sim 100$) and processes with weak memory ($\varepsilon_1(0)$, $\delta_1(0) \rightarrow \infty$). As can be seen from the obtained results, the studied biomedical data show the effects of moderate statistical memory.

Based on the calculated values, a diagram was drawn up showing the electrodes, the signals from which showed the greatest relative differences in statistical parameters for two groups of people (Fig. 2).

Considering the values of the calculated parameters, the electrodes were determined, in which the correlation and spectral features of human brain activity are most pronounced. In the case of the perception of music task

(Fig. 2(a)), the greatest differences were manifested in the signals from the electrodes T_5 , P_3 and Fp_1 , Fp_2 . In the text perception task, the greatest differences were also found in areas T_3 , T_4 , T_6 , Fp_1 (Fig. 2(b)).

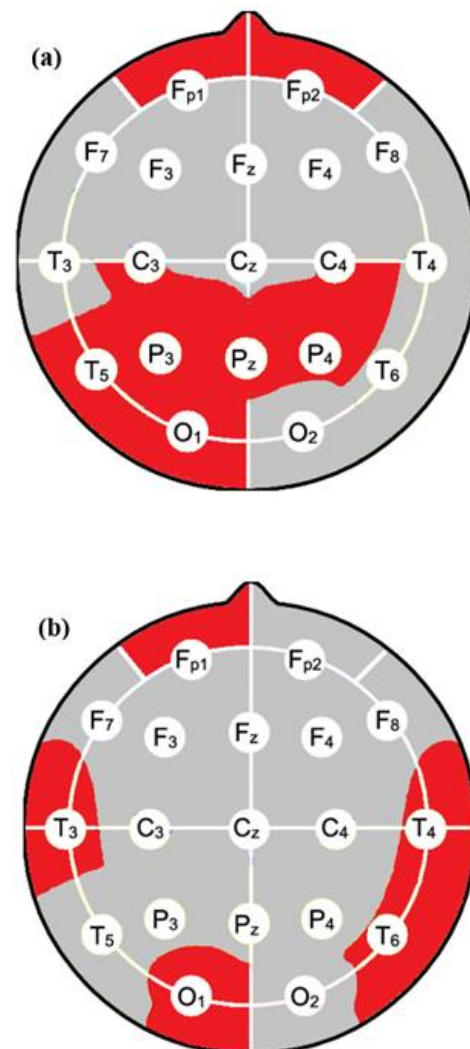


Fig. 2 Electrodes for which the differences in the values of the non-Markov parameters and the autocorrelation coefficient are the most significant; (a) corresponds to the task of music perception, (b) corresponds to the task of text perception.

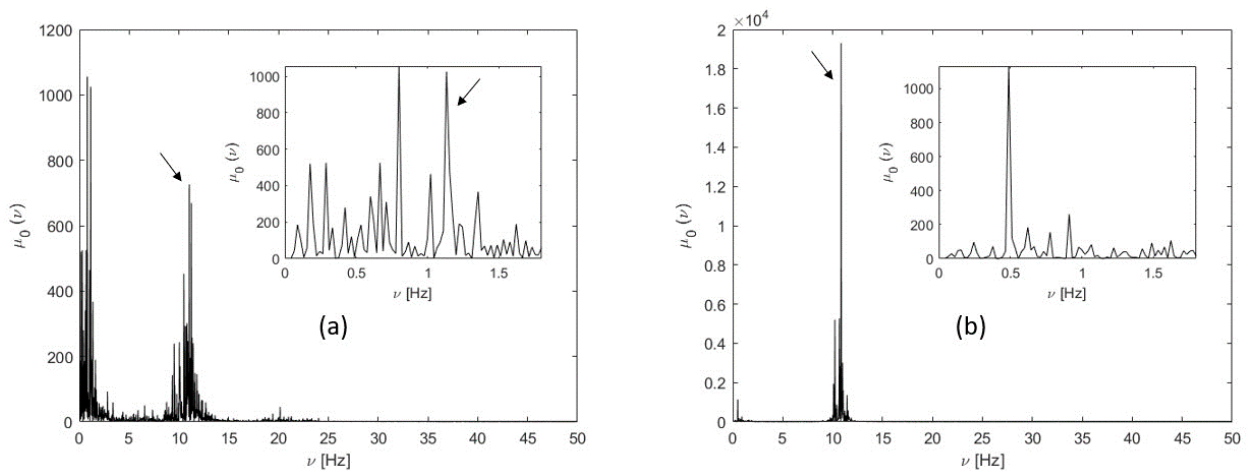


Fig. 3 Power spectra of the statistical memory functions of the signal from the T_5 electrode for the task of music perception for a person from the expert (a) and a control group (b). The arrows mark the peaks with the highest intensity.

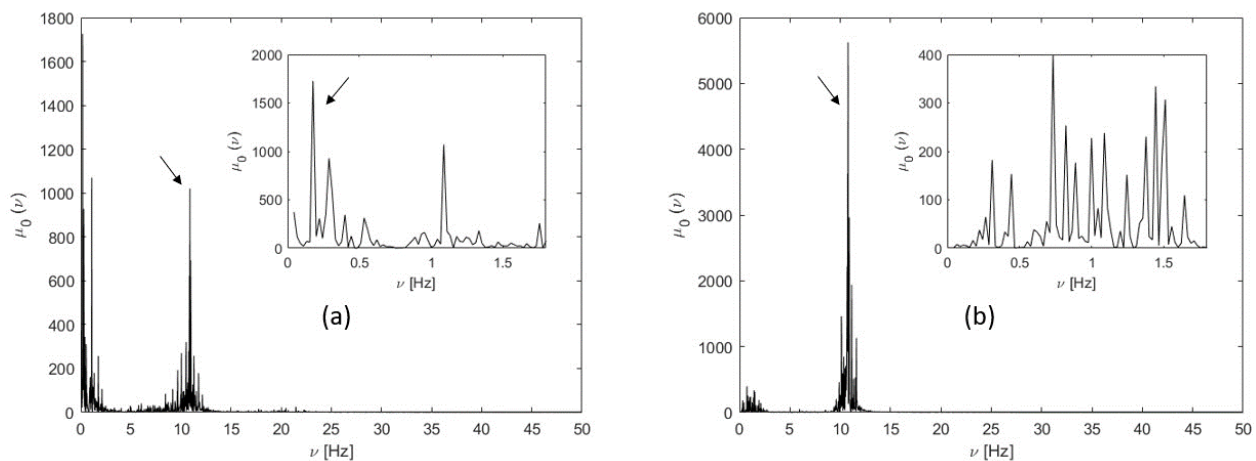


Fig. 4 Power spectra of the statistical memory functions of the signal from the T_3 electrode for the task of text perception for a representative from the expert (a) and a control group (b). The arrows mark the peaks with the highest intensity.

In the case of the task of perceiving music, the intensity of the power spectrum peaks of the control group subject (Fig. 3(b)) is significantly higher than that of a subject from a group of musicians (Fig. 3(a)). Also, for a group of non-musicians, only high-frequency periodic activity (~ 10 Hz) is significantly manifested, and for a group of experts, also low-frequency activity (~ 0.5 Hz) along with the higher periodic activity (~ 8 Hz).

In the case of the text perception task, the maximum intensity of the power spectrum peaks of non-musicians (Fig. 4(b)) turned out to be significantly greater than the intensity of the power spectrum peaks of a subject from a group of musicians (Fig. 4(a)). Also, for the control group, high-frequency periodic activity (~ 10 Hz) is significantly manifested, and for the representative of the group of musicians, in addition, low-frequency activity (~ 0.5 Hz) is also observed.

For each task, the experimental data of one person from each group with non-Markovian parameters and memory information measures close to the group

averages were selected for subsequent cross-correlation analysis.

6 Analysis of Cross-Correlation and Spectral Features of Brain Activity

For a more complete identification of the specific features of the studied biomedical data within the framework of the MFF, in addition to the above analysis of autocorrelations, a cross-correlation analysis was carried out. Cross-correlation coefficients were calculated and averaged over the study groups. For visualization, the relative values of the cross-correlation coefficients were calculated and presented in the form of a 3D graphs (Fig. 5 and Fig. 6).

Comparative analysis shows that the difference between the experts and the control group manifest itself to the greatest extent in the task of perceiving a piece of music. In addition, the absolute value of the ratio of cross-correlation coefficients is maximum for pairs of electrodes F_7-P_2 , Fp_2-P_2 , F_8-C_4 , Fp_1-T_6 when

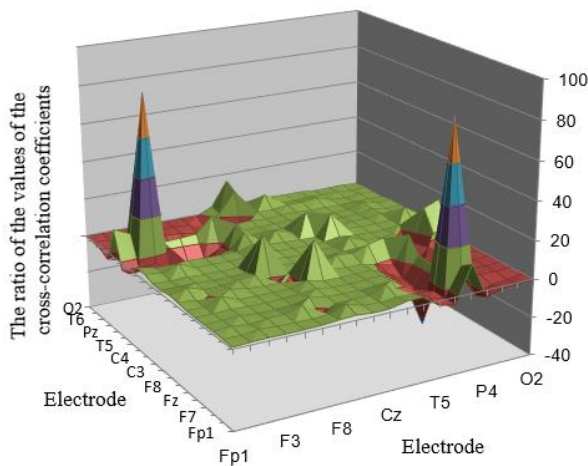


Fig. 5 The ratio of the cross-correlation coefficient of experts to the cross-correlation coefficient of the control group depending on the choice of interacting electrodes in the task of music perception.

performing tasks of music perception (Fig. 5); for time series recorded by pairs of electrodes F_8-O_2 , Fp_2-O_2 , Fp_1-O_1 , Fp_1-T_6 in the task of text perception (Fig. 6). It can be seen that the greatest differences appear when considering the signals from the electrodes in the frontal and occipital regions of brain.

The identification of such correlation features is necessary for further analysis to reduce the number of considered electrode interactions.

Further, a cross-correlation analysis of typical representatives of their groups was carried out according to the combination of Fp_1-T_6 electrodes. During the analysis, graphs of the power spectra of the statistical memory functions were obtained (Fig. 7 and Fig. 8).

As a result, it was found that, on average, the intensity of the power spectrum peaks is significantly higher for the control group (Fig. 7(b) and Fig. 8(b))

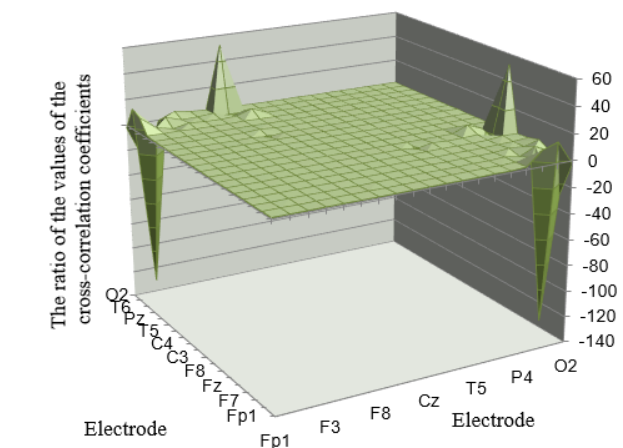
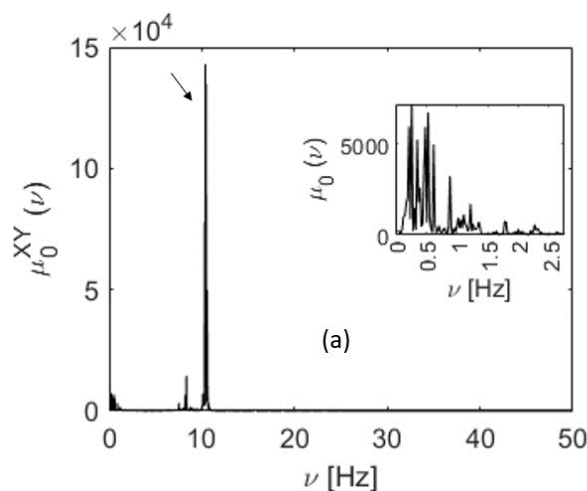


Fig. 6 The ratio of the cross-correlation coefficient of experts to the cross-correlation coefficient of the control group depending on the choice of interacting electrodes in the task of text perception.

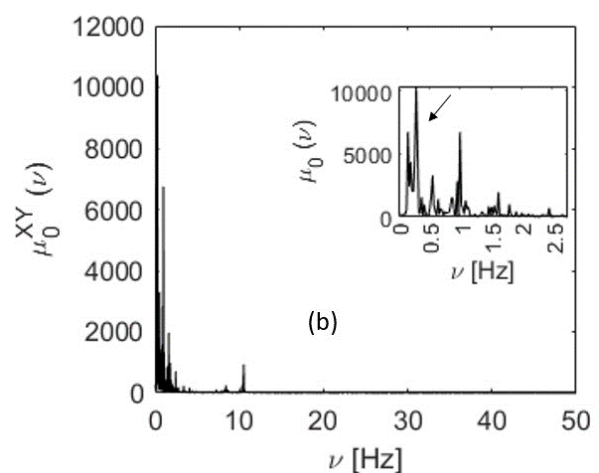


Fig. 7 Power spectra of the statistical memory functions of the signal from the Fp_1-T_6 electrodes for the task of music perception for a subject from the expert (a) and control group (b). The arrows mark the peaks with the highest intensity.

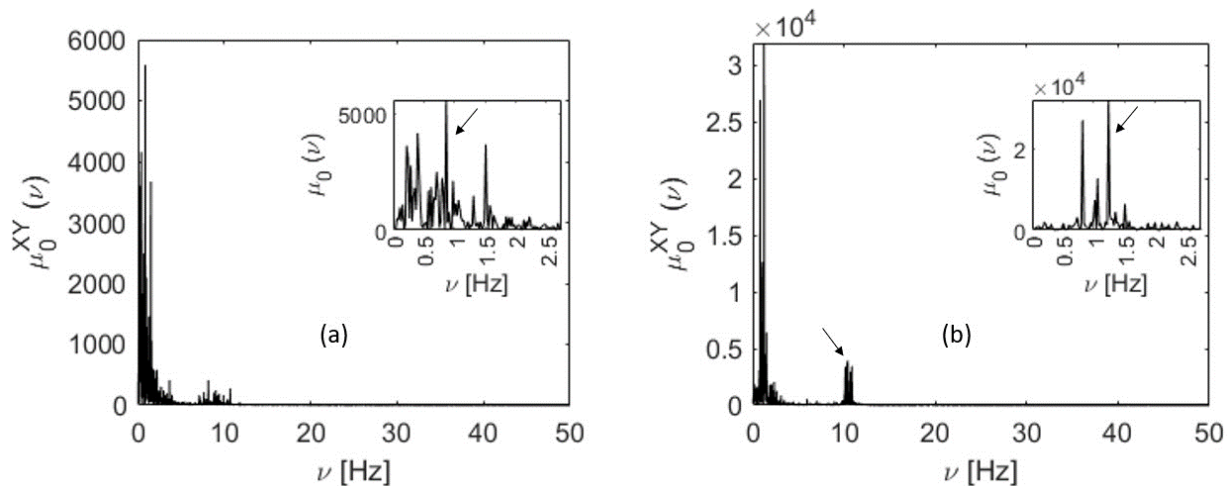


Fig. 8 Power spectra of the statistical memory functions of the signal from the Fp_1-T_6 electrodes for the task of text perception for a subject from the expert (a) and control group (b). The arrows mark the peaks with the highest intensity.

7 Conclusion

In this work, an original method for analyzing auto- and cross-correlations of human biomedical data is being developed. The approach is based on the finite-difference analogue of the Zwanzig-Mori equations intended for studying the discrete stochastic dynamics of complex systems.

In the framework of Memory Functions Formalism, we discovered that the dynamics of biomedical parameters is characterized by more random nature for non-experts when listening to a fragment of a musical work; for experts – while listening to the text. This indicates the occurrence of periodic processes in their biomedical parameters, and, consequently, a greater degree of self-consistency of their signals when performing these tasks.

Also, while performing all tasks in the biomedical data of the representatives of the expert group, in contrast to the representatives of the control group, high-frequency periodic activity was manifested to a much greater extent.

Moreover, when analyzing the effects of frequency-phase synchronization, significant differences were found in the degree of correlation of biomedical signals recorded in remote areas of the cerebral cortex for two groups of subjects.

In conclusion, it should be noted that the proposed MFF approach, as a tool that is sensitive to identifying

the features of the measured signals during their parameterization, can be used in a comprehensive analysis of the phenomenon of high individuality of biomedical data. At the same time, certain ranges of changing resonant frequencies and the limits of permissible changes in the values of MFF parameters with a set of “standard” influences are considered as “indicators of individuality” of each organism.

Our further research into the search for statistical patterns in the dynamics of human EEG signals during various cognitive processes will be associated with other methods of statistical analysis, such as Flicker-Noise Spectroscopy [17, 18], and machine learning [19, 20]. Within the framework of Flicker-Noise Spectroscopy, additional possibilities appear for calculating information parameters that characterize the chaotic components of the studied signals in different frequency ranges, as well as for studying frequency-phase correspondences.

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Disclosures

The authors declare no conflict of interest.

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