The study of the biological aging mechanisms of the human neuromuscular system based on statistical analysis of physiological signals

Valentin Yunusov
Institute of Computational Mathematics and Information Technologies
Institute of Physics
Kazan Federal University
Kazan, Russia
valentin.yunusov@gmail.com

Sergey Demin
Institute of Physics
Kazan Federal University
Kazan, Russia
serge_demin@mail.ru

Alexander Elenev
Institute of Physics
Kazan Federal University
Kazan, Russia
a.elenev6345@gmail.com

Alexander Minkin
Yelabuga Institute
Kazan Federal University
Kazan, Russia
avminkin@yandex.ru

***Abstract*—In present work, we conduct a statistical analysis of age-related changes in the neuromuscular system of healthy subjects. The experiment involved 29 volunteers who were assigned to different age groups: 20–24 years old, 64–69 years old and 75–90 years old. Within the framework of the Memory Functions Formalism, a quantitative assessment of the statistical memory effects and relaxation times for the dynamometric signals of the subjects recorded at different force impulses was performed. We have found that the dynamics of force signals of volunteers of the second and third groups is characterized by shorter lifetimes of statistical memory, as well as a transition from periodic to more probabilistic behavior. The calculated relaxation times for the subjects from older age groups were 2–3 times higher than those for young volunteers. An analysis of the spectral behavior of the temporal correlation function and memory functions allows establishing additional age-related changes in human hand-eye coordination. The presented results will be of interest to specialists in the field of biophysics, physics of complex systems, as well as neurosciences and gerontology.**

***Keywords*—Neurosciences, data science, complex systems, biological aging, brain, neuromuscular system, hand-eye coordination, statistical memory effects, relaxation processes.**

I. Introduction

At present, the attention of scientists from various fields of human knowledge has been drawn to the study of the evolution and properties of complex systems. A true triumph for the «complexity sciences» was the awarding of the Nobel Prize in Physics in 2021 to three scientists: "...for fundamental contributions to the human understanding of complex physical systems". Climatologists Syukuro Manabe and Klaus Hasselmann managed to perform a mathematical description of the relationship between constantly changing weather conditions and the relatively stable climate of the Earth [1, 2]. The theoretical physicist Giorgio Parisi, using the example of the physical properties of spin glasses, demonstrated the key role of chaos and fluctuations in the evolution of complex systems from atomic to planetary scales [3]. The development of computer technology and recording equipment contributes to the accelerated development of methods for analyzing signals generated by complex systems. Initially, the extraction of information from time signals of experimental parameters was conducted based on statistical physics methods, probability theory and mathematical statistics, while now machine learning methods are actively used in this area: classical methods, genetic algorithms or reinforcement learning, ensemble methods, neural networks and deep machine learning [4, 5].

In this paper, we study the physical mechanisms of human biological aging using the analysis of physiological signals based on the human neuromuscular system. Most often, this phenomenon is described as an inevitable biological process of gradual degradation of individual organs, tissues, and the organism as a whole. Scientists are constantly making attempts to find optimal mathematical models and methods for a quantitative description of the aging mechanism. Scientists are constantly making attempts to find optimal mathematical models and methods for a quantitative description of the mechanisms of aging. Thus, in his work [6], T. Penna proposes a numerical model that establishes the relationship between biological aging and the death of an individual. Other scientists [7, 8] based on the ideas of spatial and temporal invariance demonstrate changes in the dynamics of human physiological signals with age. A significant part of the work is devoted to the study of "physiological complexity" [9–11], the change in which can be established by considering the number of variables, the relationships between them, or stochastic and deterministic contributions that describe living systems. To study the mechanisms of biological aging, we propose to use the concepts of the effects of statistical memory and relaxation times, developed by the authors based on the Memory Functions Formalism [12, 13].

II. Theoretical framework of Memory Functions Formalism

The Memory Functions Formalism is a discrete generalization of the Zwanzig-Mori formalism [14, 15],

This paper has been supported by the Kazan Federal University Strategic Academic Leadership Program (PRIORITY–2030).

conducted by the authors of this work together with the scientific adviser, Professor R.M. Yulmetyev to study the stochastic dynamics of complex systems [16, 17].

The proposed approach is based on the representation of the time dynamics of the process under study in the form of a multidimensional state vector that obeys the equation of motion written in a discrete form. The experimentally observed process is a separate link in the hierarchy of interrelated relaxation processes that are simultaneously realized in a complex system. According to the idea of an abbreviated description of relaxation processes, only individual relaxation processes, which are directly included in the theoretical description, play a key role in the evolution of complex systems. The use of the Zwanzig-Mori projection technique [14, 15] and the Gram-Schmidt orthogonalization procedure allows shortening of the description. Within the framework of the approach for the studied time series, a chain of finite-difference linked kinetic equations of the Zwanzig-Mori type is constructed for the time correlation function (TCF) and statistical memory functions for interrelated variables. In fact, we consider the description of aftereffects at different relaxation levels.

As a result, we obtain a large set of characteristics and dependencies: time dependences of orthogonal dynamic variables, phase portraits of dynamic variables combinations, relaxation and kinetic parameters, statistical memory functions and their power spectra, frequency dependences of statistical memory measures calculated directly from sequences of dynamic variables of complex systems [18, 19].

In particular, to describe the statistical memory effects, the parameter $\varepsilon_1=\varepsilon_1(0)$ is introduced, which allows comparing the relaxation times of the TCF and the lifetimes of the statistical memory [12, 16, 17]. In the case of ε_1»1 the process under study is characterized by short-term (weak) statistical memory. With a parameter value comparable to one, the process under study is characterized by a long-term (strong) statistical memory. In addition, cases with intermediate (moderate) statistical memory are considered. The values of the parameter $\varepsilon_1(0)$, estimated at zero frequency, make it possible to compare the relaxation and statistical memory times for the entire length of the dynamometric signal under study [20, 21].

It should be noted that in this section we do not present mathematical relations for the entire array of quantitative parameters and qualitative characteristics introduced within the Memory Functions Formalism.

III. EXPERIMENTAL METHODS

The experimental data are the result of the synergistic activity of the human muscular and nervous systems – recording of dynamometric signals. A round Entran ELFS-B3 dynamometric sensor with a diameter of ~1.3 cm was

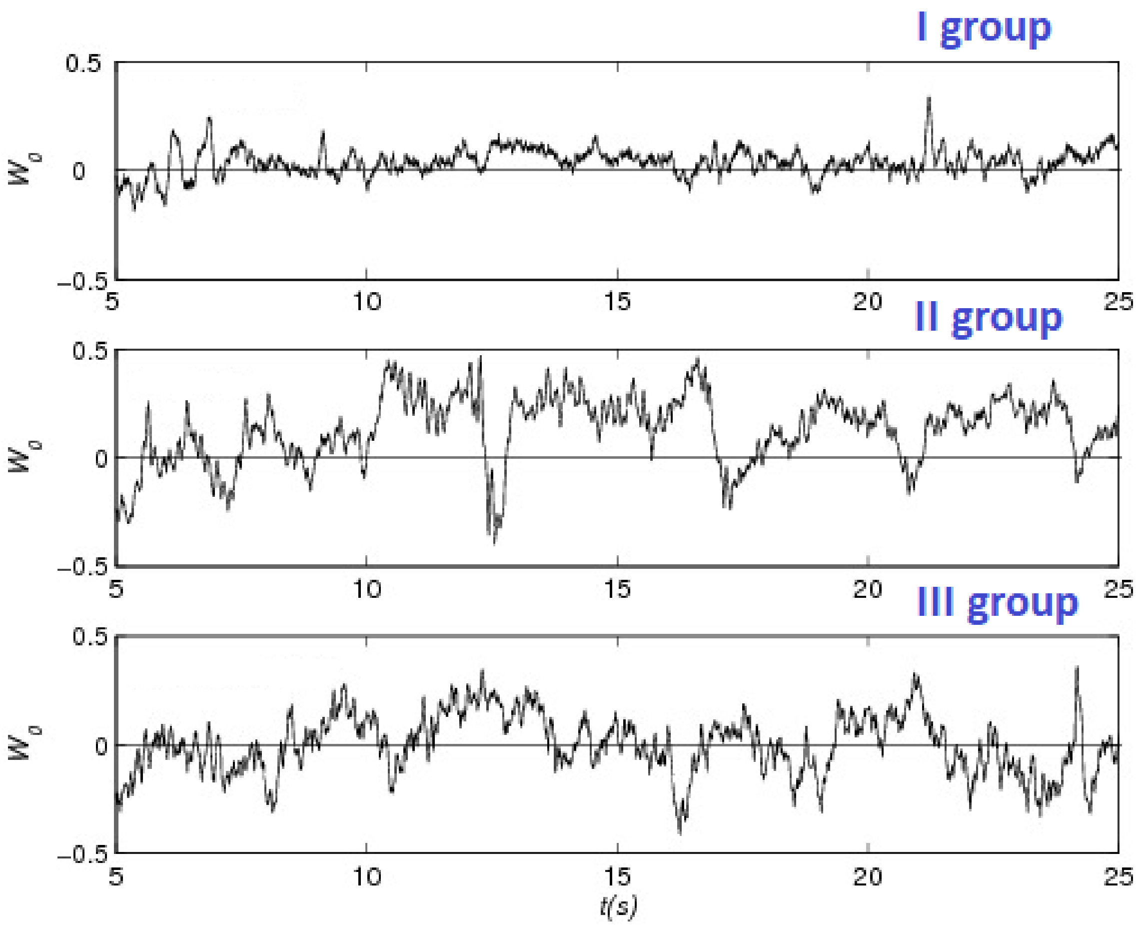

Fig. 1. Representative time dependences of the orthogonal dynamic variable $\mathbf{W}_0$ for subjects of different age groups. A dynamic variable is built from the original time signal and contains information about its fluctuations relative to the zero value.

fixed on the table. The wrists, middle fingers, ring fingers and little fingers of the volunteers were also fixed on the table surface. The position of the elbows of the participants in the experiment remained constant during the entire time of signal recording. The analog signal was amplified and converted to digital format. The resulting output signal was reflected on the monitor screen.

Fig. 1 shows representative (typical) time dependences of the orthogonal dynamic variable $\mathbf{W}_0$ for a representative of each age group. In the Memory Functions Formalism, orthogonal dynamic variables $\mathbf{W}i$ are used to calculate the autocorrelation function and memory functions, as well as measures of statistical memory (for example, the parameter $\varepsilon_1(0)$) [16, 17]. The orthogonal dynamic variable $\mathbf{W}_0$ is composed of the deviations of the initial dynamometric parameter relative to the zero value: $\mathbf{W}_0 = \{\delta x_j\}$. Other orthogonal variables are defined through the Gram-Schmidt orthogonalization procedure.

The time dynamics of an experimentally recorded parameter of a complex system can be represented as a discrete time series x_j of a variable X:

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

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

At the preparatory stage, subjects from three age groups: the first group, volunteers aged 20–24 years, the second, 64–69 years, and the third, 75–90 years old, pressed the dynamometer sensor with maximum force with the side of the index finger [10, 11]. Table I provides a description of the participants in this study.

TABLE I. DESCRIPTION OF PARTICIPANTS.

Group number	Number of men	Number of women	Average age, years
I group	5	5	22
II group	4	5	67
III group	5	5	82

After that, the subjects pressed the sensor with a force of 5, 10, 20, and 40% of the maximum pressing force. Compliance with the required pressure value on the sensor was carried out by visual control: the participants in the experiment saw two lines on the monitor screen – the calculated and experimental values of the pressing force. The noted conditions for recording dynamometric signals for subjects of different age groups allow concluding about age-related changes not only in the human neuromuscular system, but also in visual-motor coordination. Recall that hand-eye coordination consists of a person's ability to simultaneously use the eyes and hands when performing actions. Two attempts were made for each level.

Visual analysis of the spatio-temporal structure of dynamometric signals allows us to come to the following conclusions. Time records for groups II and III are distinguished by stronger fluctuations and large oscillating structures. Oscillations of hand-eye coordination are associated with physiological brain rhythms. However, the results presented are only primary data that poorly reflect the physical mechanisms of biological aging of the human neuromuscular system.

IV. RESULTS AND DISCUSSION

Here we consider only the results of a qualitative analysis of the spectral behavior of the temporal correlation functions and statistical memory functions, as well as a quantitative comparison of the values of the parameter $\varepsilon_1(0)$ calculated for the dynamometric signals of the subjects of different age groups. In addition, the relaxation time for the time correlation functions will be calculated.

The study of the TCF spectral behavior and memory functions calculated for the dynamometric signals of three age groups allows establishing their periodic patterns. On the power spectra of the TCF and memory functions for the muscle contraction signals of subjects of group I, bursts of intensity at frequencies of 20 Hz and 40 Hz are clearly manifested. These bursts reflect the synchronization of the rhythms of muscle contractions of motor units with brain rhythms. The structure of the spectra is disturbed for representatives of groups II and III, which may indicate age-related changes in the transmission of nerve impulses from the brain to peripheral motor units. We observe a shift of these peaks to higher frequencies. In addition, the appearance of additional oscillations in the dynamics of the output power pulse was found.

Fig. 2 shows the spread of values of the parameter $\varepsilon_1(0)$, calculated for the dynamometric signals of volunteers from different age groups. For each level of force pressing, the calculation was performed in two attempts. The range of $\varepsilon_1(0)$ values for representatives of all age groups corresponds to the scenario with moderate statistical memory. The average values of the parameter $\varepsilon_1(0)$ for all four levels (two attempts for each level) for representatives of group I is 39.7, group II – 68.2, group III – 83.4. Comparison of the average values of the parameter indicates a twofold weakening of the memory effects for the signals of group III representatives in comparison with young volunteers. The weakening of the memory effects of visual-motor coordination with age leads to an increase in stochastic components in the regulation of motor units by the human neuromuscular system.

Fig. 3 shows the spread of values of relaxation times τ_R, calculated for dynamometric signals of representatives of three age groups. Two attempts were recorded for each level of the power impulse.

Calculation of relaxation times was conducted by estimating the area under the temporal correlation function determined for each dynamometric signal:

$$\tau_R = \Delta t \sum_{j=1}^{N} a(t_j).$$

Average values of relaxation time τ_R or all four levels (two attempts for each level) for representatives of group I is 57τ, group II – 107.4τ, group III – 180.5τ. Comparison of the average values of relaxation times for different age groups indicates a significant lengthening of these times for subjects of groups II and III. In addition, in the case of young volunteers, increased pressure leads to a lengthening of relaxation times, while in the case of representatives of groups II and III, an ambiguous picture is observed.

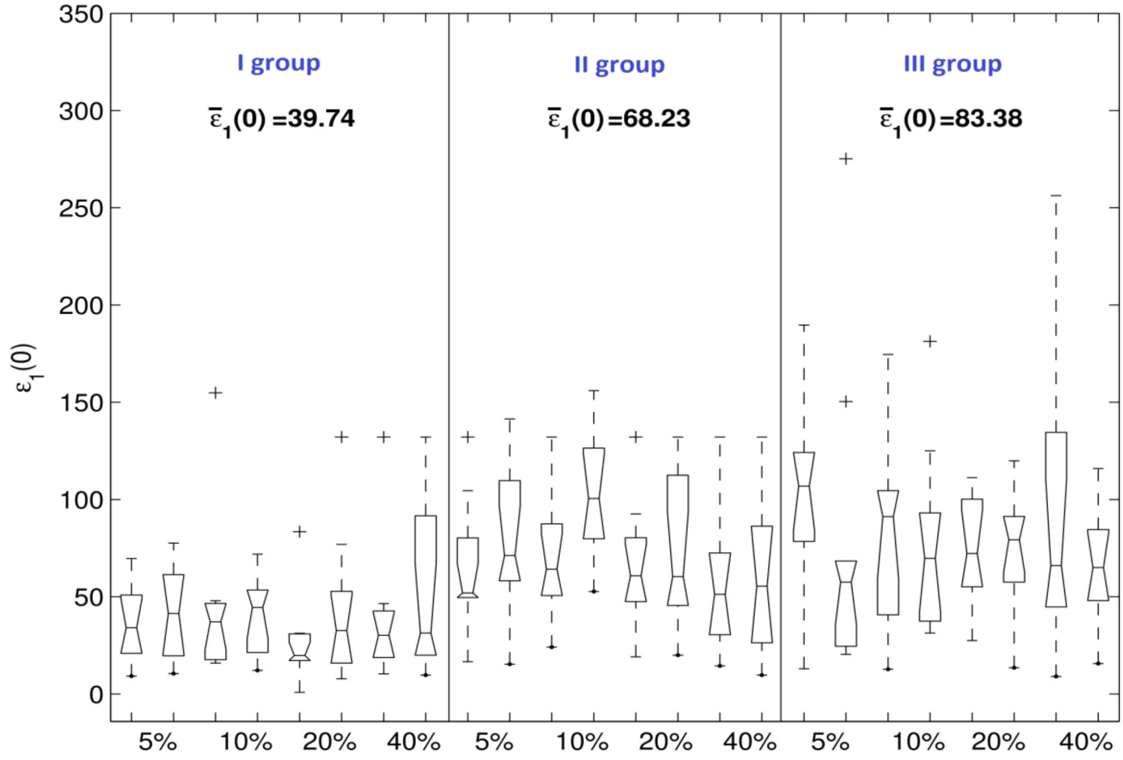

Fig. 2. The scatter of the parameter $\varepsilon_1(0)$ values for dynamometric signals recorded at different levels of depression in three age groups of people. Two attempts were made for each level. The average values of the parameter $\varepsilon_1(0)$ for each age group are indicated.

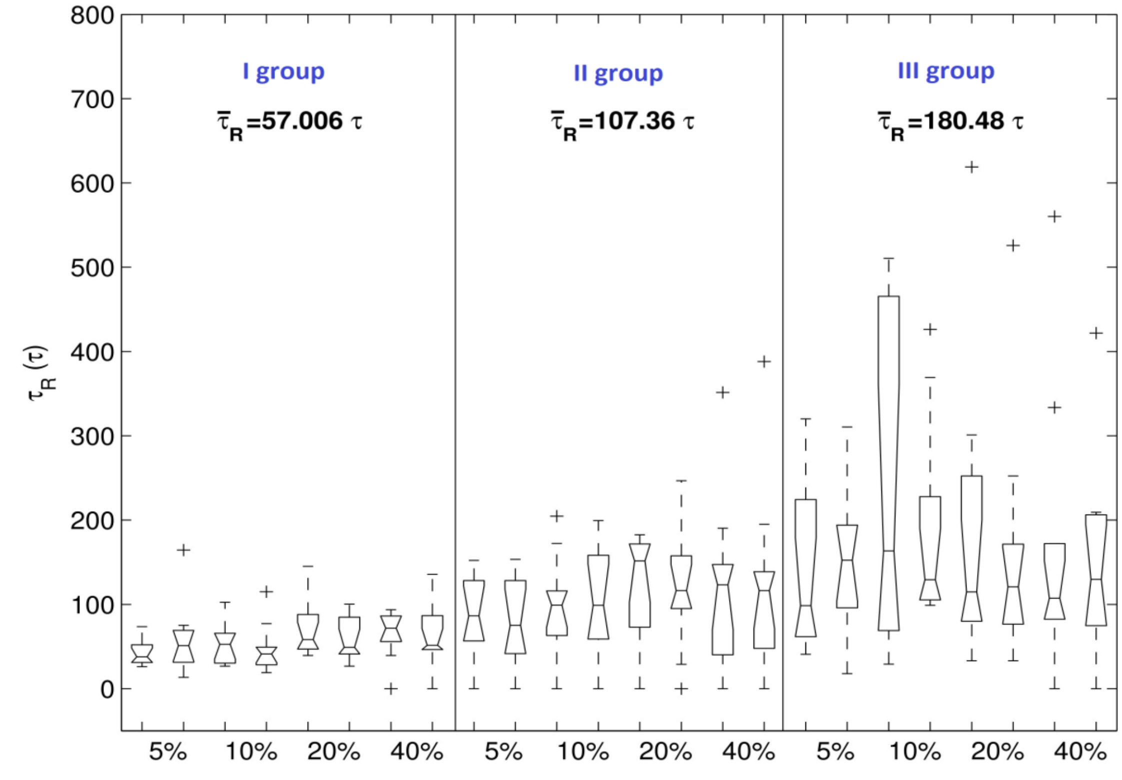

Fig. 3. Scatter of relaxation time τ_R values or dynamometric signals recorded at different levels of depression in three age groups of people. Two attempts were made for each level. The average values of the parameter τ_R for each age group are indicated.

We have found that the dynamics of the force signals of volunteers of the second and third groups is characterized by shorter lifetimes of statistical memory, as well as a transition from periodic to more probabilistic behavior. We established periodic patterns of dynamometric signals of healthy subjects from different age groups. They reflect the synchronization of the rhythms of muscle contractions of motor units with brain rhythms. With age, this synchronization occurs in a higher frequency region. The calculated relaxation times for the subjects from older age groups were 2–3 times higher than those for young volunteers.

V. Conclusions

Living systems produce physiological signals on various spatio-temporal scales with a complex structure. Biological aging processes lead to obvious changes in these structures. The observed changes can be quantified using various statistics and parameters.

In this work, we studied the physical mechanisms of biological aging of visual-motor coordination in healthy subjects from different age groups. As experimental data, signals of pressing the index finger on the dynamometric sensor were considered. Subsequently, the volunteers pressed the sensor with varying degrees of pressure from the maximum value. Within the framework of the Memory Functions Formalism, we performed an of the statistical memory effects and relaxation features of time signals.

The obtained results will be of interest from the point of view of biophysics, physics of complex systems, gerontology, and neurophysiology [22, 23]. In addition, these results can be used to control robotic devices and cyber-physical systems, for example, bionic limb prostheses, neurocomputer interfaces, as well as to consider vibro- and mechanotactile communication [24, 25].

Further research will be aimed at studying age-related changes in short- and long-term relaxation patterns of human muscle activity. This will allow us to consider the physical mechanisms of biological aging of the human neuromuscular system from the point of view of detailing the nature of relaxation processes [26–28].

References

[1] S. Manabe and R.T. Wetherald, “The Effects of Doubling the CO2 Concentration on the climate of a General Circulation Model”, J. Atmos. Sci., vol. 32, pp. 3–15, 1975.

[2] K. Hasselmann, “Multi-pattern fingerprint method for detection and attribution of climate change”, Clim. Dyn., vol. 13, pp. 601–611, 1997.

[3] G. Altarelli and G. Parisi, “Asymptotic freedom in parton language”, Nucl. Phys. B., vol. 126, no. 2, pp. 298–318, 1977.

[4] G. Biagetti, P. Crippa, L. Falaschetti, G. Tanoni and C. Turchetti, “A comparative study of machine learning algorithms for physiological signal classification”, Procedia Comput. Sci., vol. 126, pp. 1977–1984, 2018.

[5] V. Mnih, K. Kavukcuoglu, D. Silver, A.A. Rusu, J. Veness, M.G. Bellemare, A. Graves, M. Riedmiller, A.K. Fidjeland, G. Ostrovski, S. Petersen, C. Beattie, A. Sadik, I. Antonoglou, H. King, D. Kumaran, D. Wierstra, S. Legg and D. Hassabis, “Human-level control through deep reinforcement learning”, Nature, vol. 518, pp. 529–533, 2015.

[6] T.J.P. Penna, “A bit-string model for biological aging”, J. Stat. Phys., vol. 78, pp. 1629–1633, 1995.

[7] A.L. Goldberger, L.A.N. Amaral, J.M. Hausdorff, P.Ch. Ivanov, C.-K. Peng and H.E. Stanley, “Fractal dynamics in physiology: Alterations with disease and aging”, PNAS, vol. 99, pp. 2466–2472, 2002.

[8] M. Costa, A.L. Coldberger and C.-K. Peng, “Multiscale entropy analysis of biological signals”, Phys. Rev. E, vol. 71, pp. 021906–1–18, 2005.

[9] A.L. Goldberger, C.-K. Peng and L.A. Lipsitz, “What is physiologic complexity and how does it change with aging and disease?”, Neurobiol. Aging, vol. 23, pp. 23–26, 2002.

[10] D.E. Vaillancourt, L. Larsson and K.M. Newell, “Effects of aging on force variability, single motor unit discharge patterns, and the structure of 10, 20, and 40 Hz EMG activity”, Neurobiol. Aging, vol. 24, pp. 25–35, 2003.

[11] D.E. Vaillancourt and K.M. Newell, “Aging and the time and frequency structure of force output variability”, J. Appl. Physiol., vol. 94, pp. 903–912, 2003.

[12] S.A. Demin, R.M. Yulmetyev, O.Y. Panischev and P. Hänggi, “Statistical quantifiers of memory for an analysis of human brain and neuro-system diseases”, Physica A, vol. 387, pp. 2100–2110, 2008.

[13] O.Y. Panischev, S.A. Demin and J. Bhattacharya, “Cross-correlation markers in stochastic dynamics of complex systems”, Physica A, vol. 389, pp. 4958–4969, 2010.

[14] R. Zwanzig, “Memory Effects in Irreversible Thermodynamics”, Phys. Rev., vol. 124, pp. 983–992, 1961.

[15] H. Mori, “A Continued-Fraction Representation of the Time-Correlation Functions”, Prog. Theor. Phys., vol. 34, pp. 399–416, 1965.

[16] R. Yulmetyev, S. Demin, N. Emelyanova, F. Gafarov and P. Hänggi, “Stratification of the phase clouds and statistical effects of the non-Markovity in chaotic time series of human gait for healthy people and Parkinson patients”, Physica A, vol. 319, pp. 432–446, 2003.

[17] R.M. Yulmetyev, S.A. Demin and P. Hänggi, “Manifestation of chaos in real complex systems: Case of Parkinson's disease”, in “The Logistic Map and the Route to Chaos”, M. Ausloos and M. Dirickx, Eds., Berlin, Heidelberg: Springer, pp. 175–196, 2006.

[18] S. Demin, O. Panischev, V. Yunusov and S. Timashev, “The Application of Statistical Methods for the Analysis of Multi-Parameter Data of Complex Composite Objects in the Field of Cyber-Physical Systems”, Studies in Systems, Decision and Control, vol. 350, pp. 27–38, 2021. DOI: 10.1007/978-3-030-67892-0_3

[19] V.A. Yunusov and S.A. Demin, “The development of statistical methods for the diagnosis of neurological diseases based on multiparameter analysis of brain activity”, J. Phys. Conf. Ser., vol. 1740, art. no. 012049, 2021.

[20] S.A. Demin, O.Y. Panischev, S.F. Timashev and R.R. Latypov, “Analysis of Interictal EEG Signal Correlations for Diagnostics of Epilepsy”, Bull. Russ. Acad. Sci.: Phys., vol. 84, pp. 1349–1353, 2020. DOI: 10.3103/S1062873820110088

[21] O.Y. Panischev, S.A. Demin, S.N. Panischeva and J. Bhattacharya, “How analyzing the interictal EEG can identify the epilepsy”, Nonlinear Phenom. Complex Syst., vol. 18, no. 2, pp. 230–235, 2015.

[22] S. Sele, F. Liem, S. Mérillat and L. Jäncke, “Age-related decline in the brain: a longitudinal study on inter-individual variability of cortical thickness, area, volume, and cognition”, NeuroImage, vol. 240, pp. 118370, 2021.

[23] Y. Guo, B.E. Phillips, P.J. Atherton and M. Piasecki, Molecular and neural adaptations to neuromuscular electrical stimulation; Implications for ageing muscle, Mech. Ageing Dev., vol. 193, pp. 111402, 2021.

[24] G. Liu, L.Tian and W.Zhou, “Multiscale time-frequency method for multiclass Motor Imagery Brain Computer Interface”, Comput. Biol. Med., vol. 143, pp. 105299, 2022.

[25] A. Kamble, P. Ghare and V. Kumar, “Machine-learning-enabled adaptive signal decomposition for a brain-computer interface using EEG”, Biomed. Signal Process. Control, vol. 74, pp. 103526, 2022.

[26] R.M. Yulmetyev, N.A. Emelyanova, S.A. Demin, F.M. Gafarov, Peter Hanggi and D.G. Yulmetyeva, “Non-Markov stochastic dynamics of real epidemic process of respiratory infections”, Physica A, vol. 331, pp. 300–318, 2004.

[27] R.M. Yulmetyev, S.A. Demin, O.Yu. Panischev and P. Hanggi, “Age-related alterations of relaxation processes and non-Markov effects in stochastic dynamics of R-R intervals variability from human ECGs”, Physica A, vol. 353, pp. 336–352, 2005.

[28] F. Hassanibesheli, N. Boers and J. Kurths, “Reconstructing complex system dynamics from time series: a method comparison”, New J. Phys., vol. 22, pp. 073053, 2020.