Diagnostics of brain neural network states from the perspective of chaos

V V Kozlova¹, V A Galkin¹ and M A Filatov²,³

¹ Federal Science Center Scientific-research Institute for System Studies of the Russian Academy of Sciences, Nakhimovsky pr., 36, Moscow, 117218, Russia
² Surgut state university, Lenina pr., 1, Surgut, 628400, Russia
³ E-mail: filatovmik@yandex.ru

Abstract. All modern brain sciences are based on the stochastic study of the brain neural networks or individual neurons. At the same time, neuroscience is dominated by the dogma of statistical repetition of any samples of neural network parameters. However, back in 1948, W. Weaver took all living systems beyond stochastics. Currently, the Eskov-Zinchenko effect in biomechanics has been proven, which also extends to the bioelectric activity of the brain. As a result, there is a big problem of accurate evaluation of electroencephalograms, which are also used in the "man-machine" system. Proposes an analog of Heisenberg's principle in the form of calculation of parameters of pseudoattractors.

1. Introduction
Modern Neuroscience actively uses various methods of stochastics. Starting with the calculation of statistical distribution functions f(x), spectral signal densities (SPS), autocorrelations, methods of fractal theory, game theory, and others. In all these cases, in fact, statistical methods of analyzing electroencephalograms (EEG) are used.

Statistical analysis of EEG is actively used in human-machine systems, in virtual reality, and in many other new areas of biological, medical, and cybernetic sciences. However, one significant question remains unaddressed: how statistically stable will the resulting samples of EEG, electroneurograms and other parameters that are widely used in Neuroscience. Is it even possible to use stochastic methods in the human brain sciences?

Recall that back in 1947, one of the founders of information theory, W. Weaver, put forward a hypothesis about special systems of the third type - STT (living systems), which are not the object of modern deterministic and stochastic science [1]. Over the past 20 years, this hypothesis has been proven in the form of the Eskov-Zinchenko effect (EZE), first in biomechanics, and then in other sections of physiology and medicine [2-9]. In this regard, there are certain perspectives in Neuroscience in the analysis of EEG [5-7].

2. Statistical instability of samples of biological systems
More than 70 years ago, W. Weaver took all living systems beyond the deterministic and stochastic sciences. He defined them as systems of the third type, which should be described within the framework of another (new) science [1]. However, during these 70 years, such a science has not yet emerged, and the work of W. Weaver [1] has not received universal recognition. As such, we now propose the theory
of chaos-self-organization, which proves the lack of statistical stability of samples of various parameters of biosystems [10-17].

First of all, this applies to biomechanical systems, since EZE was initially proved in biomechanics [1-3, 7-8, 12]. EZE proved in biomechanics the hypothesis of N.A. Bernstein about "repetition without repetition". This hypothesis required the test of repeatability of samples of tremorogramm (TMG) and tappingramm (TPG) [2,3,6,12-14]. Later, this EZE was proved in the analysis of the parameters of the heart (on the example of RR intervals) [8,9,13,14] and in the work of muscles [17].

In recent years, EZE has also been proven in the organization of brain neural networks [18-20]. Such a proof can be performed in any neurophysiological laboratory, if the EEG is recorded in a row from the same subject (from the same brain surface), and then these samples are compared in pairs. We usually implement this comparison in the form of matrices of paired comparisons of samples of body parameters.

For example, we offer a typical matrix of paired comparisons of 15 EEG samples for one subject (in a calm state, rest) in table. 1. Here, the elements of this matrix represent the probability \( P_{ij} \) of statistical coincidence of the \( i \)-th and \( j \)-th EEG samples. The total number of such comparison pairs is shown in table. 1 we have 105, but only a small part of them has \( P_{ij} \geq 0.05 \). For example, in table.1 the number of such pairs \( K \) (for them \( P_{ij} \geq 0.05 \)) is small: \( K_i=33 \).

**Table 1.** Matrix of paired comparisons of EEG parameters of the same healthy person (15 consecutive EEG samples) at rest (channel T6-Ref, number of matches \( K_i=33 \)).

|   | 1    | 2    | 3    | 4    | 5    | 6    | 7    | 8    | 9    | 10   | 11   | 12   | 13   | 14   | 15   |
|---|------|------|------|------|------|------|------|------|------|------|------|------|------|------|------|
| 1 | -    | 0.00 | 0.32 | 0.05 | 0.10 | 0.64 | 0.01 | 0.55 | 0.00 | 0.28 | 0.31 | 0.00 | 0.90 | 0.00 | 0.00 |
| 2 | 0.00 | -    | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| 3 | 0.32 | 0.00 | -    | 0.75 | 0.00 | 0.03 | 0.67 | 0.19 | 0.00 | 0.01 | 0.30 | 0.02 | 0.10 | 0.00 | 0.00 |
| 4 | 0.05 | 0.00 | 0.75 | -    | 0.00 | 0.07 | 0.83 | 0.00 | 0.00 | 0.00 | 0.06 | 0.03 | 0.04 | 0.00 | 0.00 |
| 5 | 0.10 | 0.00 | 0.00 | 0.00 | -    | 0.00 | 0.00 | 0.41 | 0.38 | 0.66 | 0.03 | 0.00 | 0.21 | 0.00 | 0.00 |
| 6 | 0.64 | 0.00 | 0.03 | 0.07 | 0.00 | -    | 0.21 | 0.86 | 0.00 | 0.21 | 0.52 | 0.00 | 0.66 | 0.00 | 0.00 |
| 7 | 0.01 | 0.00 | 0.67 | 0.83 | 0.00 | 0.21 | -    | 0.02 | 0.00 | 0.00 | 0.01 | 0.19 | 0.00 | 0.00 | 0.00 |
| 8 | 0.55 | 0.00 | 0.19 | 0.00 | 0.41 | 0.86 | 0.02 | -    | 0.08 | 0.93 | 0.15 | 0.00 | 0.97 | 0.00 | 0.00 |
| 9 | 0.00 | 0.00 | 0.00 | 0.00 | 0.38 | 0.00 | 0.00 | 0.08 | -    | 0.06 | 0.00 | 0.00 | 0.07 | 0.00 | 0.01 |
|10 | 0.28 | 0.00 | 0.01 | 0.00 | 0.66 | 0.21 | 0.00 | 0.93 | 0.06 | -    | 0.00 | 0.00 | 0.36 | 0.00 | 0.00 |
|11 | 0.31 | 0.00 | 0.30 | 0.06 | 0.03 | 0.52 | 0.01 | 0.15 | 0.00 | 0.00 | -    | 0.00 | 0.05 | 0.00 | 0.00 |
|12 | 0.00 | 0.00 | 0.02 | 0.03 | 0.00 | 0.19 | 0.00 | 0.00 | 0.00 | 0.00 | -    | 0.00 | 0.00 | 0.00 | 0.00 |
|13 | 0.90 | 0.00 | 0.10 | 0.04 | 0.21 | 0.66 | 0.00 | 0.97 | 0.07 | 0.36 | 0.05 | 0.00 | -    | 0.00 | 0.00 |
|14 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | -    | 0.00 | 0.00 | 0.00 |
|15 | 0.00 | 0.58 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 | 0.00 | -    | 0.00 | 0.00 |

The remaining EEG pairs have \( P_{ij} \leq 0.05 \), which means that these two samples cannot have one (common) general population. They are statistically different, and as a result, we have a very low percentage of statistical matches of EEG samples. Recall that in statistics, it is at least 95% of matches. Otherwise, the statistics do not work, and for EEG, the number of \( K \) pairs for which \( P_{ij} \geq 0.05 \) usually does not exceed 35%.

All other samples do not match statistically. We emphasize that we have obtained more than a hundred such tables similar to table 1 and in all matrices of paired comparisons of EEG samples (for this subject) we have \( K \leq 35\% \). All this proves the extremely low efficiency of using statistical methods in the analysis of EEG and neural networks [18-20].
3. New methods for diagnosing the state of biosystems

Since EZE has also been proven for the neural networks of the brain (BNN) of a person who is in a single, unchanging physiological state (in this case, we are talking about relaxation), there is a global problem for all Neuroscience: how to measure and diagnose stationary (unchanging) brain states? At the same time, a second global problem arises: how to diagnose a change in the BNN [2-8]?

We emphasize that table 1 and hundreds of other similar matrices of paired comparisons of EEG samples demonstrate a continuous and chaotic kaleidoscope of EEG parameters. Which of the EEG samples (we have 15 of them) should be taken as a basis, which of the 15 samples actually describes the relaxation of the human brain? It is obvious that the low values of K in table 1 prove the loss of causal relationships in the BNN. The past EEG sample cannot characterize the future state of the BNN.

How in general can we then diagnose the variability of the BNN state or register real changes in the BNN if they are continuously and chaotically changing? Obviously, there is no deterministic understanding of the stationary mode for EEG (in the form of dx/dt=0 and x=const, where x=x1(t) is the value of the brain’s biopotentials, its EEG). There is also no stochastic stationary mode, since all samples are continuously and chaotically changing. In the framework of a new science – the theory of chaos-self-organization, we also introduce an analog of the Heisenberg principle [2-6].

For the variable x1(t), in the form of an EEG, we find its derivative x2=dx/dt and on the phase plane of the vector x=(x1, x2) we construct the phase trajectories of this vector x(t). As a result, we get a phase portrait for the EEG, which, as we proved in the theory of chaos-self-organization, is a real characteristic of the state of the BNN. It turned out that during relaxation, the area of the rectangle S=Δx1 × Δx2, where Δx1 is the variation range for x1, and Δx2 is the variation range value for x2, will be statistically unchanged for this subject.

We emphasize that in the framework of calculating the matrices of paired comparisons of EEG samples, the value of K can also characterize the norm and pathology, for example, in a patient with epilepsy, the value of K2 increases sharply, reaching 80-99%. This K clearly shows how a patient with epilepsy differs from a healthy person (both in rest). For example, table 2 is given, where K2=103.

Table 2. Matrix of paired comparisons of EEG parameters of the same person with epilepsy (15 consecutive EEG samples) without effects (channel T4-T6, number of matches K2=103).

|   | 1  | 2  | 3  | 4  | 5  | 6  | 7  | 8  | 9  | 10 | 11 | 12 | 13 | 14 | 15 |
|---|----|----|----|----|----|----|----|----|----|----|----|----|----|----|----|
| 1 | -  | 0.02 | 0.03 | 0.82 | 0.90 | 0.43 | 0.48 | 0.53 | 0.5 | 0.55 | 0.55 | 0.59 | 0.54 | 0.51 | 0.51 |
| 2 | 0.02 | -  | 0.60 | 0.33 | 0.30 | 0.89 | 0.91 | 0.91 | 0.96 | 0.95 | 0.92 | 0.88 | 0.91 | 0.94 | 0.93 |
| 3 | 0.03 | 0.60 | -  | 0.09 | 0.06 | 0.42 | 0.48 | 0.49 | 0.6 | 0.63 | 0.65 | 0.67 | 0.67 | 0.66 | 0.62 |
| 4 | 0.82 | 0.33 | 0.09 | -  | 0.86 | 0.45 | 0.55 | 0.68 | 0.63 | 0.67 | 0.7 | 0.74 | 0.74 | 0.72 | 0.75 |
| 5 | 0.90 | 0.30 | 0.06 | 0.86 | -  | 0.03 | 0.19 | 0.36 | 0.37 | 0.47 | 0.52 | 0.6 | 0.61 | 0.61 | 0.59 |
| 6 | 0.43 | 0.89 | 0.42 | 0.45 | 0.03 | -  | 0.98 | 1  | 0.81 | 0.91 | 0.93 | 0.99 | 0.95 | 0.93 | 0.96 |
| 7 | 0.48 | 0.91 | 0.48 | 0.55 | 0.19 | 0.98 | -  | 0.85 | 0.82 | 0.92 | 0.93 | 0.98 | 0.95 | 0.92 | 0.97 |
| 8 | 0.53 | 0.91 | 0.49 | 0.68 | 0.36 | 1  | 0.85 | -  | 0.57 | 0.78 | 0.82 | 0.89 | 0.87 | 0.88 | 0.95 |
| 9 | 0.50 | 0.96 | 0.60 | 0.63 | 0.37 | 0.81 | 0.82 | 0.57 | -  | 0.91 | 1  | 0.93 | 1  | 1  | 0.95 |
| 10| 0.55 | 0.95 | 0.63 | 0.67 | 0.47 | 0.91 | 0.92 | 0.78 | 0.91 | -  | 0.9 | 0.95 | 0.98 | 1  | 0.93 |
| 11| 0.55 | 0.92 | 0.65 | 0.70 | 0.52 | 0.93 | 0.93 | 0.82 | 1  | 0.9 | -  | 0.81 | 0.96 | 1  | 0.96 |
| 12| 0.59 | 0.88 | 0.67 | 0.74 | 0.60 | 0.99 | 0.98 | 0.89 | 0.93 | 0.95 | 0.81 | -  | 0.91 | 0.92 | 0.97 |
| 13| 0.54 | 0.91 | 0.67 | 0.74 | 0.61 | 0.95 | 0.95 | 0.87 | 1  | 0.98 | 0.96 | 0.91 | -  | 0.93 | 0.99 |
| 14| 0.51 | 0.94 | 0.66 | 0.72 | 0.61 | 0.93 | 0.92 | 0.88 | 1  | 1  | 1  | 0.92 | 0.93 | -  | 0.86 |
| 15| 0.51 | 0.93 | 0.62 | 0.75 | 0.59 | 0.96 | 0.97 | 0.95 | 0.95 | 0.93 | 0.96 | 0.97 | 0.99 | 0.86 | -  |
However, even more characteristic changes occur with the values of the pseudoattractor area (PA) S, within which the phase portrait of this subject is located. For example, it was found that with external photostimulation of the visual analyzer (with a flickering frequency \( v = 10 \text{ Hz} \)), in a healthy person, the area S for PA decreases, and for a patient with epilepsy, S increases sharply. In other words, S allows you to register changes in the functions of the BNN.

For example, in table 3, we present for comparison the samples S for the PA of a healthy person (\( S^N_1 \)) and a sick person (\( S^P_1 \)) in a calm state. It is obvious that the average value of \( \langle S^P_1 \rangle = 4759 \text{ a.u.} \) and the average value of \( S^P_1 \) for the patient (\( S^P_1 = 572470 \text{ a.u.} \)) are sharply different. This is demonstrated in table 3.

Table 3. The value of the pseudoattractor areas S of the electroencephalogram samples of a healthy person and a person with epilepsy during the relaxation period.

|       | Healthy       | With epilepsy |
|-------|---------------|---------------|
|       | \( S^N_1 \), rest | \( S^P_1 \), rest |
| 1     | 6240          | 664058        |
| 2     | 3595          | 626364        |
| 3     | 3494          | 866433        |
| 4     | 3430          | 737606        |
| 5     | 2983          | 568073        |
| 6     | 3338          | 516819        |
| 7     | 6834          | 504262        |
| 8     | 7986          | 508445        |
| 9     | 4508          | 509555        |
| 10    | 2533          | 512527        |
| 11    | 4244          | 512692        |
| 12    | 4178          | 511651        |
| 13    | 4933          | 514056        |
| 14    | 4810          | 520925        |
| 15    | 8282          | 513591        |
| \( \langle S \rangle \) | 4759          | 572470        |

These values clearly show the differences in the EEG parameters (on the phase plane of the vector \( x(t) = (x_1, x_2) \)) between a sick and healthy person.

In fact, based on the calculation of PA parameters, we now have accurate models for the diagnosis of human conditions (in normal conditions, during illness, during the transition from one mental state to another). The analog of the Heisenberg principle, when the phase coordinate \( x_1(t) \) and \( x_2 = dx_1/dt \) are subject to restrictions in the form of inequalities, allows us to identify stationary modes of the BNN (by EEG parameters) or changes in the state of the BNN for the same person or for a whole group of subjects.

Table 3 clearly shows the difference in EEG parameters for a healthy person (\( S^N_1 \)) and for a patient with epilepsy. Within the framework of stochastics, such distinctions cannot be made. Due to EEG, we observe continuous and chaotic changes in EEG samples (see table 1). As a result, we are now coming to a new understanding of the stationary modes of the BNN or their real changes (see table 1 and table 2).
4. Discussion
More than 70 years ago, one of the founders of information theory, W. Weaver, presented a general classification of all systems of nature. At the same time, he took all living systems beyond the limits of deterministic and stochastic science. In fact, he declared the uselessness of stochastics in the description of any biosystems. After 50 years, the scientific schools of Surgut, Moscow, Tula and Samara managed to prove that the hypothesis of W. Weaver about the third type of systems has a real quantitative justification. In the mode of multiple repetitions of TMG registrations, TPG was proved by EZE. Later, this EZE was extended to RR intervals (cardiointervals), electromyograms (EMG), and other parameters of the human body [2-9].

Brain function remained the last area where stochastics continued to be actively used. All Neuroscience is now based on stochastic research methods. However, the proof of the statistical instability of EEG samples ends the further application of stochastics in all neuroscience. If any sample is unique, then we cannot use stochastics in the study of BNN.

It is necessary to create new models and other theories in the description of the human brain. The brain demonstrates statistical chaos and it requires a new theory in its study. Diagnostics of brain neural network states can now be based on calculations of matrices of paired comparisons of EEG samples (see table 1 and table 2) or on the calculation of the parameters of pseudoattractors, their area S.

As a result, we get more accurate dynamic methods in assessing the norm and pathology in the state of the human brain.

5. Conclusions
Based on the hypothesis of W. Weaver about systems of the third type that cannot be the object of deterministic and stochastic science, we prove the statistical instability of the bioelectric activity of the brain (in the form of EEG analysis). It turned out that the BNN generates continuously changing EEG samples, which even in a calm state in a healthy subject (relaxation) cannot show a statistical coincidence of the EEG samples. This proves the lack of statistical stability of the EEG, i.e. EZE.

However, the calculation of the matrices of paired comparisons of EEG samples of a healthy and sick person demonstrates their significant difference in the values of the K numbers (pairs of samples with the Wilcoxon criterion P\(p\geq0.05\)). This means that the K numbers can provide a diagnosis of the BNN. Because of the EEG, we introduce the concept of the pseudoattractor area S for EEGs, which in the two-dimensional phase space of the vector \(x(t)=(x_1, x_2)^T\) can quantitatively characterize the state of the BNN. As a result, we come to a new understanding of the specifics of chaos in the BNN and to new methods for identifying (diagnosing) the states of a complex dynamic object – the human brain. A new method for analyzing the bioelectric activity of the brain as a complex physical object is proposed.

Reference
[1] Weaver W 1948 Science and Complexity American Scientist 36(4) 536-44
[2] Eskov V M, Eskov V V and Filatova O E 2011 Characteristic features of measurements and modeling for biosystems in phase spaces of states Measurement techniques 53(12) 1404-10
[3] Eskov V M, Kulaev S V, Popov Yu M and Filatova O E 2006 Computer technologies in stability measurements on stationary states in dynamic biological systems Measurement techniques 49(1) 59-65
[4] Eskov V M, Gavrilenko T V, Vokhmina Y V, Zimin M I and Filatov M A 2014 Measurement of chaotic dynamics for two types of tapping as voluntary movements Measurement techniques 57(6) 720-4
[5] Betelin V B, Eskov V M, Galkin V A and Gavrilenko T V 2017 Stochastic volatility in the dynamics of complex homeostatic systems Doklady Mathematics 95(1) 92-4
[6] Eskov V V, Gavrilenko T V, Eskov V M and Vokhmina Y V 2017 Phenomenon of statistical instability of the third type systems – complexity Technical physics 62(11) 1611-6
[7] Zilov V G, Eskov V M, Khadartsev A A and Eskov V V 2017 Experimental Verification of the Bernstein Effect “Repetition without Repetition” Bulletin of experimental biology and
[8] Eskov V M, Eskov V V, Vochmina J V and Gavrilenko T V 2016 The evolution of the chaotic dynamics of collective modes as a method for the behavioral description of living systems Moscow university physics bulletin 71(2) 143-54

[9] Eskov V M, Eskov V V, Braginskii M Ya and Pashnin A S 2011 Determination of the degree of synergism of the human cardiorespiratory system under conditions of physical effort Measurement techniques 54(7) 832-7

[10] Zilov V G, Khadartsev A A, Eskov V V and Eskov V M 2017 Experimental Study of Statistical Stability of Cardiointerval Samples Bulletin of experimental biology and medicine 164(2) 115-7

[11] Eskov V M, Papshev V A, Eskov V V and Zharkov D A 2003 Measuring biomechanical parameters of human extremity tremor Measurement techniques 46(1) 93-9

[12] Eskov V M, Eskov V V, Vochmina Y V, Gorbunov D V and Ilyashenko L K 2017 Shannon entropy in the research on stationary regimes and the evolution of complexity Moscow University Physics Bulletin 72(3) 309-17

[13] Vokhmina Y V, Eskov V M, Gavrilenko T V and Filatova O E 2015 Measuring order parameters based on neural network technologies Measurement techniques 58(4) 462-6

[14] Eskov V V, Filatova D Y, Ilyashenko L K and Vochmina Y V 2019 Classification of uncertainties in modeling of complex biological systems Moscow university physics bulletin 74(1) 57-63

[15] Grigorenko V V, Eskov V M, Nazina N B and Egorov A A 2020 Information-analytical system of cardiographic information functional diagnostics Journal of Physics: Conference Series 1515 052027

[16] Zilov V G, Khadartsev A A, Ilyashenko L K, Eskov V V and Minenko I A 2018 Experimental analysis of the chaotic dynamics of muscle biopotentials under various static loads Bulletin of experimental biology and medicine 165(4) 415-8

[17] Eskov V M, Papshev V A and Filatova O E 2003 A Computerized system for measuring mammalian-tissue biomechanical parameters Measurement techniques 46(3) 304-10

[18] Eskov V M 1996 Models of hierarchical respiratory neuron networks Neurocomputing 11(2-4) 203-26

[19] Eskov V M, Filatova O E and Ivashenko V P 1994 Computer identification of compartmental neuron circuits Measurement techniques 37(8) 967-71

[20] Zilov V G, Khadartsev A A, Eskov V V, Ilyashenko L K and Kitanina K Yu 2019 Examination of statistical instability of electroencephalograms Bulletin of experimental biology and medicine 168(7) 5-9