Analysis technology of neurological movements considering cognitive feedback influences of cerebral cortex signals

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Abstract

A high-performance information technology for evaluating human neurological movements has been developed based on a hybrid model of wave signal analysis, considering the cognitive feedback effects of cerebral cortex neuro-nodes.

With the use of hybrid Fourier transforms, a high-speed analytical solution of the model in vector form was implemented, which allows determining the elements of movements on each segment of a complex spiral trajectory performed by the patient with an electronic pen on a digital tablet, and identified the parameters of the studied neuro-systems with feedback.

Keywords

Neurological movements, cognitive neuro-feedback signals, abnormal tremor, numerical diagnostics, hybrid Fourier transform, hardware and software

1. Introduction

New modeling methods are used to provide an approach to the design of digital diagnostic health systems for patients with neurological diseases. The creation of new software and hardware solutions for medicine and automated diagnostic systems to identify new phenomena of the body and human health is an urgent task.

The latest information technologies and modeling methods in the design of a computer diagnostic system improve the solution to the problem of treating critical diseases in the world, especially people affected by neurological diseases, such as abnormal neurological movements (ANM) or tremors and their extreme forms in the form of Alzheimer's, Parkinson's diseases [1]. ANM - unwanted oscillating movements of certain part of the body (hands, organs of speech, eyeballs), arising as a result of involuntary contraction of human muscles [2]. Movement regulation disorders signs of human movements are an increase in their amplitude, a change in the frequency and form of oscillations. The analysis of these ANM parameters is crucial for understanding the role of feedback dysfunction in cerebral cortex (CC) neural nodes in cognitive control processes of human movements and early detection of neuromotor disorders. The difficulty of identifying ANM lies in the imperfection of existing diagnosis methods, their low accuracy, and the lack of mathematical and software tools for identifying the neurofeedback influences of CC nodes on their behavior [2].

Studies of neuro-systems related to the analysis of the behavior of patients with tremor symptoms (T-objects) were conducted by a number of researchers, such as Pullman S. L., Legrand A.-P., Vidailhet M. (ESPCI Paris Tech, ICEM CNRS), Wang J.-S., Louis E., Haubenberger D., Kalowitz D. and others. Here, the main attention was paid to the analysis of parameters of relatively normal conditions and behavior of patients using classical methods of digital processing based on the Fourier transform [2-4]. However, such methods have already exhausted themselves to date and do not allow the analysis of

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abnormal states with complex, hard-to-predict behavior, which is inherent in real T-objects with a high degree of tremor. Due to the imperfection of such methods, there is loss of 60-80% of important information from the description of patients' real conditions, which de facto determines the low quality level of such analysis.

The authors proposed a high-performance information technology for ANM research, built on the basis of a hybrid model analysis of neuro-system's signals, which describes the state and behavior of the 3D elements of ANM trajectories of the T-object, considering the cognitive neuro-feedback effects of the identified CC nodes. Using the methods of hybrid Fourier transform, high-speed analytical solutions of the model were built in the form of vector functions that determine the elements of the trajectories on each ANM segment. On their basis, high-performance algorithms for the identification of tremor-movements parameters are proposed for the component-wise evaluation of neuro-feedback effects, which allow parallelization of calculations.

2. A brief description of the hardware used in the research

2.1. The method of collecting movement data using a graphic tablet

In addition to qualitative characterization, quantitative improvement of this test requires knowledge of the position and pressure as a function of the time the patient uses the handle throughout the experiment. This requires the use of a graphics tablet with specially adapted software. Basically, this common tool is usually used for artistic drawing, which is provided by specialized software. The goal here is not the same as above, we need to collect the X and Y coordinates as a function of time, the frequency and accuracy of which depends on the manufacturer.

Figure 1: A visual representation of how to use a Wacom Bamboo graphics tablet

For these reasons, the WACOM Bamboo Fun Medium graphics tablet was chosen. Its active area (corresponding to 217mm x 137mm) is compatible with the generally accepted patterns of Fahn-Tolosa-Marin Tremor Rating Scale (FTRS). The reader has a pen input resolution of 2540 dpi, an accuracy of 0.25 mm and a recognition speed of 133 points per second (according to the manufacturer's specifications). In addition, this tablet allows you to display pen pressure while drawing on a plane and measure movements at a distance of up to 16 mm above the surface of the pen, which allows you to visualize the patient's movements in space.

2.2. NeuroCom computer electroencephalography system produced by KHAI-MEDYKA

The NEUROKOM computer electroencephalograph, the fifth generation of developed computer electroencephalography complexes [6], was chosen for the study of electroencephalography (EEG) signals of the brain. The encephalograph in the complex is designed for registration, in-depth analysis and interpretation of EEG and evoked potentials, conducting various analyzes for scientific research.

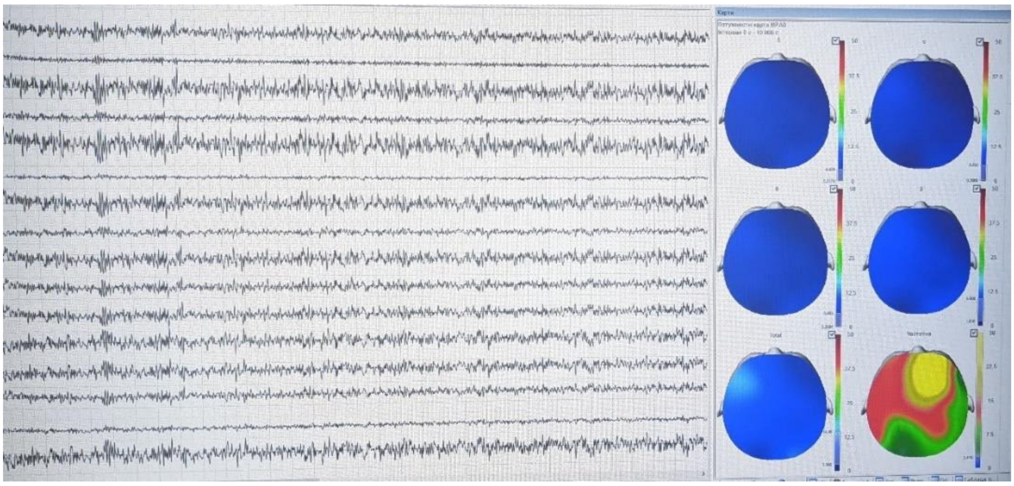

Figure 2: Visual representation of the data collection process from the NeuroCom electroencephalography complex

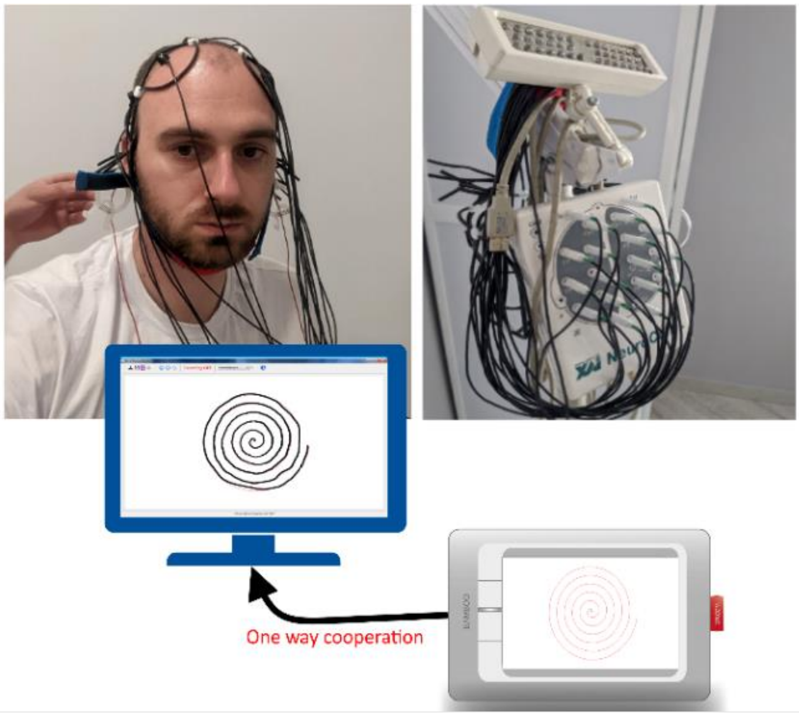

Figure 3: Demonstration of using research hardware

The helmet with the installed hardware and software platform of the manufacturer provides 16-channel selection of encephalograms and their transmission to a personal computer using the appropriate protocol. Software conditioning of EEG signals and post-processing takes place on a PC. Data is stored both in raw text and in a visualized representation at each point in time. Data is read from each lead channel at 2ms intervals (500 Hz frequency).

3. A hybrid mathematical model of ANM-analysis considering the cognitive neuro-feedback-influences of CC nodes

The hybrid model analysis of ANM built on the basis of the concept of propagation of a wave signal determines the segment-by-segment description of the elements of ANM trajectories (hands of the patient) considering the matrix of cognitive effects of groups of neuro-nodes of the CC on the movement segments [5]. The implementation is based on the method of determining the position of the patient's hand with an electronic pen, which reproduces the trajectory of the template (Archimedes' spiral) on the screen of the interactive tablet [7, 8]. The deviation of the trajectory of the pen movement from the template has a complex shape (Figure 4) and provides digitized information for determining the patient's neurological condition. The pen movement trace is broken down into simpler elements for the purpose of decomposing complex ANM-movements within the schematization of the model. The number of divisions depending on the complexity of the ANM image can be chosen arbitrarily. The hybrid model provides quantitative amplitude and frequency characteristics of ANM.

For considering the cognitive neurofeedback effects of the system, the obtained digital sets of indicators of EEG signals are used, which synchronously with the movement of the electronic pen in the patient's limb, come from a certain set of CC neuro-nodes. EEG signals in general determine the dynamics of ANM for each j -th segment of the trace, $j = \overline{1, n_1 + 1}$ where n_1 is the number of points of breakdown of the ANM track (Figure 4). In the model, the partition can be set automatically in an arbitrary way, with any finite number of segments. Their lengths can be different depending on the level of detail of the traffic sections.

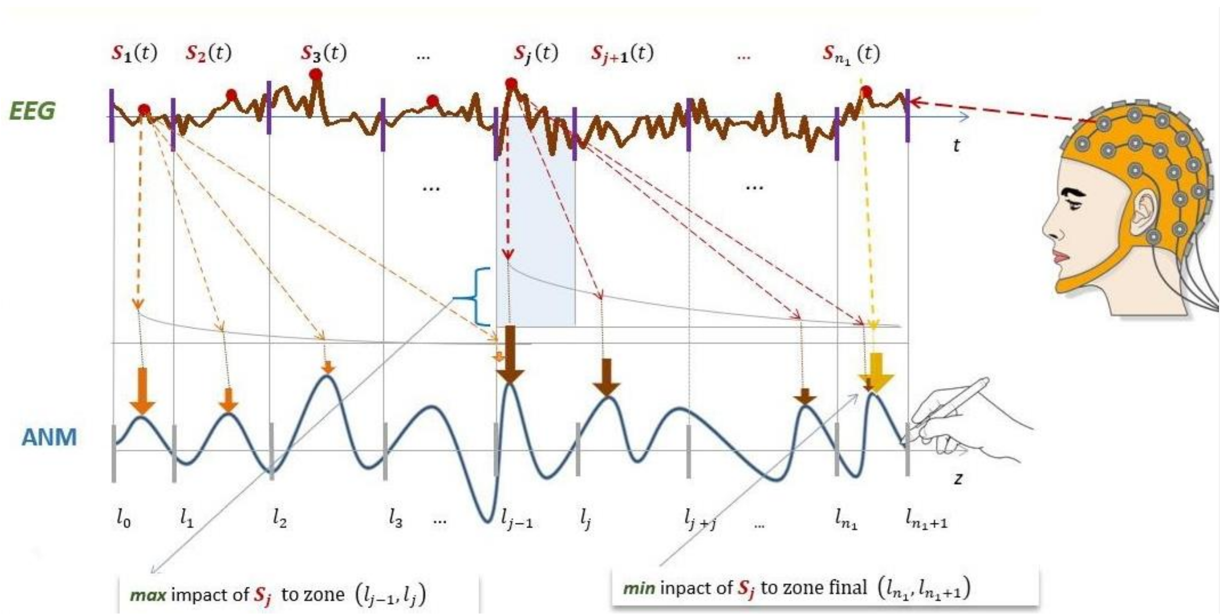

Figure 4: Schematization and visualization of the influence of vector of connections components of the of cognitive feedback-influences of EEG-signals of neuro-nodes $S(t)$ on individual elements of the ANM–trace (l_{j-1}, l_j), $j = 1, n_1$ within the framework of the hybrid model of analysis

Model description. In order to present a mathematical solution in the form of implementing the procedure for the functional identification of the amplitude components and the phase velocity of the ANM wave propagation $b_k^2, k = \overline{1, n_1 + 1}$ as functions of time in the framework of the model decomposition, taking into account the conditions that the traces (observation data in the form of digital data of ANM-movements of the patient) of the solution for each k-th segment are known, $k = \overline{1, n_1 + 1}$, a system of initial-boundary value problems (micromodels) is obtained for successive segments of ANM [6, 9]:

$$\frac{\partial^2}{\partial t^2}u_k(t,z) = b_k^2\frac{\partial^2}{\partial z^2}u_k + S_k^*(t,z), \tag{1}$$

with initial conditions:

$$u_k(t,z)|_{t=0} = 0, \qquad \left.\frac{\partial u_k}{\partial t}\right|_{t=0} = 0, \quad k = \overline{1, n_1+1}, \tag{2}$$

Boundary conditions on each of the ANM segments along z:

$$u_{k-1}(t,z)|_{z=l_{k-1}} = U_{L_{l_{k-1}}}, \qquad u_k(t,z)|_{z=l_k} = U_{l_k}, \quad k = \overline{1, n_1+1}, \tag{3}$$

Selection of the residual functional. We assume that the components of the phase velocity of the ANM wave propagation b, $k = \overline{1, n_1+1}$ of the boundary value problem (1) - (3) are unknown functions of time. With known values of the position of the pen $u_k(t,z)$ at observation points on ANM-segments$\gamma_k \subset \Omega_k$, $k = \overline{1, n_1+1}$

$$uk(t,z)|_{\gamma_k} = U_{l_k}(t,z)\big|_{\gamma_k}, \tag{4}$$

problem (1) - (4) can be considered for each point z for each k_1-th segment of the ANM-trajectory and will consist in finding the functions $b_k \in D$, where $D = \left\{v(t,z):\ v|_{\Omega_{k_{1T}}} \in C\left(\Omega_{k_{1T}}\right),\ \ v > 0, k = \overline{1, n_1+1}\right\}$.

Functional-incoherence$\gamma_{k_1} \in \Omega_{k_1}$, according to [6, 10] will be written in the form

$$J_k\left(b_{k_k}\right) = \frac{1}{2}\int_0^T \left(\|u_k(t,z,b_k) - U_k^*\|^2\right) dt, \tag{5}$$

The construction and mathematical substantiation of the solution of the hybrid model is included in [9].

4. Modeling and identification of parameters of neurological movements signals of a person under the influence of cognitive neuro-feedback effects of cerebral cortex neuro-nodes

To configure the model of identification, fragments of the ANM-trajectory of the spiral type, which was performed by the patient on a digital tablet (Figure 1) were used.

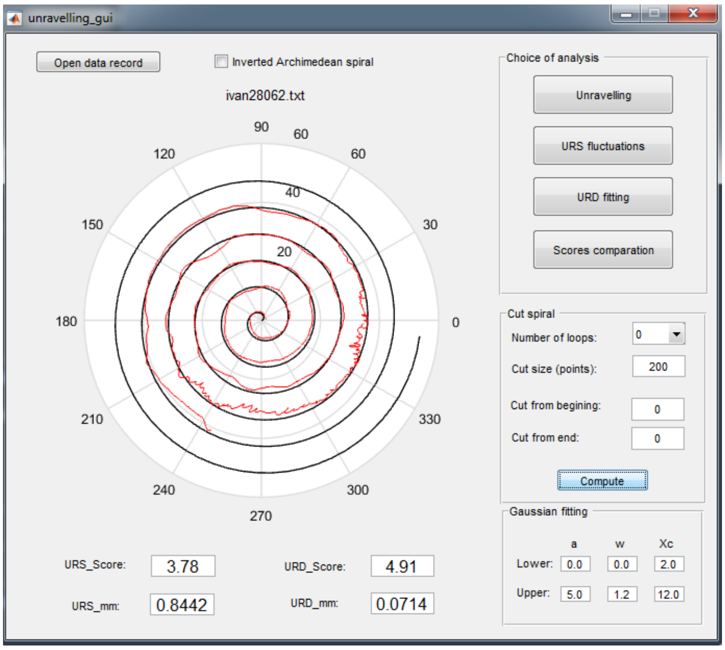

Figure 5: Spiral-type ANM trace created by the patient on an interactive tablet

Modeling and identification of the parameters of ANM movements was carried out within the framework of the task of identifying parameters of cognitive neuro-feedback effects of EEG on ANM trajectories developed using the ANM hybrid model considering the feedback effects of EEG-signals. To set up the identification model, we used a fragment of the ANM-trace, made by the patient using an electronic pen on an interactive digital tablet according to Figure 5.

The corrected fragment of the trace of this spiral example of the test pattern (Archimedes spiral) by the patient with an electronic pen on a digital tablet in the number of discretized 2400 points - positions of the track is presented in Figure 6. Here, the abscissa k is the number of positions of the deviation of the pen from equilibrium during the passage of the spiral sample.

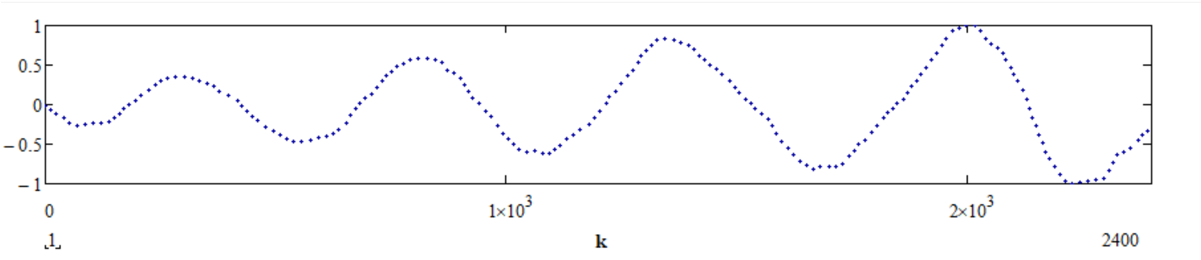

Figure 6: Straightened fragment of the electronic trace of the spiral circuit with an electronic pen on the tablet. Number of points $n = 2422$

The analysis used a test set of EEG signals of the Fp1- tap sensors of NeuroCom (according to the CC node classification map), which was measured synchronously with the movement of the electronic pen when the patient traced the test pattern (Figure 7).

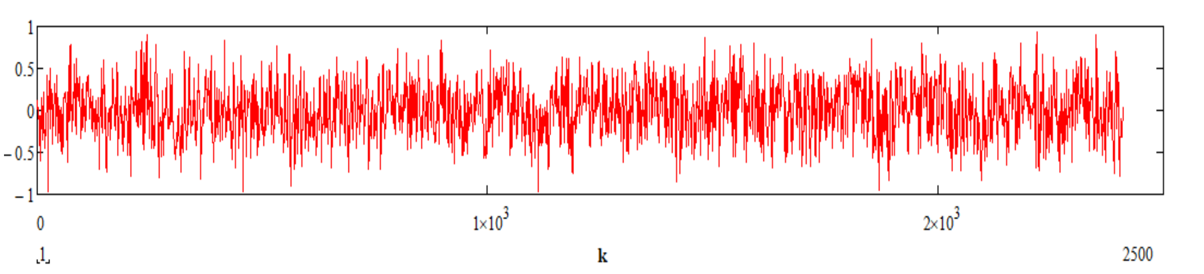

Figure 7: Test set of EEG-signals of the Fp1- tap sensors of the CC of the patient when tracing the test pattern

Setting up the model ANM track and their step-by-step and segment-by-segment identification (amplitude and frequency parameters for each segment taking into account the integrity of the system) to a specific sample of the trace performed by the patient (observation curve or experimental curve) was performed according to the feedback scheme and the analytical solution of the hybrid ANM model tracks (Figure 8).

The degree of tremor in this part of the recording ETG (essential tremors graphic), which is based on the matrix of interactions of brain signals (EEG) S.

$$
\begin{bmatrix} u_1(t,z) \\ \dots \\ u_j(t,z) \\ \dots \\ u_{n+1}(t,z) \end{bmatrix} = \int_0^t \begin{bmatrix} \int_{l_0}^{l_k} \mathcal{H}_{11}(t-\tau,z,\xi) & \dots & \int_{l_n}^{l_{n+1}} \mathcal{H}_{1,n_1+1}(t-\tau,z,\xi) \\ \dots & \dots & \dots \\ \int_{l_0}^{l_k} \mathcal{H}_{j1}(t-\tau,z,\xi) & \dots & \int_{l_n}^{l_{n+1}} \mathcal{H}_{j,n+1}(t-\tau,z,\xi) \\ \dots & \dots & \dots \\ \int_{l_0}^{l_k} \mathcal{H}_{n+1,1}(t-\tau,z,\xi) & \dots & \int_{l_n}^{l_{n+1}} \mathcal{H}_{n_1+11,n_1+1}(t-\tau,z,\xi) \end{bmatrix} \cdot \begin{bmatrix} S_1(\tau,\xi) \\ \dots \\ S_i(\tau,\xi) \\ \dots \\ S_n(\tau,\xi) \end{bmatrix} d\xi d\tau
$$

ETG

EEG

feedback

Figure 8: Model of the ANM track with feedback

The results of simulation of ANM of the limb with an electronic pen of the patient, their verification according to the data of the neuro-experiment according to Figure 4, which were accompanied by the synchronous cognitive neuro-feedback effect of the Fp1 neuro-node (a set of EEG signals according to Figure 7) and the use of a hybrid model of ANM analysis (based on the hybrid Fourier transform) are presented in Figure 9-Figure 13. At first, we took a relatively small number of points in an effort to reproduce the profile of the observation curve (the profile of the ANM-track performed by the patient taking into account the picture of the EEG feedback curve (Figure 7).

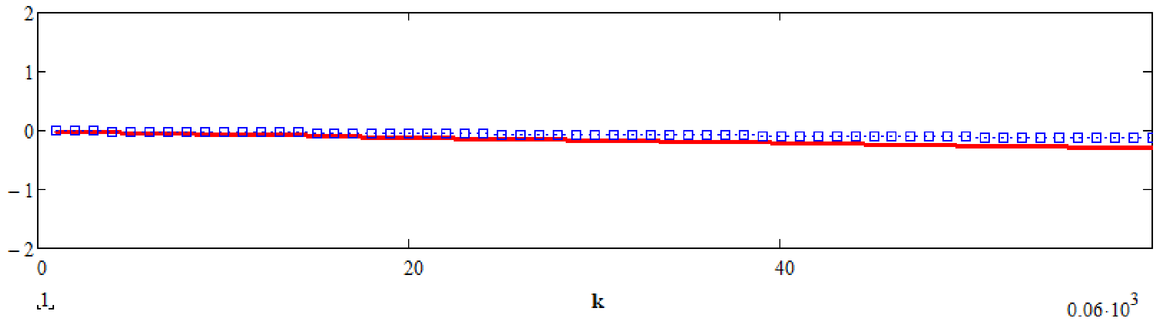

Figure 9: Comparative analysis of the ANM-model track (red solid line) and the real patient trace (blue square markers) for the first 60 points (the degree of model verification is more than sufficient)

As can be seen from Figure 9, the accuracy of matching the model track and the patient's real trace is very high (up to 1.5-2%) for 60 observation points. Amplitude and frequency characteristics due to the hybrid spectral function built by us, built systematically for all segments of the breakdown (taking into account their connectivity, not each separately), made it possible to obtain an almost complete coincidence of the model track with the real patient trace. Then we gradually increased the number of points on the track. For the number of points 200, the results turned out to be practically the same (Figure 10).

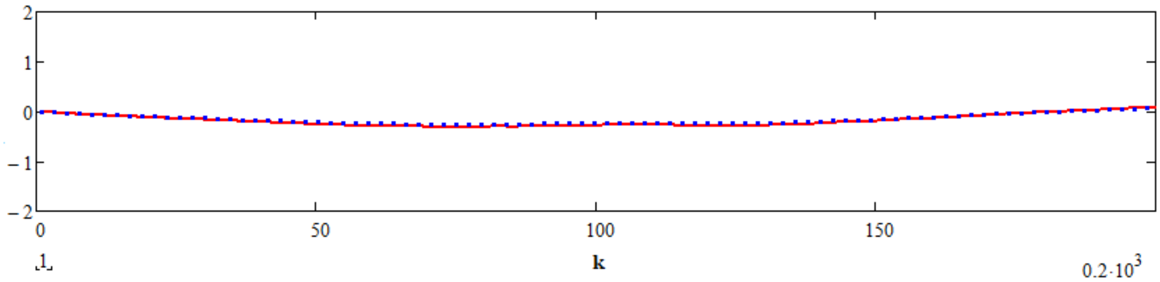

Figure 10: Comparative analysis of the ANM model track (red solid line) and the real patient trace (blue dot markers) for the first 200 points (a deeper level of model verification on real data)

In the future, we again gradually increased the number of points to 600, 1200, 2400 and 4 and studied the behavior of the model curves, evaluating their possible deviations from the patient's experimental ANM-traces.

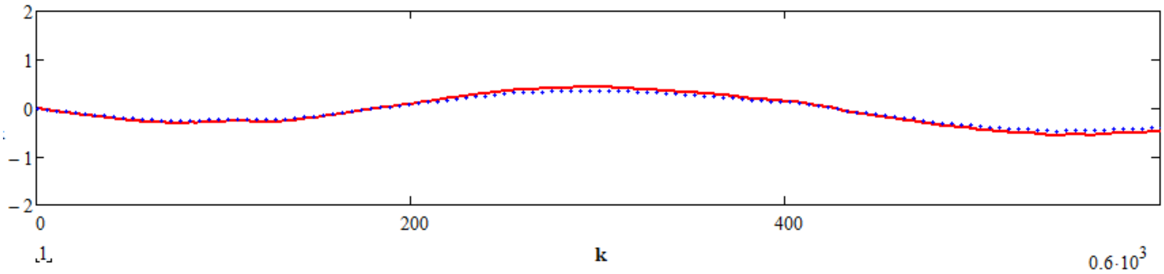

Figure 11: Analysis of the ANM model track (red solid line) and the patient's real trace (blue dot markers) for the first 600 points (model verification by track curvature elements)

In Figure 11, for a segment with 600 points, we observe a slight deviation in the saddle zone around the 60th point of the track, about 3-5%. However, this problem can be technically solved by making the track segmentation in this area smaller. By the way, the model itself allows for arbitrary partitioning with arbitrary sizes of each segment and making them as small as necessary.

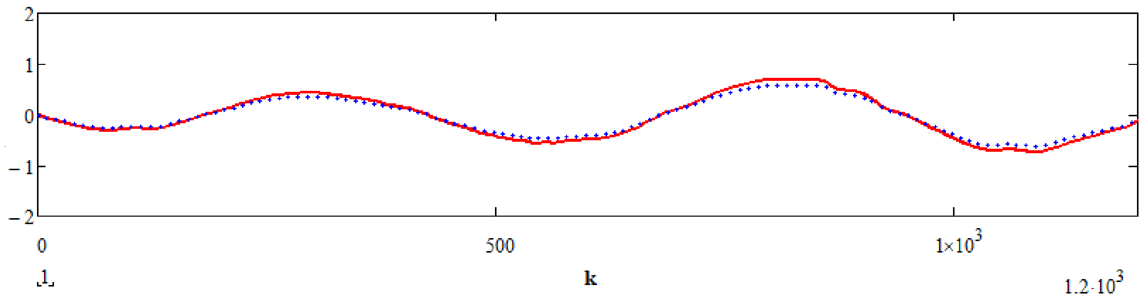

Figure 12: Analysis of the ANM model track (red solid line) - and the patient's real trace (blue dot markers) for the first 1200 points (broader verification of the model by elements, which includes several sinusoidal inhomogeneous sections of the wave motion)

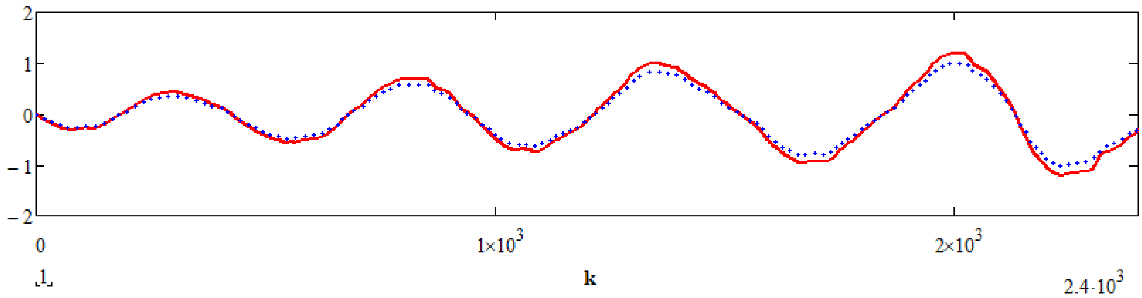

Figure 13: Analysis of the ANM model track (red solid line) - and the patient's real trace (blue dot markers) for the first 2400 points (model verification in a wide range of the track with complex sections of wave motion)

A positive point is that on all graphs we see a complete reproduction of the frequency characteristics of the track (the periodicity of the model curves almost completely corresponds to the periodicity of the curves performed by the patient). As the number of examined points in individual saddle or ridge points increases, it decreases. But this can be corrected by choosing a smaller division in these zones.

As can be seen from the presented graphs, the developed model reproduces the patient's behavior at a high level, displaying an ANM track that practically coincides with the one drawn by him on the tablet. The most important thing is that the model includes the possibility of displaying the mechanisms of its feedback effects of CC signal in the form of a matrix of EEG signals that determine the behavior of these movements. Further research may include a change in this behavior, apparently for the better, depending on the change in the magnitude of these EEG feedback effects after certain therapeutic procedures and expand the limits of application.

5. Conclusions

Information technology for evaluating the neurological movements of a person is proposed, the one is based on a hybrid model of wave signal analysis, considering the reverse cognitive effects of cerebral cortex neuro-nodes. Using hybrid Fourier transform, a high-speed analytical solution of the model in vector form was obtained and implemented. It determines the elements of trajectories on each segment of a complex spiral-drawing performed by the patient with an electronic pen on a digital tablet with the identification of the parameters of the researched feedback systems.

The proposed hybrid model provides deep decomposition of the system without affecting its integrity and connections, which is not possible for by classical methods of signal processing, that lead to the loss of 60-80% of information about the real condition of the object. Weighting coefficients which characterize the influence of the digital recordings sets of the cognitive influence signals produced by neuro-nodes of the patient's cerebral cortex are pre-specified by machine learning methods during of the patient-executed test examples of drawing spiral trajectories on a Wacom digital tablet.

Compared to the paper method of drawing a spiral, the following indicators were obtained:

- reduction of test duration by 2.5-3 times (about 1 minute instead of 2.5-3 minutes of manual input);
- efficiency and accuracy of the assessment - a significant increase in productivity due to the high speed of data analysis, the quality of the process of obtaining input data of the 3D drawing of the spiral, the unambiguous interpretation of the results.

This approach makes it possible to more qualitatively describe the complex mechanisms of human neurological conditions under the influence of cognitive connections of the nervous system, which determine abnormal behavior deviations caused by various man-made and other factors providing a high degree of data completeness, clarifying diagnoses for treatment.

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