From healthy to pathology through a fall in dynamical complexity of involuntary oscillations of the human hand

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The task is to estimate quantitative features in involuntary oscillations of shaking (tremor) of fingers accompanied the performance of the motor task by healthy subjects, patients with Parkinson’ disease and individuals with the essential tremor. For solving the task the tremor patterns are examined by the wavelet-transform modulus maxima method and the recurrence quantification analysis. The physiological tremor is characterized by the minimal energy of the wavelet spectrum, the maximal degree of multifractality, the minimal degree of determinism and the maximal recurrence time density entropy, reflecting the greatest uncertainty of the period value. During the essential tremor the significant enhancement of the wavelet spectrum energy and the decrease of the dynamical complexity of involuntary oscillations are observed. It is evident as the fall in the multifractality degree, the growth of determinism in recurrence plots, the decrease of the recurrence time density entropy and the emergence of unstable periodic orbits in involuntary oscillations. For the parkinsonian tremor all the trends are enhanced that lead to more definite dynamics of patterns. Therefore, our results demonstrate that the dynamical complexity of patterns of involuntary oscillations decreases in larger degree for Parkinson’ disease, than for patients with the syndrome of the essential tremor, that is, it declines with increasing the severity degree of motor disorders. The results obtained for the first time can be applied for evaluating the degree of deviation of the motor function from the healthy one.

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1. Introduction

Tremor, defined as rapid involuntary oscillations of parts of the human body, is a motor phenomenon found both in normal individuals and in sick subjects [1]. Tremor may result from different reasons and sources but it is important that these involuntary oscillations (physiological tremor) have small amplitude under normal conditions and do not impair motor performance [2]. Pathological tremors appear to arise as a distortion of central or peripheral components of physiological tremor and disrupt the movement performance [1]. In spite of enormous advantages in studying of properties of physiological and pathological tremors [3–5], the topic is of immediate interest of physiologists, clinicians, physicists and mathematicians. It is explained by the necessity of searching new methods for the guaranteed differential diagnostics capable to exclude possible errors in clinical practice. For example, so called essential tremor, when individuals have tremor symptoms but not have Parkinson’ disease, and parkinsonian tremor are difficult to distinguish in more than 25% cases, especially in the first years of disease and for patients with elderly age [2].

It is known that resting tremor is typical for Parkinson’ disease and action tremor, when the body parts are involved into involuntary shaking during the movement performance, is more intrinsic for the essential tremor [1]. However, under long lasting disease the resting tremor adds in 20% cases of the essential tremor [1]. It is also known that, the parkinsonian tremor has more low characteristic frequencies of 4–6 Hz, whereas the essential tremor has more high frequencies (5–10 Hz), but overlapping frequencies of these two types of tremor in the range of 5–6 Hz does not permit to use the frequency characteristic as a clear diagnostic criterion [6,7]. In addition, with age the frequency in the essential tremor declines in the side of the parkinsonian tremor frequency [8,9] so that oldest patients can be objects of clinical errors. The tremor amplitude cannot be also a guaranteed diagnostic measure, although in most cases the parkinsonian tremor amplitude exceeds the essential tremor amplitude. It is known that intensive physiological action tremor, arising under states leading to excitation of peripheral β - adrenoreceptors in stress, has larger amplitude, than the physiological tremor, accompanied the performance of the given motor tasks without stress [2,3,10]. Thus, the use of amplitude-frequency response does not allow us to find definitive features of pathological and physiological tremors.
By contrast, methods of nonlinear dynamics, capable to evaluate dynamical complexity of involuntary oscillations accompanied the performance of the motor task, make it possible. In dynamical complexity we consider the complexity of temporal organization of patterns of time series. The basis of this complexity forms the complexity of control process of creating and disrupting functional networks by the human brain [11].

As is known, under normal conditions physiological time series are extremely inhomogeneous and nonstationary, fluctuating in an irregular and complex manner [12]. So, temporal dynamics of EEG, ECG or the step-to-step intervals in human walking rhythm is intermediate between randomness and order [11]. These intervals exhibit noisy fluctuations with deviations from a local average. It is believed that these fluctuations contain useful hidden information about the underlying control mechanism [13]. The absence of one or several characteristic intervals in bioelectrical activity of the human heart or brain inhibits the emergence of periodic or close to periodic behaviors, which would narrow functional responsiveness on external actions [14]. However, ensembles of healthy neurons generating bioelectrical activity are capable to respond to unpredictable stimuli and stress. It is also known that these fluctuations have multifractal properties demonstrating a self-similarity in wide range of scales [15,16]. This similarity is not complete but it remains on the statistical level, i.e. after averaging statistically independent samples of the time series. Tremor arising under keeping the effort by fingers of the hand also has the multifractal dynamics properties [17]. Multifractal scale-invariance can reflect the complexity of the control mechanism, on the one hand, and the fact that this mechanism is connected with a memory effect, on the other hand [13,18,19]. The memory effect means that the value of the interval at a given time is related not just to immediately preceding values, but also to fluctuations in remote past.

Certain pathologies are marked by a breakdown of this organization (long-range correlations), sometimes producing an uncorrelated randomness of intervals similar to noise as in the case of stride interval fluctuations in Huntington’s disease or heart rate fluctuations in a cardiac arrhythmia [13,18] or recordings of the acceleration of the hand of individuals with essential and parkinsonian tremors [20]. Other pathologies can be connected with emergence of pathologic periodicity as strongly periodic oscillations, which are associated with Cheyne-Stokes breathing (a pathologic type of cyclic respiratory pattern) [13] or with obstructive sleep apnea [12] and even with sudden cardiac death [21]. Thus, the breakdown of physiologic complexity may be associated with excessive order, on the one hand, or uncorrelated randomness, on the other hand [12,18]. Both routes to pathology are the degradation of correlated and multiscale dynamics.

The question about an excessive order or an enhanced breakdown of pathological tremor remains unsolved yet. Buckwell and Gesty [22] showed that sometimes tremor could be modeled as a chaotic, i.e. a low-dimensional deterministic process. Timmer et al. [23] rejected the chaotic dynamics of the essential and parkinsonian tremor data and demonstrated their stochasticity, i.e. the absence of correlated dynamics. Gao and Tung [24] studied the same data and found that pathological tremors have properties of an anomalous diffusional process characterizing by a power-law divergence of nearby trajectories in its phase space. However, these anomalous diffusions, with an extremely large diffusional exponent can be considered as precursors of noise-induced chaos [20]. Variations in the frequencies of the pathological tremors are smaller than variations in the amplitude that reflects the stable nature of the neural network generating around a well-defined mean frequency value. However, the insignificant variation is enough to destroy any pronounced correlations among the firing of individual neurons [20].

In previous work [17] we have shown that multifractal parameters (the width and asymmetry of the singularity spectrum) significantly differ in tremor of healthy subjects and patients with motor dysfunction. We have found also the relations between the changed state of the patient with Parkinson’ disease connected with the drug relief of parkinsonian symptoms and variations of the multifractal parameter values [25]. Differences in multifractal features of various types of pathological tremors remain unclear. It raises the question about their alterations with severity of disease and the potential of multifractal parameters for clinical monitoring.

The other promising method for the study of involuntary oscillations of the human hand is the recurrence quantification analysis allowing us to visualize definitive characteristics in patterns of complex nonstationary oscillations [26–28].

The aims of the work are (1) to compare wavelet, multifractal and recurrent features of involuntary oscillations of shaking (tremor) of fingers accompanied the performance of the motor task by healthy subjects, patients with Parkinson’ disease and individuals with the essential tremor; (2) to validate or reject the hypothesis that dynamical complexity of patterns of the human hand tremor accompanied the motor task performance decreases with increasing the disease severity.

2. Materials and methods

2.1. Patients

We examined 15 healthy volunteers (men, mean age 45.7 ± 5.2 years) and 14 parkinsonian patients with bilateral akinesis and tremor (men, mean age 41.7 ± 6.7 years) and 12 patients with a syndrome of the essential tremor and without other symptoms of Parkinson’ disease (men, mean age 48.7 ± 7.2 years). The patients with Parkinson’s disease did not take any drugs before the test on the day of testing. Usually, these patients received an antiparkinsonian preparation madopar containing levodopa and benserazide at doses of 200 and 50 mg, respectively, or nakom containing levodopa and carbidopa at doses of 250 and 25 mg three times a day to compensate for dopamine deficiency. The subjects with syndrome of essential tremor did not have tremor medication. The data were collected in the St. Petersburg Human Brain Institute during the neurotological treatment of the patients. All the subjects were restudied in three trials, each at least one week apart. The study was approved by the local Ethics Committee. Written informed consent was obtained from all the participants.

2.2. Tremor recording

The motor task was to control the isometric muscle effort with the strength of muscle contraction shown by the positions of marks on a monitor. The subjects sat in front of a monitor standing on a table and pressed their fingers on platforms containing stress sensors that transformed the pressure strength of each hand into an electric signal. The rigidity of the platforms made it possible to record the effort in the isometric mode, i.e., without noticeable movement of fingers at the points of contact with the sensors. The subjects’ fingers sustained an upward muscle effort, with the back of each hand pressing against the base of the platform. The isometric effort was recorded for 100 s at a sampling frequency 256 Hz, so that the sampling time interval was 0.004 s and the time series contained of 25,000 points. The recorded trajectory of isometric effort consisted of a slow oscillatory trend and a fast involuntary component (tremor), which was isolated from the recorded trajectory using the adaptive detrending method [29]. The method is based on partitioning a time series into segments of length w and fitting of each segment with a best polynomial of order m. As
it has been shown in the work [30], the algorithm can more effectively reduce noise in the signals than linear filters and wavelet denoising.

Fig. 1 illustrates trends obtained from the original recorded trajectory of isometric effort with both the adaptive detrending and the wavelet denoising algorithms. Comparing two thick curves of the Fig. 1, depicting the found trends, we can conclude that the second algorithm is really more accurate can remove the slow oscillatory trend in our recordings then the first algorithm.

2.3. Estimation of the energy properties of the tremor

To evaluate the difference between physiological and pathological tremors, we used the wavelet transform modulus maxima (WTMM) method [31] based on the continuous wavelet transform [32] of a time series describing the examined tremor \( x(t) \):

\[
W(a, t_0) = a^{-1/2} \int_{-\infty}^{\infty} x(t) |\psi^*(t - t_0)/a| dt,
\]

where \( a \) and \( t_0 \) are the scale and space parameters, \( \psi((t - t_0)/a) \) is the wavelet function obtained from the basic wavelet \( \psi(t) \) by scaling and shifting along the time, symbol * means the complex conjugate. As the basic wavelet we use the complex Morlet wavelet [32]:

\[
\psi_0(t) = \pi^{-1/4} \exp(-0.5 t^2) (\exp(\text{i}o_0 t) - \exp(-0.5 o_0^2 t^2)),
\]

where the second component in brackets can be neglected at \( o_0 = 2\pi > 0 \), the multiplier factor \( \exp(\text{i}o_0 t) \) is a complex form of a harmonic function modulated by the Gaussian \( \exp(-0.5 t^2) \), the coefficient \( \pi^{-1/4} \) is necessary to normalize the wavelet energy. The value \( o_0 = 2\pi \) gives the simple relation \( f = 1/a \) between the scale \( a \) and the frequency \( f \) of the Fourier spectrum. Then expression has the form:

\[
W(f, t_0) = \pi^{-1/4} \sqrt{f} \int_{-\infty}^{\infty} x(t) \exp(-0.5(t - t_0)^2 f^2) \exp(-i2\pi(t - t_0)f) dt.
\]

The modulus of the wavelet spectrum \( |W(f, t_0)| \) characterizes the presence and intensity of the frequency \( f \) at the moment \( t_0 \) in the analyzed tremor and \( |W(f, t_0)|^2 \) describes the instantaneous distribution of the tremor energy over frequencies, that is, the local spectrum of the tremor energy at the time \( t_0 \). The value

\[
E(f) = \int_{t_1}^{t_2} |W(f, t_0)|^2 dt_0
\]

determines the global wavelet spectrum, i.e., the integral distribution of the wavelet spectrum energy over frequencies on the time interval \([t_1, t_2]\).

2.4. Estimation of tremor multifractality

Information about possible multifractal feature of the examined signal and its localization \( t_0 \) reflects in the asymptotic behavior of coefficients \( |W(a, t_0)| \) at small \( a \) values and large \( f \) values, respectively [16]. The faster the wavelet coefficients decrease at \( f \to \infty \), the more regular the signal is around the point \( t_0 \). The small decrease of the wavelet coefficients at \( a \to 0 \) in a neighborhood of the point \( t_0 \) testifies about non-regularity or singularity of the signal at the point. Thus, the rate of the change of the modulus of the wavelet coefficients enables to determine the presence or absence of singularities of the signal. The degree of singularity of the signal \( x(t) \) at the point \( t_0 \) is described by the Hölder exponent,\( h(t_0) \), the largest exponent such that the analyzed signal in a neighborhood of the point \( t_0 \) can be represented as the sum of the regular component (a polynomial \( P_0(t) \) of order \( n + h(t_0) \)) and a member describing a non-regular behavior [31]:

\[
x(t) = P_0(t) + c|t - t_0|^h(t_0).
\]

The value \( h(t_0) \) is the measure of singularity of the signal at the point \( t_0 \) since the smaller \( h(t_0) \), the more non-regular (more singular) the signal. The Hölder exponents characterize the presence of correlations of different types in the analyzed process, e.g., anti-correlated (for \( h < 0.5 \)) or correlated (for \( h > 0.5 \)) dynamics or absence of correlations (if \( h = 0.5 \)).

In view of the simple dependence \( W(a, t_0) \sim a^{h(t_0)} \) at \( a \to 0 \) [32], the Hölder exponent can be calculated by \( h(t_0) \sim \log_{10} W(a, t_0)/\log_{10} a \). However, with increasing the scale \( a \), the influence of neighboring non-regularities can lead to inaccuracy, that is why we determined the Hölder exponents on the basis of statistical description of local singularities by partition functions [33] constructed with the wavelet-transform modulus maxima (WTMM) method. A detailed description of the method and its application to experimental data may be found in the review by Muzy et al [31].

The algorithm of estimating the tremor multifractality consists of the following procedures.

1. The continuous wavelet transform of the time series is used.
2. A set \( l(a) \) of lines of local modulus maxima of the wavelet coefficients is found at each scale \( a \).
3. The partition functions are calculated by the sum of \( q \) powers of the modulus maxima of the wavelet coefficients along the each line at the scales smaller the given value \( a \):

\[
Z(q, a) = \sum_{l \in l(a)} (\sup_{\sigma \in \sigma_l} |W(a^\sigma, t_l(a^\sigma))|)^q.
\]

where \( t_l(a^\sigma) \) determines the position of the maximum corresponding to the line \( l \) at this scale.
4. The partition function is \( Z(q, a) \sim a^{\tau(q)} \) at \( a \to 0 \) [33], therefore, the scaling exponent can be extracted as

\[
\tau(q) = \log_{10} Z(q, a)/\log_{10} a.
\]

5. Choosing different values of the power \( q \) one can obtain a linear dependence \( \tau(q) \) with a constant value of the Hölder exponent \( h(q) = d\tau(q)/dq = \text{const} \) for monofractal signals
and nonlinear dependence \( \tau(q) = qh(q) - D(h) \) with large number of the Hölder exponents for multifractal signals.

(6) The singularity spectrum (distribution of the local Hölder exponents) is calculated as

\[ D(h) = qh(q) - \tau(q). \]

Using the algorithm and the global wavelet spectra for the different tremor recordings we obtain the maximum of the global tremor energy (\( E_{\text{max}} \)) and two multifractal parameters: a) the width of the singularity spectrum \( \Delta h = h_{\text{max}} - h_{\text{min}} \), where \( h_{\text{max}} = h|_{q=5} \) and \( h_{\text{min}} = h|_{q=5} \) are the maximal and minimal values of the Holder exponent corresponding to minimal and maximal tremor fluctuation, respectively; b) the asymmetry of the singularity spectrum \( \Delta = |\Delta_2 - \Delta_1| \), where \( \Delta_1 = h_{\text{max}} - h_0 \) and \( \Delta_2 = h_0 - h_{\text{min}} \), \( h_0 = h \) \((q = 0)\).

The parameter \( \Delta h \) is a measure determining the degree of multifractality since small \( \Delta h \) indicates that the time series tends to be monofractal and large \( \Delta h \) testifies the enhancement of multifractality. The asymmetry parameter \( \Delta \) characterizes where in the region of strong singularities \((q > 0)\) or in the region of weak singularities \((q < 0)\), the singularity spectrum is more concentrated.

2.5. Estimation of recurrent properties of the tremor

To visualise regularities in tremor patterns and to evaluate their characteristic features the recurrence quantification analysis (RQA) [27] was applied. Subroutines of the CRP Toolbox are available at https://www.pik-potsdam.de/crp.php.

A recurrence plot (RP) is a graphical representation of a matrix defined as

\[ R_{ij}(m, \varepsilon) = \Theta(|y_i - y_j| - \varepsilon), \quad i, j = 1, \ldots, N. \]

The RP serves for mapping the \( m \)-dimensional phase trajectory of states \( y(t) \) on the plane, in which the coordinate axes are time axes [34]. A black point corresponds to the repetition of the state at time \( t \) at the other time \( j \), where \( N \) is the number of considered states; \( \varepsilon \) is a neighborhood of the point \( y \) (a threshold distance for RP computation), symbol \(|.|\) denotes a norm, \( m \) is the embedding dimension, \( \Theta(\cdot) \) is the Heaviside function (taking values 0 or 1) [27]. Thus

\[ R_{ij}(m, \varepsilon) = \begin{cases} 1, & y_i \approx y_j \\ 0, & y_i \neq y_j \end{cases} \]

The values \( R_{ij} = 1 \) and \( R_{ij} = 0 \) are plotted on the recurrence plot as gray and white dots, reflecting events that are termed as recurrence and nonrecurrence, respectively, with the accuracy of \( \varepsilon \) – error. The recurrence is determined as the sufficiently vicinity of state \( y_i \) around state \( y_j \), i.e. the states \( y_j \) falling into the \( m \)-dimensional neighborhood with the radius \( \varepsilon \) and the center in \( y_j \) are recurrent.

The phase trajectory of states \( y(t) \) can be reconstructed from a time series \( x(t) \) by the Takens’s method based on using the time delay coordinates [35]:

\[ y(t) = (x(t), x(t + d), \ldots, x(t + (m - 1)d)), \]

where \( d \) is the delay time, \( m \) is the embedding dimension (the minimal dimension of the space in which the reconstructed attractor reconstructs properties of the original attractor), i.e. the minimal number of independent variables definitely determining its properties. Thus, a point \( (x(t_1), x(t_1 + d), x(t_1 + 2d), x(t_1 + (m - 1)d)) \) corresponds to each value \( x(t_i) \) of a time series \( x(t) \), and a set of these points restores the attractor of the time series.

To reconstruct the phase state trajectory \( y(t) \) from the original time series correctly it is necessary to choose the time delay \( d \) so that coordinates of the point \( (x(t_i), x(t_i + d)) \) have duplicated information as small as possible. The optimal time delay was fitted on the basis of first minimum of the mutual information function [35].

Then the optimal embedding dimension \( m \) was searched by the false nearest neighbor method [36]. The size of the \( \varepsilon \) neighborhood (the threshold distance \( \varepsilon \)) was chosen to be equal to 1% of the standard deviation of the data series [27].

Recurrence plots show structure properties of patterns of the analyzed signal and its evolution, i.e. changes in patterns during the recording [27,34]. Single, isolated points on the recurrence plot indicate strong fluctuations, taking place in the analyzed process. The presence of diagonal lines, parallel to “the line of identity”, always existing and passing under the angle \( \pi/4 \) gives evidence the similarity of patterns in various times. Hence, the appearance of long diagonal lines demonstrates emergence of periodicity in the examined process, vertical distances between diagonal lines correspond to periods of oscillations. The appearance of vertical and horizontal lines argues about occurrence of patterns which do not change in time or change very slowly. Irregular black clusters corresponding to gathering vertical and horizontal lines, as well as white regions, point at non-regularity of the process.

Using the RQA method we determined the quantitative characteristics of recurrence plots, such that

(1) a measure for determinism (or predictability) of the system

\[ \text{DET} = \frac{\sum_{i,j} IP(\varepsilon, l)}{N} \]

as the ratio of recurrence points that form diagonal structures (of at least length \( l_{\text{min}} \)) to all recurrence points, where

\[ P(\varepsilon, l) = \left\{ l, l = 1, \ldots, N \right\} \]

is the frequency distribution of the diagonal lines of lengths \( l \) in RP and \( N \) is the number of all diagonal lines;

(2) a measure of divergence

\[ \text{DIV} = 1/L_{\text{max}} \]

where \( L_{\text{max}} = \max(\left\{ l, l = 1, \ldots, N \right\}) \) is the longest diagonal line found in the RP;

(3) a recurrence time

\[ T_j = \left\{ \left\{ t, j : y_i, y_j \in R_i, y_{j-1} \notin R_i \right\} \right\}, \]

defined as the time needed for a trajectory to return into a previously visited \( \varepsilon \) neighborhood of a point, that is, as the vertical distance between the onset and end of the sequent recurrence structure in the recurrence plot, where \( R_i \) are recurrence points belonging to the state \( y_j \) [37];

(4) a recurrence time density entropy

\[ \text{RTDE} = -\frac{\sum_{T=1}^{T_{\text{max}}} P(T) \ln P(T)}{\ln T_{\text{max}}}, \]

where \( T_{\text{max}} \) is maximal recurrence time in the RP, \( P(T) \) is the recurrence time density function obtained after normalization of the recurrence time histogram \( H(T) \):

\[ P(T) = \frac{H(T)}{\sum_{T=1}^{T_{\text{max}}} H(T)}. \]

The measure for determinism \( \text{DET} \) or predictability of the process behavior is maximal \((= 1)\) for a periodic process and minimal \((= 0)\) for a stochastic one since the processes with stochastic behavior can cause very short diagonals or have no them, whereas deterministic processes cause long diagonals and small number of single, isolated recurrence points [27]. The measure of divergence, vice versa, is minimal \((= 0)\) for a periodic process and characterizes the divergence of segments of the phase space trajectory (as
the process goes forward the periodic, the shorter are the diagonal lines and the higher is the measure $DIV$ [27].

The recurrence time histogram $H(T)$ has a single maximum for perfectly periodic signals and a set of maxima for a strongly noisy non-uniform signal. The recurrence time density function $P(T)$ has a value changing from 1 for a periodic signal to $1/T_{\text{max}}$ for a purely random signal [38]. The recurrence time density entropy $RTDE$ reflects the complexity of deterministic component of the signal and characterizes uncertainty of its period. The value can be equal to 0, that means the absence of uncertainty of the period value for the purely periodic signal, or equal to 1, that testifies the maximal uncertainty for the purely uniform signal [38]. For real time series the $RTDE$ value is in the range from zero to one.

To examine the differences between the mean values of the calculated measures of the each examined group of patients and the mean measures of the control group the non-parametric Mann–Whitney test ($p < 0.05$) is used.

2.6. Localization of unstable periodic orbits in involuntary oscillations

The pattern corresponding to periodic oscillations (periodic orbits) is reflected in the $RP$ by non-interrupted equally spaced diagonal lines. The vertical distance between these lines corresponds to the period of the oscillations. The chaotic pattern leads to the emergence of diagonals which are seemingly shorter. The vertical distances become irregular. When the trajectory of the system comes close to an unstable periodic orbit (UPO), it stays in its vicinity for a certain time interval, whose length depends on how unstable the UPO is [39,40]. Hence, UPOs can be localized by identifying such windows inside the $RP$, where the patterns correspond to a periodic movement [40,41]. If the distance between the diagonal lines varies from one chosen window to the other then various UPOs coexist with different periods.

The period of UPO can be estimated by the vertical distance between recurrence points in the periodic window multiplied by the sampling time of the data series [40]. The algorithm for finding UPOs consists of the following procedures.

1. A search of the recurrence times for the recurrence neighborhood of radius $\varepsilon$.
2. The values of recurrence periods are determined as recurrence times multiplied by the sampling time of the data series. The values are recorded in a histogram. The periods of UPOs are the maxima of the histogram of the recurrence periods.
3. To exclude the noise influence the obtained UPOs are tested for statistical accuracy. For this purpose the procedure is repeated for 30 surrogates obtained as randomized versions of the original data. In the surrogate data the time interval sequences are destroyed by randomly shuffling the locations of the time intervals of original data [42].

The statistical measure of the presence of statistically significant UPOs in the original time series is given by the ratio

$$k = (A - \bar{A})/\sigma,$$

where $A$ is the value of maximum of the histogram, $\bar{A}$ is the mean of $A$ for surrogates and $\sigma$ is a standard deviation. The value of $k$ characterizes the existence of statistically significant UPOs in the original data in comparison with its surrogate (noisy) version. The value $k > 2$ means the detection of UPOs with a greater than 95% confidence level [43].

3. Results and discussion

The examples of fast component of the isometric force trajectory of the human hand (detrended tremor) for the healthy subject, the patient with Parkinson disease and for the subject with essential tremor are given in Fig. 2. All the oscillations are not regular and the amplitude of the parkinsonian and essential tremors exceeds the amplitude of the healthy tremor.

The examples of the three-dimensional wavelet surfaces in the $(f, t_0, |W(f, t_0)|^2)$ space for the same subjects are shown in Fig. 3. The values of maxima gained for the healthy and essential tremors are comparable but they are larger for the parkinsonian tremor.

The global wavelet spectra $E(f)$ determining the integral distribution of the tremor energy over frequency range on the whole time interval are given in the right lower corner of Fig. 3. The maximum ($E_{\text{max}}$) of the global wavelet energy spectrum of the physiological tremor is in the frequency range of the alpha rhythm [7.5, 14] Hz and its value is smaller as compared with the pathological tremor. For the parkinsonian tremor the value of $E_{\text{max}}$ is shifted in the range [4, 7.5] Hz and it increases in ten times. For the essential tremor the value of $E_{\text{max}}$ is comparable to the value obtained for the healthy tremor. The similar results were observed for all the subjects from the examined groups. It allowed us to use further the common practice of averaging the gained tremor characteristics of all subjects among each group.

Figs. 4 and 5 illustrate fractal features of the studied tremors. The averaged (over the subjects) dependences $r(q)$ of the scaling exponent on the power $q$ value are depicted in Fig. 4.

Fig. 5 gives examples of the averaged singularity spectra, $D(h)$, of the tremor data. The spectra were obtained by both multifractal algorithms, the WTMM algorithm (solid curves) and MF-DFA algorithm [44] (dotted curves in Figs. 4 and 5).

For comparison we give the spectra for a typical monofractal signal, namely, for the fractional Brownian motion of a Brownian particle (solid curve in Fig. 4 and a single point in Fig. 5), and for the signal obtained by superposition of the Brownian motion and normally distributed random series (solid curve in Fig. 5). The monofractal signal has the unique Hölder exponent $h(q) = 0.6$. Homogeneous monofractal time series that involve singularities of unique Hölder exponent are characterized by a $r(q)$ spectrum, which is a linear function of $q$ (Fig. 4). For the noised version of the monofractal signal we observe a small deviation from a constant value ($h(q) \neq \text{const}$). The singularity spectrum $D(h)$ depicted in Fig. 5 displays in this case a single humped shape that characterizes intermittent fluctuations corresponding to Hölder exponent values spanning the interval of width $\Delta h = 0.04$. However, the
small value of the singularity spectrum width does not allow us to think about the loss of monofractality.

On the contrary, the shape of the represented curves for the tremor data indicates that all the time series describing tremors are not monofractal signals but the studied recordings actually have multifractal properties. It reflects in the broad singularity spectra $D(h)$ and, hence, in large number of Hölder exponents both for the healthy and pathological tremors (Fig. 5) and in nonlinearity of curves $\tau(q)$ (Fig. 4).

Involuntary oscillations of the human hand of the healthy subject, arising during the performance of the given motor task, are characterized by the maximal width $\Delta h = 0.83 \pm 0.08$ of the singularity spectrum and, by the largest degree of multifractality, respectively. The parkinsonian tremor multifractality is considerably less.

The increase in the width of the spectrum for the physiological tremor as compared with the pathological one takes place due to growing contribution of weak fluctuations (for $q < 0$). These fluctuations lead to the enhancement of the singularity spectrum at negative values of $q$, and, hence, large values of $h$ (Fig. 5). It in its turn explains the largest asymmetry of the singularity spectrum $\Delta = 0.41 \pm 0.04$ of the healthy tremor, whereas the value of $\Delta$ does not exceed $0.23 \pm 0.03$ for pathological oscillations.

The parkinsonian tremor is characterized by the smallest width $\Delta h = 0.26 \pm 0.02$ and asymmetry $\Delta = 0.07 \pm 0.007$ of the singularity spectrum and by the minimal degree of multifractality, respectively. Statistical differences of these multifractal parameter values and the values gained for the healthy subjects are determined by statistics $p = 0.025$ and $p = 0.031$ (Mann–Whitney test).

Multifractal parameters of the essential tremor have intermediate values $\Delta h = 0.45 \pm 0.05$ and $\Delta = 0.23 \pm 0.02$. Thus, the values of $\Delta h$ and $\Delta$ for the essential tremor are larger than for the parkinsonian one but they do not exceed the values for healthy tremor, differing statistically from ones obtained in healthy patterns ($p = 0.041$ and $p = 0.042$, Mann–Whitney test). The decline in the multifractality degree found in the parkinsonian and essential tremors means a reduction of non-uniformity of the pathological tremors as compared with the healthy one.

Previously we proved that involuntary fast oscillations of the human hand arising during the performance of the motor task under sustaining isometric effort of fingers are not useless noise component, but solve the control task of voluntary slow oscillations with aim of their stabilization during observing the position of marks on a monitor [45]. The rise of the multifractality degree of these oscillations means the enhancement of their complexity [17,25] and, hence, the growth of dynamical complexity of the control process during realization of the given motor task. Thus, in this work we have shown that the dynamical complexity decreases during the essential tremor and still more falls during the parkinsonian tremor. The latest facts are in agreement with results of the works [46,47] demonstrating the decline of correlation dimension as one of the measure of the dynamical complexity and more simple dynamics of patterns of the human magnetic electroencephalogram (MEG) during parkinsonian seizure as compared with the state of the same patient without seizure. However, the correlation dimension, in contrast to an estimation of multifractality, is not a reliable indicator for considerably nonstationary signals such as MEG or EEG time series. That is the reason, probably, the attempts to find differences in the correlation dimension values in
Fig. 4. Examples of the averaged (over the subjects) spectra of scaling exponents, \( \tau(q) \) for the tremor data obtained by the WTMM algorithm (solid curves) and by MF-DFA algorithm (dotted curves). For comparison the curve for the monofractal Brownian process is shown.

Fig. 5. Examples of the averaged (over the subjects) singularity spectra, \( D(h) \), of the tremor data obtained by the WTMM algorithm (solid curves) and by MF-DFA algorithm (dotted curves). For comparison the curves for the monofractal Brownian process and its noisy version are shown.
the resting state of healthy subjects and patients with Parkinson's disease failed [48]. What's more the correlation dimension for the patients increased in comparison with the healthy subjects values during the performance of the complex motor task [48].

The enhancement of dynamical complexity of the hand tremor of a healthy subject is also connected with the emergence of both the long-range correlations (for \( h > 0.5 \)) and anticorrelated dynamics (\( h < 0.5 \)), unlike the parkinsonian and essential tremors, for which the characteristic feature is only correlated dynamics (\( h > 0.5 \), for parkinsonian tremor) or only anticorrelated dynamics (\( h < 0.5 \), for essential tremor). As known, for the long-range correlations the oscillatory process will persistent (maintaining the tendency) and the level of random factors will fall [15]. Therefore, our results show that the damage of the brain leading to the development of the motor dysfunctions, can cause breakdown or modification in correlations of involuntary oscillations and, in the case of parkinsonian tremor, can maintain involuntary movements, that, in its turn, can disrupt the performance of the given motor task.

Examples of the three dimensional reconstructions of the tremor data by using delay coordinates also testify about the decrease of the pathological tremor complexity in comparison with physiological one (Fig. 6). These reconstructions are built with the delay time \( d = 2 \) and the embedding dimension \( m = 8 \) for the healthy tremor, and \( m = 3 \) for the parkinsonian and essential tremors. The decline in the embedding dimension and the emergence of a clear expressed structure of the phase state trajectory reconstructed from the original time series demonstrates the fall in the dynamical complexity of these pathological tremors. For comparison we give the three dimensional time delay reconstructions of oscillations of the noisy Lorenz system, exhibiting the noisy chaotic behavior, as well as the reconstruction of noisy periodic data and the fractional Brownian process built with the delay time \( d \) and the embedding dimension parameter \( m \), values of which are given in Fig. 6. It is obvious that although all the three phase trajectories reconstructed from the tremor data do not have the clear periodicity they exhibit the well defined structure unlike the reconstructed trajectory of the fractional Brownian motion.

To visualise regularities in tremor patterns we give the examples of recurrence plots (\( \mathrm{RPs} \)) for the different tremor data in Fig. 7. The \( \mathrm{RPs} \) are obtained with the delay time \( d = 2 \) and the embedding dimension \( m = 8 \) for the healthy tremor and \( m = 3 \) for the parkinsonian and essential tremors. The threshold distance was chosen as \( \varepsilon = 1\% \) of the standard deviation of the data series. All the three recurrence plots exhibit non-homogeneous structures, that reflects nonstationarity of involuntary oscillations of the human hand. The \( \mathrm{RP} \) of the healthy tremor is characterized by small black rectangles, whereas the \( \mathrm{RPs} \) from the pathological tremors show larger rectangles. These rectangles reflect time intervals when the trajectory is travelling near the corresponding UPOs [41].

The \( \mathrm{RP} \) of the physiological tremor contains a small number of single, isolated points and interrupted diagonal lines, demonstrating the presence of strong fluctuations, taking place in the analyzed process, and weak periodicity in the form of the small similarity of patterns in different times. The recurrence plots of the parkinsonian and essential tremors have a large number of diagonal lines, embedding into a well-defined structure.

To compare the obtained recurrences in tremor patterns with recurrences in the noisy periodic data as well as in the fractional Brownian process and in the Lorenz system exhibiting the chaotic behavior, we give the examples of recurrence plots for these time series in the Fig. 8. The time series are depicted in Fig. 9. The \( \mathrm{RPs} \)
are constructed with the embedding dimension $m = 3$ and the delay time $d = 15$ for the noisy periodic data, with $d = 40$ for the fractional Brownian process and with $d = 5$ for the Lorenz system. The threshold distance $\varepsilon = 2 \sigma$ for the noisy periodic series, $\varepsilon = 0.1 \sigma$ for the Lorenz data and $\varepsilon = 0.8 \sigma$ for the fractional Brownian process, where $\sigma$ is the standard deviation of the data series. The RP of the noisy period 1 signal has equal distanced black and white bands corresponding to noising the signal. The fractional Brownian process has abrupt changes in the dynamics that causes the appearance of disrupted irregular white and black structures. A chaotic dynamics of the Lorenz data leads to short diagonals and certain vertical structures, which are not as regular as in the case of a periodic motion. In other words, the chaotic process causes complex quasi-periodic recurrent structures with various distances between the diagonal lines gathering in irregular black clusters like as irregular checkerboard structures. The noising of the Lorenz data does not interrupt this well-defined structure of the RP.

Examples of histograms of recurrence periods for the tremor data are shown in Fig. 10. Parameters of the embedding dimension $m$, the delay time $d$ and the threshold distance $\varepsilon$ are the same as in Fig. 7. The dash-and-dot lines in Fig. 10 depict histograms found for surrogate tremor data. The recurrence time were defined as the time needed for a trajectory to return into a previously visited $\varepsilon$ neighborhood of a point in the recurrence plot. The histogram of recurrence periods for the healthy tremor has a lot of peaks, suggesting that the time series is non-uniform. The number of the histogram maxima for the pathological tremor, contrasting, is limited, that testifies about a less complex structure of patterns of these oscillations. The recurrence periods extracted as peaks of the histograms in Fig. 10 are equal to $0.23 \pm 0.02$ (s) for the healthy

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**Fig. 7.** Examples of recurrence plots for the different tremor data. Parameters: the delay time $d = 3$, the embedding dimension $m = 8$ for the healthy tremor, $d = 15$ and $m = 2$ for the parkinsonian and essential tremors, the threshold distance $\varepsilon = 1\%$ of the standard deviation of the data series.

**Fig. 8.** Examples of recurrence plots. Parameters: $d = 15$, $m = 3$ for the noisy periodic data, $d = 40$, $m = 9$ for the fractional Brownian process, $d = 5$, $m = 3$ for the Lorenz system, the threshold distance $\varepsilon = 2 \sigma$ for the noisy periodic series, $\varepsilon = 0.1 \sigma$ for the Lorenz data, $\varepsilon = 0.8 \sigma$ for the fractional Brownian process, where $\sigma$ is the standard deviation.
Fig. 9. Examples of time series for which the recurrence plots are given in Fig. 8.

Fig. 10. Examples of histograms of recurrence periods for tremor data and their surrogates (solid and dash-and-dot lines, respectively). Parameters of the embedding dimension $m$, the delay time $d$ and the threshold distance $\varepsilon$ are the same as in Fig. 7.
tremor, 0.17 ± 0.01 and 0.34 ± 0.03 (s) for the parkinsonian data and 0.15 ± 0.01 (s), 0.45 ± 0.04 (s) and 0.90 ± 0.08 (s) for the essential data. The peak of the histogram of recurrence periods for the Lorenz data corresponds to 5.75 ± 0.3 (s).

The periods obtained were used for searching and localization of UPOs. Testing the surrogate data we excluded the values 0.23 (s) and 0.34 (s) since the statistical measure $k < 1$ in both cases. For other recurrence periods extracted from Fig. 10 the value $k > 2$ that supports the detection of UPOs with a greater than 95% confidence level. Thus, for the healthy tremor data represented in Fig. 10 there are no statistically significant UPOs. By contrast, the UPO of period 1 (0.17 s) is gained for the parkinsonian tremor and the UPOs of periods 1, 3 and 6 are obtained for the essential tremor ($0.45/0.15 = 3, 0.90/0.15 = 6$). Examples of a period 1, a period 3 and a period 6 recurrent orbits found for the Lorenz and essential tremor data are shown in Fig. 11.

The similar dynamics of the wavelet and multifractal parameters as well as measures of recurrence plots and UPOs localization is observed for involuntary oscillations of the examined subjects. The averaged (over the subjects in each group) values of the tremor characteristics are given in Table 1. The data of Table 1 testify about the absence of statistically significant differences in mean values of the tremor characteristics for the left and right hands of the healthy and essential groups ($p_1 > 0.05$ by the Mann–Whitney test). For the parkinsonian group the noticeable differences are observed in mean values of the tremor amplitudes of the left and right hands ($p_1 = 0.045$) and in $E_{max}$ and $k(p_1)$ values. The significant differences between the states (parkinsonian or physiological tremor) are identified by all the parameters ($p_2 < 0.05$ by the Mann–Whitney test).

The measure for determinism (DET) calculated for the constructed recurrence plots and describing the ratio of the number of recurrence points that form diagonal structures to all recurrence points, is largest (0.88 ± 0.08) for the parkinsonian tremor and smallest (0.27 ± 0.02) for the healthy tremor. For the essential tremor the measure takes the intermediate value (0.52 ± 0.06). The statistically significant differences in mean values of DET for the healthy and parkinsonian tremor and for the parkinsonian and essential tremor are observed at $p_2 = 0.017$ and $p_3 = 0.036$, respectively (Mann–Whitney test). The results obtained enable us to argue that involuntary oscillations of the hand of a healthy subject are less deterministic than pathological oscillations and the degree of determinism enhances with increasing the pathology degree. Hence, the dynamical complexity decreases.

The measure of divergence (DIV) characterizing the divergence of segments of the phase space trajectory is greatest (0.1 ± 0.01) for the physiological tremor, it is less for the essential tremor (0.02 ± 0.002) and it is minimal (0.003 ± 0.0003) for the parkinsonian one, suggesting a more limited determinism of the essential tremor as compared with the parkinsonian tremor. The mean values of DIV for the pathological tremors significantly differ from the values obtained for the healthy subjects at the confidence level $p < 0.05$ by the Mann–Whitney test.

The decrease of the recurrence time density entropy RTDE is an added reason for falling the complexity of involuntary oscillations under motor disorders. The RTDE value reflects the complexity of deterministic component of the time series and characterizes uncertainty of its period. The value of RTDE is largest (0.77 ± 0.07) for the healthy tremor and it is smallest (0.25 ± 0.03) for the parkinsonian tremor. For the essential tremor the measure of RTDE takes intermediate value (0.56 ± 0.05) that means the increase of uncertainty of the period value for the essential tremor in contrast to the parkinsonian tremor. The mean values of RTDE for the pathological tremors significantly differ from the values
obtained for the healthy subjects at the confidence level \( p < 0.05 \) by the Mann–Whitney test.

Thus, for the essential and parkinsonian tremor we found the significant differences in the singularity spectrum width \( \Delta h \) and asymmetry \( \Delta \) values and in the quantitative characteristics of recurrence plots such that the determinism \( DET \), the divergence \( DIV \) and the recurrence time density entropy \( RTDE \) (\( p < 0.05 \)) by the Mann–Whitney test).

In summary, for all the considered healthy subjects the hand tremor was characterized by the minimal amplitude and energy of the wavelet spectrum, maximal degree of multifractality, minimal determinism and the maximal recurrence time density entropy, reflecting the greatest uncertainty of the period value. During the essential tremor we observed the enhancement of the wavelet spectrum energy and the decline of the oscillation complexity, reflecting in the decrease of the multifractality degree, the emergence of a certain structure in recurrence plots, the growth of determinism and the decrease of the recurrence time density entropy. In all the cases of the parkinsonian tremor these trends were enhanced, that led to more clear dynamics of patterns. It is agreed with the results of the work [48], in which it has been shown that the rate of changing of the instantaneous frequency of the first principal component of the tremor is minimal, and, hence, the instantaneous frequency is more stable for the parkinsonian tremor than for the essential one. In other words, the tremor in Parkinson' disease is related to more wide range of stable frequencies and the essential tremor is connected with the narrow frequency range. The authors [48] associate this feature with the fact that in the essential tremor the nervous system is able to maintain the smaller resonance frequencies than in the parkinsonian one.

It is known that the dynamical complexity of functional networks is characterized by the possibility of creating and destructing these networks [11]. In addition to the above, the higher the dynamical complexity in a functional network, the lower level of synchronization between coupling neurons or neuron ensembles. Since the networks are non-stationary (they change in time and space), the level of synchronization of the system elements is variable, that is, weak non-stationary networks provide the liability of creation of new functional networks [11,49]. The pathology of the control process can be connected with the multifractality decrease, the fall of the dynamical complexity of functional networks, an enhancement of the level of their synchronization and an emergence of a dominate pattern or even a dominate frequency, resulting in the failure to response to unpredictable stimuli differently and adequately [11]. As our results show, the dynamical complexity of patterns of involuntary oscillations of the human hand decreases in larger degree for the patients with Parkinson’ disease, than for the patients with the syndrome of the essential tremor.

### Table 1
Comparison of the mean values of wavelet, multifractal and recurrent characteristics and statistical measure of UPOs (averaging over subjects in each group of subjects).

<table>
<thead>
<tr>
<th>Tremor characteristics</th>
<th>Hand</th>
<th>Healthy</th>
<th>Parkinsonian</th>
<th>Statistic ( p_1 )</th>
<th>Essential</th>
<th>Statistic ( p_2 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Maximal amplitude ( (N) )</td>
<td>Left</td>
<td>0.67 ± 0.06</td>
<td>1.35 ± 0.08</td>
<td>0.025</td>
<td>1.99 ± 0.06</td>
<td>0.079</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.54 ± 0.05</td>
<td>1.43 ± 0.09</td>
<td>0.032</td>
<td>1.21 ± 0.07</td>
<td>0.043</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.081 )</td>
<td>( p_1 = 0.041 )</td>
<td></td>
<td>( p_1 = 0.085 )</td>
<td></td>
</tr>
<tr>
<td>Maximal global wavelet energy</td>
<td>Left</td>
<td>0.03 ± 0.003</td>
<td>0.45 ± 0.04</td>
<td>0.011</td>
<td>0.19 ± 0.01</td>
<td>0.022</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.024 ± 0.002</td>
<td>0.31 ± 0.03</td>
<td>0.012</td>
<td>0.27 ± 0.02</td>
<td>0.063</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.087 )</td>
<td>( p_1 = 0.052 )</td>
<td></td>
<td>( p_1 = 0.066 )</td>
<td></td>
</tr>
<tr>
<td>Singularity spectrum width ( \Delta h )</td>
<td>Left</td>
<td>0.83 ± 0.05</td>
<td>0.21 ± 0.02</td>
<td>0.025</td>
<td>0.45 ± 0.04</td>
<td>0.041</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.76 ± 0.09</td>
<td>0.26 ± 0.02</td>
<td>0.012</td>
<td>0.41 ± 0.04</td>
<td>0.047</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.078 )</td>
<td>( p_1 = 0.083 )</td>
<td></td>
<td>( p_1 = 0.094 )</td>
<td></td>
</tr>
<tr>
<td>Singularity spectrum</td>
<td>Left</td>
<td>0.41 ± 0.04</td>
<td>0.07 ± 0.007</td>
<td>0.010</td>
<td>0.23 ± 0.03</td>
<td>0.021</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.35 ± 0.03</td>
<td>0.11 ± 0.01</td>
<td>0.031</td>
<td>0.21 ± 0.02</td>
<td>0.041</td>
</tr>
<tr>
<td>Asymmetry ( \Delta )</td>
<td></td>
<td>( p_1 = 0.091 )</td>
<td>( p_1 = 0.065 )</td>
<td></td>
<td>( p_1 = 0.083 )</td>
<td></td>
</tr>
<tr>
<td>Determinism ( DET )</td>
<td>Left</td>
<td>0.30 ± 0.02</td>
<td>0.88 ± 0.08</td>
<td>0.017</td>
<td>0.52 ± 0.06</td>
<td>0.027</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.27 ± 0.03</td>
<td>0.81 ± 0.08</td>
<td>0.015</td>
<td>0.61 ± 0.06</td>
<td>0.036</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.094 )</td>
<td>( p_1 = 0.089 )</td>
<td></td>
<td>( p_1 = 0.084 )</td>
<td></td>
</tr>
<tr>
<td>Divergence ( DIV )</td>
<td>Left</td>
<td>0.1 ± 0.01</td>
<td>0.003 ± 0.0003</td>
<td>0.003</td>
<td>0.02 ± 0.002</td>
<td>0.009</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.09 ± 0.01</td>
<td>0.001 ± 0.0001</td>
<td>0.011</td>
<td>0.05 ± 0.005</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.093 )</td>
<td>( p_1 = 0.097 )</td>
<td></td>
<td>( p_1 = 0.081 )</td>
<td></td>
</tr>
<tr>
<td>Peaks in histograms</td>
<td>Left</td>
<td>&gt; 10</td>
<td>1–2</td>
<td>2–3</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>&gt; 10</td>
<td>1–2</td>
<td>2–3</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Recurrence time density</td>
<td>Left</td>
<td>0.66 ± 0.07</td>
<td>0.31 ± 0.03</td>
<td>0.043</td>
<td>0.56 ± 0.05</td>
<td>0.044</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>0.77 ± 0.07</td>
<td>0.25 ± 0.03</td>
<td>0.032</td>
<td>0.53 ± 0.05</td>
<td>0.026</td>
</tr>
<tr>
<td>Entropy ( RTDE )</td>
<td></td>
<td>( p_1 = 0.092 )</td>
<td>( p_1 = 0.087 )</td>
<td></td>
<td>( p_1 = 0.090 )</td>
<td></td>
</tr>
<tr>
<td>Measure of period1 ( k (p_1) )</td>
<td>Left</td>
<td>&lt; 1</td>
<td>4.75 ± 0.61</td>
<td>0.005</td>
<td>5.43 ± 0.53</td>
<td>0.032</td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>&lt; 1</td>
<td>3.27 ± 0.31</td>
<td>0.006</td>
<td>4.26 ± 0.41</td>
<td>0.065</td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.031 )</td>
<td>( p_1 = 0.021 )</td>
<td></td>
<td>( p_1 = 0.021 )</td>
<td></td>
</tr>
<tr>
<td>Measure of period3 ( k (p_3) )</td>
<td>Left</td>
<td>&lt; 1</td>
<td>&lt; 1</td>
<td>2.01 ± 0.20</td>
<td>0.008</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>&lt; 1</td>
<td>&lt; 1</td>
<td>2.32 ± 0.21</td>
<td>0.009</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.051 )</td>
<td>( p_1 = 0.051 )</td>
<td></td>
<td>( p_1 = 0.051 )</td>
<td></td>
</tr>
<tr>
<td>Measure of period6 ( k (p_6) )</td>
<td>Left</td>
<td>&lt; 1</td>
<td>&lt; 1</td>
<td>3.47 ± 0.32</td>
<td>0.005</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Right</td>
<td>&lt; 1</td>
<td>&lt; 1</td>
<td>4.03 ± 0.43</td>
<td>0.003</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>( p_1 = 0.052 )</td>
<td>( p_1 = 0.052 )</td>
<td></td>
<td>( p_1 = 0.052 )</td>
<td></td>
</tr>
</tbody>
</table>
5. Conclusion

The work is further evidence in favor of an assumption that the dynamical complexity of time intervals declines with increasing the severity degree of motor disorders. It exhibits in the decrease of the multifractality degree, maintenance of long-range correlations and transitions to strongly periodic dynamics including the emergence of unstable periodic orbits in involuntary oscillations of the human hand.

The successive proofs for decreasing the dynamical complexity with the enhancement of the pathology degree of the human motor system are given for the first time.

The found features give an opportunity to evaluate quantitatively the degree of motor disorder and can help to exclude possible errors in unclear cases of clinical practice.

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References