Modeling of Cognitive Process Using Complexity Theory Methods

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Abstract. The features of modeling of the cognitive component of social and humanitarian systems have been considered. An example of using multiscale, multifractal and network complexity measures has shown that these and other synergetic models and methods allow us to correctly describe the quantitative differences of cognitive systems. The cognitive process is proposed to be regarded as a separate implementation of an individual cognitive trajectory, which can be represented as a time series and to investigate its static and dynamic features by the methods of complexity theory. Prognostic possibilities of the complex systems theory will allow to correct the corresponding pedagogical technologies.

Keywords: cognitive systems, complex systems, complex networks, synergetics, degree of complexity, new pedagogical technologies.

1 Introduction

Recently, it has become clear that pedagogical science operates on the transmission of a kind of structured information that is knowledge. Information, as the main concept of cybernetics, is characterized by a metric function and, thus, the search for optimal management of educational processes is translated into a plane of mathematical modeling [1-3].

In science, starting with R. Descartes, I. Newton and P.-S. Laplace determinism and strict conditional constructions had been predominant for a long time. Initially, these views were developed in science and mathematics, and then moved into the humanitarian field, in particular, in pedagogy. As a result, many attempts have been made to organize education as a perfectly functioning machine. According to the dominant ideas then, for the education of a person the only need was to learn how to manage such a “machine”, that is to turn education into a kind of production and technological process. The emphasis was on standardized training procedures and fixed patterns of learning. Thus appeared the beginning of the technological approach in teaching and, consequently, the predominance of teaching the reproductive activity of students.

For many complex systems, the phenomenon of self-organization is characteristic [4]. It leads to the fact that very often a few variables, the so-called order parameters, are detected very often for the description of an object, which is described by a large or even infinite number of variables [5]. These parameters “subordinate” other variables, defining their values. The researchers are aware of the mechanisms of self-organization, which lead to the allocation of parameters of order, methods of their description as well as the corresponding mathematical models. However, it is likely, our brain has a brilliant ability to find these parameters, to “simplify reality”, finding more effective algorithms for their selection. The process of learning and education allows one to find successful combinations that can be the order parameter in certain situations or the mechanisms of searching for such parameters (“learn to study”, “learn to solve non-standard tasks”).

It is also advisable to use the ideas of a soft (or fuzzy) simulation. All said by V.I. Arnold, in the case of hard and soft models [6], takes place in pedagogical science. Since in humanitarian systems the results of their interaction and development can not be predicted in detail, by analogy with complex quantum systems one can speak the principle of uncertainty for humanitarian systems. In the process of learning unplanned small changes always occur as well as fluctuations in the various pedagogical systems (and the individual, and the team of students, and knowledge systems). Therefore, the basis of modern educational models should lie in the principle of uncertainty in a number of managerial and educational parameters.

Network education refers to a new educational paradigm [7], which is called “networking”. Its distinctive features are learning based on the synthesis of the objective world and virtual reality by activating both the sphere of rational consciousness and the sphere of intuitive, unconscious. The networking of a student and a computer is characterized as an intellectual partnership representing the so-called “distributed intelligence”. Unlike the traditional, network education strategy is focused not on the systematization of knowledge and the assimilation of the next main core of information, but on the development of abilities and motivation to generate their own ideas [8].

Within the framework of recent research in the Davos forum, 10 skills were identified, most demanded by 2022 [9]: (1) Analytical thinking and innovation; (2) Active learning and learning strategies; (3) Creativity, originality and initiative; (4) Technology design and programming; (5) Critical thinking and analysis; (6) Complex problem-solving; (7) Leadership and social influence; (8) Emotional intelligence; (9) Reasoning, problem-solving and ideation; (10) Systems analysis and evaluation. Obviously, the cognitive component in the transformation processes of Industry 4.0 is dominant, which actualizes attention to the study of cognitive processes.

The complexities here are reduced to the fact that cognitive processes are poorly formalized. Therefore, the field of theoretical works until recently was virtually empty. The picture has fundamentally changed with the use of recent synergetic studies. The fact is that the doctrine of the unity of the scientific method asserts: for the study of events in the social-humanitarian systems, the same methods and criteria apply to the study of natural phenomena. Significant success was achieved within the framework of interdisciplinary approaches and the theory of self-organization – synergetics [4, 5].

The process of intellection is a cognitive process characterized by an individual cognitive trajectory whose complexity is an integro-differential characteristic of an individual. The task is to quantify cognitive trajectories and present them in the form of a time series that can be analyzed quantitatively. The theory of complexity introducing various measures of complexity, allows us to classify cognitive trajectories by complexity and choose more complex, as more efficient ones. The analysis procedure can be done dynamically, by correcting the trajectories by means of progressive pedagogical technologies.

Previously, we introduced various quantitative measures of complexity for particular time series, in particular: algorithmic, fractal, chaos-dynamic, recurrent, nonreversible, network, and others [10]. Significant advantage of the introduced measures is their dynamism, that is, the ability to monitor the time of change in the chosen measure and compare with the corresponding dynamics of the output time series. This allowed us to compare the changes in the dynamics of the system, which is described by the time series, with characteristic changes in concrete measures of complexity and draw conclusions about the properties of the cognitive trajectory.

Objects of research are cognitive processes that control neurophysiological and other cognitive characteristics of a person:

- the length of the full step of different age children [11], a healthy young person and the elderly, or those with neurodegeneration (Alzheimer's, Parkinson's, Huntington's, etc. [12]);
- human recalls of words [13];
- objects of cognitive linguistics – the works of various authors, different genres, written in different languages [14];
- discretized multi-genre musical compositions [15].

The corresponding databases in the form of time series are in open access [16].

In this paper, we consider some of the informative measures of complexity and adapt them in order to study the cognitive processes. The paper is structured as follows. Section 2 describes previous studies in these fields. Section 3 presents information mono- and multiscale measures of complexity. Section 4 describes the technique of fractal and multifractal. Network measures of complexity and their effectiveness in the study of cognitive processes are presented in Section 5.

2 Analysis of previous studies

Researchers interested in human cognitive processes have long used computer simulations to try to identify the principles of cognition [17]. Existing theoretical developments in this scientific field describe complex, dynamic, and emergent processes that shape intra- (e.g., cognition, motivation and emotion) and inter- (e.g., teacher-student, student-student, parent-child interactions, collaborative teams) person phenomena at multiple levels. These processes are fundamental characteristics of complex systems but the research methods that are used sometimes do not match the complexity of processes that need to be described.

From the set of methods of the theory of complex systems we consider only those related to information, fractal, and network complexity measures.

Entropic measures in general are relevant for a wide variety of linguistic and computational subfields. In the context of quantitative linguistics, entropic measures are used to understand laws in natural languages, such as the relationship between word frequency, predictability and the length of words, or the trade-off between word structure and sentence structure [18]. Together with Shannon's entropy, more complex versions are used: the Approximate entropy, Sample entropy [19].

In order to demonstrate the scale-invariant properties of cognitive processes, these types of entropy were used in a multiscale version in the study of cognitive processes of cerebral activity [20], human locomotion functions [21], in linguistics [19].

Cognitive processes like most complex systems [22] exhibit fractal properties [23, 24], analysis and the use of results requires careful research.

In recent years, the complex networks methods [25] have become widespread. They not only allow the construction and exploration of networks with obvious (as in linguistics) nodes and links [26], but also those reproduced from the time series by actively developing methods [27, 28].

In our recent works, we have used some of the modern methods of the theory of complex systems for the analysis of such a complex system as cryptocurrency [29, 30]. In this paper, we adapt them to cognitive signals.

3 Information mono- and multiscale measures of complexity

Based on the different nature of the methods laid down in the basis of the formation of the measure of complexity, they pay particular demands to the time series that serve the input. For example, information requires stationarity of input data. At the same time they have different sensitivity to such characteristics as determinism, stochasticity, causality and correlation. In this paper, we do not use classical information measures (for example, the complexity behind Kolmogorov, entropy measures), since complex signals manifest complexity inherent to them on various spatial and temporal scales, that is, they have scale-invariant properties. They, in particular, are manifested through the power laws of distribution.

Obviously, the classic indicators of algorithmic complexity are unacceptable and lead to erroneous conclusions. To overcome such difficulties, multiscale methods are used.

The idea of this group of methods includes two consecutive procedures: 1) coarse graining ("granulation") of the initial time series – the averaging of data on non-intersecting segments, the size of which (the window of averaging) increased by one when switching to the next largest scale; 2) computing at each of the scales a definite (still mono scale) complexity indicator.

The process of “rough splitting” consists in the averaging of series sequences in a series of non-intersecting windows, and the size of which – increases in the transition from scale to scale [31].

Each element of the “granular” time series is in accordance with the expression:

$$y_j^{\tau} = 1/\tau \sum_{i=(j-1)\tau+1}^{j\tau} x_i \ , \quad 1 \le j \le N/\tau, \tag{1}$$

where τ characterizes the scale factor. The length of each “granular” row depends on the size of the window and is even N/τ. For a scale equal to 1, the “granular” series is exactly identical to the original one.

We demonstrate the work of multi-scale measures of complexity on examples of Approximate Entropy and Sample Entropy [19]. Approximate Entropy (*ApEn*) is a “regularity statistic”, which determines the possibility of predicting fluctuations in time series. Intuitively, it means that the presence of repetitive patterns (sequences of a certain length constructed from successive numbers of sequences) fluctuations in the time series leads to a greater predictability of the time series than those in which there are no repetitions of the templates. The comparatively large value of *ApEn* shows the likelihood that similar observation patterns will not follow one another. In other words, a time series containing a large number of repetitive patterns has a relatively small *ApEn*, and the *ApEn* value for a less predictable (more complex) process is greater.

When calculating *ApEn* for a given time series S_N consisting of N values $t(1)$, $t(2)$, $t(3)$, ..., $t(N)$ two parameters are chosen, m and r. The first of these parameters, m, indicates the length of the template, and the second – r – defines the similarity criterion. The sequences of time series elements S_N consisting of m numbers taken starting from the number i are called, and are called vectors $p_m(i)$. The two vectors (patterns), $p_m(i)$ and $p_m(j)$, will be similar if all the difference pairs of their respective coordinates are less than the values of r, that is, if $|t(i+k)–t(j+k)|<r$, $0 \le k \le m$.

For the considered set of all vectors p_m of the length m of the time series S_N, values:

$$C_{im}(r) = \frac{n_{im}(r)}{N-m+1} \tag{2}$$

can be calculated. Where $n_{im}(r)$ – the number of vectors in p_m, similar to the vector $p_m(i)$ (taking into account the chosen similarity criterion r). The value $C_{im}(r)$ is the fraction of vectors of length m, which are similar to the vector of the same length, whose elements begin with the number i. For a given time series, the values $C_{im}(r)$ for each vector in p_m are calculated, after which there is an average value $C_m(r)$ that expresses the prevalence of similar vectors of length m in a row S_N. Directly the *ApEn* for the time series S_N using the vectors of length m and the similarity criterion r is determined by the formula:

$$ApEn(S_N, m, r) = \ln\left(C_m(r)/C_{m+1}(r)\right) \tag{3}$$

that is, as a natural logarithm of the ratio of the repetition of vectors of length m to the repetition of vectors in length m+1+1.

Thus, if there are similar vectors in the time series, *ApEn* will estimate the logarithmic probability that the subsequent intervals after each of the vectors will be different. The smaller *ApEn* values correspond to the greater likelihood that vectors follow similar ones. If the time series is very irregular, the presence of such vectors can not be predictable and the value of *ApEn* is relatively large.

Sample Entropy (*SampEn*) is similar to the *ApEn*, but when calculating the *SampEn*, two conditions are added:

- does not take into account the similarity of the vector to itself;
- when calculating the probabilistic values of *SampEn*, the length of the vectors is not used.

In **Ошибка! Источник ссылки не найден.**a shows the *ApEn* dependence of the scale to the test signals – flicker (1/*f*) white noise (wnoise) and electrocardiogram (ECG) signal compared to the shuffled signal (ECG shuffled).

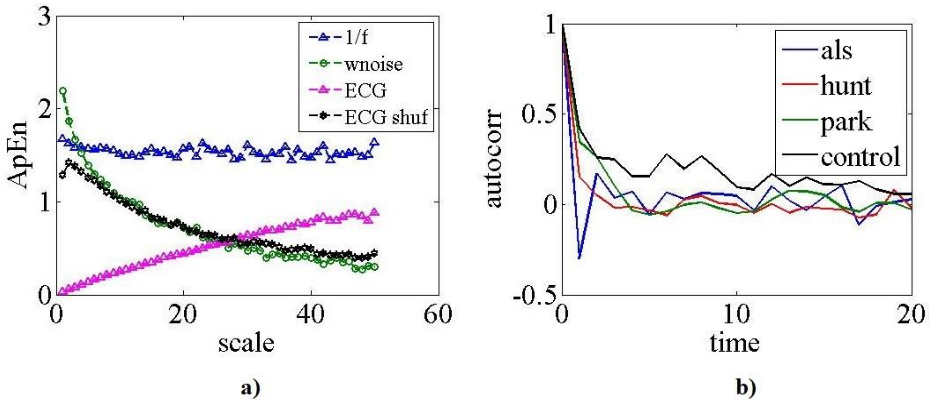

Fig. 1. (a) *ApEn* of artificial and natural signals, depending on the scale; (b) autocorrelation functions for control the stride intervals fluctuations and Alzheimer's disease (als), Huntington's (hunt) and Parkinson's (park)

From Fig. 1a it is evident that, as expected, a flicker signal was a scale-invariant one. The ECG signal is complex on a large scale. Its complexity is lost when shuffled and becomes very close to a random signal.

Cognitive signals differ in the functions of autocorrelation: the more complex ones have a longer "memory", which is manifested in the slowdown of the function of autocorrelation with the lag (Fig. 1b).

Accordingly, the signal of a healthy person and a multiscale entropy measure is more complicated (Fig. 2a). We also investigated multiscale complexity measures for time series of stride intervals in children from 40 to 163 months (Fig. 2b).

Obviously, the complexity of the signal for an older child is increasing.

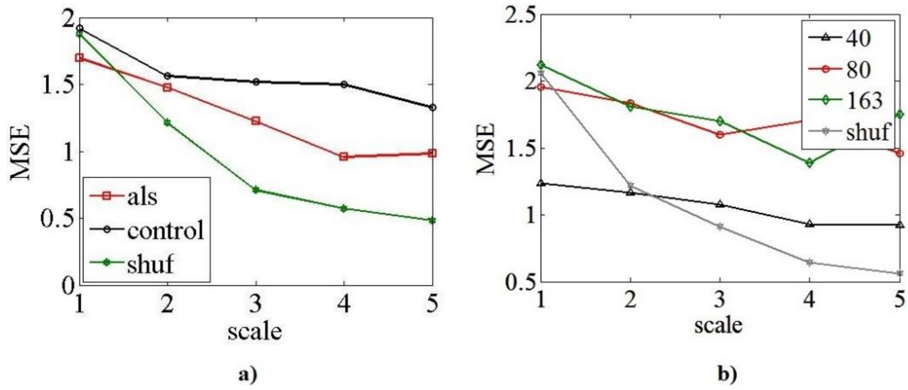

Fig. 2. Multiscale entropy of stride intervals time series templates for healthy and Alzheimer's disease (a) and children of all ages (b)

The next study cognitive signal is the time series of time intervals between human-to-word responses (human recalls of words). Recall in memory refers to the mental process of retrieval of information from the past and is a way to study the memory processes of humans and animals [13]. Recall describes the process in which a person is given a list of items to remember and then is tested by being asked to recall. For the autocorrelation function and the multiscale *SampEn* we obtain the results presented in Fig. 3.

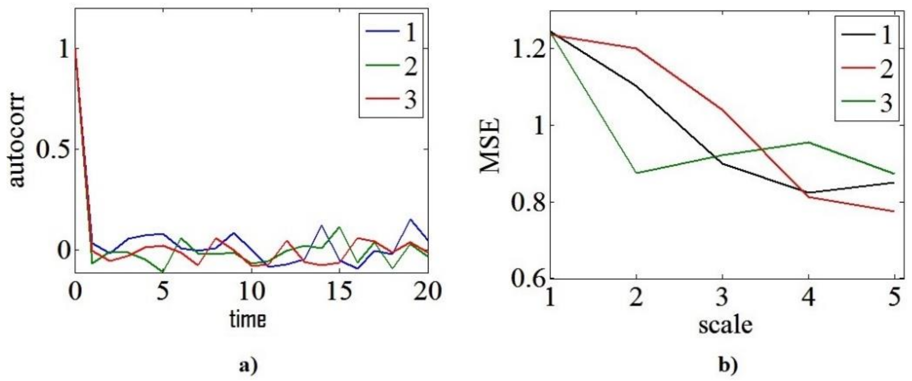

Fig. 3. Autocorrelation functions (a) and MSE measures of complexity (b) signals 1-3 series of recalls

Unfortunately, due to insufficient statistics and short-term time series, identification of differences in these methods is not possible.

Similar studies for musical works of various genres (aria, blues, brazilian samba) and literary works by famous authors (L. Tolstoy's "War and Peace", L. Carroll "Alice in Wonderland", C. Dickens "Cricket on the Hearth") gave the results shown in Fig. 4.

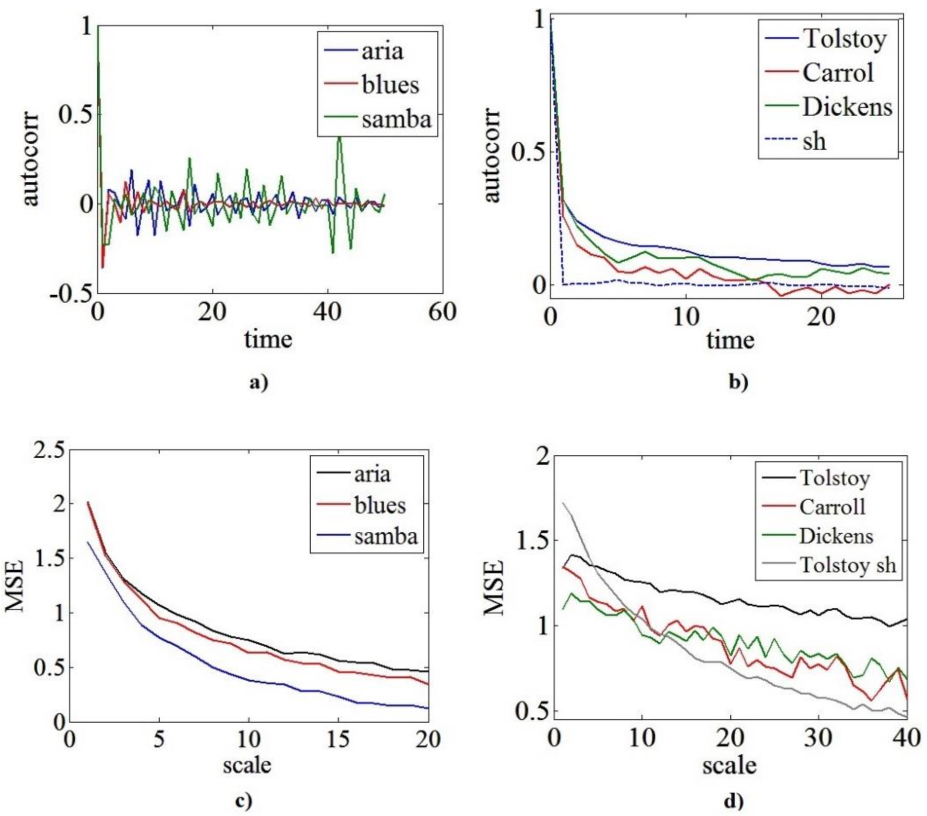

Fig. 4. Autocorrelation of musical (a) and literary (b) works; (c) and (d) are the corresponding multiscale entropy measures of complexity

Obviously, MSE allows classification of the analyzed cognitive signals in terms of complexity.

4 Multifractal measures of complexity

In the general case, the procedure of popular Multifractal Detrended Fluctuation Analysis (MF-DFA) is implemented by the following algorithm. Let be a sequence of length N. Then determine the accumulation $Y(i) \equiv \sum_{k-1}^{i}(x_k - \bar{x}),\ i = \overline{1..N}$. We divide it into N_s=int(N/s) segments of the same length S that do not overlap. For each of the N_s sequences, we calculate the local trend by the least squares method, determine the deviations $F^2(v,s) = 1/s\sum_{k-1}^{s}(Y((v-1)s+i) - y_v(i)))^2$ for each segment v, $v = \overline{1..N}$ and for each $v = \overline{N_s + 1..2N_s}$. There $y_v(i)$ is an interpolating polynomial on the segment v. Find the mean for all subsequences to obtain the function of q-order fluctuations $F_q(s) = \left(\frac{1}{2N} \sum_{\nu=1}^{2N_s} \left(F^2(s,\nu) \right)^{q/2} \right)^{1/q}$. The standard DFA method corresponds to the case q=2. Determine the scaling behavior of the fluctuation function by analyzing the double logarithmic scale of the dependence $F_q(s)$ on q. If the sequence x_i has long-term correlations, $F_q(s)$ increases with increasing s according to the power law $F_q(s) \cong s^{h(q)}$. For stationary time series, $h(2)$ identical to the Hurst exponent. Thus, the function $h(q)$ can be called the generalized Hurst exponent.

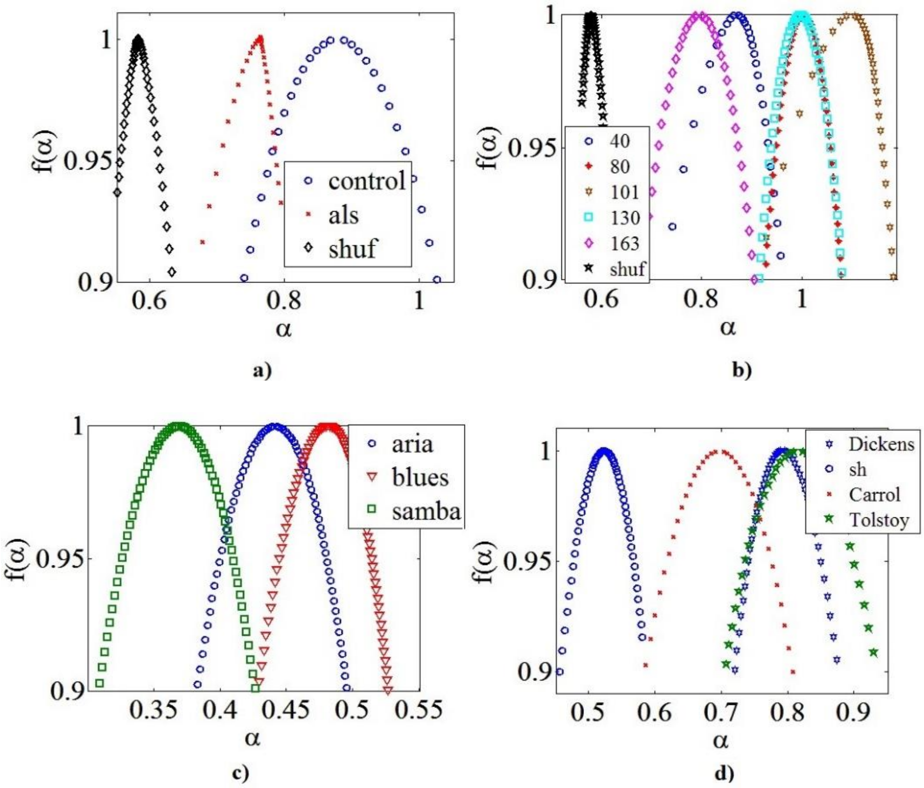

Fig. 5. Spectra of multifractality (a) reaching the stage of healthy and sick patients; (b) children of all ages; (c) musical works of different genres; (d) literary works

Together with the generalized Hurst exponent, a spectrum of generalized fractal dimensions D_q is introduced that characterize the distribution of points in a given domain and is determined by the relation D_q=$\tau(q)/(q–1)$, where the function $\tau(q)$ has the form $\tau(q) = \lim_{s\to 0} [\ln z(q,s) / \ln s]$, and $Z(q, s)$ is a generalized statistical sum which is characterized by an index of degree q.

To characterize the multifractal set, the so-called multifractal spectrum function $f(\alpha)$ (the spectrum of singularities of a multifractal) is used, which is actually equal to the Hausdorff dimension of a homogeneous fractal subset of the initial set, giving a dominant contribution to the statistical sum for a given q value. The connection between the values $f(\alpha)$ and $\tau(q)$ is determined by the relationship $\tau(q)=q\alpha-f(\alpha)$.

The extremum of the function $f(\alpha)$ determines some average value of the Hurst exponent, and the value $\Delta\alpha=\alpha_{max}-\alpha_{min}$ – the width of the spectrum of the multifractality – characterizes the degree of complexity of the system.

In Fig. 5 shows the spectra of multifractality of some of the cognitive systems described above.

We see that more complex signals have wider spectra of multifractality. Consequently, the multifractal measure of complexity can be used to analyze cognitive signals. We have implemented a dynamic procedure for calculating multifractal parameters, which allows you to follow the change in the complexity of the signal in time.

5 Complex network methods for studying cognitive processes

One of the most important areas of cognitive science is cognitive linguistics. Cognitive linguistics is a trend in linguistics that studies and describes the language in terms of cognitive mechanisms that underlie human mental activity. Thus, cognitology is, so to speak, a computer that characterizes a person by analyzing his psyche, mental activity, and on the first place among the tasks put forward research language that is inextricably linked with human.

The significance of language for cognition is extremely great, because it is through language that one can objectivize the mental activity, that is, verbalize it. On the other hand, learning a language is an indirect way of studying cognition, because cognitive and language structures are in certain proportions. One of the tools of the study of cognitive linguistics is the theory of complex networks. The nodes in such networks are elements of these complex systems, and the links between nodes – the interaction between the elements.

In the last decade, the structural properties of language, the texts of literary works and texts related to religious consciousness, as well as the organization of musical works and painting began to be studied and analyzed from the point of view of the application of methods of the complex networks theory. Relevant networks form a special, little-known category, which is called cognitive networks [25].

The term "cognitive networks" was proposed in studies on the research of the network structure of the natural language. Of particular interest is the study of cognitive networks for understanding the principles of brain function. To date, research using the theory of complex networks in the study of the brain contributed to a deeper understanding of the general patterns of interconnection of different levels of its structural organization, and the involvement in these studies of the concept of cognitive networks will take into account some of the features of the human creative functions.

Let us consider the peculiarities of the application of the theory of complex systems in the problems of cognitive linguistics. The first step in applying the theory of complex networks to the analysis of the text is the presentation of this text as a set of nodes and links, the construction of a language network. There are different ways of interpreting nodes and connections, which leads, accordingly, to different representations of the network of languages. Along with the sequential, "linear" analysis of texts, the construction of networks, whose nodes are their elements - words or phrases, fragments of natural language, can reveal structural elements of the text, without which he loses his connectivity. In this case, the task of determining which of the important structural elements are also important information, such as determining the information structure of the text, is relevant. Such elements can also be used to identify still poorly defined components of the text, such as collocation, paraphrase unity, for example, when searching for similar snippets in different texts.

We know several approaches to constructing networks of texts, so-called word networks, and different ways of interpreting nodes and relationships, which leads, accordingly, to different types of representation of such networks. The nodes can be connected to each other, if the corresponding words are next to the text, belong to the same sentence or paragraph, connected syntactically or semantically. Preserving syntactic relationships between words leads to the image of a text in the form of a directed network, where the direction of link corresponds to the subordination of the word.

Thus, if from a certain text (or another linguistic unit) a complex cognitive network (for example, a semantic graph) is created by a certain algorithm, then it is expedient to use the topological and spectral measures [10] of such complex cognitive networks and even trace their dynamics within the framework of the algorithm of the moving window [29, 30].

We will conduct a preliminary study of the frequency distribution of words in some well-known English-language literary works. The software developed by us analyzes the text of the work, creates a dictionary, each word of which has a unique code, in the process of analysis, the number of each of the words of the work is calculated, and also exports a text file of word codes that can be subjected to further analysis (frequency analysis, graph construction, its analysis).

Detailed results of the analysis of the spectral and topological properties of cognitive networks will be presented in a separate paper. At the same time, we will show only the fact that the constructed cognitive warnings convey the individual properties of complex networks in general.

In Fig. 6 on the logarithmic scale, the frequencies of words in the works are given. The linear trend corresponds to the distribution of α from the Zipf law [26]: $P(k){\sim}ck^{-\alpha}$.

It is known that in order to comply with the Zipf law, the index should be approximately equal to units. Execution on this linguistic unit (text) of a rank distribution of the type of the Zipf law may be a sign of "correctness" (a good organization) of this text taken as a whole. In this case, Twain's novel is better organized, although this usually requires a wider and more profound analysis.

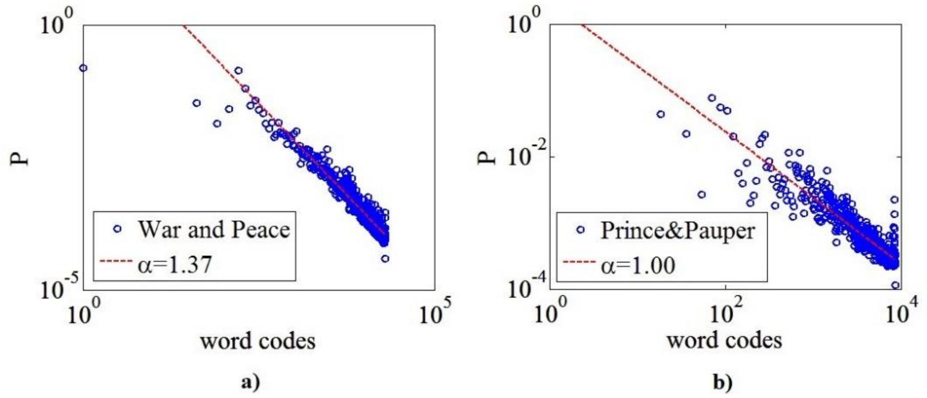

Fig. 6. The distribution of the frequency of words in the in novels of L. Tolstoy's "War and Peace", α=1.37 and of Mark Twain "The Prince and the Pauper" by, α=1.00

6 Conclusions

Thus, the modeling of social and humanitarian systems, the core of which is a cognitive component, can be carried out within the framework of a synergetic paradigm, the modern point of which is the theory of complex networks. The considered separate methods of the theory of complex systems demonstrate the possibility of quantitative analysis of cognitive functions. In particular, the results obtained in this paper suggest that informational (mono and multiscale), fractal and multifractal, as well as network measures of complexity can be used to quantify cognitive processes. This allows us to classify normal and anomalous phenomena, to offer a method for analyzing the cognitive trajectory over time, to model possible methods for its correction, taking into account external conditions.

In addition to the fundamental scientific significance – the understanding of the work of the human brain – work in this direction aims to overcome the general crisis of the educational system, the essence of which is the inadequacy of the goals, content, forms and methods of education new conditions.

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