
DOI: <https://doi.org/10.15407/kvt199.01.019>

UDC 004.942+519.2+519.7+616.8

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THE USE OF COMPLEXITY AND VARIABILITY CHARACTERISTICS FOR THE ANALYSIS OF COMPLEX DYNAMIC SYSTEMS

Introduction. *The normal dynamics of a healthy organism is chaotic and the observed "chaos" is inherent in the very nature of the dynamic processes taking place in the organism and the degree of chaotic of these processes may vary in case of pathology in one direction or another. The electrical activity of the brain is also characterized by signs of deterministic chaos, and changes in parameters of its nonlinear dynamics testify to the characteristic changes in brain functioning. The problem of diagnostics and identification of the moment preceding an epileptic seizure or other periods of brain functioning in epileptic patients is not only a problem of choosing a classification method but also of determining quantitative estimates of dynamics reflecting the complexity and variability of the Electroencephalography (EEG) signal.*

The purpose of the paper is to form an effective ensemble of features from the characteristics reflecting the complexity and variability of the EEG signal, to construct the prognostic models for the course of epilepsy and to develop the information technology to support diagnostic decision-making based on them.

Methods. *The methods of mathematical statistics for the processing of diagnostic information, the methods of mathematical modeling (stepwise logistic regression) — for the construction of prognostic models for estimating the course of epilepsy were used; methodological bases for the creation of information technology for the diagnosis of epilepsy according to the EEG.*

Results. *Changes in indicators such as Hurst Index, fractal dimension, logistic mapping, and algorithmic signal complexity have been investigated. The mathematical models*

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ISSN 2663-2586 (Online), ISSN 2663-2578 (Print). *Cyb. and comp. eng.* 2020. № 1 (199)

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include variables that are calculated from the EEG data and are available during patient observation. As a result of the application of step-by-step algorithms, the most informative features are included in the models. The selected features allow for the most accurate identification of individual periods of epilepsy flow from the EEG data. It has been established that the use of a decision support system increases the reliability of determining the periods of an epileptic seizure (conditional norm, before, during and after an attack) by an average of 6.6% for children and 8% for adults.

Conclusions. The proposed prognostic models allow to obtain additional information about the periods of epileptic seizures and to predict their onset in time.

Keywords: information technology, EEG, epileptic seizures, epilepsy, complexity and variability indicators, predictive models, logistic regression.

INTRODUCTION

The objects, the analysis of which is offered in the work, belong to the class of dynamic systems, classifying states of which is one of the most difficult task. It is impossible to apply directly the classical methods of object analysis, set by one multidimensional observation, to solve the problems of this class. The reason for the discrepancy of the developed methods is that the state of such systems can be described only by the type and character of the movement, and it can be both chaotic movement and steadfast trajectory. Consequently, the various types of integral characteristics of the system movement according to a class of dynamic systems were developed and they have become an instrumental bridge to the application of classical methods of classification of objects. Below it is suggested to consider the use of indicators of complexity and variability of the system motion to assess changes in functional states in patients with a focal form of epilepsy.

The prevalence of epilepsy in developed countries is 5–10 cases per 1000 population. According to the results of population studies conducted in developed countries, the incidence of epilepsy ranges from 0.28 to 0.53 cases per 1000 population. In Europe about 6 million people suffer from epilepsy, 40 % of them are not receiving proper treatment [1, 2]. In the diagnosis and treatment of epilepsy, photo stimulating and hyperventilation tests are used, which are performed under EEG control. They allow estimating readiness for epileptic seizures and reaction to treatment, i.e. efficiency of medication therapy. In this case, the doctor's knowledge of the functional state of the cortex for situational decision-making is essential for the effectiveness of the treatment process. Therefore, the development of mathematical means of recognition of brain functioning features before, during and after an epileptic seizure, as well as in the periods between seizures, is an actual task.

PROBLEM STATEMENT

It was found that the normal dynamics of a healthy organism is chaotic and the observed "chaos" is inherent in the very nature of the dynamic processes taking place in the organism [3–5], and the degree of chaotic of these processes may vary in case of pathology in one direction or another [6]. It has been proved that besides periodic processes, the electrical activity of the brain is also characterized by signs of deterministic chaos, and changes in parameters of its nonlinear dynamics testify to characteristic changes in brain functioning [7, 8].

Such apparent changes can also be observed in epileptic signals of electroencephalograms. The nature of epilepsy is such that corresponding pathological

changes in the brain cause certain differences in the signs of chaotic dynamics (i.e. "degree of chaoticity") of the signal. There are a number of works devoted to the analysis of chaotic dynamics, which use such indicators of complexity as Hurst index, logistic mapping, fractal dimensionality and algorithmic complexity of the signal. A number of studies of dynamic systems of the healthy human brain based on EEG methods of nonlinear analysis have been conducted [5, 9]. In the opinion of the authors of the work, the increase in complex dimensionality of the EEG superficial in the performance of tasks related to memory operation is shown and reflects the increase in degrees of freedom in competitive interactions between neural ensembles [7, 10]. However, to solve the problem of identification of periods of brain bioelectrical activity in epileptic seizures, it is necessary to investigate the suitability of the developed indicators for solving problems of the corresponding classification. Therefore, the problem of diagnostics and identification of the moment preceding an epileptic seizure or other periods of brain functioning in epileptic patients is not only a problem of choosing a classification method but also of determining quantitative estimates of dynamics reflecting the complexity and variability of the EEG signal.

The purpose of the article is to form an effective ensemble of features from the characteristics reflecting the complexity and variability of the EEG signal, to construct the prognostic models for the course of epilepsy and to develop the information technology to support diagnostic decision-making based on them.

THE FUNCTIONAL STATES CLASSIFICATION METHODS OF THE CEREBRAL CORTEX-EPILEPTIC AND BETWEEN EPILEPTIC PERIODS

The data of recorded signals are structured in such a way that for each patient the data structures characterizing the following functional cortical states are allocated [11, 12, 13, 14]:

- between seizures or periods of the conditional norm (interictal) — periods between the seizures in which there are no manifestations of the pathological activity;
- before the seizure (preictal) — periods characterized by the appearance of noticeable deviations from the normal state;
- seizure (ictal) — existing characteristic manifestations of the pathological activity of the brain.
- after the seizure (postictal) — attenuation of the pathological activity.

Based on existing nonlinear analysis methods studies of epileptic EEG signals in order to assess the suitability for classifying these periods, the following parameters of chaotic dynamics were selected: Hurst index, fractal dimension, Kolmogorov algorithmic complexity, logistic mapping and LZW archiving.

The Hurst Index is a measure of the smoothness of the fractal time series, based on the evaluation of the expression of its long-term dependence [15]. Due to its clear range boundaries, the Hurst Index is widely used in the analysis of time series of complex systems. It contains minimum assumptions about the system under study and allows us to determine the classification of time series depending on the nature of the signal [16, 17]. Studies [18] have shown that periods between seizures (conditional norm) correspond to smaller values of the Hurst index than for the seizure period. Values for the period after an seizure are close to 0.5. The pre-seizure and postseizure periods vary greatly, but a notice-

able difference can be seen. The pre-seizure and postseizure periods are characterized by lower values, which indicate antipersetic properties.

Fractal dimensional (FD) is a natural tool for detecting the level of complexity and compactness of chaotic processes. It can be used to measure the complexity of biological signals. The analysis of the fractal dimensionality of the Minkovsky EEG signal calculated by the Box Counting method shows that epileptic seizures are a state with a lower fractal dimensionality of the EEG signal compared to a conventionally normal state [6, 13]. Intermediate values of fractal dimensionality are characteristic for the periods between seizures (conventional norm) because this period is more complex. In the period before the seizure and during the seizure, an increase in fractal dimensionality is observed, which indicates a decrease in the signal complexity.

The Lempel Ziv archiving method (LZ or CrossTable) is an algorithm for lossless data compression, and is a convenient estimation of complexity, characterizing the degree of order or disordered space-time patterns [19]. The parameter LZ-complexity as a measure of regularity and complexity of time series is included in nonlinear parameters of estimation, and it is expedient to use it for the analysis of the non-stationary biomedical signals of small length.

The Lempel-Ziv-Welch (LZW) data compression method [20] is based on calculating the number of letter pair repetitions in an encoded sequence and replacing the most common pairs with a new value. The method can be used to determine the level of complexity of a sequence and is analyzed. When working with EEG signals, the efficiency of the method is higher, the more pronounced is the epileptic seizure. The results of the study of patients with focal epilepsy showed high values of complexity during the period of the conditional norm, progressively less before and during the seizure, and increased (even in comparison with the conditional norm) after the seizure.

One of the possible ways to determine the nature of the trajectories of nonlinear systems after signal sampling can be realized by means of logistic (square) map. Below is the map (1), for which the character of trajectory changes from the value of r :

$$x_{n+1} = rx_n(1 - x_n), \quad (1)$$

where n is a discrete-time step, r is a control parameter. According to the graph of dependence of x_n on r , it is possible to track changes in the state of such a system, including the transition from chaotic motion to stable trajectories. [21]. After substitution a number of neighboring points x_n, x_{n+1} of the EEG trajectories in (1) and determination of the value (moving average) of the r parameter, it is possible to obtain an estimate of the trajectory character by the logistic map.

According to the obtained values, the postseizure period coefficients are in the range of $2 < r < 3$ and indicate that the signal is going to a stationary value $(r - 1) / r$, but will first oscillate around it. The pre seizure and postseizure periods are characterized by values in the range of $3 < r < 1 + \sqrt{6}$ which indicates that the system is moving chaotically.

The development of the classifiers models of brain activity periods with EEG can provide three possible strategies for comparing periods with each other [22]:

The strategy "one to three" or "one against all": the comparison of one period with respect to three other periods (Fig. 1). Scope: standard procedure for determining membership class.

1. The strategy "one to one": a pairwise comparison of periods with each other. Scope: solving the conflict of the classifiers, that can be obtained according to item 1.

2. Strategy "two to two": a comparison of any two periods combination with any two others; Scope: indirect definition of the class by the classifiers for "groups" of classes, when the allocated class is surrounded by other classes.

Further, we will focus on the strategy "one against all" only.

The selection of informative channels was also carried out. There is the own set of informative channels for each brain area in focal epilepsy [23–25]:

- the set for frontal area consists from Fp1, Fp2, F3, F4, F7 and F8;
- the set for frontal parietal area consists from Fp1, Fp2, F3, F4, F7, F8, P3 and P4;
- the set for the parietal area consists from P3 and P4;
- the set for the central area consists from C3 and C4;
- the set for the central area consists from C3 and C4;
- the set for the parietal-occipital area consists from P3, P4, O1 and O2;
- the set for temporoparietal central area consists from T3, T4, C3, C4, T5, T6, P3 and P4.

To obtain the classifiers, a standard procedure was used to select the best linear combination of activity periods features and a complicated procedure using functional transformations of primary features. For this purpose, the inverted indicators ($1/x_i$) and variables of the type $(x_i \cdot x_j)$ and (x_i/x_j) were included in the models as the applicants besides the initial features. Further, we will call them generalized variables.

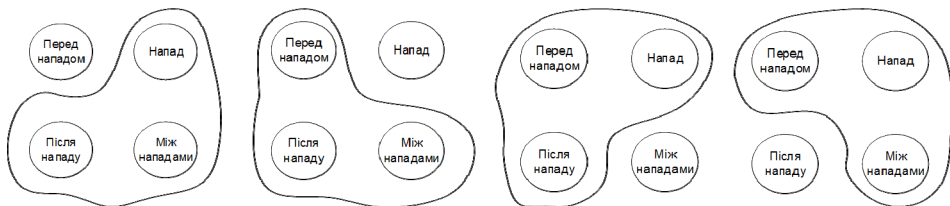


Fig. 1. Possible combinations of strategies "one against all" comparing the periods of epileptic seizures among themselves

Multivariate statistical methods were used to solve the following problems. The primary selection of features was carried out on a degree of statistical connection between the bioelectric indicators calculated by the methods of nonlinear dynamics and the indicators of patients' states. Next, the classifiers were found on the basis of statistical methods of modeling, and periods of an epileptic seizure were distinguished with high accuracy.

Methods of regression and discriminant analysis, logistic regression method were used to construct the classifiers. The best results were obtained by step algorithm of the logistic regression method, classifier models were built as a logistic regression model:

$$p(y) = \frac{1}{1 + e^{-y}}, \quad (2)$$

where $y = y(x)$ was obtained in linear (3) or non-linear (4) form:

$$y = b_0 + \sum_{k=1}^m b_k x_{i_k} \quad (3)$$

$$y = b_0 + \sum_{k=1}^m b_k \varphi_{i_k}(\mathbf{x}), \quad (4)$$

where $x_i, i = 1, \dots, M$ are the primary features, $x_{i_k}, k = 1, \dots, m$ is the best linear ensemble of features, $\varphi_{i_k}(\mathbf{x}), k = 1, \dots, m$ is the best nonlinear ensemble of generalized variables, $b_0, b_k, k = 1, \dots, m$ is the regression coefficients.

DEVELOPMENT AND APPLICATION OF MODELS TO CLASSIFY PERIODS OF BRAIN ACTIVITY STATUS

Classification models for each pathological zone of the brain are given below in the form of linear (3) and nonlinear equations (4). The contenders for inclusion in the predictive models are the selected complexity indicators (Hurst index, fractal dimensionality, logistic mapping, Kolmogorov algorithmic complexity, LZW method archiving) and variability indicator (standard deviation). Informative channels of electroencephalograms in a certain pathological region of the brain in prognostic models are indicated by the indices of the corresponding indicator.

EEG studies were conducted at the Department of Functional Diagnostics and Ultrasound of the Cardiovascular System of the Consulting and Diagnostic Center of the State Institution of Science «Research and Practical Center of Preventive and Clinical Medicine» State Administrative Department. Two age groups of volunteers — children (under 18 years) and adults (over 18 years) — were formed from the Center's patients. All the participants gave their written consent to the anonymous use of the data and research based on it. Fifteen people with focal epilepsy were investigated. A diagnostic study and advisory opinion on the International Classification of Diseases (ICD-10) resulted in the diagnosis of G40 epilepsy (11, 12, 26). The models used the following designations of brain regions for focal epilepsy: frontal (F), frontal-parietal (FP), parieto-occipital (PO), parietal (P), central (C), temporal-parietal (PTC).

Models for groups of children and adults were developed separately.

Prognostic models to study focal epilepsy [22] in the frontal area (F) of the brain for children using linear functions were obtained in the form:

$$\begin{aligned}
 y_{(F) \text{ preictal}} &= 0,018 \cdot \sigma_{F7} + 0,058 \cdot \sigma_{F8} + 71,151 \cdot LZW_{Fp1} - 109,845 \cdot LZW_{F8} - \\
 &\quad - 40,937 \cdot FD_{F3} + 52,680; \\
 y_{(F) \text{ ictal}} &= 32,275 \cdot LZW_{F7} - 12,908 \cdot CrossTab_{F4} - 27,527 \cdot FD_{F3} + \\
 &\quad + 21,577 \cdot FD_{F7} - 0,715 \cdot LogRefl_{F7} + 5,563; \\
 y_{\text{postictal}} &= 15,819 \cdot Hurst_{F4} + 20,547 \cdot FD_{F3} - 25,528; \\
 y_{(F) \text{ interictal}} &= -15,986 \cdot Hurst_{F4} + 15,210 \cdot LZW_{F8} + 3,773,
 \end{aligned}$$

where σ_{F7} and σ_{F8} are standard deviations of channel signals F7 and F8 respectively, LZW_{Fp1} and LZW_{F8} — the method LZW archiving of channel signals Fp1 and F8 respectively, FD_{F3} and FD_{F7} is the fractal dimension of channel signals F3 and F7 respectively, $CrossTab_{F4}$ is the Kolmogorov algorithmic complexity of channel signals F4, $LogRefl_{F7}$ — logistic map of channel signals F7, $Hurst_{F4}$ — Hurst index of channel signals F4;

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(F) \text{ preictal}} &= 19867,414 \cdot FD_{F8} + 116,577 \cdot \sigma_{F8} \cdot LZW_{Fp1} - 62190,942 \cdot LZW_{F8} \cdot FD_{F7} - \\
 &\quad - 3116,873 \cdot \frac{\sigma_{F8}}{\sigma_{F7}} + 9792,292 \cdot \frac{LZW_{Fp1}}{Hurst_{F4}} - 1802,285 \cdot \frac{FD_{F3}}{Hurst_{F4}} - 18475,975 \cdot \frac{FD_{F3}}{FD_{F7}} + 15963,319; \\
 y_{(F) \text{ ictal}} &= 0,106 \cdot \sigma_{Fp1} - 0,121 \cdot \sigma_{F4} - 85,626 \cdot FD_{F8} - 16,224 \cdot \frac{FD_{F3}}{LZW_{F8}} + 2098,599 \cdot \frac{FD_{F7}}{\sigma_{F7}} + \\
 &\quad + 54,981 \cdot \frac{FD_{F7}}{LogRefl_{F7}} + 103,510; \\
 y_{(F) \text{ postictal}} &= -0,014 \cdot \sigma_{Fp1} + 28,714 \cdot FD_{F8} + 15,856 \cdot \frac{1}{Hurst_{F4}} + 169,545 \cdot Hurst_{F4} \cdot FD_{F3} - \\
 &\quad - 16,884 \cdot \frac{LZW_{Fp1}}{LZW_{F8}} + 32,035 \cdot \frac{LogRefl_{F7}}{\sigma_{F8}} + 0,468 \cdot \frac{LogRefl_{F7}}{LZW_{F3}} - 124,749; \\
 y_{(F) \text{ interictal}} &= -723,256 \cdot CrossTable_{Fp1} + 13885,269 \cdot \frac{1}{\sigma_{F7}} - 65504,719 \cdot \frac{Hurst_{F4}}{\sigma_{F7}} - \\
 &\quad - 497,085 \cdot \frac{LZW_{F3}}{LZW_{Fp1}} + 1071,683,
 \end{aligned}$$

where, σ_{Fp1} , σ_{F4} , σ_{F7} and σ_{F8} — are standard deviations of channel signals Fp1, F4, F7 and F8 respectively, LZW_{Fp1} , LZW_{F3} and LZW_{F8} — the method LZW archiving of channel signals Fp1, F3 and F8 respectively, FD_{F3} , FD_{F7} and FD_{F8} — is the fractal dimension of channel signals F3, F7 and F8 respectively, $CrossTable_{Fp1}$ is the Kolmogorov algorithmic complexity of channel signals Fp1, $LogRefl_{F7}$ logistic map of channel signals F7, $Hurst_{F4}$ — Hurst index of channel signals F4.

The prognostic models to study focal epilepsy in the frontal- parietal (FP) region of the brain for children using the linear functions are obtained in the form:

$$\begin{aligned}
 y_{(FP)preictal} &= -53,773 \cdot LZW_{F3} + 34,476 \cdot LZW_{P4} + 7,626; \\
 y_{(FP)ictal} &= -0,05 \cdot \sigma_{F8} - 0,018 \cdot \sigma_{P4} - 45,589 \cdot Hurst_{F7} + 88,175 \cdot LZW_{F3} - \\
 &\quad -142,462 \cdot LZW_{F4} + 40,366 \cdot FD_{F7} - 3,998; \\
 y_{(FP)postictal} &= 17,682 \cdot FD_{F8} - 17,350; \\
 y_{(FP)interictal} &= -25,651 \cdot Hurst_{F8} + 10,644,
 \end{aligned}$$

where σ_{F8} and σ_{P4} — standard deviations of channel signals F8 and P4 respectively, LZW_{F3} , LZW_{F4} and LZW_{P4} — the method LZW archiving of channel signals F3, F4 and P4 respectively, FD_{F7} and FD_{F8} is the fractal dimension of channel signals F7 and F8 respectively, $Hurst_{F7}$ and $Hurst_{F8}$ — Hurst index of channel signals F7 and F8 respectively.

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(FP)preictal} &= 39,411 \cdot LZW_{P4} - 57,386 \cdot LZW_{F3} \cdot FD_{F7} - 0,603 \cdot FD_{F8} \cdot LogRefl_{F7} + 10,530; \\
 y_{(FP)ictal} &= 41,336 \cdot \frac{1}{FD_{F7}} - 0,306 \cdot \sigma_{P4} \cdot Hurst_{F7} + 0,257 \cdot \frac{\sigma_{F4}}{LogRefl_{F7}} - \\
 &\quad -4,359 \cdot \frac{\sigma_{F8}}{\sigma_{F4}} - 2159,452 \cdot \frac{LZW_{F4}}{\sigma_{F8}} + 90,158 \cdot \frac{FD_{F7}}{FD_{F4}} - 100,411; \\
 y_{(FP)postictal} &= 14,164 \cdot FD_{F4} \cdot FD_{F8} - 14,216; \\
 y_{(FP)interictal} &= 9,866 \cdot LogRefl_{F8} - 230,279 \cdot \frac{Hurst_{F8}}{FD_{F7}} - 13,741 \cdot \frac{FD_{F4}}{Hurst_{F7}} + 95,697,
 \end{aligned}$$

where, σ_{F4} , σ_{F8} and σ_{P4} are standard deviations of channel signals F4, F8 and P4 respectively, LZW_{F3} , LZW_{F4} and LZW_{P4} the method LZW archiving of channel signals F3, F8 and P4 respectively, FD_{F4} and FD_{F7} is the fractal dimension of channel signals F4 and F7 respectively, $LogRefl_{F7}$ and $LogRefl_{F8}$ logistic map of channel signals F7 and F8 respectively, $Hurst_{F7}$ and $Hurst_{F8}$ — Hurst index of channel signals F7 and F8 respectively.

The prognostic models to study focal epilepsy in the frontal-parietal (FP) region of the brain for adults using the linear functions are obtained in the form:

$$\begin{aligned}
 y_{(FP)ictal} &= -0,014 \cdot \sigma_{F4} + 2,296; \\
 y_{(FP)postictal} &= 2568,138 \cdot Hurst_{P3} - 28,909 \cdot LogRefl_{F7} - 594,780; \\
 y_{(FP)interictal} &= -56,141 \cdot Hurst_{P4} + 23,304,
 \end{aligned}$$

where σ_{F4} is standard deviations of channel signal F4, $LogRefl_{F7}$ — the method LZW archiving of channel signal F7, $Hurst_{P3}$ and $Hurst_{P4}$ — Hurst index of channel signals P3 and P4 respectively.

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(FP)preictal} &= 29778,394 \cdot \frac{Hurst_{F7}}{\sigma_{F4}} - 10611,242 \cdot \frac{FD_{F8}}{\sigma_{F4}} + 43,472; \\
 y_{(FP)ictal} &= -0,016 \cdot \sigma_{F4} \cdot FD_{F7} + 2,463; \\
 y_{(FP)postictal} &= -287,725 \cdot \frac{1}{Hurst_{P3}} - 0,053 \cdot \sigma_{P4} \cdot LogRefl_{F7} + 1014,848; \\
 y_{(FP)interictal} &= -8290,740 \cdot Hurst_{F7} \cdot Hurst_{P4} + 1311,756,
 \end{aligned}$$

where σ_{F4} and σ_{P4} are standard deviations of channel signals F4 and P4 respectively, FD_{F7} and FD_{F8} is the fractal dimension of channel signals F7 and F8 respectively, $LogRefl_{F7}$ — logistic map of channel signal F7, $Hurst_{F7}$, $Hurst_{P3}$ and $Hurst_{P4}$ — Hurst index of channel signals F7, P3 and P4 respectively.

The prognostic models to study focal epilepsy in the parietal (P) region of the brain for children using the linear functions are obtained in the form:

$$\begin{aligned}
 y_{(P)preictal} &= -24,651 \cdot LZW_{P3} + 10,655 \cdot CrossTable_{P3} + 3,545; \\
 y_{(P)ictal} &= -0,002 \cdot \sigma_{P3} + 24,725 \cdot LZW_{P4} - 16,024 \cdot CrossTable_{P4} + 1,424; \\
 y_{(P)postictal} &= -6,280 \cdot FD_{P3} - 5,478; \\
 y_{(P)interictal} &= -10,782 \cdot Hurst_{P3} - 12,988 \cdot CrossTable_{P4} + 10,927,
 \end{aligned}$$

where σ_{P3} is standard deviations of channel signal P3, LZW_{P3} and LZW_{P4} — the method LZW archiving of channel signals P3 and P4 respectively, FD_{P3} is the fractal dimension of channel signal P3, $CrossTable_{P3}$ and $CrossTable_{P4}$ are the Kolmogorov algorithmic complexity of channel signals P3 and P4, respectively, $Hurst_{P3}$ — Hurst index of channel signals P3.

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(P)preictal} &= -3,892 \cdot \frac{LZW_{P3}}{Hurst_{P3}} + 4,061; \\
 y_{(P)ictal} &= -0,009 \cdot \sigma_{P3} \cdot LZW_{P4} - 4,064 \cdot \frac{CrossTable_{P3}}{LZW_{P3}} + 7,700; \\
 y_{(P)postictal} &= -4,648 \cdot \frac{LZW_{P4}}{CrossTable_{P4}} + 4,410; \\
 y_{(P)interictal} &= -29,175 \cdot Hurst_{P3} \cdot CrossTable_{P4} + 6,045,
 \end{aligned}$$

where σ_{P3} is standard deviations of channel signal P3, LZW_{P3} and LZW_{P4} — the method LZW archiving of channel signals P3 and P4 respectively, $CrossTable_{P3}$ and $CrossTable_{P4}$ are the Kolmogorov algorithmic complexity of channel signals P3 and P4 respectively, $Hurst_{P3}$ — Hurst index of channel signals P3.

The prognostic models for studying focal epilepsy in the parietal (P) region of the brain for adults using the linear functions are obtained in the form:

$$\begin{aligned} y_{(P)ictal} &= -51,835 \cdot FD_{P_4} - 54,674; \\ y_{(P)postictal} &= 26,498 \cdot CrossTable_{P_4} - 9,427; \\ y_{(P)interictal} &= -5895,187 \cdot Hurst_{P_3} - 9107,335 \cdot FD_{P_4} + 12515,278, \end{aligned}$$

where FD_{P_4} is the fractal dimension of channel signal P4, $CrossTable_{P_4}$ is the Kolmogorov algorithmic complexity of channel signal P4, $Hurst_{P_3}$ — Hurst index of channel signals P3.

The found models using the non-linear functions:

$$\begin{aligned} y_{(P)preictal} &= -5,035 \cdot \frac{CrossTable_{P_3}}{Hurst_{P_3}} + 7,825; \\ y_{(P)ictal} &= 0,049 \cdot \frac{\sigma_{P_3}}{CrossTable_{P_4}} + 1923,627 \cdot \frac{FD_{P_4}}{\sigma_{P_3}} - 36,725; \\ y_{(P)postictal} &= -4,553 \cdot \frac{FD_{P_3}}{CrossTable_{P_4}} + 13,637; \\ y_{(P)interictal} &= -65,351 \cdot Hurst_{P_3} \cdot CrossTable_{P_3} + 12,834, \end{aligned}$$

where σ_{P_3} is standard deviations of channel signals P3, FD_{P_3} and FD_{P_4} are the fractal dimension of channel signals P3 and P4 respectively, $CrossTable_{P_3}$ and $CrossTable_{P_4}$ are the Kolmogorov algorithmic complexity of channel signals P3 and P4 respectively, $Hurst_{P_3}$ — Hurst index of channel signals P3.

The prognostic models for studying focal epilepsy in the parieto-occipital (PO) region of the brain for adults using the linear functions are obtained in the form:

$$\begin{aligned} y_{(PO)preictal} &= 0,005 \cdot \sigma_{P_3} + 25,671 \cdot Hurst_{P_4} + 27,684 \cdot CrossTable_{P_4} - \\ &\quad - 60,768 \cdot FD_{P_3} + 44,055; \\ y_{(PO)ictal} &= -34,620 \cdot CrossTable_{O_1} + 12,894; \\ y_{(PO)postictal} &= 38,967 \cdot Hurst_{P_3} - 49,711 \cdot Hurst_{O_1} + 64,554 \cdot CrossTable_{O_2} + \\ &\quad + 25,089 \cdot FD_{P_3} - 40,953; \\ y_{(PO)interictal} &= 0,018 \cdot \sigma_{O_1} - 278,473 \cdot Hurst_{P_4} + 110,532, \end{aligned}$$

where σ_{P_3} and σ_{O_1} are standard deviations of channel signals P3 and O1 respectively, FD_{P_3} is the fractal dimension of channel signal P3, $CrossTable_{P_4}$, $CrossTable_{O_1}$ and $CrossTable_{O_2}$ are the Kolmogorov algorithmic complexity of channel signals P4, O1 and O2 respectively, $Hurst_{P_3}$, $Hurst_{P_4}$ and $Hurst_{O_1}$ — Hurst index of channel signals P3, P4 and O1 respectively.

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(PO)preictal} &= 245,764 \cdot FD_{P4} + 108,356 \cdot \frac{1}{CrossTable_{P4}} + 0,037 \cdot \sigma_{O1} \cdot Hurst_{O1} - \\
 &\quad - 113,627 \cdot \frac{FD_{P3}}{CrossTable_{P4}} - 232,824; \\
 y_{(PO)ictal} &= -0,501 \cdot \sigma_{P3} \cdot CrossTable_{O1} - 3239,140 \cdot CrossTable_{O1} \cdot CrossTable_{O2} + 613,546; \\
 y_{(PO)postictal} &= 245,981 \cdot Hurst_{P3} \cdot CrossTable_{O2} - 20,143 \cdot \frac{Hurst_{O1}}{CrossTable_{O1}} + \\
 &\quad + 2,522 \cdot \frac{FD_{P3}}{CrossTable_{P4}} - 11,320; \\
 y_{(PO)interictal} &= -9814,647 \cdot \frac{Hurst_{O1}}{\sigma_{O1}} + 7,892.
 \end{aligned}$$

where σ_{P3} and σ_{O1} are standard deviations of channel signals P3 and O1 respectively, FD_{P3} and FD_{P4} are the fractal dimension of channel signals P3 and P4 respectively, $CrossTable_{P4}$, $CrossTable_{O1}$ and $CrossTable_{O2}$ are the Kolmogorov algorithmic complexity of channel signals P4, O1 and O2 respectively, $Hurst_{P3}$ and $Hurst_{O1}$ — Hurst index of channel signals P3 and O1 respectively.

The prognostic models for studying focal epilepsy in the temporoparietal occipital (PTC) region of the brain for children using the linear functions are obtained in the form:

$$\begin{aligned}
 y_{(PTC)preictal} &= 0,231 \cdot \sigma_{T5} - 21,572; \\
 y_{(PTC)ictal} &= -6,560 \cdot \sigma_{T5} - 80,380 \cdot LogRefl_{T3} + 1013,659; \\
 y_{(PTC)interictal} &= 904,653 \cdot LZW_{T3} - 277,853.
 \end{aligned}$$

where σ_{T5} is standard deviations of channel signal T5, LZW_{T3} is the method LZW archiving of channel signal T3, $LogRefl_{T3}$ — logistic map of channel signal T3.

The found models using the non-linear functions:

$$\begin{aligned}
 y_{(PTC)preictal} &= -3390,068 \cdot \frac{LZW_{T3}}{\sigma_{T5}} + 13,639; \\
 y_{(PTC)ictal} &= 483,953 \cdot \frac{1}{LogRefl_{T3}} - 8,054 \cdot \sigma_{T5} \cdot LZW_{T3} + 199,664; \\
 y_{(PTC)interictal} &= -86,406 \cdot \frac{1}{LZW_{T3}} + 282,378.
 \end{aligned}$$

where σ_{T5} is standard deviations of channel signal T5, LZW_{T3} is the method LZW archiving of channel signal T3, $LogRefl_{T3}$ — logistic map of channel signal T3.

The prognostic models for studying focal epilepsy in the central (C) area of the brain for children using the linear functions are obtained in the form:

$$y_{(C)postictal} = 70,859 \cdot Hurst_{C3} - 61,025 \cdot Hurst_{C4} + 17,968 \cdot FD_{C3} - 20,258;$$

$$y_{(C)interictal} = -21,227 \cdot Hurst_{C3} + 10,020,$$

where FD_{C3} is the fractal dimension of channel signal C3, $Hurst_{C3}$ and $Hurst_{C4}$ — Hurst index of channel signals C3 and C4 respectively.

The found models using the non-linear functions:

$$y_{(C)preictal} = -13,350 \cdot \frac{Hurst_{C3}}{Hurst_{C4}} + 15,023;$$

$$y_{(C)postictal} = -18,864 \cdot \frac{1}{FD_{C3}} - 21,649 \cdot \frac{Hurst_{C4}}{Hurst_{C3}} + 41,673;$$

$$y_{(C)interictal} = -33,659 \cdot Hurst_{C3} \cdot Hurst_{C4} + 6,813.$$

where FD_{C3} is the fractal dimension of channel signal C3, $Hurst_{C3}$ and $Hurst_{C4}$ — Hurst index of channel signals C3 and C4 respectively.

The quality of the forecast of built models for children was tested on the test sample (Table 1).

The results of the comparison showed the advantage of applying a nonlinear basis, and the accuracy was obtained over 92 %. When applying the linear basis, the accuracy was about 81 %.

The quality of forecast of built models for adults was tested on a test sample (Table 2).

The results of the comparison showed the advantage of applying a nonlinear basis, while the accuracy was obtained over 95 %. When applying the linear basis, the accuracy was received on the average 83 %.

Studies of epileptic seizures periods for children using logistic regression yielded lower results in sensitivity, specificity and classification accuracy than those of adults, confirming that the children's nervous system is formed before the age of 18.

The algorithms for calculating complexity (Hurst, LZW, CrossTable, FD) and variability (σ), as well as the obtained classifier models to determine the probability of a certain period of epilepsy flow with EEG, were applied to support diagnostic decision making of automatic determination of the epileptic seizure periods.

A decision support system [22] has been developed to improve the information support for the doctor and to promote the objectification of the treatment process through automatic classification of EEG fragments in accordance with the calculated values of the functions of predictive models.

Table 1. Comparison of learning and test sample results in a study of focal epilepsy for children

Period	Function type	Sensitivity, %		Specificity, %		Accuracy, %	
		training	test	training	test	training	test
1	2	3	4	5	6	7	8
Focal epilepsy in the frontal area							
Preictal	Linear	87,5	83,1	96,5	100	93,8	91,7
	Non-linear	100	84,2	100	88,5	100	86,5
Ictal	Linear	69,2	86,3	87,3	89,7	81,5	88,2
	Non-linear	92,3	86,5	98,2	92,1	96,3	93,2
Postictal	Linear	53,3	92,7	93,3	75	87,7	87
	Non-linear	91,4	100	93,3	100	91,8	100
Interictal	Linear	50	88,5	95,8	82,7	87,7	85,3
	Non-linear	100	96,7	100	93,3	100	96,1
Focal epilepsy in the frontal parietal area							
Preictal	Linear	60	55,5	94,9	54,5	85,2	58,3
	Non-linear	96,7	91,9	94,9	90,9	95,6	90,9
Ictal	Linear	73,3	91,9	94,9	91,3	88,9	81,8
	Non-linear	93,3	89,7	97,4	91,7	96,3	91,3
Postictal	Linear	67,5	82,7	97,4	86,1	88,9	91,7
	Non-linear	83,3	100	94,7	100	96,3	100
Interictal	Linear	50	75	95,7	100	88,9	100
	Non-linear	100	100	97,8	100	98,1	100
Focal epilepsy in the parietal area							
Preictal	Linear	38,5	68,3	95,4	81,4	79,1	81
	Non-linear	78,5	76,4	92,3	85,7	86,9	86,4
Ictal	Linear	44,4	67,3	89,1	75,6	75,8	77,3
	Non-linear	96,1	86,4	92,6	85,4	98	86,4
Postictal	Linear	42,5	64,2	97	83,3	78,7	84,2
	Non-linear	85,5	78,9	95,5	76,7	92,6	78,9
Interictal	Linear	71,6	65,7	98,7	77,5	84,6	85,7
	Non-linear	87,1	85,7	97,4	85	93,5	85,7
Focal epilepsy in the parieto-occipital area							
Preictal	Linear	76,9	88,9	87	89,5	83,3	90
	Non-linear	92,3	100	95,7	100	94,4	100
Ictal	Linear	66,7	100	87,5	100	80,6	100
	Non-linear	100	100	100	100	100	100
Postictal	Linear	88,9	90	100	88,9	97,2	87
	Non-linear	93,1	90	100	88,9	97,2	87
Interictal	Linear	100	80	100	71,4	100	76,5
	Non-linear	90	80	100	71,4	97,2	76,5
Focal epilepsy in the temporo-parietal central area							
Preictal	Linear	75	85,7	100	85,7	93,3	77,5
	Non-linear	85	85,7	100	85,7	96,3	85
Ictal	Linear	100	85,7	100	81,8	100	84,4
	Non-linear	100	90,5	100	72,7	100	84,4
Interictal	Linear	100	81,8	100	72,7	100	78,8
	Non-linear	100	81,8	100	86,4	100	83,7
Focal epilepsy in the central area							
Preictal	Linear	-	-	-	-	-	-
	Non-linear	87,6	100	93,3	100	91,1	100
Ictal	Linear	78,6	75	93,3	100	86,1	87,5
	Non-linear	86,3	87,5	93,3	91,7	90,5	88,7
Interictal	Linear	53,3	65	100	100	88,5	92,3
	Non-linear	83,3	100	100	100	90,5	100

Table 2. Comparison of learning and test sample results in a study of focal epilepsy for adults

Period	Function type	Sensitivity, %		Specificity, %		Accuracy, %	
		training	test	training	test	training	test
		training	test	training	test	training	test
1	2	3	4	5	6	7	8
Focal epilepsy in the frontal parietal area							
Preictal	Linear	-	-	-	-	-	-
	Non-linear	100	100	100	100	100	100
Ictal	Linear	40	62,9	100	100	81,3	92,3
	Non-linear	80	90,9	100	100	91,5	94,1
Postictal	Linear	100	81,8	100	86,4	100	83,7
	Non-linear	100	80	100	77,8	100	75
Interictal	Linear	66,7	73,8	92,3	100	87,5	100
	Non-linear	100	100	100	100	100	100
Focal epilepsy in the parietal area							
Preictal	Linear	-	-	-	-	-	-
	Non-linear	75	100	93,8	100	90	100
Ictal	Linear	66,7	-	92,9	-	85	-
	Non-linear	83,3	75	92,9	80	90	77,8
Postictal	Linear	40	100	93,3	100	80	100
	Non-linear	91,3	-	93,3	-	92,1	-
Interictal	Linear	100	100	100	80	100	88,9
	Non-linear	80	85,7	93,3	84,2	95	85

Receiving information about the EEG period classes, the doctor makes an informed decision about the EEG as a whole.

To check the efficiency of the developed system, a comparative evaluation of the results of the classification of EEG fragments performed by functional diagnostics physicians during the EEG visual analysis and with the help of the developed decision support system on the examination sample (25 EEG — 10 children and 15 adults) was made.

The use of the developed information technology of EEG processing due to the classification of a certain period according to the EEG allows to orient the doctor in decision-making, to increase the accuracy of the classification of the conditional norm periods, before and after an seizure, on the average by 5.5 %, 4.4 %, 9, 9 % and 6.6 % respectively for children, and for adults by 9.2 %, 7.4 %, 8.5 %, and 6.9 % respectively. By reducing the time it takes for a physician to determine the period of epilepsy with the EEG, the use of developed information technology makes it possible to classify the conditional norm periods, before, during and after seizure more quickly for children by 19 %, 15.5 %, 15.4 %, 16 9 % respectively, and for adults by 23.9 %, 18 %, 23.3 %, 17.8 % respectively.

The application of the developed information technology is useful in evaluating the effectiveness of treatment at the stages of patient monitoring.

CONCLUSIONS

The described methods of nonlinear dynamics allow quantitatively to distinguish the periods of epilepsy flow according to the EEG data. Changes in indicators such as Hurst Index, fractal dimension, logistic mapping, and algorithmic signal complexity have been investigated. Significant differences between these indicators due to changes in the functional state of the brain, are well reflected in the EEG. The complex calculation of such indicators allows to quantitatively distinguish the periods of epileptic activity by EEG, and further is used to build classification and prediction models.

With the help of step-by-step logistic regression analysis, prognostic models were built to detect the risk of a certain period of EEG activity. The application of nonlinear models allowed to significantly increasing the sensitivity, the specificity, and the accuracy even test samples. The determining accuracy of the seizure period on a test sample was about 6–10 % higher than with the use of models with linear functions.

The mathematical models include variables that are calculated from the EEG data and are available during patient observation. As a result of the application of step-by-step algorithms, the most informative features are included in the models. The selected features allow for the most accurate identification of individual periods of epilepsy flow from the EEG data. The accuracy of classification by the test sample was in the range from 71 % to 99 %. Analysis of composition and structure of the features is also of interest for clinical analysis.

The results of the EEG classification were comparatively evaluated using the proposed technology and without it. It was found that the use of the decision support system increases the reliability of determining the periods of the conditional norm, before, during and after a seizure by an average of 6.6 % for children and 8 % for adults. It was also possible to reduce the doctor's determination of the conditional norm period based on the EEG before, during and after seizure by an average of 16.7 % for children and 20.8 % for adults.

A decision support system has been developed to be useful in the diagnostic departments of health facilities and in psychoneurological hospitals where EEG is registered and analyzed.

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Received 27.12.2019

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Отримано 27.12.2019

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ВИКОРИСТАННЯ ПОКАЗНИКІВ СКЛАДНОСТІ ТА ВАРІАБЕЛЬНОСТІ ДЛЯ АНАЛІЗУ СКЛАДНИХ ДИНАМІЧНИХ СИСТЕМ

Вступ. Нормальна динаміка здорового організму є хаотичною, оскільки спостережуваний «хаос» властивий самій природі динамічних процесів, що протікають в організмі. Окрім періодичних процесів, для електричної активності мозку також є характерними ознаки детермінованого хаосу і зміни параметрів її нелінійної динаміки свідчать про характерні зміни у функціонуванні мозку. Такі виражені зміни можна спостерігати і у епілептичних сигналах електроенцефалограм. Розроблення математичних засобів розпізнавання особливостей функціонування головного мозку до, під час та після епілептичного нападу, а також у періоди між нападами є актуальним завданням. Проблема діагностики та виявлення моменту, який передуює епілептичному нападу, або інших періодів функціонування головного мозку у хворих на епілепсію є проблемою не тільки вибору методу класифікації, але і визначення кількісних оцінок динаміки, які відображають складність та варіабельність сигналу ЕЕГ.

Метою статті є формування ефективного ансамблю ознак з характеристик, що відображають складність та варіабельність сигналу ЕЕГ, побудова прогностичних моделей для перебігу епілепсії та розроблення на їх основі інформаційної технології підтримки прийняття діагностичних рішень.

Методи. Було використано методи математичної статистики для оброблення діагностичної інформації, методи математичного моделювання (покрокова логістична регресія) для побудови прогностичних моделей оцінювання перебігу епілепсії; методи створення інформаційних технологій діагностики епілепсії за даними ЕЕГ.

Результати. Було досліджено зміни таких показників, як показник Херста, фрактальна розмірність, логістичне відображення та алгоритмічна складність сигналу. За допомогою покрокового логістичного регресійного аналізу побудовано прогностичні моделі для виявлення ризику настання певного періоду за ЕЕГ. Застосування нелінійних моделей дало змогу суттєво підвищити чутливість, специфічність та точність навіть на тестових вибірках. Застосування розробленої інформаційної технології надало можливість підвищити достовірність визначення періодів епілептичного нападу (умовної норми, перед нападом, нападу та після нападу) в середньому на 6,6 % у дітей та на 8 % у дорослих.

Висновки. Запропоновані прогностичні моделі дають змогу отримати додаткову інформацію про періоди епілептичних випадків та вчасно передбачити їх настання.

Ключові слова: інформаційна технологія, ЕЕГ, епілептичні напади, епілепсія, показники складності та варіабельності, прогностичні моделі, логістична регресія.

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ИСПОЛЬЗОВАНИЕ ПОКАЗАТЕЛЕЙ СЛОЖНОСТИ И ВАРИАБЕЛЬНОСТИ ДЛЯ АНАЛИЗА СЛОЖНЫХ ДИНАМИЧЕСКИХ СИСТЕМ

Проблема диагностики и выявления момента, предшествующего эпилептическому припадку или других периодов функционирования головного мозга у больных эпилепсией является проблемой не только выбора метода классификации, но и определения количественных оценок динамики, отражающих сложность и вариабельность сигнала ЭЭГ.

Были исследованы изменения таких показателей, как показатель Херста, фрактальная размерность, логистическое отображение и алгоритмическая сложность сигнала. С помощью пошагового логистического регрессионного анализа построены прогностические модели для выявления риска наступления определенного периода по ЭЭГ. Применение нелинейных моделей позволило существенно повысить чувствительность, специфичность и точность даже на тестовых выборках. Применение разработанной информационной технологии позволило повысить достоверность определения периодов эпилептического припадка (условной нормы, перед нападением, нападением и после приступа) в среднем на 6,6 % у детей и на 8 % у взрослых.

Ключевые слова: *информационная технология, ЭЭГ, эпилептические приступы, эпилепсия, показатели сложности и вариабельности, прогностические модели, логистическая регрессия.*