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# Software and Hardware Complex of Anthropomorphic Type Robot as an Assistant for a Teacher. Decision-Making Subsystem Using Multiscale Entropy Analysis of EEG Signals

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***Abstract*—The paper presents research on the use of the results of the analysis of signals of brain activity of students for decision-making in educational robotics. Signals of brain activity were obtained using electroencephalograms (EEG). Assessment of the state of the student was carried out on the basis of the multiscale entropy. The object of the study was a man aged 17 years who was diagnosed with focal (structural) epilepsy, mesial sclerosis on the left and focal cortical dysplasia of the left temporal lobe and a control group. Comparison of the results of entropy estimates was carried out in the form of topographic images. Topographic images of the surface of the head are obtained on the basis of a spherical spline. The study showed that multiscale entropy of EEG signals can be a useful tool in the classification of patients with epilepsy and the control group. It is anticipated that such an analysis will be useful for early detection of neurological changes. The use of multiscale entropy in educated robotics as a means of obtaining objective information will help increase objectivity in decision-making in the choice of educational technologies to improve the quality of the educational process.**

***Index Terms*—Educational Robotics, Decision-Making, Artificial Intelligence, EEG Signal, Epilepsy, Acute Wave, Spike Wave, Rhythmic Slowdown, Multiscale Entropy, Visualization**

## I. Introduction

The decision-making process is actually a process of identifying the available alternatives, characteristics and choosing from them the one on the basis of which the problem will be solved. Such situations are encountered in the management of economic and social processes, in research and development, in medical research, and also in the creation of artificial intelligence and robots.

Such situations occur in the management of economic and social processes, in research and development, in medical research and also in the creation of artificial intelligence systems, robotic systems. Currently, educational robotics is widely developed, aimed at the creation and use of Autonomous robots as an assistant for the teacher. The educational process on the one hand is carried out in accordance with a pre-established plan. On the other hand, it is a pronounced dynamic process, due to the influence of a number of factors, both objective and subjective. Educational robotic systems are designed to support the teacher in the management of the educational process, taking into account the individual differences in the intellectual and psychophysical condition of students on the basis of objective data assessment of the current state.

One of the most important tasks of controlling Autonomous robots is to plan robot actions in a dynamically changing external environment. At the same time, the decision-making process to achieve this goal is carried out on the basis of existing knowledge and data of an objective assessment of the current state.

There are known problems with obtaining accurate information about a student's condition. The situation is complicated by the trend of lifelong learning. As a consequence, there are additional difficulties due to the increasing proportion of persons with disabilities, increasing with age. In this regard, it seems very relevant to study the brain activity of the brain activity of a healthy person and with paroxysmal States. The most striking paroxysmal event is epilepsy – a disease that affects more than 60 million people. It can be both innate and acquired. For example, of the 2.2 million troops returning from Iraq and Afghanistan, 100000 will develop post-traumatic epilepsy (PTE) [1]. This is a neurological disease that is accompanied by attacks due to periodic violations of the normal functioning of the brain. The most important aspect of the diagnosis of this disease is the fastest possible determination of the localization of the epileptogenic focus.

Studies are based on EEG. EEG readings are time-varying signals of brain activity – time series. In fact, the task is to determine the degree of randomization and identify the characteristic patterns of EEG signals. Non-linear dynamics methods are involved in solving such problems [2]–[5]. One of the effective characteristics of the randomness of the time series is entropy. There are quite a few types of entropy.

The most widely used information-theoretical measure for quantifying the stimulus-response ratio is the transition entropy (TE) [6]. With its help, cause-effect relationships are determined and quantitative estimates of delays of directed connections between the time series of EEG of different brain channels are established. For a randomly selected patient from the Children's Hospital (Boston) database, 18 EEG records were considered, including ten ictal periods lasting 6–13 s. The use of TE made it possible for the authors to make a statistical analysis of multivariate processes from the observed time series and to detect interregional brain interactions. In articles [7]–[9], the sample entropy (SampEn) model entropy is used to analyze EEG epileptic signals. In [7], the authors apply SampEn to analyze scalp EEG and submerged electrode signals and magnetoencephalograms (MEGS) in patients during various states of consciousness: wakefulness, sleep stages, and epileptic seizures. The signals were analyzed using statistical (permutation entropy) and deterministic (Lempel-Ziv permutation complexity) analytical methods. In [8], EEG signals are analyzed using the permutations entropy (PE) and the samples entropy (SE). As a result of the algorithm, the authors were able to recognize the EEG without signs of ictal activity. In [9] define a sample entropy SampEn internal functions mode (IMFs) generated by EMD process, determine the differences of EEG signals with ictal activity from EEG without ictal activity. In [10] uses the approximated entropy (ApEn), a model entropy (SampEn), Phase Entropy 1 (S1) and Phase Entropy 2 (S2) for automatically determining normal predicting and ictal events from EEG signals. For 200 signals with normal and predictable events, 100 ictal patterns (database of University of Bonn, Germany) revealed that all of the entropy, except for the spectral entropy values indicate lower values for predicting and ictally classes. In [11], [12], multiscale entropy (MSE) is used. In [11], multiscale entropy is used to assess the dynamic EEG characteristics of rats with epileptic seizures before, during, and after seizures. As a result, it was found that MSE makes it possible to more accurately classify all three types of conditions in this disease. In [12], when comparing multiscale entropy (MSE) and SampEn model entropy to analyze 32 EEG signals of infants under 2 months of age (Children's Hospital of National University of Taiwan), it was found that MSE is more sensitive and accurate compared to SampEn, which provides more information about functional changes in the brain. MSE allows us to evaluate the behavior of signals over a long time interval [13]. In this paper, multiscale entropy was used to study the EEG signals of epilepsy patients. The resulting value, along with other factors, is used in the subsystem of decision-making developed in Yuri Gagarin State technical University of Saratov robot assistant of the teacher to determine the appropriate action for the management of educational process.

## II. The Method of Estimating the State of a Person Based on the Calculation of Entropy Values

### A. Multiscale Entropy (MSE)

The method for calculating the multiscale entropy (MSE) was presented in [14]. For a given discrete time series $\{x_1, \ldots, x_i, \ldots, x_N\}$, a sequence of simplified time series $\{y^{(\tau)}\}$ is determined with respect to the scaling parameter $\tau$. The initial time series is divided into non-overlapping windows of length $\tau$, and then the values are averaged for each window. Thus, each element of the simplified tie series is calculated by the formula

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

For the first scale, the time series $\{y^{(1)}\}$ is equivalent to the original time series. The length of each time series corresponds to the length of the original time series divided by the scaling parameter $\tau$.

The calculation of the quantitative measure of entropy $S_E$ for each simplified time series is carried out according to the formula

$$S_E(m, r, N) = \ln \frac{\sum_{i=1}^{N-m} n'^m}{\sum_{i=1}^{N-m} n'^{m+1}}, \tag{2}$$

where $m$ – is the increment of the length of the data vector, $r$ is the size of the cell in the phase space (error), $n_i'^m$ is the probability of repeating a sequence of data of a given length in the source data.

### B. Sample Entropy (SampEn)

Model entropy was developed by Richman and Murman to eliminate the weaknesses of approximated entropy (ApEn) [15]. In approximated entropy (ApEn), signal self-similarity is taken into account. Sample entropy (SampEn) is the probability that the data sequence m will be the same as the other data sequence in the signal with an error r, which will remain the same if the data sequences are increased by $m+1$. Sample Entropy (SampEn) is determined by the formula

$$SampEn(m, r) = \lim_{N \to \infty} - \ln \frac{A^m(r)}{B^m(r)}, \tag{3}$$

where $A^m(r)$ – is the probability that two data sets will coincide for the number of points $m+1$ with an error $r$; $B^m(r)$ – is the probability that two data sets will coincide for the number of points $m$ with an error $r$. Thus, the model entropy (SampEn) does not take into account self-similarity, which avoids the possible problems of $\ln(0)$ by performing the logarithm at the very last step. SampEn does not depend on data formatting as much as ApEn. This property makes the SampEn algorithm suitable for applications with a relatively small amount of data.

### C. Approximated Entropy (ApEn)

An algorithm for determining approximated entropy was proposed by Pinkas [16]. Approximated Entropy (ApEn) is a statistical characteristic that can be used to quantify the complexity or irregularity of signals [17]. It describes the amount of new information in the signal. A reliable estimate of the approximated entropy can be obtained by analyzing short and noisy signals. A positive number is assigned to time series with large values, which corresponds to greater complexity or irregularity of the data. Entropy is determined by the formula

$$ApEn(m, r, N) = \phi^m(r) - \phi^{m+1}(r), \tag{4}$$

where $m$ – is the increment of the length of the data vector, $r$ is the size of the cell in the phase space (error). The components $\phi^m(r) and \phi^{m+1}(r)$ are defined as

$$\phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} \ln C_r^m(i), \tag{5}$$

where $C_r^m(i)$ – the number of matches of intervals of length $m$ with an error of $r$ on the data interval $N$.

### D. Spherical spline

To construct topographic images of the head surface, a spherical spline is used. The equations for determining the spherical spline of entropy along the surface of the skull were obtained by analogy with the determination of the spline of potential presented by Ferry [18].

Let the vector $\bar{r}_j$ determine the position of the measuring electrode on the spherical surface of the scalp, with $j = 1, ..., J$. The function $V(\bar{r}_j)$ will determine the entropy at this point (relative to some reference point). The spherical spline for calculating the entropy $V(\bar{r}_j)$ is determined by the formula

$$V(\bar{r}_j) = c_0 + \sum_{i=1}^{J} c_j g_m(\rho \cdot \rho_j), \tag{6}$$

where $c_0$ and $c_j$ are constants corresponding to the data. The operator $\rho \cdot \rho_j$ is the cosine of the angle between the interpolation point $\bar{r}$ and the position of the electrode $\bar{r}_j$. The $g_m$ function is defined as

$$g_m(x) = \frac{1}{4\pi} \sum_{i=1}^{\infty} \frac{2n+1}{(n(n+1))^m} P_n(x), \tag{7}$$

where $P_n(x)$ is Legendre polynomial.

### E. Electrode placement system

To implement the “10–20%” system (Fig. 1), the longitudinal size of the head is measured from the nose bridge (nasion point) to the occipital protuberance (inion point) and the transverse size between the external auditory canals. These two sizes are taken as 100% (for each direction separately). Then carry out the conditional “meridians” from the frontal to the occipital region and % of the “parallel” in the transverse direction through the crown. At a distance of 10% from the starting points (nasion and inion), the bottom line electrodes are installed, the remaining electrodes are installed at the intersection points of the “meridians” and “parallels” at a distance of 20% of the full length in the transverse and longitudinal directions. Lead points are indicated in capital letters corresponding to the initial letters of the zone name. Odd numbers mark the points of the left hemisphere. The electrodes located on the midline are indicated with the z index: Fz, Cz, Pz and are called sagittal S – sagitalis. Ear electrodes are indicated by the letter A – auriculus A1, A2 [19].

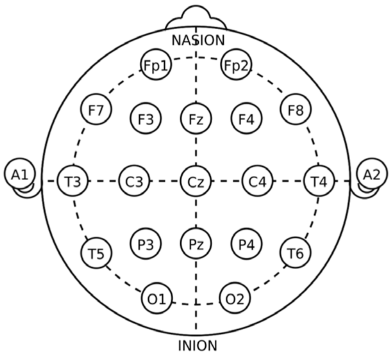


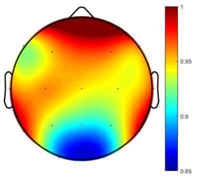

Fig. 1. Electrode placement system ”10–20%”.

### F. Object of Study

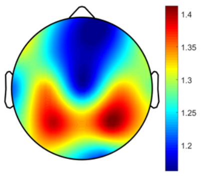
The object of study was a man aged 17 years, who was diagnosed with focal (structural) epilepsy, mesial sclerosis on the left and focal cortical dysplasia of the left temporal lobe. The disease was characterized by focal seizures (motor, cognitive, with impaired consciousness) and bilateral tonic-clonic seizures with focal debut. At the time of examination, the patient had seizures up to 2 times a year. EEG recording of a patient with epilepsy was performed at the medical center for neurology, diagnosis and treatment of epilepsy “Epineiro” in Saratov, Russia. During the examination, an EEG analysis was used with the electrode arrangement shown in Fig. 1. EEG recording was carried out on 21 channels: O2, O1, P4, P3, C4, C3, F4, F3, Fp2, Fp1, T6, T5, T4, T3, F8, F7, Pz, Cz, Fz, A2, A1. Purification from artifacts was performed by a neurophysiologist. To compare the results of the study, the EEG signals of adolescents from the control group were analyzed. The group consisted of 39 healthy adolescents. EEG recording was carried out in a calm state of the examined adolescents with their eyes closed. To record the EEG data, a 10–20 arrangement of 16 electrodes was used: O1, O2, P3, P4, Pz, T5, T6, C3, C4, Cz, T3, T4, F3, F4, F7, F8. The resistance of the electrodes was less than 10 kOm, the sampling frequency was 128 Hz, and the passband was from 0.5 Hz to 45 Hz. Clearing of artifacts from head and eye movements was carried out by two experts. Recording was made within 60 seconds. The control signal source database is publicly available on the Internet at: http://brain.bio.msu.ru/eeg_schizophrenia.htm.

### *G. Results*

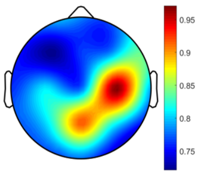
The work analyzed EEG signals containing pathological changes: "acute wave", "spike", "spike wave" (according to the international classification of EEG disorders, Luders H, Noachtar S, 2000). As an example, we cite the results of multiscale entropy (MSE), which were calculated using the following parameter values: $m = 5$, $r = 0.2$, and $\tau = 4$. Based on the calculated values of multiscale entropy, topographic images were constructed (Fig. 2), visualizing brain activity determined by the corresponding channels.



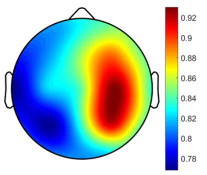
a) control group



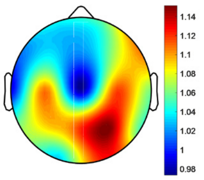
b) patient without abnormal activity



c) patient, "Sharp waves"



d) patient, "spike-wave"



e) patient, "spikes"

Fig.2. Distribution of multiscale entropy (MSE) across channels for different epileptiform activities

The maximum value of entropy for the control group is observed in the channels Fp2, Fp1, T6, T5, and the minimum – in the channels O1, O2 (Fig. 2a). When calculating the multiscale entropy for the patient's EEG signal at the moment of absence of epileptiform activity, topographic images are characterized by symmetrical hemisphere activity, however, in the T3 channel, the entropy value is minimal (Fig. 2b).

"Sharp waves" – this phenomenon as well as "spikes" has a peak-like shape, but its period is longer, 80–200 ms. "Sharp waves" may occur in isolation or precede a slow wave. Sharp waves can occur in isolation (especially with focal forms of epilepsy) or precede a slow wave. The phenomenon is highly specific for epilepsy. The maximum value of entropy for the "sharp wave" is observed in channel C4, and the minimum in channels T3, C3, T5, F7, Fp2, Fp1 (Fig. 2c).

The spike-wave complex is a pattern consisting of a peak and a slow wave following it. For the patient, the maximum entropy value for the spike-wave complexes is observed in the channels C4, P4, and the minimum in the channels T3, T5 (Fig. 2d). (Fig. 2d).

"Spike" is an epileptiform phenomenon that is different from the main activity and has a pike shape. The peak period is from 40 to 80 ms. Adhesions can occur with various forms of epilepsy. Single peaks are rare, usually they precede the appearance of waves. The peaks themselves reflect the processes of excitation of neurons, and slow waves reflect the processes of inhibition. For the patient, the maximum value of entropy for the epileptiform activity of the "commissure" is observed in the channels O2, P4, and the minimum in the channels T3, Cz (Fig. 2e).

Comparison of topographic images of multiscale entropy of EEG signals allows us to conclude that the subjects from the control group and the patient with epilepsy have clear differences in the readings of activity in the areas of the cerebral cortex. The study of topographic images of the patient's multiscale entropy made it possible to localize the foci with pathological changes that are located in the T3 channel.

## III. Subsystem of Decision-Making Robot Assistant for Teacher

At the Yuri Gagarin State Technical University of Saratov are works on creation of a robotic complex for support of educational activity of the teacher is conducted. The control system of robotic complex contains subsystems of data acquisition (receiving) and information processing about a status of trained, control of execution of educational tasks, planning of operations of the robot for increase in efficiency of educational process, modeling of operations of the robot for the purpose of feasibility check and adoption of the constructed action plan, control of speech and physical activity of the robot in compliance of the accepted action plan, etc. The most important subsystem of a robotic complex is the subsystem of planning of actions and decision making for achievement of a goal, what are providing possibilities of autonomous behavior of the robot in the dynamic environment of educational process.

The subsystem of decision-making of the developed robot of the teacher's assistant uses a production model of knowledge representation. Knowledge is presented in the form of axiomatic system [20] products in form

$$o_1 f_1 v_1, o_2 f_2 v_2, \ldots, o_n f_n v_n \rightarrow d_j \Rightarrow f_{j1}, f_{j2}, \ldots, f_{jk} \quad (8)$$

where $f_i$ – is factor, $o_i$ is a logical operator (& – AND, $|$ – OR, $\sim$ – NOT), $v_i$ – weighting factor $f_i$, $d_j$ – is the action to be performed in the current situation, $f_{ji}$ – i-th result of application of the action $d_j$.

The decision-making process is based on the calculation of the assessment of the conditions of applicability of products. The result of the subsystem planning robot assistant is automatically built procedure, hereinafter referred to as the active procedure, and includes a set of products that are adequate to the current situation of the educational process. At the stage of execution of the constructed procedure, a set of factors may change. Therefore, the evaluation of the values of the factors is carried out continuously. The current values are entered into the database of the robotic complex. In the parallel processing mode, the values of the applicability conditions of the products included in the active procedure of the robot actions are recalculated. At the same time, the software and hardware complex of the robot teacher's assistant performs the following actions in parallel:

- calculation of factor values;
- calculation of the conditions of applicability of products;
- selection of products with dominant values of applicability conditions;
- forming a new procedure robot;
- modeling the performance of actions of active procedures [2];
- comparison of simulation results of the active procedure with the desired goal of solving the problem;
- decision to replace the current active procedure with a new newly built procedure.

Therefore, the sequencing process is dynamic. In this regard, planning artificial networks are used to plan robot actions [12], [13]. In general, the software and hardware complex of the robot assistant for the teacher is a distributed computing system. At the same time, computationally complex procedures are implemented on stationary servers of the classroom. The computational resources of the robot itself are used to obtain and analyze the current situation and perform actions automatically constructed active procedure, adequate to the current situation of the educational process.

## IV. Conclusion

The aim of this work was to investigate the possibility of multiscale entropy to detect abnormal brain activity. The constructed topographic images made it possible to localize areas of the brain in which pathological changes are observed. According to the high resolution MRI of the brain according to the epileptological program, structural changes were revealed in the form of a combination of focal cortical dysplasia of the mediobasal parts of the left temporal lobe and left hippocampal sclerosis, as well as metabolic disorders of the right hippocampus. It should be noted that the revealed deviations are located in the temporal parts of the hemispheres, which advise the T3 channel identified in this work. The studies illustrate the possibility of using methods for assessing the state of the student based on the analysis of brain activity to support decision-making hardware and software complex robot assistant for a teacher.

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