The Method for Increasing of EEG Signal Sample Entropy Stability and its Application for Human State Monitoring

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***Abstract*—New approach for calculation of electroencephalogram Sample Entropy, experimental data and peculiarities of its interpretation are presented. Main aim of the research to formulate rules that allow to use Sample Entropy in human state monitoring by electroencephalogram more efficiently and give new information about electroencephalogram signal that can be useful for different researchers. This method is suitable for any non-linear, non-stationary signals with a chaotic nature. Moreover, it is recommended for descrying as additional technique for other entropy-based methods.**

I. Introduction

Modern methods of signal processing and analysis are increasingly turning to non-linear algorithms. In particular, in the last decade the interest of researchers from different areas in using of entropy has significantly increased.

First studies that describe the behavior of the entropy of electroencephalographic signals started 10-15 years ago [1-5] but the results of the studies cannot be unambiguously evaluated. Entropy estimation is specific and several features should be taken to ensure the reproducibility of the results into account. That is not always respected. These issues have not been investigated earlier, and it has influence to the lack of reproducibility in the scientific press experimental electroencephalogram (EEG) entropy estimation.

To solve the problem of a human operator state estimation by EEG the authors suggest to use Sample Entropy [6] and offer some improvements in calculation technology in order to improve the stability of the algorithm and ensure its reproducibility.

The article presents the results of a study of this problem and provides methodological and algorithmic approaches to ensure the robustness of the EEG entropy estimation under the influence of typical psychophysiological experiment factors.

II. Sample entropy based method

A. Sample Entropy

Sample entropy is one of the youngest entropy types and has already shown the best results in the EEG analysis in comparison with other methods.

As noticed in [7] Sample Entropy calculation is similar to the calculation of Approximate Entropy, but a few basic features are distinguishing:

- logarithms and averaging procedure is changed;
- private assessment of the probability is less for 1 (the number of points that lie inside a given radius of the hypersphere doesn't include a point of comparison with itself);

Let us introduce the definition of Sample Entropy for a digital signal. Suppose there is EEG signal *x(n)* which is presented as a sequence of samples.

Modified Sample Entropy algorithm takes the following form:

- Partial correlation sums are figured out according to the equation:

$$C_r^m(i) = \frac{1}{N-m-1} count\left[\{n\}\middle| n \neq i \& \max_{i=1,m} |x_{n+1} - x_{i+1}| < r\right] \quad (1)$$

where N – size of the calculation window, m – number of space dimension, n – current number of the element, r – radius of the hypersphere.

- Averaging of the correlation sums:

$$\theta^m(r) = \frac{1}{N-m}\sum_{i=1}^{N-m} C_r^m(i) \quad (2)$$

- Calculation of the Sample Entropy:

$$SE(m,r,N) = ln\frac{\theta^m(r)}{\theta^{m+1}(r)} \quad (3)$$

As a result of EEG entropy calculation we obtain a new set of data and a new repetition period that depends on the size of a given calculation window. Besides the calculating window we should define the space dimension and the sphere radius. It is proposed to use the following values: m = 3, r = 1. High

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dimension entails complexity of the calculations and the radius r =1 is chosen as the minimum non-zero difference between adjacent samples in a locally-ranking code (see below).

B. Signal characteristics standardization

Let us consider a series of signal characteristics that significantly affect to Sample Entropy estimation. These characteristics vary within a wide range depending on the laboratory equipment, and are often not accounted by researchers within their studies

The lack of a unified methodological basis of measurement is confirmed by comparison of the Sample Entropy change ranges (Table I) obtained by different authors. It is easy to see that range of Sample Entropy values is high and it significantly obstructs result comparison and interpretation.

TABLE I. VALUES OF THE EEG SAMPLE ENTROPY IN DIFFERENT STUDIES

№ at References	Range of Sample Entropy values bit/count		Sampling frequency, Hz
	Min	Max	
2	0,3	0,9	100
3	0,5	0,9	256
4	0,2	0,5	256
5	0,9	2	125
6	0,9	2,2	125
7	1	1,9	50
2	0,3	0,9	100
3	0,5	0,9	256
4	0,2	0,5	256
5	0,9	2	125

To overcome the research results comparability problem it is necessary:

1) To standardize the conditions of EEG registration and EEG analysis for entropy estimation;
2) To ensure the entropy evaluation independence of the factors that can not be standardized.

Increasing of the results reproducibility can be achieved by selecting the optimum values for sampling frequency and filtering band. And to provide the invariance to the amplitude proceed to locally-ranking code of the signal. These parameters can be considered as the most important due to transition from the signals, which are continuous by their nature, to digital representation. Parameters of this EEG transmission significantly influence the entropy estimation.

As shown at [7], stability of entropy estimation (obtained by using a standard algorithm for the Sample Entropy) to a variety of interfering factors may be improved through the use of a prior locally-ranking coding of the input signal samples.

Comparison of each sample with the nearest to the left and to the right in a given window, building a symbol sequence and saving the results of the comparison is the basic idea of this coding (Fig. 1). It is easy to see that the relations (>, <, =) between symbols, separated from each other by no more than 4 positions (window size is 8) correspond to the relations between the original samples.

It is proved in [7] that locally-ranking code (also has known as a ranking signal core) has invariance to the continuous one-to-one signal transformations. As a result, factors described by these transformations have no effect on final entropy estimation. Such as contact nonlinearity, instability of subelectrode resistance as well as other factors that change the signal amplitude in unknown way. As experiments show [7], locally-ranking coding substantially increases estimation resistance in case of a noise impact, uneven of frequency response and instability of a recording device.

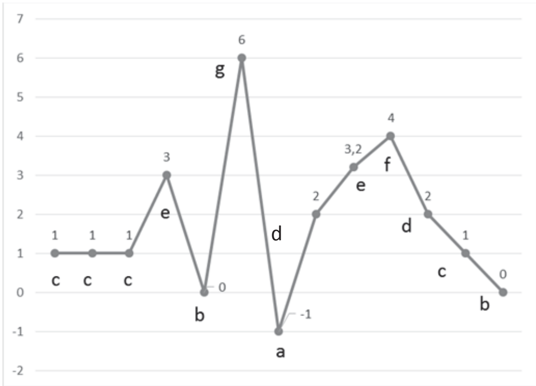


Fig. 1. Number sequence and its ranking core.

Locally-ranking code is a symbol sequence, which length coincides with the original numerical sequence length and algorithm of Sample Entropy computing can be applied to that code. As already mentioned, the minimum size of the sphere for locally-ranking code is equal to 1.

As a result, authors have obtained an algorithm for robust EEG processing and estimation of its entropy. It includes following steps:

1) *Standard frequency characteristics*. Input signal is reduced to the standard conditions (bandwidth 0.5–35 Hz, sampling frequency 500 Hz). These values are chosen because of algorithm features and in order to cover all common encephalographs with a high range of their frequency characteristics.
2) *Locally-ranking coding.* Input sequence is converted into a locally-ranking code. It allows to reduce influence of the EEG amplitude.
3) *Sample Entropy.* Sample Entropy is computed using previously obtained locally-ranking code.

4) *Converting units from bit/count to bit/s.* Multiplication of the obtained entropy values to correction coefficient (0.86) and sampling frequency (500) to obtain an unbiased estimate, measured in bit/s:

$$H(X) = b \cdot F_d \cdot H(X)^* \tag{4}$$

where $H(X)$ – Sample Entropy in bit/s, b – correction coefficient, F_d – signal sampling frequency, $H(X)^*$ – Sample Entropy estimation in bit/count.

Correction coefficient *b*=0.86 has been calculated on the base of nonlinear signal model [6].

III. Material and methods

To test the hypothesis of Sample Entropy value changes during implementation of different tasks for subjects several experiments were carried out. It should be noticed that all tests were realized within the framework of global university study with different goals. One of the most important result is set out in this article.

A. Short-term series

All experiments might be divided into two categories - short and long term. Short-term series had the durations from 0.5 to 1 hours. 14 series with 4 different variation of a scripts were carried out, 5 people (4 male, 1 female) were involved.

Participants received instructions related to the implementation of the mental activity at each stage of the experiment.

The standard experimental protocol can be described as following:

- Closed eyes
- Watching video
- Closed eyes
- Reading
- Closed eyes
- Logic task
- Closed eyes

Countdown, watching a relaxing and dynamic films were added to some protocols besides the presented script. Also in some cases several tasks were ruled out. However, the main order Closed eyes/Task/Closed eyes was constant. With the closed eyes, subjects were asked to relax.

Script variability can be explained by the necessity to test the studies results reproducibility in different contexts and an attempt to find common dynamic that is typical for the entropy of the EEG. Furthermore, all stages of the experiment will be reflected in the form of signatures on the entropy graphs in order to avoid discrepancies of interpretation.

All visual material were shown on a widescreen TV, the general lighting was turned off.

The subject was sitting in a chair. To obtain different physiological parameters respiration sensor, pulseoximetry sensor, ECG electrodes on the wrist and the EEG cap were fixed on the subject. EEG cap recorded signal in the standard leads for unipolar international 10-20 system: Fp1 and Fp2 (frontal), C3 and C4 (central), O1 and O2 (occipital). Odd digital codes correspond to the electrodes on the left, even over the right hemisphere of the brain. In this paper, only EEG signals with event markers were used for analysis, excluding communication with other physiological indicators.

The authors used encephalograph Neuron-Spectrum 5 with the following characteristics of EEG recording: sampling frequency 500 Hz, high-pass filter (HPF) – 0.5 Hz, low-pass filter (LPF) – 35 Hz.

B. Long-term series

Long-term experiments were held 1 time per week for 6 weeks, every session duration was 2–2.5 hours. 10 man were involved. As a result, 60 series were carried out. EEG recording was performed in a laboratory, which is different from that where the short-term experiments were carried out, by other investigators and also by using encephalograph of another manufacturer.

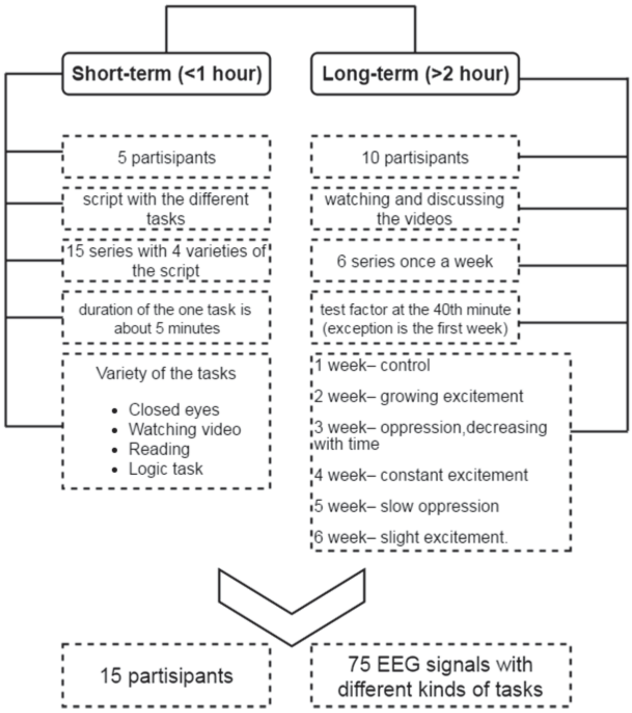


Fig. 2. Structure of the experiments

Each week participants were exposed to the test factor, which entailed either excitation or inhibition (at the 40th minute of the test, exception is the first week). During the signal registration process, the subjects were viewing video clips and small documentaries. Further, discussion of the videos and reports about the health state for 5–7 minutes between views has occurred. 5 interviews were carried out in each experiment. In the long-term cases there were no mobility limitations, as in the short-term experiments.

In the long-term series encephalograph NVX 36 was used: sampling frequency 2000 Hz, HPF – 0.5 Hz, LPF – 70 Hz. Subsequently obtained EEG data sets were filtered by LPF 35 Hz, and then thinned to 500 Hz to ensure comparability with the results of the short-term series and for the possibility of processing technology standardization.

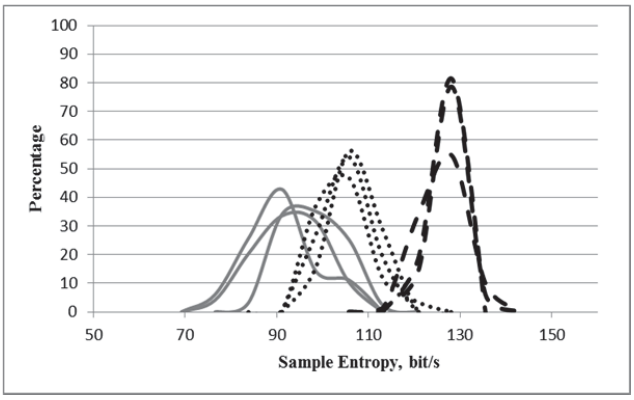
In total, at the experiments 15 middle-aged men have participated, 75 series were carried out. 75 EEG records were received and processed.

Generalized structure of the experiments is shown in Fig. 2.

IV. Results

A. Histograms' interpretation

To assess the reproducibility of the results and identify common trends in the entropy values histograms of their distribution were built. Fig. 3 shows histograms of entropy values for three subjects in 8 short-term experiments.



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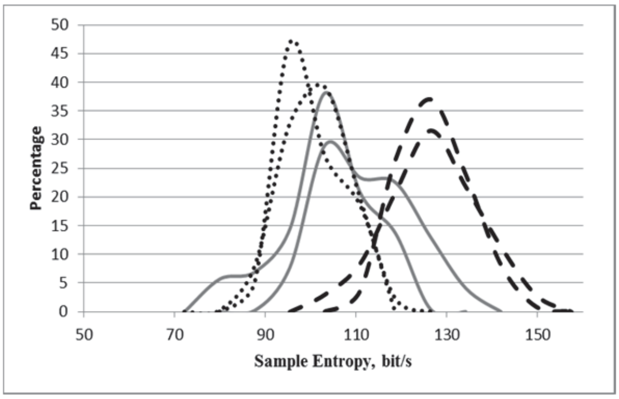

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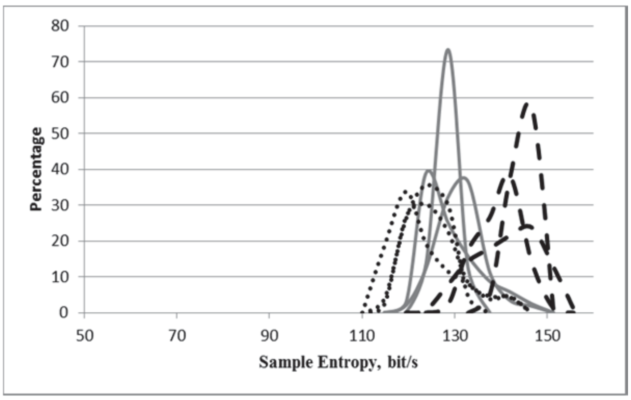


c

── - O(O1+O2), ······ - C(C3+C4), ─ ─ ─ - Fp(Fp1+Fp2)

Fig. 3. Histograms of the entropy average values for different derivations. A – subject №1 , 3 short-term series; b – subject №2 , 2 short-term series; c – subject №3 , 3 short-term series.

Tests were carried out on different days for all subjects, test scripts also had some modifications. Despite this, entropy value varies within a narrow range under a single diversion. The strongest deviations are observed in case of subject №2. This is due to the subject psychophysical state – during one of the tests he was more tired than other days, that caused the expansion of the entropy range. For a more complete picture and for assessment of entropy values sustainability let us consider histograms of the 1st control week of long-term experiments for 4 subjects (Fig. 4).

Derivations were grouped by combined occipital (O1 + O2), central (C3 + C4) and frontal (Fp1 + Fp2) derivations.

Note, that after reduction of the received signal to a sampling frequency of 500 Hz and a frequency band 0.5–35 Hz despite the substantial differences in EEG recording and technical maintenance in comparison with the short-term experiments, the sustainability of the entropy estimate had achieved. It would not be possible to achieve without translation to a single characteristics. Analyzing the histogram, you can see the following:

1) Range of EEG entropy values in case of long-term experiments expanded. The subjects were not restricted in the motion and signal artifacts (e.g., which occurred during talking) increased the value of signal entropy, that is actually expected. However, in all experiments entropy values fall within the range 70–210 bit/s, in short-term experiments 70–150 bit/s.

2) There is a high individual repeatability of entropy values for derivations in repeated experiments, regardless of the script and the state of the subject.

3) For frontal derivations (Fp1, Fp2) in all cases the measured Sample Entropy values is higher than for central and occipital derivations.

4) Entropy values for derivations O1, O2, and C3, C4 are generally similar, but their individual variability is observed, as well as the peaks shift with respect to each other.

Let us consider the results of short-term experiments data processing, taking into account the specifics of the steps (Fig. 5). Stages "eyes closed", "watching videos", "logical task" are marked. Data was selected from the short-term experiments in all the tests, which a particular subject have passed, and grouped according to the tasks.

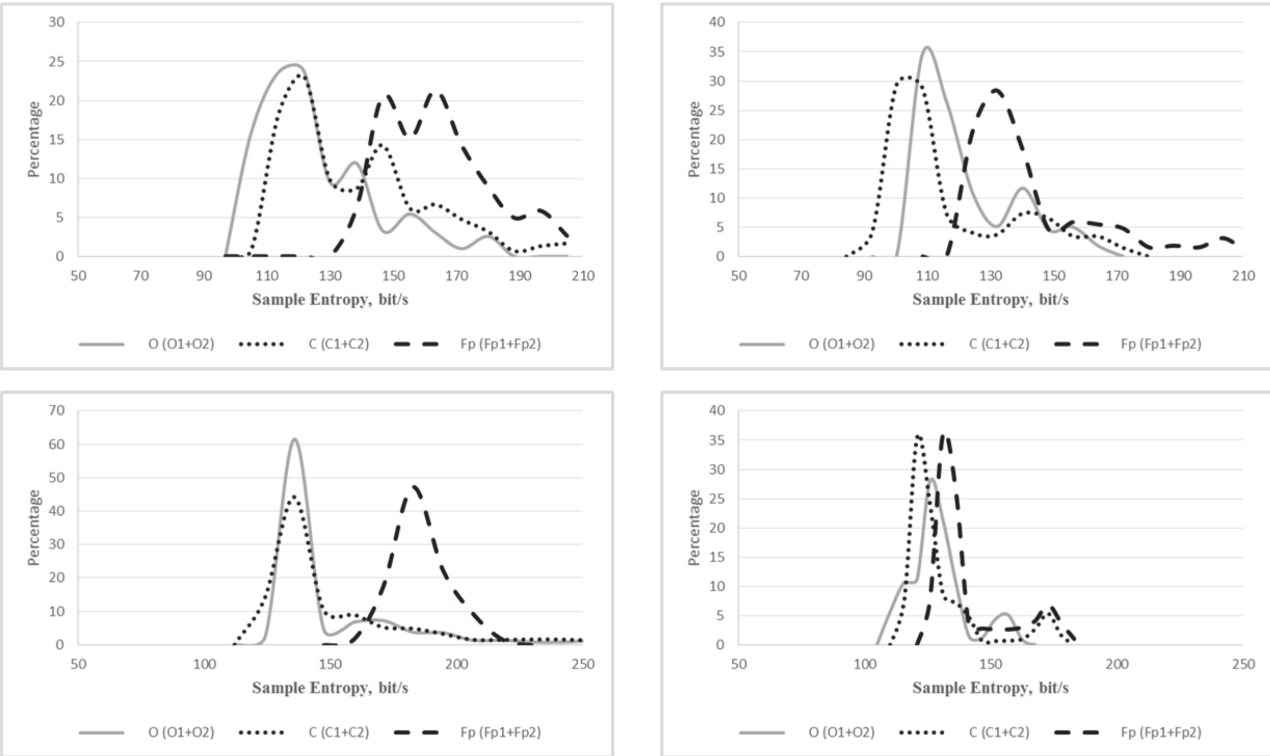
Following regularities may be noted:

1) Despite a clearly expressed nature of individual changes in general, there is a coincidence in the subjects histograms obtained from different tests. It indicates a sufficient high level of reproducibility, although some range changes exist (Fig. 5, b). This is due to differences in the state of the subject at the time of passing the tests, which is reflected in the character of its internal work and, as a result, EEG entropy.

2) At the stage "closed eyes" there is a shift of entropy values to the left for all of subjects and all derivations in varying degrees. The strongest shift for entropy value is in

derivations O1, O2. It is explained by the fact that the occipital derivations reflects the activation level of visual apparatus.

3) In general, it is not clear that the entropy values uniquely varies between the stages (except for the situation "closed eyes"). However, we can talk about some tendencies – during "logic task" Sample Entropy of the frontal derivations C3, C4 is growing; Sample Entropy of frontal derivations Fp1, Fp2 is higher than in other leads.



—— - O(O1+O2), ······ - C(C3+C4), — — — - Fp(Fp1+Fp2)

Fig. 4. Histograms of the entropy average values for different derivations, 4 subjects, 1st control week of the long-term experiment

B. Sample Entropy charts and their interpretation for monitoring of human state

Consider as an example the entropy of the EEG signal from the subject 2 (Fig. 6) during the passage of the two short-term experiments. All stages are reflected in the figure in the form of inscriptions, recording time is about 40 minutes.

All signal parameters correspond to the description for the short-term experiments. EEG prefiltration is absent. Sample entropy is calculated in a window with the size of 2000 samples, with a subsequent shift value of 1000 samples. With a sampling frequency of 500 Hz we have received that 1 point of the EEG signal entropy corresponds to 2 seconds of the original signal. To simplify the illustration in the article we use combined diversion, calculated as mean values of two original: O (O1 + O2), C (C3 + C4), Fp (Fp1 + Fp2).

Subject conscientiously performs tasks, level difference between the stages in entropy derivations is clearly visible (this is expressed most clearly for F-derivation). This may be an indicator of a person active internal work, his "inclusion" in the process. Of course, the specifics of this kind of experiments requires taking into consideration the contribution of non-controlled mental processes and factors distracting the subject concentration from perform tasks.

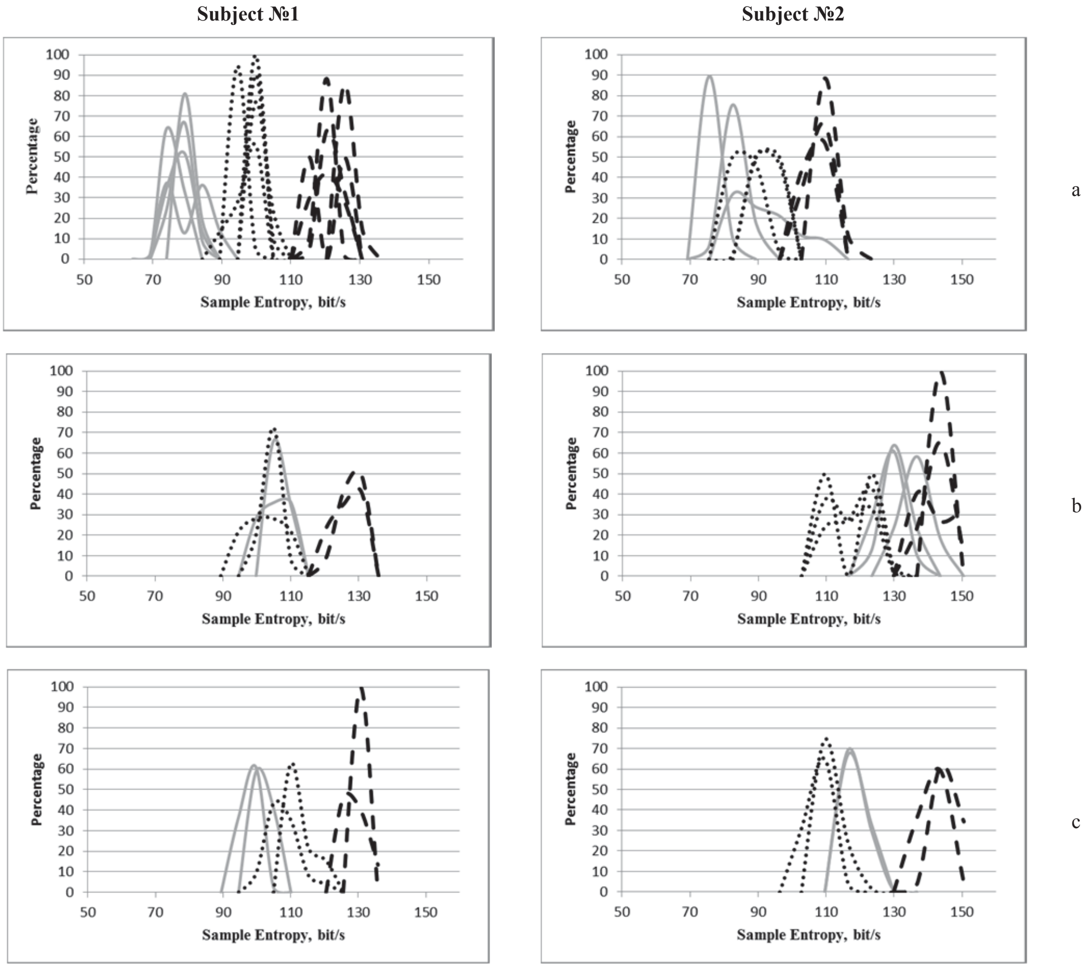
The average entropy value for sub.№2 is about 100 bit/s, while during mental workload in Fp derivations its values increase to 140. When sub.№2 relaxing with eyes closed values drop to 70 in C derivations. We can clearly see stability of the reactions and entropy values achieved by using suggested method.

Recording artifacts include part with a pronounced splash – during the transition from the closed eyes to the logical problem (Fig. 6, a, b) and to watching video (Fig. 6, b). We may assume that it has myographic nature, therefore this portion is excluded from the analysis.

Naturally, the proposed observations do not reflect all information that can be extracted from the visual analysis of the signal in its entropy charts. For the researcher it is essentially important to understand the basic "anchors", that signalize changes in the structure of EEG signal. They are presented in detail in [6]. They can also serve as criteria for automatic selection of episodes and to be a part of special program complex for monitoring the human state.

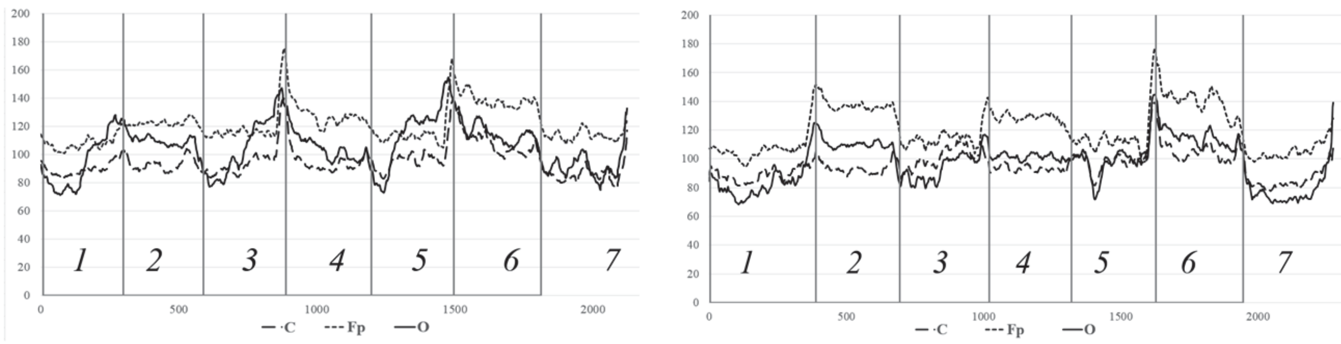
V. CONCLUSION

Naturally, only the values of Sample Entropy (both relative and absolute) do not reflect all the processes in the human condition, but carry a significant part of the information and have a pronounced tendency. Moreover, it is impossible to claim that the existing experimental material allows fully identifying them. In addition, we would like to focus, that the proposed method makes it possible to introduce a segment of EEG signals of any length in a compressed form for subsequent visual analysis and at this stage it does not include the automatic criterias for the episodes selection (it is included in the authors plans). However, it does not cancel the opportunities for process automation.



— - O(O1+O2), ······ - C(C3+C4), — — — - Fp(Fp1+Fp2)

Fig. 5. Histograms of the entropy average values for different tasks, 2 subjects, short-term experiment. a– closed eyes, subject №1, 5 samples for 5 min. from 3 short-term series; subject №2, 3 samples for 5 min. from 2 short-term series. b – watching videos, subject №1, 2 samples for 5 min. from 2 short-term series; subject №2, 3 samples for 5 min. from 1 short-term series. c – logic task, subject №1 and №2, 2 samples for 5 min. from 2 short-term series.



a b

Fig. 6. Sample Entropy of the EEG signal, bit/s. Smoothed by moving average with the window 20. a,b - different short-term series with the same script, subject №2. 1,3,5,7-closed eyes; 2- watching video; 4-reading; 6-logic task

Therefore, method for increasing of Sample Entropy sustainability includes the following points:

- Conversion to a single sampling frequency and EEG filtering band (500 Hz, 0.5–35 Hz);
- Transition to locally-rank code of EEG signal;
- Recalculation of the entropy values from bit/count to bit/s, according to the correction coefficient which is calculated on the basis of simulation results.

Existing experimental material allows saying about high efficiency of the proposed solutions and also about perspectives of using the method for a wide range of researchers for various problems solving. It remains to be questions about the development of algorithms for the automatic detection of the signal sections with certain parameters; identification of physiological bases of the observed processes of activation/deactivation, synchronization/resynchronization between derivations; approbation of technology on more signals from different laboratories to control the stability of results; influence of the signal filtering to Sample Entropy estimation and necessity of the signal preprocessing.

Main program for Sample Entropy calculation can be download at the official website of the “LETI” University [8] with all necessary instructions. We hope that it helps other researchers in their studies and will be grateful for e-mail with the results.

ACKNOWLEDGMENT

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We would like to express a special gratitude and thanks to our programmer who has developed main program for a fast calculating of Sample Entropy. We are highly indebted to our statisticians. They have processed about 1000 EEG signals to find the most important and useful information for the further analysis.

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REFERENCES

[1] B. A. Mathew, *Entropy of electroencephalogram (EEG) signals changes with sleep state*, master's theses, University of Kentucky, 2003.

[2] N. Bruce Eugene, C. Bruce Margaret, S. Vennelaganti, “Sample entropy tracks changes in EEG power spectrum with sleep state and aging”, *Journal of Clinical Neurophysiology*, vol. 26(4), 2009, pp. 257-266.

[3] D. Abásolo, R. Hornero, P. Espino, “Entropy analysis of the EEG background activity in Alzheimer’s disease patients”, *Physiological Measurement*, vol. 27(3), 2006, pp. 241-253.

[4] R. Shalbaf, H. Behnam, J. Sleigh , L. Voss, “Measuring the effects of sevoflurane on electroencephalogram using sample entropy”, *Acta Anaesthesiol Scand.*, vol. 56, 2012, pp. 880-889.

[5] B. Bein, “Entropy”, *Best Practice & Research Clinical Anaesthesiology*, vol. 20(1), 2006, pp. 101 – 109.

[6] Y. A. Zhivolupova, *Information analysis technology of the brain's electrical activity for evaluation of the human-operator functional state*, master's theses, Saint Petersburg Electrotechnical University "LETI", 2016.

[7] O.V. Tcvetkov, *Entropy data analysis in physics, biology and engineering*. Saint-Peterspurg: SPb ETU “LETI”, 2015.

[8] Spb ETU “LETI” official website, Program for Sample Entropy calculating, Web: http://www.eltech.ru/ru/fakultety/fakultet-informacionno-izmeritelnyh-i-biotehnicheskih-sistem/sostav-fakulteta/unl-i-nil/nauchno-issledovatelskaya-laboratoriya-na-baze-kafedry-bts.