Study of Parameters and Properties of Approximate Entropy of EEG at Various Anesthesia Stages

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Abstract—**The approach to recognition of anesthesia stages by electroencephalogram (EEG) based on the parameters of theapproximate entropy (Kolmogorov entropy estimation) is considered. The performance properties were studied on model signals and the experiments were conducted that allowed selecting a set of parameters of approximate entropy for EEG analysis. It was shown that this method provides reliable recognition of two states: deep anaesthesia and wake condition after awakening.**

I. Introduction

During surgeries it is required to have reliable monitoring of anaesthesia depth. Both insufficiently deep anesthesia and overdosing of anaesthetics is dangerous to a patient's health and life [1],[2].

In view of the fact that the target organ of an anesthetic is the brain, the changes in the neurophysiological parameters are indicators of the anesthesia depth [1]. Electroencephalogram record alone is difficult to use for monitoring the patient's condition so automated EEG processing systems are increasingly being developed and used. Such systems are used to solve the problem of controlling the depth of anesthesia.

One of the most common devices is BIS-monitor allowing to measure the effect of the anesthetic and depth of sleep by EEG using bispectral analysis [1],[3],[4]. BIS-index is a complex parameter consisting of combination of feature measured in time, frequency domain and higher order spectral parameters.

To solve the problem of control of the anesthesia depth the frequency algorithms are used. Analysis of the spectral power of signals is important because the signal frequency change is associated with the change of EEG activity and hence the pattern of brain activity during anesthesia. Spectral edge frequency (SEF) is the one of the most common features to to quantify the EEG. SEF is the frequency of the right edge of the EEG spectrum below which the total capacity of all the frequencies makes a particular percentage (95%, 90%, 50% or medium frequency MF) from the total capacity of EEG [1],[2],[5].

There are various algorithms to assess the anesthesia depth based on calculation of entropy (spectral entropy, Shannon entropy, Kolmogorov entropy and others). The commercialization based on the time-frequency balanced spectral entropy belongs toDatex-Ohmeda, GEHealthcare [6].

The devices based on the principles outlined above are widely used in practical medicine. In accordance with established practice, the depth level of anesthesia can be estimated on a scale of 0 to 100. A value of zero indicates absence of electrical brain activity and a value of 100 - complete wakefulness. In anesthesia this value isusually from 10 to 80 [1],[7].

However, this problem cannot be considered as finally solved as the existing equipment in some cases gives erroneous readings. In this regard, the development of new algorithms for automatic EEG processing has priority.

Application of nonlinear dynamics approaches has highlighted new patterns and features of biological signals. This makes it possible to determine differences in the dynamics of the studied processes that were previously impossible to distinguish. In particular, to estimate randomness S.M. Pincus [8] suggested the use of the Approximate Entropy (ApEn) that has several properties that determine its significance in analysis of physiological time series: low sensitivity to the influence of noises and random artefacts, the possibility to do analysis on relatively few samples. Due to a number of theoretical features, the approximate entropy is best suited to assess the degree of irregularity and unpredictability in the data. Due to the above features ApEn can be used in practical real-time signal analysis systems [2],[5-7],[9],[10].

The aim is to study the possibility of practical application of the approximate entropy to analyse the patient's electroencephalogram signal during anesthesia.

II. Materials and methods

To study the properties of the approximate entropy the test signals were generated: harmonic, white noise and Henon map.

For the pilot study there was arrangement of real EEG records taken from patients during surgeries. EEG was recorded on a single channel via electrodes placed on the patient's forehead. As anaesthetic we used propofol.

Simultaneously with EEG recording to assess the depth of anesthesia the control device's (BIS-monitor) readouts were recorded. The device was connected to the same patient using a separate set of electrodes. At the initial and final stages of the surgery, the control device readings were recorded every 1 minute. In other periods - at 1 time every 3 minutes.

The EEGs were converted into digital form with sampling frequency of 500 Hz and using a 24-bit analog-to-digital converter.

In order to conduct pilot studies on optimization of the parameters of EEG analysis algorithms a separate set of signal fragments of 10 and 5 seconds each was generated for three patient's states during surgery. The readings of the BIS-monitor corresponding to the state of deep anaesthesia are 15-25 a few minutes after administration of the anestheticIn light anesthesia, a few hours after applying of anesthetic, the BIS values are 55-65. State of recovery after general anesthesia is indicated by values equal to 85-95.

42 10-second fragments of the three states (126 fragments of total 1260 seconds long) were selected.And 48 5-second fragments of the three states (144 fragments of total 1440 seconds long) were selected.

A. Approximate entropy

The approximate entropy can be calculated as follows: First, set m – length of the analysed sequences of readings and r – threshold defining the size of the phase-space cells. Suppose there is sampling $u(1)$, $u(2)$,…,$u(N)$, which is represented by equally distributed in time values of some physical quantity. The sequence of vectors is formed from it - $\mathbf{X}(1)$, $\mathbf{X}(2)$,…, $\mathbf{X}(N\text{-}m\text{+}1)$, defined as

$$\boldsymbol{X}(i) = [u(i), u(i+1), \dots, u(i+m-1)] \quad (1)$$

For vectors $\mathbf{X}(1), \mathbf{X}(2), \dots \mathbf{X}(i), \dots\ \mathbf{X}(N-m+1)$, $, 1 \le i \le (N-m+1)$ we calculate

$$C_i^m(r) = \frac{N_i}{N-m+1} \quad (2)$$

where N_i - number of such $\mathbf{X}(j)$, for which the condition$d[x(i), x(j)] \le r$ is met.

$$d[x(i), x(j)] = \max_{k=1,2,\dots,m}(|u(i+k-1) - u(j+k-1)|) \quad (3)$$

As appears from (3) $d[x(i), x(j)]$ represents the distance between vectors $\mathbf{X}(i)$and $\mathbf{X}(j)$ that is defined as the maximal difference of the corresponding scalar components.

Calculate

$$\Phi^m(r) = \frac{1}{(N-m+1)} \sum_{i=1}^{N-m+1} \ln(C_i^m(r)) \quad (4)$$

Determine the approximate entropy as

$$ApEn(m, r) = \lim_{N\to\infty}[\Phi^m(r) - \Phi^{m+1}(r)] \quad (5)$$

In practice the incoming signal has a limited length, so:

$$ApEn(m, r, N) = [\Phi^m(r) - \Phi^{m+1}(r)] \quad (6)$$

The size of phase-space cell r can be both a fixed value or calculated depending on the amplitude or mean-square deviation (MSD) of the signal.

S.M. Pincus [3] in his paper states that if m=1 or m=2 and value r changes from 0.1*MSD to 0.25*MSD then good statistical confidence of theapproximate entropy estimation is provided.

Parameters approximate entropy are selected by the researcher depending on the input data [4-9].

B. Criterion J

Criterion J was used as a value illustrating the difference degree of any two states.

$$J_{1,2} = \frac{|m_1 - m_2|^2}{S_1^2 + S_2^2} \quad (7)$$

where $m_1$and m_2 – mean values of the calculated parameter for some two states; S_1^2 и S_2^2 – variance estimates of this parameter for these. The high discriminating power of the analyzed parameter, the higher values Criterion J takes up.

The methods were simulated and studied in programming environment MATLAB.

III. Results

Model experiments allowing selecting the basic parameters of the approximate entropy were done. Harmonic signal, white noise and Henon map were used as test signals.

First, the effect of the tested fragment length on the values of approximate entropy ApEn was studied. For the test signals with duration of N=100, 1000, 2000 samples we obtained dependence of the approximate entropy to parameter m. In this case, r=0.2 as the most frequently recommended value [4-9].

Fig.1 and 2 show that for the harmonic signal ApEn decreases drastically during the transition to the first sample and then goes to zero fast. With increasing N the values ofapproximate entropy remain unchanged. The same stable pattern can be observed for Henon map. The ApEn values in this case decreasegradually to zero regardless of the fragment length. For white noise, the increased length of fragment N leads to a slower decline of the approximate entropy curve.

Increasing of the fragment length to N=2000 affects only the ApEn curve for white noise: during transition from m= 0 to m= 1 its values are changed slightly.

Besides the effect of threshold value r on *ApEn (2) (*value of ApEn for m=2*)* estimation was studies. The fragment length is set equal to 2000. From Fig. 3 it can be seen that for white noise (dotted line) ApEn value grows rapidly and reaches the maximum at r=0.15,...,0.2, then slowly decreases. For a sine wave (solid line),the approximateentropy is maximal when r=0.1 then decreases rapidly. ForHenonmap (dashed line),the ApEn values remain practically unchanged with increasing r.

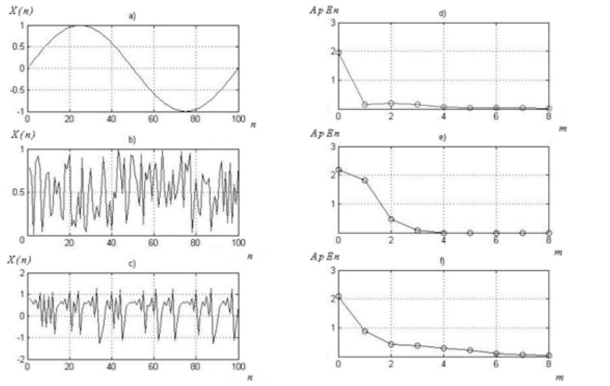

Fig. 1. Simulation signals and dependencies of the approximated entropy on m, number of samples of signals N=100: a, d –harmonic signal; b, e –white noise; c, f –Henon map

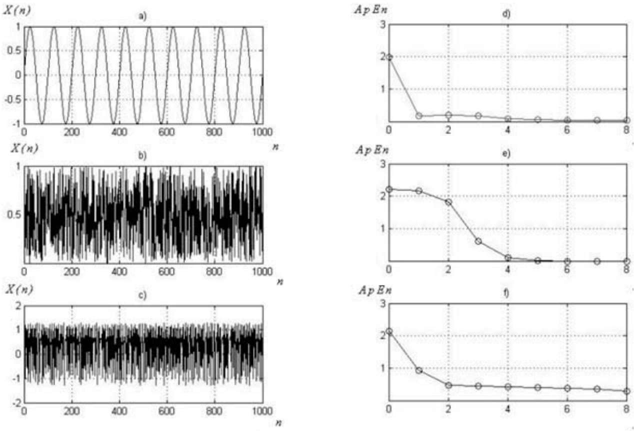

Fig. 2. Simulation signals and dependencies of the approximated entropy on m, number of samples of signals N=1000: a, d – harmonic signal; b, e – white noise; c, f – Henon map

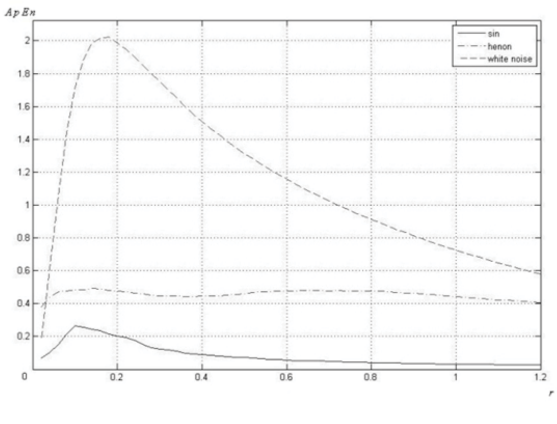

Fig. 3. Change of the approximated entropy value in relation to parameter r for simulation signals for m=2

According to the results of the model experiments it was stated that for white noise length N=1000 is optimal since with increasing up to N=2000 no significant differences were found. To analyse the periodic signals the fragments of shorter duration can be used. Threshold value r varies depending on the type of signal. Optimal value of r varies from 0.15 to 0.2 for white noise. For harmonic signals themaximal ApEn value can be observed at r=0.1.

Using the sampled real EEG records, the experiments were carried out that allowed selecting parameters m, N of the approximate entropy to ensure the best distinguishing of the anaesthesia stages. Fig.4 illustratesthe10-second electroencephalogram fragments recorded during the surgery from a patient for three different states (BIS=20, BIS=60, BIS=90).

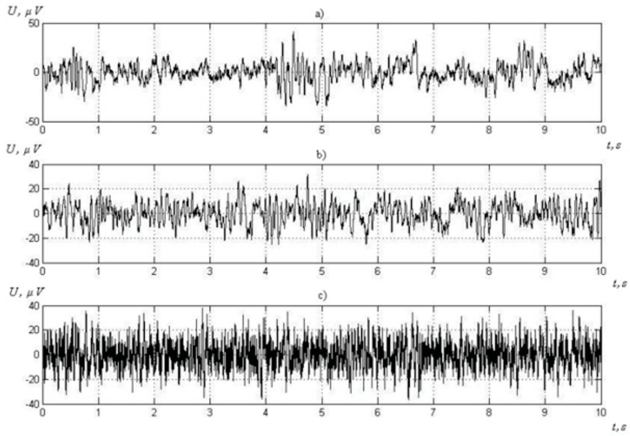

Fig. 4. Examples of 10-sc EEG fragments for three different states: a - BIS=20, b - BIS=60, c - BIS=90

As an example, Fig. 5 shows the dependencies of the approximate entropy on m for three states. As it can be seen the values of absolute entropy *ApEn(0)* for them are practically equal. If m=1 or m=2 it is possible to see evident differences in the values of the approximated entropy. For example, if m=2 ApEn value for deep anaesthesia (BIS=20) is 0.68, for the state of light anaesthesia (BIS=60) – 0.90, for the state of wakefulness (BIS=90) 1.99.

The pattern of change of the curve for state BIS = 90, similar to the curve changes for white noise (Fig. 2e). It follows that in wakefulness the random components are the most pronounced in the EEG signal. The dependences of the approximated entropy change for BIS= 60 and BIS=20 have a similar pattern - a sharp decline for m=1 and then a gradual decline. This course of the curve is close to ApEn for the harmonic signal that indicates the presence of pronounced quasiperiodic components in the EEG signal for the anesthesia state.

The values of the approximate entropy at m=2, r=0.2 and with 10- and 5-second fragments were analysed.

Fig. 6 illustrates the distribution of the approximate entropy values for 5-second EEG fragments.

When comparing the states corresponding readings BIS=20 and BIS=60 with 10-second fragment of criterion $J_{20,60} = 0.036$,, these states are almost indistinguishable. When comparing BIS=20 and BIS=90, the distinguishing has improved slightly, $J_{20,90} = 0.888$ but this is not enough for significant recognition of two states. When reducing the duration of the fragments to 5 seconds Criterion J takes value $J_{20,60} = 0.199$ and $J_{20,90} = 3.149$, which indicates better recognition of the compared states.

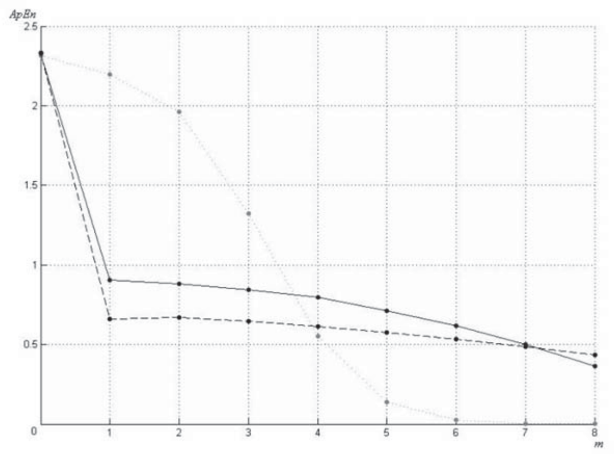

Fig. 5. Dependencies of the approximated entropy on m: dashed line - BIS=20; solid line - BIS=60; dotted line - BIS=90

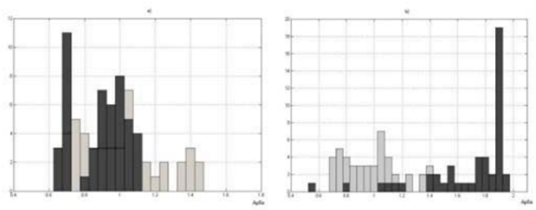

Fig. 6. Distribution of the approximated entropy values a) BIS=20 (light grey) and BIS=60 (dark-grey), b) BIS=20 (light grey) and BIS=90 (dark-grey), the duration of the fragments is 5 seconds

This analysis shows that recognition of the adjacent states of anesthesia is reasonable to perform at parameters *m*=2 и *N*=2500 (5-sec EEG records). At the same time the significant distinction by selected parameter *m*=2 can be achieved only when comparing the extreme states (BIS=20 and BIS=90).

IV. Discussion

The study examined the characteristics of the entropy description of different model signals. It was found that the influence curves of the approximate entropy for a harmonic signal and Henon map do not depend on the fragment duration. While for white noise the duration of the fragment matters.

It was found that the change in the parameter *r* did not affect the approximate entropy value for Henon map. At the same time its influence is considerable for white noise: with increasing *r* ApEn increases quickly to 2 then decreases slowly to zero. For the harmonic signal the pattern of changes is the same but they are slight.

According to the results of the model experiments N=1000 is optimal.

The optimum parameters to calculate of the approximate entropy for EEG at the record length 5 sec: *m*=2, *r*=0.15, *N*=2500 sample.

The use of optimal parameters for ApEn allowed to distinguish the states corresponding to BIS=20 and BIS=90 ($J_{20,90} = 3.149$). When comparing the states corresponding readings BIS=20 and BIS=60 J is 0.199. That indicates that it is impossible to recognition these states using ApEn. The recognition of the interstate states requires introduction of additional entropy parameters, which is the subject of further studies. The ability to recognize the extreme states allows discussing the prospects of the use of the approximate entropy for the purpose of recognition of the stages of anaesthesia depth.

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