NATIONAL AVIATION UNIVERSITY
INSTITUTE OF AERONAVIGATION

RADIO-ELECTRONIC COMPLEXES DEPARTMENT

RADIO-ELECTRONICS DEPARTMENT

IEEE UKRAINE SECTION JOINT SP/
AES CHAPTER (KIEV)

STATISTICAL METHODS OF SIGNAL AND DATA PROCESSING (SMSDP-2010)

PROCEEDINGS
OCTOBER 13-14, 2010 KIEV, UKRAINE

Publishing of National Aviation University «NAU-Druk»
Kiev 2010

UDC 621.391: 519.2 (063)

Матеріали конференції складаються із тез доповідей науковців з Іспанії, Мексики, Польщі, України, Росії та ін.

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Statistical Methods of Signal and Data Processing (SMSDP-2010): Proceedings. Kiev, Ukraine, October 13-14, 2010 / General Chairman I. Prokopenko. – Kiev: National Aviation University "NAU-Druk" Publishing House, 2010. – 180 p.

ISBN 978-966-598-662-1

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The materials presented can be used in further scientific and academic process at universities and colleges, are of interest both for the general reader and professionals.

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ISBN 978-966-598-662-1

International Conference on

STATISTICAL METHODS OF SIGNAL AND DATA PROCESSING (SMSDP-2010)

October 13-14, 2010 Kiev, Ukraine

ORGANIZED

by IEEE Ukraine Section Joint SP/AES Chapter (Kiev) and National Aviation University – Radio-electronic Complexes Department and Radio-Electronics Department

OBJECTIVES AND GROUNDS

The Conference is planned to be a forum of ideas exchange and results discussion in the field of methods, algorithms and means of data and signal processing. Submissions that contain novel results is signal detection, parameter estimation, and other kind of statistical processing of signals and data in telecommunication, remote sensing and information systems are welcome.

SESSIONS

1. Statistical models of signals and fields.
2. Detection of signals. Signal and interference parameters estimation.
3. Signal and data processing in remote sensing.
4. Discrete signals processing in telecommunication systems.
5. Data and signal processing in information systems.

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Approximate entropy of real and simulated electroencephalogram

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bstract **– The new nonlinear measure of signal's properties – pproximate entropy (ApEn) – is utilized for ectroencephalogram (EEG) processing. The difference between eal and simulated EEG signals from healthy and sick persons is vestigated and totally 19 signals for each class were used to lculate average ApEn. The results showed applicability of the EG model for simulating the EEG signal for healthy person.**

Keywords – entropy; approximate entropy; EEG analysis; EEG imulation

I. Introduction

Electroencephalography is widely used in modern europhysiology, neuropathology and psychiatry. The brain, ke other electrically active tissues and organs in a state of xcitation is a source of time-varying electromagnetic field. lectrical brain activity is of magnitude of microvolts and ould be registered using surface electrodes on the scalp with pecial highly sensitive amplifiers. Analysis of ectroencephalogram (EEG) is of great importance for iagnostics of different brain diseases and for evaluating the ate of normal brain.

There are many mathematical methods to analyze EEG gnals to obtain useful information about functioning of the ain. To add more efficiency and versatility to diagnostic ocedure, the new methods are being developed. For having e possibility to verify the methods before using them for alyzing real signals, the simulated EEG signals are often sed [1]. This allows testing the methods in various conditions d seeing the results of application to signals with different haracteristics.

Typically EEG signal is analyzed in the frequency domain sing Fourier transform. However, neural system demonstrates ome types of nonlinear and chaotic behavior, making ppropriate application of nonlinear dynamics methods to EEG gnal. One of recently developed method to analyze iomedical signals is entropy analysis [2, 3]. Entropy was efined in thermodynamics to describe the state of gas or liquid ystems and the probability distribution of molecules. This ethod is considered as promising tool to investigate the onlinear and chaotic characteristics of brain activity.

The aim of this work is to evaluate entropy characteristics f real and simulated EEG signals for different states of the rain. In the first part the basics of signal's entropy estimation are given. In the second part the experimental results are presented and then some conclusions are made.

II. Approximate Entropy of EEG

A. *General Considerations*

Entropy has been adapted to the information theory by Shannon as a measure of the information contained in signals. When entropy is used in signal analysis, it is considered describing irregularity, complexity and unpredictability characteristics of a signal [2].

Approximate entropy (ApEn) is an estimate of real entropy and the parameter of invariance and independence, which assesses dominant and subdominant patterns in data and provides a new data sequence which is difficult to define with distinct features. ApEn determines total number of time periods with similar properties, which falls within the range of complexity or irregularity of data values. Basically ApEn is modified Kolmoghorov-Sinai entropy, which was developed for calculations of biological patterns of signals in the presence of white noise. Approximate entropy is also considered as a measure of predictability of future amplitude values of EEG, based on knowledge of previous amplitude values. Maximum entropy of completely random data set depends on the length of data set and the number of previous values used to predict these values. A low value of ApEn reflects a high degree of regularity while a random signal has a relatively higher value of ApEn. Several studies have shown that the approximate entropy is a useful tool for determining the depth of anesthesia and can be compared with other EEG parameters such as bispectral spectral index and cutoff frequency.

B. *ApEn Algorithm*

Approximate entropy algorithm was first published in 1991 [3, 4]. For a sampled data $\{x(n)=x(1),x(2),...,x(N)\}$, where N is the length of the signal, two parameters are to be defined first: m, the embedded dimension of the vector to be formed and r, a threshold that serves as a noise filter [5].

Computation of ApEn consists of following steps.

1) Form m-vector sequence $X(1)$,..., $X(N-m+1)$ defined as:

$$X(i) = [x(i), x(i+1), \ldots, x(i+m-1)],$$
$$i = \overline{1, N-m+1}$$

These vectors represent the sequence of EEG values of length m, beginning from i-th sample.

2) Determinate the distance between $X(i)$ and $X(j)$, $d[X(i), X(j)]$ as maximum value of absolute difference between corresponding scalar components:

$$d[X(i), X(j)] = \max_{k=1,2,\ldots,m} |x(i+k-1) - x(j+k-1)|$$

3) For given $X(i)$ calculate the number $N^m(i)$ of elements j $(j = 1, 2, \ldots N-m+1,\ j \neq i)$, for which the condition holds: $d[X(i), X(j)] \leq r$. Then for $i = 1, 2, \ldots N-m+1$ calculate

$$C_r^m(i) = \frac{N^m(i)}{N-m+1}.$$

Here $C_r^m(i)$ is measure of occurring frequency of similar m-length patterns with tolerance r.

4) Calculate the sum of logarithm of all $C_r^m(i)$:

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

5) Increase the dimension from m to $m+1$ and repeat steps 1-4, calculating $C_r^{m+1}(i)$ and $\phi_r^{m+1}(i)$.

6) Find ApEn as:

$$ApEn(m, r, N) = \phi_r^m(i) - \phi_r^{m+1}(i).$$

III. Experimental Results

In this work real and simulated EEG signals were used. Real signals were recorded using Galileo Planet 200 computerized electroencephalograph. To simulate EEG signals the model described in [1] was used. The task of experimental part was to compare the entropy for two different types of real and simulated signals: from healthy and sick person. Signal from sick person was EEG from patient with epilepsy with right side central-temporal spikes. Totally 19 EEG signals were used for each case.

Real EEG signals used in this work are presented on Fig. 1 (for healthy person) and Fig. 3 (for sick person) and corresponding simulated signals are shown on Fig. 5 and 7. On Figures 2, 4, 6 and 8 the time dependencies for ApEn for real EEG from healthy person, real EEG from sick person, simulated EEG for healthy person and simulated EEG from sick person respectively are presented. In Table I the averaged value of approximate entropy is shown for four classes of EEG signals.

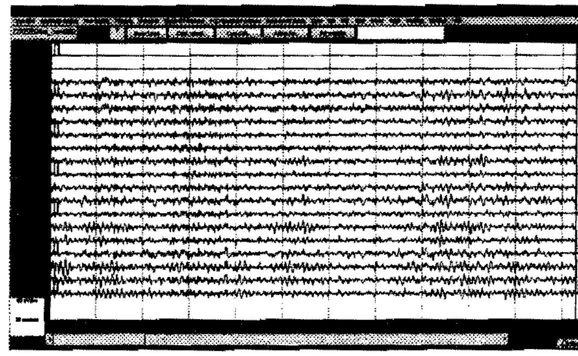

Figure 1. Real EEG signal from conditionally healthy person

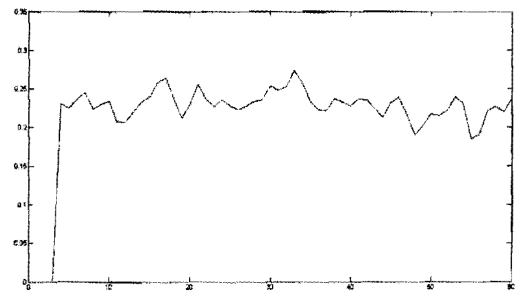

Figure 2. Time dependence of approximate entropy for real EEG signal fr conditionally healthy person

Figure 3. Real EEG signal from sick person

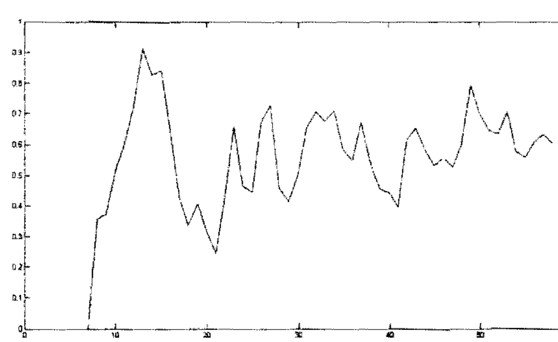

Figure 4. Time dependence of approximate entropy for real EEG signal sick person

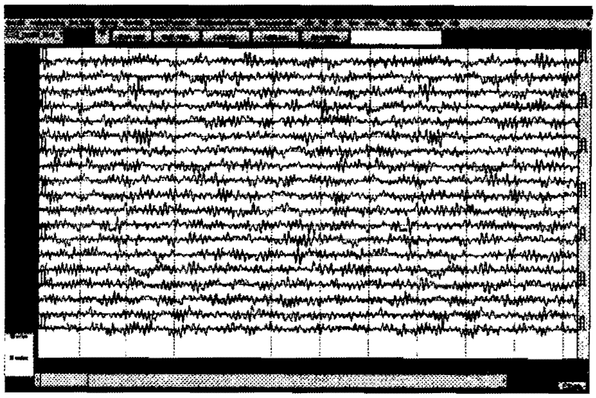

Figure 5. Simulated EEG signal for conditionally healthy person

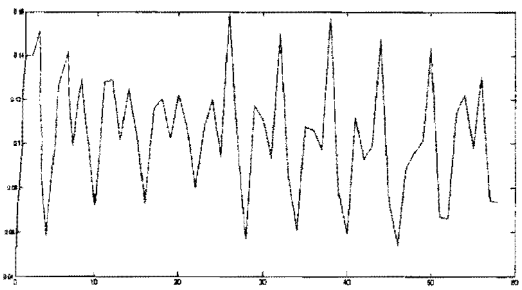

Figure 6. Time dependence of approximate entropy for simulated EEG signal for conditionally healthy person

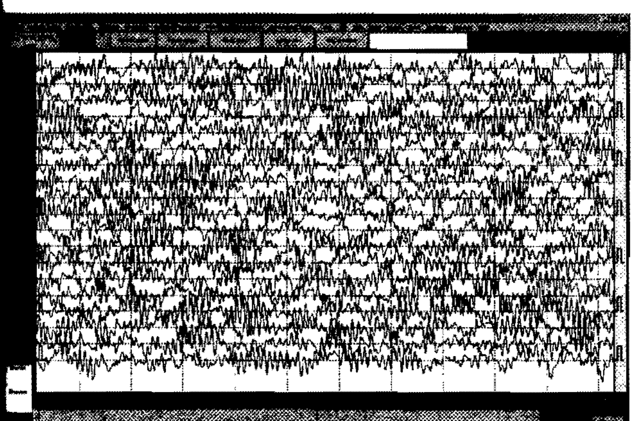

Figure 7. Simulated EEG signal for sick person

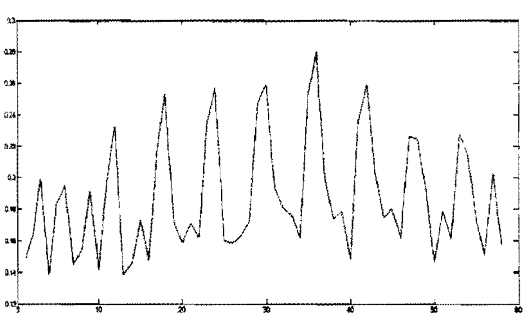

Figure 8. Time dependence of approximate entropy for simulated EEG signal for sick person

TABLE I. AVERAGED APPROXIMATE ENTROPY

Signal	Entropy value
Real signal from conditionally healthy person	$0,2113 \pm 0,1250$
Simulated signal from conditionally healthy person	$0,1844 \pm 0,0276$
Real signal from sick person	$0,5436 \pm 0,2266$
Simulated signal from sick person	$0,1129 \pm 0,0235$

IV. DISCUSSION

As can be seen from Table I, entropy value for real signals for healthy and sick person are different, thus this parameter in principle can be used for discrimination between the brain states. But taking into account the value of standard deviation it can be concluded that the values of entropy are rather scattered around the mean value. To derive the measure with less scattering the modification of algorithm is needed, and possible ways are increasing duration of signal part for which entropy is calculated or adjusting tolerance parameter.

After comparing entropy values for real and simulated signals from healthy person it can be seen that the mean values are generally the same: approximately 0.21 for real signal and 0.18 for simulated. But the range of variation is three times larger for real signal than for simulated signal: ± 0.12 vs. ± 0.03. This could mean that time dependence of EEG entropy is not stable and smooth for chosen set of parameters. To decrease the variation of entropy value further tailoring of tolerance and embedded dimension is needed. Overall conclusion to be made after experiments is that huge work is needed to be done for selecting parameters of entropy calculation to achieve reliable results which allow distinguishing EEG belonging to different classes.

V. CONCLUSIONS

This paper utilizes approximate entropy as a nonlinear signal processing method for EEG processing. The simulated and real EEG for epileptic and healthy persons was analyzed. The values of ApEn of EEG for healthy person are found to be the same that prove applicability of the model used in this work to simulating such signals.

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