Analiza sygnału EEG za pomocą entropii wieloskalowej

Multiscale entropy analysis of EEG signals

Jacek Kapica*, Jolanta Masiak**, Andy R. Eugene***, Katarzyna Ziniuk**

*Department of Electrical Engineering and Measurement Systems, University of Life Sciences in Lublin
** Department of Psychiatry of Medical University of Lublin
*** Institute for the Study of Child Development, Department of Pediatrics, UMDNJ-Robert Wood Johnson Medical School

Streszczenie

Artykuł przedstawia nową metodę analizy sygnałów biologicznych, zwaną entropią wieloskalową i jej zastosowanie w psychiatrii. Jako metoda oparta na entropii, mierzy ona stopień złożoności danego sygnału. Cecha wieloskalowości daje możliwość oceny funkcjonowania ludzkiego mózgu w różnych zakresach częstotliwości sygnału EEG. Złożoność czynności bioelektrycznej mózgu może odzwierciedlać zdolność systemu do reakcji na zmiany zachodzące w otoczeniu i dlatego może być markerem choroby.

We wstępie zaprezentowano klasyczną definicję entropii oraz entropię wieloskalową. Następnie przedstawiono trzy przykłady zastosowania entropii wieloskalowej w psychiatrii: zmiany krzywej entropii wraz z wiekiem, w chorobie Alzheimera oraz do wczesnej diagnostyki autyzmu u niemowląt.

Słowa kluczowe: entropia wieloskalowa, EEG, złożoność, diagnostyka

Abstract

The paper presents a novel way to analyze biological signals using an signal processing technique, called multiscale entropy and its applications in psychiatry. As an entropy-based algorithm, it measures degree of complexity of a given signal. The multiscale feature enables to assess the performance of the human brain over the various frequency bands of the electroencephalography (EEG) signal. The complexity of the EEG signal may reflect the ability of the system to react to the changes in the surrounding environment and thus be a marker of disease.

In this paper, the classical definition of entropy and multiscale entropy (MSE) is presented. Then three examples of the application of the MSE in psychiatry are shown, namely changes of the MSE curve with age, as well as in Alzheimer's disease and for early diagnosis of autism in infants.

Keywords: multiscale entropy, EEG, complexity, diagnosis

1. Introduction

Electroencephalography (EEG) is widely used as a non-invasive diagnostic tool in psychiatry. This is based on assessment of electrical potentials measured on the scalp of the head which is a result of the electrical activity of the brain neurons. The spectrum of the signal can traditionally be divided into five bands (delta, theta, alpha, beta, gamma), which are related to various tasks performed by the brain. Malfunction of that organ caused by missing or improperly functioning interconnections between neurons or brain regions are reflected in the EEG signal [1]. One way of comparing signals between two groups (for example healthy and ill people) is using a procedure called multiscale entropy, which has been described in [2] and has demonstrated its usefulness in analysis of biological signals, including EEG.

2. Entropy and a concept of multiscale entropy

Entropy can be viewed as a way to measure complexity or information content of a given time series (signal). Thus, it is expected that improper functioning of a particular signal source (human brain for example) will be reflected in lower information content in that signal. Shannon entropy is classically defined as [2]:

$$H(X) = -\sum_{x_i \in \Theta} p(x_i) \log p(x_i) = -E[\log p(x_i)] \quad (1)$$

where X represents a random variable with a set of values Θ and $p(x_i)$ is a probability that X will be equal x_i. For a time series representing output of a stochastic process, joint entropy is calculated. A major disadvantage of this definition of entropy is that its value strongly depends on the length of the time series.

In 2000, Richman and Moorman proposed a new algorithm for the calculation of entropy, called sample en-

tropy (S_E) [3]. S_E is precisely equal to the negative of the natural logarithm of the conditional probability that sequences close to each other for *m* consecutive data points will also be close to each other when one more point is added to each sequence [2]. When Entropy is calculated in the previously stated method, it is less dependent on the length of the time series.

One of disadvantages of calculating sample entropy, only for the original time series, is that it does not take into consideration information content over various frequencies. In the EEG analysis it means that not all of the frequency bands are represented in the analysis. Therefore, Costa, Goldberger and Peng in 2002 proposed to calculate S_E for multiple scales [4]. The higher scales are calculated according to equation:

$$y_j^{(\tau)} = \frac{1}{\tau} \sum_{i=(j-1)\tau+1}^{j\tau} x_i, \quad 1 \le j \le N/\tau \tag{2}$$

in which x_i is a data point of the original time series, y_j is a data point of the resulting time series and τ is the scale of the signal.

In other words, the higher scales are obtained by dividing the original time series into non-overlapping windows of the length equal to τ and then calculating the arithmetic average of the data points for each of the window. The averages become data points of the time series at the scale τ. The original signal forms scale one.

The procedure of calculating higher scales gives a possibility to measure complexity of the given signal over multiple frequencies. Results of the analysis are usually presented in a graphical form as a plot of S_E values versus scales. Moreover, they are used to compare two or more signals generated by different systems or the same system under different conditions. If for majority of the entropy scales for one signal is higher than that of the other signal, then the first signal is considered to have higher complexity. In EEG, higher entropy over a range of scales may be related to changes in functioning of the brain in a particular frequency band. This property is what makes this procedure a promising tool to better understand and even diagnose psychiatric disorders using multiscale analysis.

The following section will present examples of application of the multiscale entropy (MSE) analysis of EEG.

3. Applications of the MSE in EEG analysis

3.1. Age-related variation in EEG

In [1] Takahashi and others presented relationship between age and MSE values calculated for the EEG signal. For analysis, artifact-free data samples of 20 seconds before and after photic stimulation were taken from two groups of people:

- 13 healthy younger people (6 male, 7 female, average age 29.2 years, range 21-34 years),
- 15 healthy older people (7 male, 8 female, average age 64.5, range 56-71 years).

The results show that the complexity increases after photic stimulation in young subjects but not in group of older people. This shows good cortical response to stimuli for young people and is consistent with hypothesis of complexity loss with age [5].

3.2. EEG complexity in Alzheimer's disease

Mizuno and others have studied influence of the Alzheimer's disease (AD) on signal complexity applying the MSE method [6]. They analyzed 60 seconds of EEG signal collected from group of people diagnosed with Alzheimer's disease (average age: 59.1, range 43-66, average onset of illness at 56.5 years - range 43-64) and control group (average age: 57.5, range 51-67 years).

The authors have observed less complexity in the AD group in frontal areas for lower scales as well as higher complexity in larger scales in all brain areas. The later was highly correlated with cognitive decline. The results show that the proposed method may serve as a complimentary approach to characterize and understand abnormal cortical dynamics in Alzheimer's disease.

3.3. Modified MSE to diagnose autism spectrum disorder (ASD)

Bosl and others have used a modified algorithm of the multiscale entropy to develop a biomarker for autism spectrum disorder risk [7]. The modification lies mainly in the way the similarity between data points are defined when calculating the sample entropy and details of the procedure can be found in [8].

The authors have collected EEG recordings from 79 infants (6 - 24 months of age), 46 of which were at high risk of ASD and 33 controls. The criterion of the inclusion to the groups was based on the fact whether the child had an older sibling with confirmed ASD (the high risk group) or the older sibling did not have ASD.

According to their results, infants with high risk for autism have a different modified MSE curve than healthy controls. The biggest differences are observed between the age of 9 to 12 months, especially for boys. The classification accuracy is almost 100% for boys at the age of 9 months. Therefore the modified MSE seems to be a useful biomarker for early diagnosis of ASD risk.

4. Summary

The use of the sample entropy method instead of classical Shannon's entropy gives higher independence of the result from the length of the sample, making it easier to compare complexity of different signal.

The multiscale entropy algorithm presents potential usefulness to better understand the phenomena lying under various psychiatric disorders. It gives a possibility to distinguish between signals coming form different systems or the same system under different input conditions. Its multiscale nature offers a possibility to investigate complexity of the signal over various frequency bands, which are connected to different functions of the human brain.

The complexity of the biological signals, including EEG, is connected with the ability of the living organism to adapt to ever-changing environmental conditions. Lower entropy value indicates lower complexity of the signal and can reflect lower ability of the system to function properly. This probably happens as a result of missing or unproperly functioning control mechanisms or connections between different parts of the system.

The presented method has a potential for being an easy, non-invasive tool to early diagnose some of the psychiatric disorders or groups of high risk of disorder. To achieve this goal more research needs to be done, with special attention paid to classifying algorithms and standarization of the patient examination.

References

1. Takahashi T. Cho R. Y. , Murata T., Mizuno T., Kikuchi M., Mizukami K., Kosaka H., Takahashi K., Wada Y. Age-related variation in EEG complexity to photic stimulation: A multiscale entropy analysis. Clinical Neurophysiology 120 (2009) 476–483.
2. Costa M., Goldberger A.L., Peng C.-K. Multiscale entropy analysis of biological signals. PHYSICAL REVIEW, 2005.
3. Richman J. S., Moorman J. R. Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circ Physiol. 278: H2039–H2049, 2000.
4. Costa M., Goldberger A. L., Peng C. K., Multiscale Entropy Analysis of Complex Physiologic Time Series. Physical Review Letters. (89) 2002.
5. Goldberger A.L.,Penga C.K., Lipsitz L.A. What is physiologic complexity and how does it change with aging and disease? Neurobiology of Aging 23 (2002).
6. Mizuno T., Takahashi T., Cho R. Y., Kikuchi M., Murata T., Takahashi K., Wada Y. Assessment of EEG dynamical complexity in Alzheimer's disease using multiscale entropy. Clinical Neurophysiology 121 (2010).
7. Bosl W., Tierney A., Tager-Flusberg H., Nelson C. EEG complexity as a biomarker for autism spectrum disorder risk. BMC Medicine 2011 9:18.
8. Xie HB, He WX, Liu H: Measuring time series regularity using nonlinear similarity-based sample entropy. Phys Lett A 2008, 372.

Correspondence address

Jacek Kapica,
Department of Electrical Engineering and Measurement Systems
University of Life Sciences in Lublin,
ul. Doświadczalna 50A, 20-280 Lublin
jacek.kapica@up.lublin.pl