Beta Wave of Sleep Electroencephalogram Analysis Based on Multiscale Sign Series Entropy

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***Abstract*-Sleep Electroencephalogram (Sleep EEG) detection and treatment can provide the basis for clinical diagnosis and treatment. According to the non-stationary random character of EEG itself, the paper proposed multiscale sign series entropy (MSSE) method and applied it to the state of sleep EEG analysis. Numerical results showed that, MSSE method can effectively differentiate awake period β wave and sleep stage β wave even if under the influence of the noise. The results show that the algorithm can aid in clinical diagnosis of sleep EEG.**

Keywords-sleep electroencephalogram; multiscale sign series entropy; clinical diagnosis

I. INTRODUCTION

When under the status of sleeping, because of shielding most of the interference, the brain is basically in the spontaneous activity state. But the brain activity is not in a simple "resting" state. On the one hand, sleep is not stable and can be divided into different sleep phase which meaning that the spontaneous activity of the brain is in different levels and in constantly spontaneous conversion. On the other hand， paradoxical sleep is believed to be the process of learning and memory in the brain to consolidate, during sleep. But dreams usually appear in this stage of sleep, when brain waves are similar to the waking state, it indicating that the brain is in active state active. So it provides a good platform for brain， cognition， brain function and structure of brain [1-2]。In the past decades, sleep studies mainly focus on the factors of how to explore the different influence factors of sleep and how to affect other physiological and cognitive function. These studies identify some of the main factors of sleep regulation, such as the constant driving force in sleep, sleep inertia and circadian rhythm [3-4]. Lo and Ivanov studied the complexity of sleep rhythm transient transformation. Based on the statistics of large amount of sleep rhythm data analysis, they discovered that sleep interval and the length of time of awakening interval distribution accords with different probability models. The sleep interval follows exponential distribution and the awakening of interval follows the power-law distribution [5]. This surprising finding suggests that sleep is not a traditional stationary process. Sleep rhythm conversion is not random, but is in line with certain regularity. Sleep complexity is not only reflected in time (sleep rhythm transient transformation), but also reflected in the space and depth of sleep. Studies have shown that sleep is not a global state of the brain but localized. Different brain regions at the same time may be in varying degrees of sleep (or active) state [6] which have relationship with sleep disorders [7]. On the other hand, the traditional sleep depth staging will artificially be divided into six time discrete phase (sober, Phase I-IV sleep and paradoxical sleep period) according to R&K standard. And recent research indicates that this method is not detailed enough. In fact, it can be broken down into smaller, more homogeneous sleep period [8]. This conclusion can also be proved by some experimental researches [9].

At present, the study of sleep EEG has scale invariance method [10]. Combined with multiscale [11] and the symbol sequence entropy concept (sign series entropy, SSE) [12], multiscale sign series entropy was proposed. The algorithm was used to analyze sleep alpha component and wake alpha component of the EEG. From the viewpoints of the data length change, word length m change, noise effects, the influence to MSSE value of alpha wave on wake, sleep EEG is discussed. The numerical results show that this method can effectively detect the change of short-term α-wave in wake and sleep state.

II. METHOD OF MULTISCALE SIGN SERIES ENTROPY

Brain waves are records of surface potential changes when a lot of nerve cells are simultaneous changes in synaptic potentials, which synchronously causing cortical potential changes. So EEG is a time series obtained at a certain sampling frequency of potential changes. Analysis of EEG time series mainly study potential changes of two sample points. Supposing the time series of R (i), i = 1,2,3 ... N, R (i) represents the potential value of the i-th sampling time points.

Potential changes of EEG signals are non-stationary random. We represent potential change variation in three ways. There are three symbols representing the EEG changes direction.

$$x(i)=\begin{cases}0, & R(i+1)<R(i),\\ 1, & R(i+1)=R(i), \quad i=1,2,3\ldots N-1\\ 2, & R(i+1)>R(i),\end{cases} \tag{1}$$

x (i) = 0 indicates a potential decrease; x (i) = 1 indicates a potential change; x (i) = 2 indicates potential rise. Three symbols represent only three states in symbol sequence generated and numerical size does not make sense. Through symbolizing of the potential changes, it only retains the change of direction information. Specific symbolic process is shown in Figure 1 and Figure 2.

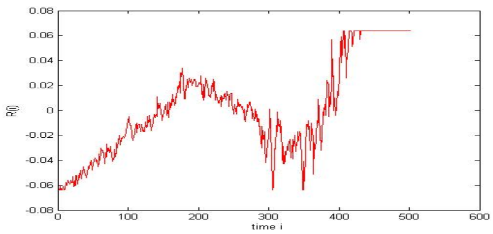


FIGURE I. POTENTIAL CHANGES IN EEG

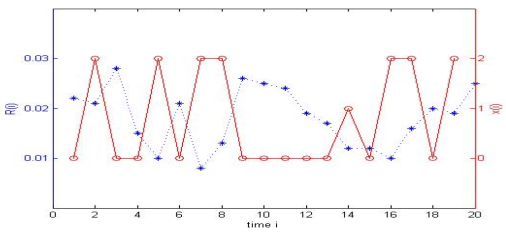


FIGURE II. SYMBOLIZING CONFIGURATION OF EEG

For symbolic direction signal, to reveal the law of timing and structure, we used the sliding window method to construct vector sequence (word width is m):

$$X(i)=[x(i),x(i+1),\ldots\ldots x(i+(m-1))],i=1,2,3\ldots\ldots N-m. \tag{2}$$

Vector X(i) represents the continuous change of direction. When the word is width m, continuously variable common species $M=3^m$ possible modes, the statistical probability of each mode appears:

$$p_j=\frac{N_j}{N-m},j=1,2,3\ldots\ldots M, \tag{3}$$

When m = 2, it will appear a total of nine kinds of modes as Figure 3. Each changes mode has a probability and the model probability is shown in Figure 3.

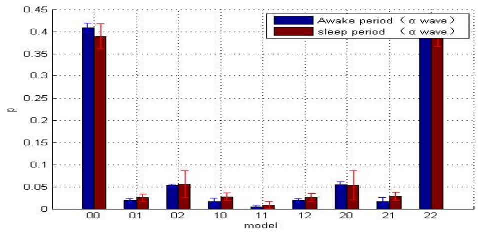


FIGURE III. STATISTICAL DISTRIBUTION OF MODES FOR ALL SAMPLES

where N_j is the number of the j-th modes appear, entropy is calculated as [18]:

$$SSE(m)=-\sum_{j=1}^{M}p_j\log_2 p_j. \tag{4}$$

Multiscale method for processing EEG time series is shown as follows:

Given a time series {x (1), ..., x (i), ..., x (N)}, to build a continuous sequence of t determined by the scale factor, the following equation is:

$$y^{(t)}(j)=1/t\sum\nolimits_{i=(j-1)t+1}^{jt}x(i), \qquad 1\le j\le N/t. \tag{5}$$

The scale factor t=1 of sequence y(j) is simplified as the original time series x(i). Each length scale of the time series is equal to the original sequence length divided by the scale factor. For each coarse-grained original time series, using SSE we can acquired the MSSE results of EEG.

III. NUMERICAL ANALYSIS

Using collected EEG to validate the algorithm, Figure 4 shows SSE results of four groups wake α component and four groups of sleep stage I alpha component while six consecutive segment data length is 500 points. The horizontal axis is the sample number of Group 1~4 beta component and group 1~4 beta component during wakefulness and sleep stage I. The vertical axis represents SSE results of each data segment. It can be seen that the result of the same object is very close to the adjacent data segments which shows that the method can get an effective characteristic parameter from the shorter data section.

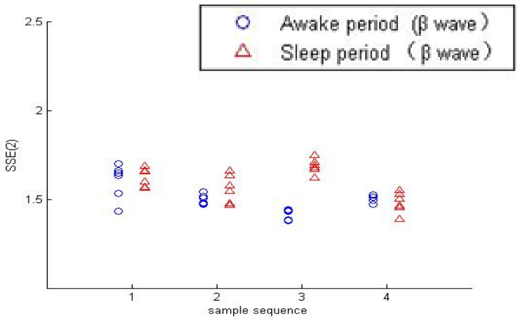


FIGURE IV. COMPARISON BETWEEN THE ADJACENT CONTINUOUS SHORT DATA SEGMENTS

In Figure 5(a), we used the mean and standard deviation respectively to describe 500 results of 4 samples during wakefulness beta component and sleep stage 1 beta component. When the data length was increased to 1000, 2000, 3000 points, the results are consistent with the short 500 point node, which shows that MSSE has the effectiveness on brain electrical signal and has a certain clinical practicability.

In Figure 5(b), it shows the influence of word length width m to the results of MSSE. The data length is 500. Under the condition of data length, if increasing the length width, pattern ($M=3^m$) will increase and it will lead to increase of SSE values. But in the analysis of the m=2~6 range, from Fig. 5 (b) we showed that the SSE can effectively distinguish the awake beta component and sleep beta component.

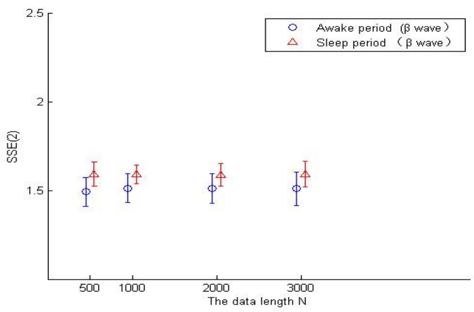
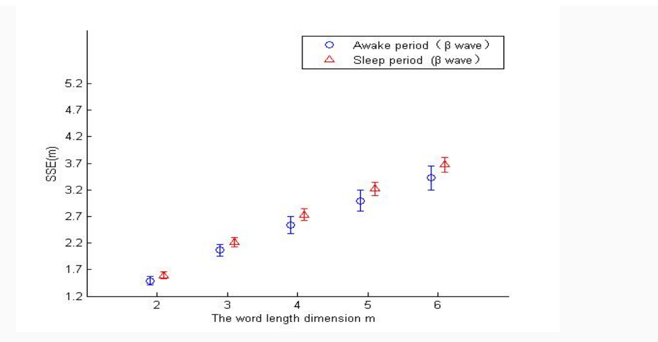


FIGURE V. (A): THE IMPACT OF THE DATA LENGTH N ON SSE



FIGUREV (B): THE EFFECTS OF WORD LENGTH DIMENSION M ON SSE

In order to study the influence of noise to the SSE value, we added noise to the collected EEG signal and deal with it with MSSE. We randomly took a group of wake beta component and sleep I beta component of the EEG signals with 2 ~ 10 sampling interval random white noise. That is, we add the noise on every 2 ~ 10 points in EEG signals respectively and do it with 20 times simulation experiments. Analysis of the data was shown in figure 6. Under the influence of noise, it can be seen that MSSE still distinguish between sleep beta component and wake beta component which showing that noise will not cause interference to MSSE.

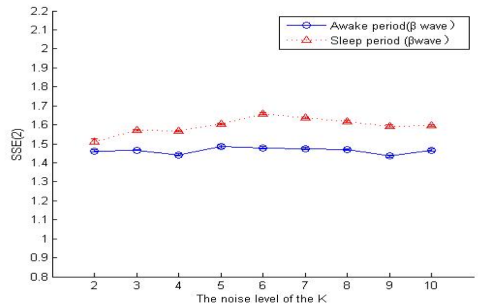


FIGURE VI. FTHE INFLUENCE OF RANDOM NOISE ON SSE

Using the multiscale processing, the signal sequence is coarse-grained according to the scale factor t. Then we analyzed each coarse-grained EEG signals with SSE algorithm and the results were shown in figure 7. It can be shown that MSSE can distinguish between the wake beta component and sleep EEG beta component. Figure 7 shows that, as the scale increases, the symbol sequence entropy synchronous decrease for wakefulness and sleep EEG, but the entropy values of sleep stage are always higher than the wake stage.

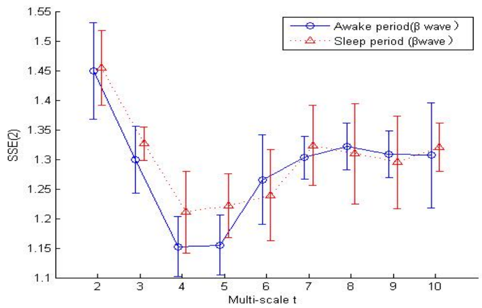


FIGURE VII. ANALYSIS OF THE SSE ALGORITHM AFTER THE TREATMENT OF MULTISCALE

IV. CONCLUSIONS

We proposed multiscale sign series entropy and applied to sleep EEG analysis. The paper studied the MSSE value changing according to the data length, word length dimension changes. Meanwhile, it was studied the influence of random noise to MSSE values on sleep EEG. The numerical calculation results show that MSSE is robust. The increasing of MSSE values means that the increasing probabilities of new mode during sleep and wakefulness are different. At multiple scales, increasing probability of new mode under sleep is always greater than wake state which showing that sleep condition has more signal complexity. It was shown that our proposed MSSE can distinguish the beta component of sleep and wake stage beta component of the EEG signals, which can assist the research of sleep staging.

ACKNOWLEDGEMENTS

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