Occupation stress analysis based on Multiscale sign series entropy analysis

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Abstract. With the rapid development of society and the economic globalization, organizations occur various reforms and system innovations, which makes people feel stressful increasingly. The pressure of long term excessive work causes occupation stress. The effect of occupation stress on health is aroused the whole society's concern. As Theorel said that "woke pressure is occupation stress that is popular in the whole world". Occupation stress is evolving as the new occupation hazard factor. The paper uses Multiscale sign series entropy analysis to analyse the occupation stress between nurses and students. Research shows that the occupation stress of nurses is higher than the students. So the occupation stress of the nurse is larger than the student. The algorithm can help clinical diagnosis.

Introduction

With the continuous development of our country modernization process, the workers of our country are facing competitive pressure increasingly. Occupation stress has became increasingly prominent, which greatly affects people's physical and mental health. Because of the occupation health problems caused by the occupation stress is very important. Mental increasing, new technology force workers to learn new method and time urgency, overtime working, irregular working, information overload, poor working atmosphere and continuous changes and so on to improve the mental load of workers and result in the stress response. The factors to nurses SCL-90 negatively correlated is psychological satisfaction, adequate confidence, peace of mind and job satisfaction($P<0.01$); positive correlation factor is working conflict, psychological needs, physical environment, job hazards, working load, working prospects, lacking of promotion opportunities, lacking of opportunities and support. ($p<0.05$)[1] .

Occupational stress known as occupation stress mainly refers to that is in a certain occupation condition. when an imbalance between the objective and subjective response needs, professionals will be some psychological changes and pressure. At the same time, when their needs can not be met timely, the professionals will be function disorder. The main factors contributed to occupational stress includes increasing mental and new technology force workers to learn new methods, time urgency, overtime working, irregular working ,information overload, poor working atmosphere, continuous changes etc and increases mental workload to response.

At present, the study of EEG has scaled in variance method[2]. based on Combined with multiscale [3] and the symbol sequence entropy concept (sign series entropy, SSEA)[4], Multiscale entropy sequence of symbols algorithms have been proposed. In this paper, the complexity analysis method based on Multiscale Sign Series Entropy Analysis was used to calculate the complexity of the occupation stress of the nurses and the students. Which can be helpful to clinical diagnosis.

Multiscale Sign Series Entropy Analysis（MSSEA)

Analysis of EEG time series mainly study two sample points of potential changes. Each time the i corresponding to $R(i)$ (i = 1,2,3 ... N, $R(i)\ i = 1,2,3 \ldots N$)represents the potential value of the i-th sampling time points. Potential changes in EEG signals are non-stationary random. we represent potential change Variation in three ways. There are three symbols representing the EEG changes direction.

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

x (i) = 0 indicates a potential decreases; x (i) = 1 indicates a potential changes; x (i) = 2 indicates potential rises. three symbols represent only three states in Symbol sequence generated. The numerical size does not make sense. Through the potential of changes symbolic and Specific changes in the potential are a rough, Retaining only the change direction information.

For symbolic direction signal, To reveal the law of timing and structure, Using the sliding window method construct word width of m vector sequence:

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

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. Changes mode statistical distribution of all samples corresponds to a probability. Where N_j is the number of the j-th modes appear, calculating entropy :

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

Increasing multiscale entropy algorithm is based on the sequence of symbols entropy. using multiscale method to process EEG time series, the algorithm is: 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 i

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

The scale factor t=1 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. Symbolic computing symbol sequence entropy after the original EEG of multiscale can obtain multiscale Symbol sequence entropy.

Data Analysis

Using collected EEG to validate the algorithm, Figure 1 shows SSE results of four groups of nurse and four groups of student while six consecutive segment data length is 500 points. The horizontal axis is the sample number of Group 1~4 nurse and group 1~4 student. 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 a effective characteristic parameter from the shorter data section.

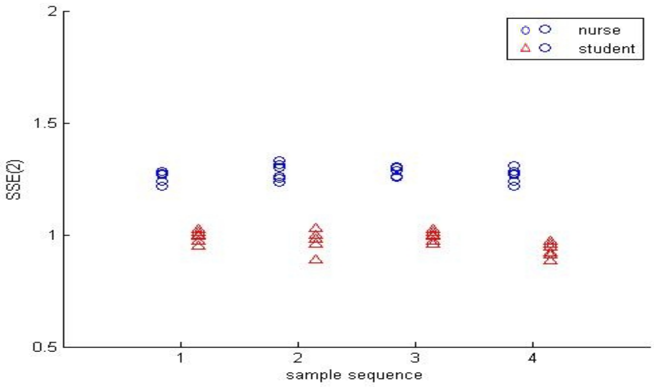

Figure 1: Comparison between the adjacent continuous short data segments.

In Figure 2, we used the mean and standard deviation respectively to describe results of 4 samples of 500 points during nurse and student. When the data length is increased to 1000,1500, 2000 points, the results are consistent with the short 500 point node, which shows that SSEA has the effectiveness on brain electrical signal and has a certain clinical practicability.

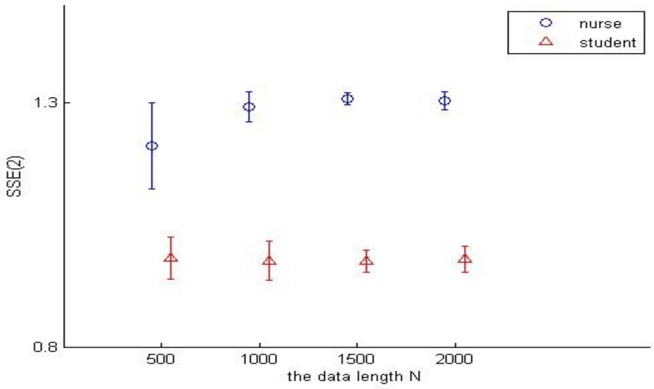

Figure 2: The impact of the data length N on SSEA

In Figure 3, it shows the influence of word length width m to the results of SSEA. The data length is 500. Under the condition of data length, if increasing the length width, pattern (M=3m) will increase and it will lead to increase of SSEA values. But in the analysis of the m=2~6 range, from Figure 3 we showed that the SSEA can effectively distinguish nurse and student.

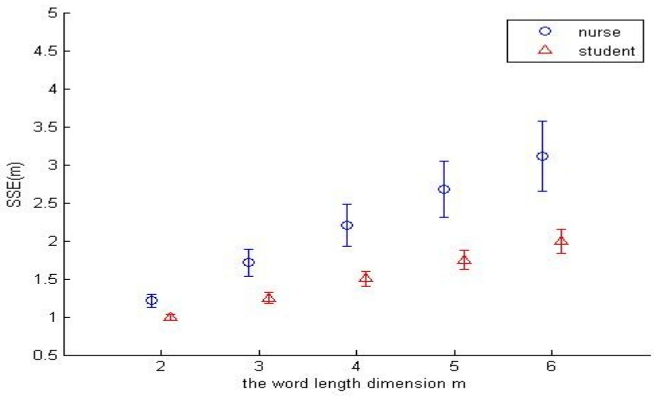

Figure 3: The effects of word length dimension m on SSEA

In order to study the influence of noise to the SSEA value, we add noise to the collected EEG signal. We randomly take a group of nurse and student of the EEG signals adding 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 4. Under the influence of noise, it can be seen that SSEA still distinguish between nurse and student which showing that noise will not cause interference to SSEA.

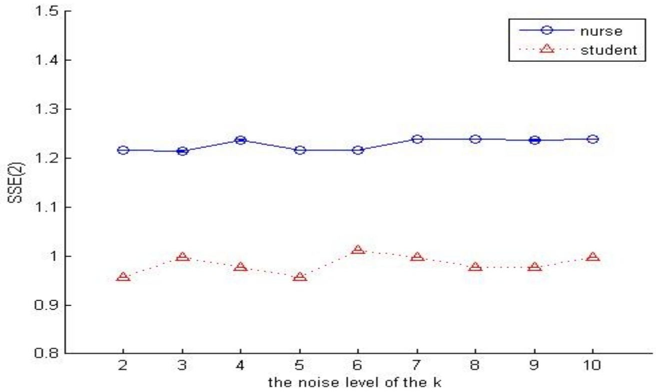

Figure 4: The influence of random noise on SSEA

The original data is disposed using the multiscale processing for the confirmed length sequence, the signal sequence is coarse-grained according to the scale factor t. Then we analyze each coarse-grained EEG signals with SSE algorithm and the results are shown in figure 5. It can be shown that MSSE can distinguish between nurse and student, Figure5 shows that, as the scale increasing, the entropy values of nurse is always higher than the wake stage.

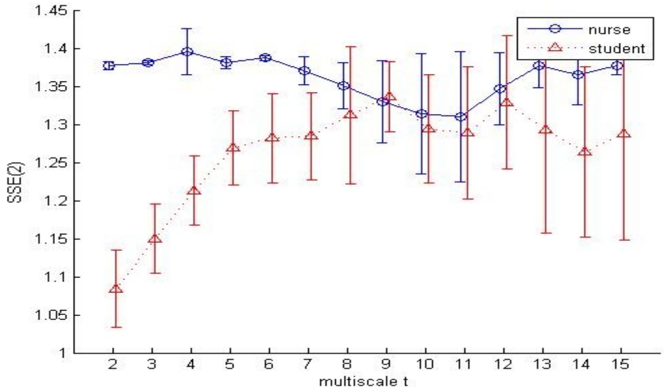

Figure 5: Analysis of the SSEA algorithm after the treatment of multiscale

Conclusion

We propose multiscale sign series entropy and apply it to EEG analysis. The paper studies the SSEA value change regulation according to the data length, word length and dimension changes. Meanwhile, it studies the influence of random noise to SSEA values on EEG. The numerical calculation results show that SSEA is robust. The paper also puts forward that combining multiscale with sign series entropy is used to research change regulation of EEG sign series entropy with the scale change. The increasing of SSEA values means that the increasing probabilities of new mode are different during the nurse and the student. Increasing probability of new mode under the nurse is always greater than student at multiple scales,. It illustrates that MSSE that our proposed can distinguish the nurse and the student of the EEG signals, which can assist the research.

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