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Electroencephalograph (EEG) Signal Processing Method of Motor Imaginary Potential for Attention Level Classification

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Abstract—**Research of visual attention is one of the important domains of psychology and neurophysiology. In this study, an attention related electroencephalograph (EEG) signal processing method was proposed to distinguish the different levels of people's attention during the imaginary limbs motor. There were two EEG feedback experiments (playing tennis and walking) to measure the different levels of visual attention. Three imaginary motor tasks (attention, inattention, and rest task) were performed with the flash stimulus displayed on the screen in the experiments. A nonlinear dynamics parameter of multi-scale entropy (MSE) was extracted from those EEG data recorded. According to the statistics analysis of 14 subjects, there was an obvious declining tendency of MSE with the level of attention declining, which validated the effectiveness of the proposed method to classify the visual attention level.**

I. Introduction

Biological signals are generated by physiologic system that operates across multiple spatial and temporal scales [1]. Time series generated by biological systems most likely contain deterministic and stochastic components [1]. The complexity of a biological system reflects its ability to adapt and function in an ever-changing environment [1-2].Thus, biological systems need to operate across multiple spatial and temporal scales and their complexity is also multiple scaled.

According to the non-linear behavior of the neurons and the ability of the brain to perform sophisticated cognitive tasks, we can infer that the brain may not be a simple stochastic system [3]. EEG signals have been extensively analyzed by linear and none linear methods [4]. These measures, such as Approximate Entropy and Sample Entropy (SampleEn), are based on single scale [2] and failed to describe the complexity of EEG time series in multiple scales [1]. Thus, these algorithms assign a higher value of entropy to pathologic time series while the presumed results are on the contrary and do not account for the feature of multiple scales of EEG [2].

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The MSE focuses on estimating the complexity of a signal by determining the information expressed on multiple time scales and it has been already used to analyze biological data. MSE analysis incorporates the interrelationship of entropy and scale, so the results are consistent with the consideration that both completely ordered and completely random signals are not really complex [1]. In addition, MSE also show that correlated random signals are more complex than uncorrelated ones. This method is more applicable to both physiologic and physical signal when compared to traditional complexity measures [1].

After we calculated the Power Spectrum of the EEG time series, we can not discriminate the attention level successfully. In this paper, we use the logarithm of MSE to handle the data of limbs motor imaginary potential in different attention states based on an EEG feedback system. According to the multiple scales trait of Motor Imaginary Potential, we hope to extract and classify the feature of EEG in order to distinguish different attention levels [5].

II. Methods

A. Power Spectum

There are several brands of EEG. The frequency of α-wave is between 8 to 13 Hz and amplitude is 20 to 100 μV. It is generated by brain when people are relaxing and having a rest quietly. The frequency of β-wave is between 14 to 35 Hz and its amplitude is 5 to 20 μV. It appears in the prefrontal brain when people are having rest quietly. When people are having visual stimulation, it appears in other parts of the brain and it represents the excitement of brain. The frequency of θ-wave is 4 to 8 Hz and its amplitude is 100 to 150 μV. It appears when people feel tired and it represents the suppression states of central nervous system [6].

When we get a time series of EEG, we calculate the power spectrum with the following equation:

$$\hat{R}(m) = \frac{1}{N}\sum_{n=0}^{N-1-|m|} x(n)x(n+m) \tag{1}$$

$$F_b(jw) = \sum_{m=-M}^{M} \hat{R}(m)e^{-jwm} \tag{2}$$

In the equation, N is the number of observing points and M is the longest delay.

After we get the power spectrum of the EEG time series, we extract the power spectrum value of β-wave and θ-wave.

Then calculate ratio of θ/β. θ-wave is generated when people are tiring and β-wave is generated when people focus their mind. Thus, the smaller the ratio is and the more alertness people have.

B. Definition of SampleEn

We firstly describe the algorithm of SampleEn because MSE is improved from it. SampleEn is based on the Approximate Entropy [7] which is an embedding entropy that quantifies the regularity of a signal [8]. Given a time series, $\{X_1, X_2, X_3, ...X_N\}$, the series have N points.

(1) We change the time series into a one dimension sector by following its original order:

$$X_i = [X_i, X_{i+1}, ..., X_{i+m-1}], i = 1,2,3,..., N-m+1 \quad (3)$$

(2) Define $d[X_i, X_j]$ as the maximum distance between the element X_i and X_j. The distance $d[X_i, X_j]$ can be calculated by the following equation:

$$d[X_i, X_j] = \max[|X_{i+k} - X_{j+k}|], j \neq i,$$
$$k = 0,1,2,.., m-1, j = 1,2,..., N-m+1. \quad (4)$$

(3) Select a threshold and get the number of $d[X_i, X_j]$ whose values are less than r. We define the threshold as r and the number as n. Then we calculate the ration between n and the total number of $d[X_i, X_j]$, the equation is as follows:

$$C_i^m(r) = \left\{\frac{n}{N-m}\right\}, i = 1,2,3,..., N-m+1. \quad (5)$$

$N-m$ is the total number of $d[X_i, X_j]$.

(4) Get the average of all the values of $C_i^m(r)$ with the equation:

$$C^m(r) = \sum \frac{C_i^m(r)}{N-m+1}, i = 1,2,3,..., N-m+1 \quad (6)$$

(5) Change the dimension into $m+1$ and repeat the procedure above to get the value $C^{m+1}(r)$

(6) We can get the SampleEn of the time series with the following equation:

$$SamplEn(m, r, N) = -\ln \frac{C^{m+1}(r)}{C^m(r)} \quad (7)$$

According to the experience of calculating Approximate Entropy, we usually select $m = 2, r = 0.1 \sim 0.2SD$. SD is the standard deviation of original time series $X_i (i = 1,2,3,..., N, N > 1000)$.

C. Definition of MSE

MSE is the advance of SampleEn. Usually, given a one dimension discrete time series $\{X_1, X_2, X_3, ...X_N\}$, then calculate MSE in the following procedures.

(1) We build successive coarse-grained series,

$$y_j^{(\tau)} = \sum_{i=(j-1)\tau+1}^{j\tau} \frac{X_i}{\tau}, j = 1,2,3,..., N/\tau. \quad (8)$$

The length of a certain coarse-grained series is N/τ and N is the length of the original time series.

(2) According to different scale factor, τ, we estimate different SampleEn of coarse-grained series, $y_j^{(\tau)}$.

SampleEn can represent the logarithmic conditional probability that sets of patterns remain similar at the next point while self-matches can not calculate the probability. Larger value of SampleEn tells that the signal series are more irregular [8]. The method of MSE analyzes time series through SampleEn of different τ based coarse-grained series, $y_j^{(\tau)}$, thus it can represent the trait of multiple scales of EEG time series.

D. The procedure of the experiment

For different concentration states, especially given the stable state when people are considerating, we designed three tasks in our experiment [5]. The first one was the attention task. There was a flash presented on the computer screen that a man was playing tennis (Figure. 1) and our subject sat in front of the computer imaging that he or she was playing tennis with the man in the flash (Figure 2). The second task was inattention task. The flash was also presented on the screen, but we asked our subject to think about something else that was not related to the flash. Lastly, subject was asked to have a rest and image nothing in the rest task. At the same time, the subject had to open his or her eyes as before to reduce the presence of artifacts. In this experiment, our subject sits on a comfortable chair and was not allowed to move during the tasks. The environment in the laboratory should be kept quiet in order to make the subject not be interrupted by others.

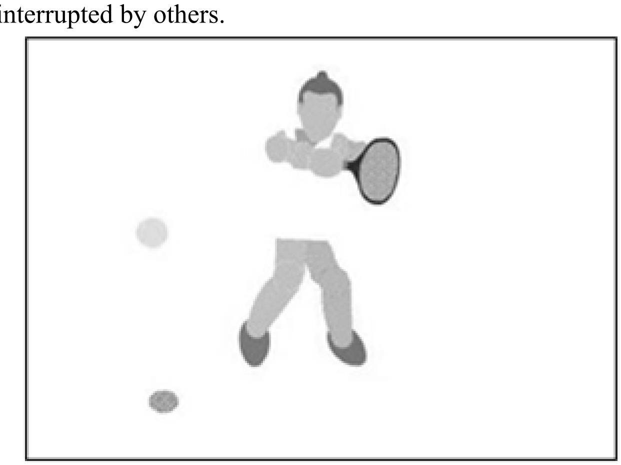

Fig.1. The experimental flash presented on the screen. The subject imaged that he was playing tennis with the man on the screen.

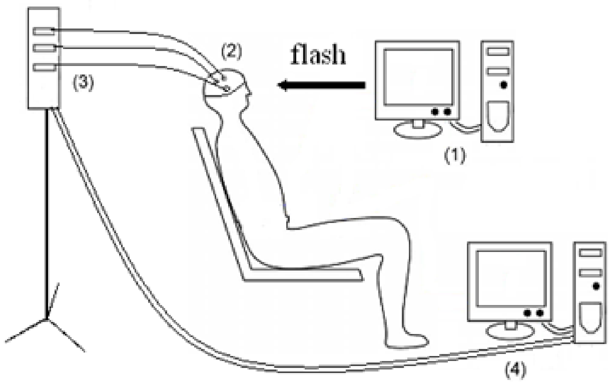

Fig.2. The EEG feedback experimental system: (1) the computer playing flash; (2) electrodes hat; (3) EMS Phoenix Digital EEG Equipment; (4) the computer recording EEG data.

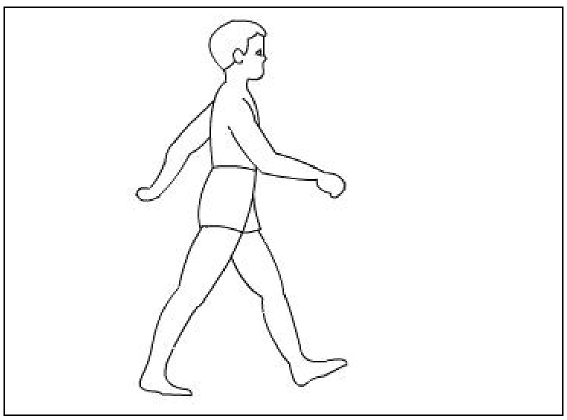

Fig.3. The experimental flash presented on the screen. The subject imaged that he was walking like the man on the screen.

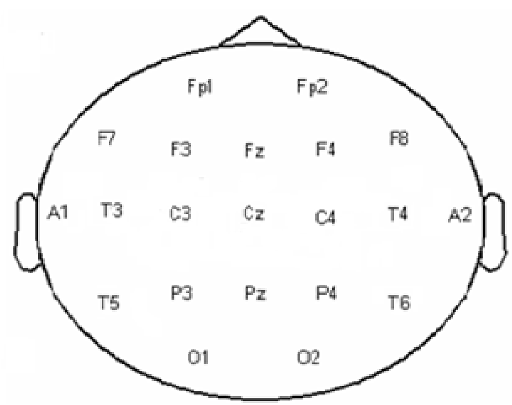

Fig.4. The international 10-20 system based electrode hat. There are 19 electrodes used in the experiment.

Another experiment is like the tennis experiment. We changed the tennis flash into the walking flash and our subjects imaged that he or she was walking like the man on the screen (Figure 3). The three tasks were operated in the same way as they did in the tennis experiment.

EEGs were recorded by an EMS Phoenix Digital EEG Equipment at electrodes F3, F4, F7, F8, Fp1, Fp2, T3, T4, T5, T6, C3, C4, P3, P4, O1, O2, Fz, Cz and Pz of the international 10-20 system (Figure 4). The sample frequency was 256 Hz. We had 10 tails in each task and each trail lasted 30 seconds. There were three tasks, attention, inattention and rest task. One experiment to a certain subject lasted for 15 minutes.

III. Results

A. The results under the algorithm of Power Spectum

In power spectrum, we use the value of θ/β to discriminate the different attention states in experiment.

θ-wave is generated when people are tiring and β-wave is generated when people focus their mind. If the subject is concentrating, β-wave is generated more by his or her brain and the value of Power Spectrum of β-wave is bigger than that of θ-wave [6]. If he concentrates more, the ration of θ/β will be smaller. So we expected the rest task has the highest value of θ/β, while attention task has the lowest.

But the result of the power spectrum is not very ideal. The accuracy in tennis experiment is 31.57% and the accuracy in walk experiment is 36.84%, as it shows in Figure 5 and Figure 6.

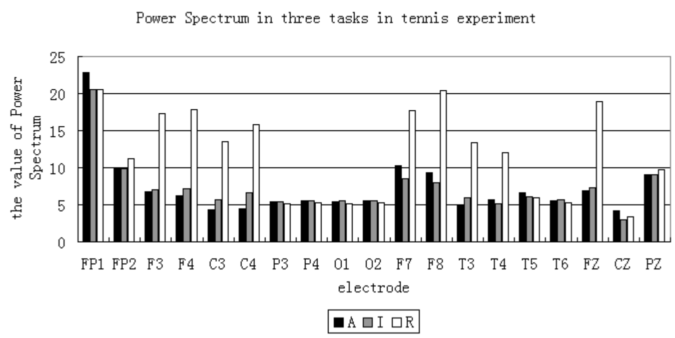

Fig.5. This the result calculated by Power Spectrum in tennis experiment. A, I, R seperately means the SampleEn of attention task, inattention task and rest task.

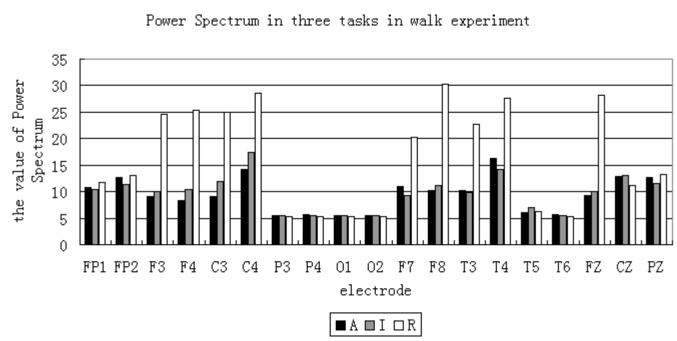

Fig.6. This the result calculated by Power Spectrum in walk experiment. A, I, R seperately means the SampleEn of attention task, inattention task and rest task.

B. The results under the algorithm of MSE

Because the inaccuracy of Power Spectrum in classifying the three tasks, we use MSE to analyze EEG time series.

The MSE analysis was performed for channels F3, F4,F7, F8, Fp1, Fp2, T3, T4, T5, T6, C3, C4, P3, P4, O1and O2 with m = 2 and r = 0.25 times the SD of the original time series.

After the visual inspection of the MSE profiles, we can see that profiles of three tasks are presenting an increasing slope

(Figure 7 and Figure 8). The SampleEn of the three tasks approximately have the same increasing trend. However, the SampleEn of the rest task is obviously lower than those of the other two tasks. And the SampleEn in attention task are higher than that in inattention task.

Entropy increases with the degree of disorder and is maximal for completely random systems [2]. We can infer that the subject had a complex EEG activity which was more irregular when he had attention and inattention task than that he had in the rest task. The EEG activity was slightly complex in attention task than that in inattention task [1]. Figure 7 and Figure 8 show the MSE profiles of SampleEn of the electrode F4 and those of the other electrodes are similar to these. SampleEn to each scale factor is the average of ten trails in order to decrease the noise to the minimum.

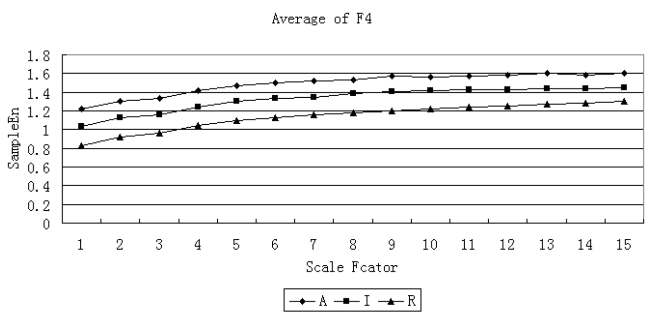

Fig.7. The result is from the tennis task of one of our subjects. MSE profiles of the SampleEn of three tasks of electrode F4. A, I, R seperately means the SampleEn of attention task, inattention task and rest task.

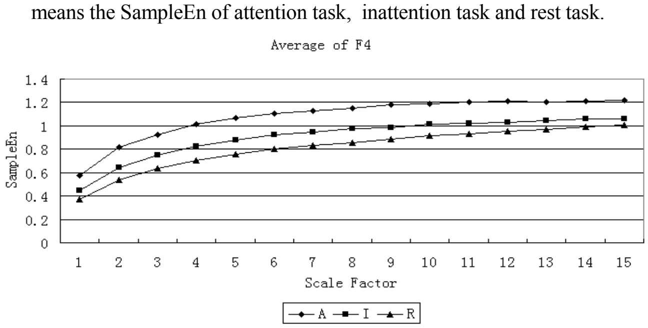

Fig.8. The result is from the walk task of one of our subjects. MSE profiles of the SampleEn of three tasks of electrode F4. A, I, R seperately means the SampleEn of attention task, inattention task and rest task.

IV. DISCUSSION AND CONCLUSION

In this preliminary study, we have applied the MSE to analyze the EEG background activity on 14 subjects. All of them are aged between 20 and 30 years old. For each subject, they had three different tasks (attention, inattention, and rest task) to finish. The MSE is a new method based on estimating the orderliness of several coarse-grained versions of the original signal by means of the SampleEn. The advantage of MSE is that it can be applied to the relatively noisy time series, irrespective of stochastic or deterministic series [1].

We have found that the SampleEn of the EEG background activity of three tasks show a typical increasing slope from the scale factor 1 to 15. This result is agreeing with other study that higher scale factors have higher SampleEn in this scale [3, 9, 10]. The SampleEn of relative scale in attention task is higher than those in inattention and rest task. And the SampleEn of rest task is the lowest. All these results means subjects had more complex EEG background activities and the imaginary motor potential were most irregular when they were in attention tasks. Further more, imaginary motor potential in inattention task were obviously more irregular than those in rest task. The values in attention task are higher than that in inattention and rest task. The values of SampleEn in rest task are the lowest. So, it is possible to discriminate the three states of people's attention with this kind of method when they concentrate.

From the Figure 7 and Figure 8, we can see the obvious increasing slope of SampleEn from scale 1 to scale 10. After scale 10, the curve is almost steady. As the scale factors increase, the SampleEn of white noise decreases, the irregularity of EEG signal can be affected less by regular white noise. Thus, the SampleEn of EEG signal increases in larger scale factors. Another reason why SampleEn become larger as scales factors increase is that MSE can describe the multiple scales traits of biological signals. It indicates the importance of calculating entropy over different scales [2]. From Figure 7, most of the electrodes have the trend that the average value of SampleEn of 14 subjects is the largest while that of the rest task is the smallest. It also means that the EEG background activity is more complex when people are inattention task.

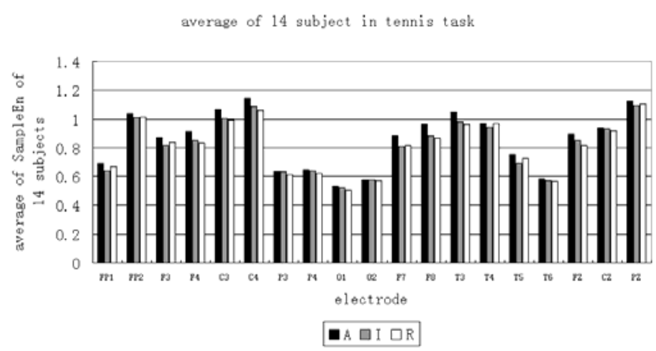

Fig.9. This histogram is the result of all the 14 subjects we have in tennis experiment. A, I and R mean the task of attention, inattention and rest. On every electrode above, the value of the SampleEn is the average of 14 people.

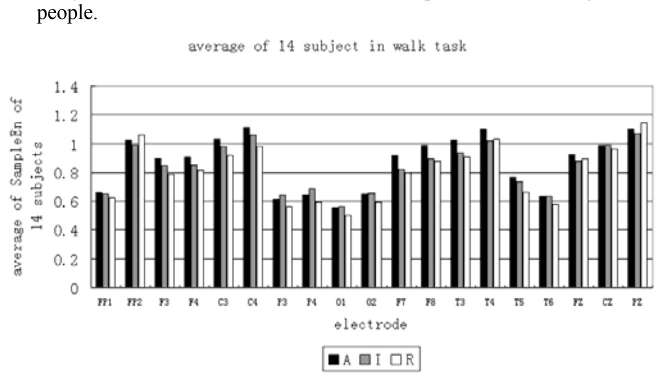

Fig.10. This histogram is the result of all the 14 subjects we have in walk experiment. A, I and R mean the task of attention, inattention and rest. On every electrode above, the value of the SampleEn is the average of 14 people.

Figure 9 and Figure 10 is the average result of all the 14 subjects we have. According to the histogram, we can see that the accuracy to discriminate three tasks in the algorithm of MSE is much higher than that in Power Spectrum. In this experiment, the discrimination between average value of inattention and rest task of other subjects is not obvious. All the attention tasks have highest histogram. In some other electrodes, there are some values of SampleEn in rest task which are higher than those in the inattention task, while the majority is that most of the SampleEn of inattention task are higher than those of reset. And we can confirm that the results will be improved to be much more obvious since clear features of EEG can be extracted after the subjects have a period of time of training [11].

To sum up, we have found the difference of SampleEn in the same scale between three tasks and we use it distinguishing the rest and attention or rest and inattention levels successfully. Although some of the results are not very ideal, as our subjects have training much more times, it will be better. And further studies should be carried out deeper in order to support our study.

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