A Specific Duration and High-energy Sine Wave Model to Reflect the Awaking and Falling Asleep Moments of Human

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Abstract. The process of falling asleep is complicated. Is there a mutation between sleep state and waking state? This paper applied a new specific duration and high-energy sine wave (SDHE) model based on single-channel brainwave to study this problem. The falling asleep moment and awaking moment could be identified through the SDHE. The closest research is AASM criterion. 30 seconds multi-channel brainwave as a frame was used to score the human sleep stage in the criterion. In the Dreams database used in this paper, an expert did the sleep classification of the 20 test subjects according to the AASM criterion. The switching step between waking stage and other sleep stages provided a basis for this paper. Within one minute of the time difference, the Cohen’s Kappa consistency of the discriminant result of the model and the expert was 0.58. In view of the strong and clear law of the SDHE, this paper would have more promising applications and significance in the signal processing of brainwave.

1. Introduction
Sleep accounts for about one-third of our life. It was significant to both the recovery of physical and physiological of human. The quality had a crucial impact on the human production and life. Rechtschaffen and Kales published a standard criterion for the scoring of normal sleep stage in 1968 [1]. It was a basis for clinical experts to quantitatively analyze the sleep of the human. At present, the most authoritative sleep classification criterion was AASM [2]. It was published in 2007 by the American Academy of Sleep Medicine. The sleep of human was very complicated, and the AASM criterion had being updated up to now.

Specific waveforms in the time domain and power spectrum characteristics in the frequency domain could partially depict the fluctuation of the human sleep state [3-6]. The attenuation of the alpha rhythm was identified as the most potent electrophysiological marker of sleep episodes [7]. However, the identification of switching moments between the waking and sleep had not been found in published work. Though the AASM criterion provides a basis, the expert knowledge of time domain waveforms was essential. The determination of each sleep stage in the criterion involves many considerations in multi-channel brainwave. Individual recognition could be different because the scoring process was subjective. It could not be judged from algorithms. Recently, the results of automatic sleep scoring through brainwave had been greatly improved [8-11]. However, these studies mainly focused on the accuracy of sleep scoring of 30 seconds brainwave slices. They did not cover the accuracy of the specific moment from the waking stage to the sleep stage or from the sleep stage to the waking stage.
2. Materials and methods

2.1. Data

The Dreams database was used in this study. It was shared by Stéphanie Devuyst, Université de Mons. This database consisted of over 160 hours of full-night multi-channel brainwave data. They were from 16 healthy female subjects aged 20-65, and 4 healthy male subjects between the ages of 20 and 30. The sampling frequency was 200 Hz. The brainwave had been marked with sleep stage. The sleep scoring work was conducted by an expert according to the original AASM criterion (2007). The brainwave from channel CZ-A1 was used in this paper.

2.2. Data preprocessing

In this experiment, the original EEG was not pre-processed because the signal was selected through energy and duration in a mixed brainwave in specific duration and high-energy sine wave (SDHE) model. The duration of ordinary noise was generally short. When the duration of the sine wave components was limited, the short duration noise was filtered. In this way, this paper also proposes a new way of noise processing. We call it sine wave fitting de-noising.

2.3. Specific duration and high-energy sine wave model

2.3.1. Sine model. In a STFT frame, signal \( x[n] \) could be decomposed as:

\[
x[n] = \sum_{r=1}^{R} A_r \cos(2\pi f_r nT + \varphi_r)
\]

R: the number of sine waves, \( A_r \) and \( f_r \) are time varying, \( \varphi_r \): the is the initial phase.

In two adjacent frames, \( f[l+1] \) and \( f[l] \) could be regarded as the same signal. If:

\[
|f[l+1] - f[l]| < \delta
\]

\( \delta \) was a threshold which related to frequency resolution.

2.3.2. Specific duration and high-energy sine wave model. Through the sine model, a time series \( X[n] \) could be fitted to:

\[
X[n] = \sum_{l=0}^{L-1} \sum_{r=1}^{R_l} A_{l,r} \cos(2\pi f_{l,r} nT + \varphi_{l,r}) = \sum_{i=1}^{I} x_i[n]
\]

l is the frame index of the short-time Fourier transform. \( R_l \) is the number of sine waves in each frame. T is the sampling interval. \( A_{l,r}, f_{l,r}, \varphi_{l,r} \) are amplitude, frequency and initial phase associated with frame index l and sine wave number r, respectively. \( x_i[n] \) are independent sine waves with different lengths of time and a different position on the time axis. Duration of the sine wave component \( x_i[n] \) was limited.

\[
X_1[n] = \sum_{i=1}^{R_1} x_i[n]^\prime, \quad t_1 < T (x_i[n]^\prime) < t_2
\]

\( R_1 \) signals \( x_{l,r_i}[n]^\prime \) with the highest energy in the time axis were picked.

\[
X_2[n] = \sum_{i=1}^{R_1} \sum_{r} x_{l,r_i}[n]^\prime
\]

3. Results

3.1. Overview of SDHE

SDHE was suitable for the analysis of brain waves. Through the optimization of the sine wave threshold, Figure 1 could be obtained. Figure 1 showed the overall effect of SDHE on sleep EEG analysis. Figure 1 (a) showed the sleep stage scored by the expert of test subject 1, according to the AASM criterion. Sleep stage 5 meant waking. Sleep stage 4 meant rapid eye movement sleep. Sleep stage 3 meant non-rapid eye movement sleep stage 1. Sleep stage 2 meant non-rapid eye movement sleep stage 2, and sleep stage 1 meant non-rapid eye movement sleep stage 3. Figure 1 (b) showed the outcome of SDHE on test subject 1 CZ-A1 brain wave. Figure 1 (c) and Figure 1 (d) were the enlarged views of two parts in figure.
1 (b).

Under the SDHE, the following 3 laws were concluded to identify the switching moments between the waking and sleep state:

1) When the sine wave was in the alpha wave band or more than 15 Hz. It indicated that the human was in waking state.

2) When the sine wave was below the α-band or in the 12 Hz-15 Hz band, human was in sleep state.

3) In principle, the sine wave switching from the waking state to the sleep state was the falling asleep moment. The sine wave switching from the sleep to the waking state was the awaking moment. Both of them were state mutations.

It could be indicated that the analysis of human sleep brainwave by SDHE showed strong regularity. The results of SDHE matched the expert in more than 8 hours of identification. It could be indicated that the analysis of human sleep brainwave by SDHE showed strong regularity.

3.2. The SDHE could reflect the awaking and falling asleep moments of the human

In the Dreams database, the expert scored the sleep of 20 test subjects in every 30 seconds multi-channel brainwave. The step was 5 seconds. The last second of the step when the sleep stage switched from stage 5 to other sleep stage was taken as a standard for the falling asleep moment. The last second of the step when the sleep stage switched from stage 1-4 to stage 5 was taken as a standard for the awaking moment. The standard from the expert had an error of more than 5 seconds. The time differences of corresponding awaking and falling asleep moments between the discriminating results of the SDHE and the expert were showed in the boxplots of Figure 2. Test subjects 1 to 10 were in Figure 5 (a). Test subjects 11 to 20 were in Figure 2 (b). The negative value indicated that the judgment of SDHE lagged behind the expert. The distribution of mean time difference of each subject was randomly around zero, through the time difference box-plot of 20 test subjects. Most of the time differences were concentrated within 60 seconds. Therefore, 60 seconds was set as a time error of the SDHE compared to the expert.
The brainwave was judged in a slice of 1.75 second in SDHE. Table 1 showed the confusion matrix of the judgment in the whole night of 20 subjects. A represented awaking and falling asleep moments. B represented other states.

Table 1. Comparison of the judgment of awaking and falling asleep moments of 20 subjects between SDHE and the expert.

|       | A   | B   |
|-------|-----|-----|
| Expert |     |     |
| A      | 606 | 603 |
| B      | 252 | 322121 |

Figure 2. The time difference of awaking moments and the falling asleep moments between the SDHE and the expert. The mean time differences of 20 objects were around zero randomly. The main time difference was concentrated within 60 seconds.

4. Conclusion
A new specific duration and high-energy sine wave model was proposed in this paper to study the sleep brainwave, which had not been seen in relevant published work. The brainwave data used in this paper was from the Dreams database, which was a public project. Multi-channel brainwave in the database had been scored by an expert. In this paper, based on a single-channel CZ-A1 brainwave, the falling asleep and awaking moment could be reflected by the SDHE. The switching step between waking stage and other sleep stages scored by the expert provided a basis for the SDHE. Within one minute of the time difference, the Cohen’s Kappa consistency of the discriminant result of the SDHE and the expert was 0.58. Expert judgment was subjective [12]. In a sleep spindle detection research, the Kappa score between an individual expert and a group of experts was 0.68 [13]. Therefore, the outcome of the SDHE based on a single channel was reasonable and promising.

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