Sleep Spindle Detection Based on Complex Demodulation

Jia-bin LI, Bei WANG* and Yu ZHANG

Department of Automation, School of Information Science and Engineering, East China University of Science and Technology, Shanghai 200237, CHINA

*beiwang@ecust.edu.cn

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Abstract. In this paper, we investigated the characteristic waveform of sleep spindle by using complex demodulation method (CDM). The ultimate purpose is to develop the automatic sleep spindle detection algorithm for overnight sleep data inspection. The main method includes four procedures. Firstly, the influences of disturbance of alpha waves, eye movement and muscle artifacts are analyzed and eliminated. Secondly, CDM is adopted to obtain the changing amplitude for sleep spindles. After CDM analysis, a set of parameters are calculated to find the candidate waveforms. Finally, the judgments of sleep spindle are made according to the defined thresholds of parameters. The overnight sleep recordings of three subjects were analyzed. Compared with the visual inspection of sleep stages by clinician, the obtained results showed that the detected sleep spindle were mostly distributed at sleep stage 2 and deep sleep stages. It is testified that CDM can well depict the instantaneous character of sleep spindle. The presented method can be an assistant tool for sleep spindle detection and sleep stage determination.

Introduction

Sleep spindle is one kind of EEG (electroencephalogram) wave whose duration is about 0.5-2 seconds. It is a transient waveform with waxing-waning amplitude. The frequency of sleep spindle is about 11-15Hz, most commonly 12-14Hz.

Sleep spindle is related to sleep stages and sleep disorders. According to R&K criteria [1], sleep spindle exhibits strong presence in stage 2 of NREM (Non-Rapid Eye Movement). P.Y. Ktonas et al used Markov model to analyze the dynamic changing of sleep spindle and found that the distribution of spindles during overnight sleep complied with static regulation [2]. Sleep spindle also corresponds to the cognitive function of brain. A. Ayoub et al pointed out that high frequency spindle relates to the cognition [3]. Q. Li et al compared the character of sleep spindle of infant and concluded that there exists relationship between abnormal sleep spindle and hypophrenia [4]. In addition, the character of sleep spindle can reflect the character of brain disease such as epilepsy. A. Bersaqliere et al discovered that electrical sources of sigma activity (12-16Hz) which included spindle activity exhibited increased activity during the ictal phase which was higher in the epileptogenic hemisphere [5].

Studying sleep spindle is of importance in medicine. Hence, many methods and characters are used to detect sleep spindle automatically. A. Parekh et al detected spindle by time-frequency sparsity [6]. M. Muammar et al mentioned an automatic sleep spindle detection algorithm based on synchrosqueenzing [7]. M. Adamczyk et al proposed an automatic sleep spindle detection method using continuous wavelet transform [8]. Machine learning is also used for spindle detection. E.M.Ventouras et al used Artificial Neural Network [9] and N.Acir et al used Supported Vector Machine to detect sleep spindle [10].

In this paper, the complex demodulation method (CDM) is adopted to detect sleep spindle automatically. CDM is a time-frequency method which can extract the instantaneous amplitude of signal [11]. It has been used to analyze R-R interval which is time elapsing between two QRS complexes in EKG (electrocardiogram) [12]. CDM is useful in analyzing changing signals. Sleep spindle has transient character of frequency and amplitude. An automatic sleep spindle detection algorithm based on CDM is developed. The overnight sleep data were analyzed to evaluate the effectiveness of presented method.

Method

Data Acquisition

The overnight polysomnographic (PSG) recordings were obtained from 3 subjects. The PSG recordings of each subject included 4 EEG channels (C3/A2, C4/A1, O1/A2, O2/A1), 2 EOG channels (LOC/A1, ROC/A1) and one chin EMG channel (chin-EMG) according to the International 10-20 system. EEGs and EOGs were recorded under a sampling rate of 100Hz, with a high frequency cut off of 35Hz and a time constant of 0.3s. Chin-EMG was recorded under a sampling rate of 200Hz, with a high frequency cutoff of 70Hz and a low frequency cutoff of 10Hz.

In this paper, EEGs recorded on C3/A2 and C4/A1 were used to detect sleep spindle. EEGs recorded on O1/A2 and O2/A1 were utilized to analyze the influence of alpha components. Meanwhile, EOGs and chin-EMG were analyzed to remove the influence of eye movement and muscle interference. Sleep spindle is detected automatically for every 30s epoch. The result is analyzed comparing with the visual inspection of sleep stages by a qualified clinician.

Sleep Spindle Detection

Pre-processing. Sleep spindle is sometimes obfuscated with alpha wave. The frequency of alpha component is 8-13Hz which is overlapped with the frequency of sleep spindle. In order to remove the influence of alpha wave, the ratio of the amount of alpha wave R_α is calculated by equation in Table 1 from O1/A2 and O2/A1 channels. If R_α is larger than 30%, the epoch is excluded. Additionally, the influence of EOG and EMG may affect the EEG waveform and cause erroneous judgment for sleep spindle detection. The amount of eye movement and muscle activity are calculated as in Table 1. If S_{LOC} or S_{ROC} is larger than 30μv^2, or $S_{chin\text{-}EMG}$ is larger than10μv^2, the epoch is excluded.

Table 1. Parameters of pre-processing

	Meaning	Parameter	Method
EEG	Ratio[%]	R_α	Max{S_α(O1)/S_T(O1), S_α(O2)/S_T(O2)}
EOG	Amount[μv^2]	S_{LOC}, S_{ROC}	S_{LOC} (LOC), S_{ROC}(ROC)
Chin-EMG	Amount[μv^2]	$S_{chin\text{-}EMG}$	$S_{chin\text{-}EMG}$(chin-EMG)

* T(0.5-25Hz); α(8-13Hz); LOC, ROC(2-10Hz); chin-EMG(25-100Hz)

Complex Demodulation

A time series $X(n\Delta t)$ can be represented as,

$$X(n\Delta t) = A(n\Delta t) * \cos[f_0 n\Delta t + P(n\Delta t)], \quad (1)$$

Where $A(n\Delta t)$ is a changing amplitude and $P(n\Delta t)$ is a changing phase. $A(n\Delta t)$ can be extracted as follows if the frequency f_0 is known:

Shift all the frequency in $X(n\Delta t)$ by $-f_0$:

$$\begin{aligned} Y(n\Delta t) &= X(n\Delta t) * 2\exp(-if_0 n\Delta t) \\ &= A(n\Delta t) * [\exp(iP(n\Delta t)) + \exp(-i\{2f_0 n\Delta t + P(n\Delta t)\})]. \end{aligned} \tag{2}$$

Let $Y'(n\Delta t)$ be the complex signal when $Y(n\Delta t)$ is passed through a low-pass filter:

$$Y'(n\Delta t) = A(n\Delta t) * \exp[ip(n\Delta t)]. \tag{3}$$

Therefore, $A(n\Delta t)$ can be obtained as :

$$A(n\Delta t) = |Y'(n\Delta t)|. \tag{4}$$

Sleep spindle usually can be observed in channel C3/A2 and C4/A1. Its frequency is around 11-15Hz , most commonly 12-14Hz. CDM is used to analyze the EEG signal of C3/A2 and C4/A1 for every 30s epoch. The changing amplitude of EEG signal around the frequency of 13Hz is analyzed. In the above equations, f_0 is set as 13Hz and $X(n\Delta t)$ is the original raw EEG data of a 30s epoch. Finally, $A(n\Delta t)$ is the obtained instantaneous amplitude for the frequency components around 13Hz by CDM.

Parameter Calculation

The frequency of EEG before or after sleep spindle is smaller. Meanwhile, the amplitude of sleep spindle increases quickly and then decreases. As a result, there will be a peak of wave in the instantaneous amplitude curve when sleep spindle appears. According to the result of CDM, candidate waveforms are selected. Here, the average of instantaneous amplitude is calculated as follow:

$$mean = \frac{1}{\mathrm{N}} \sum_{n=1}^{\mathrm{N}} A(n\Delta \mathrm{t}), \tag{5}$$

where, N is the total data number of an epoch. At first, all of the local maximum points within one epoch are found. If its instantaneous amplitude is larger than twice of the *mean*, a peak point t_p is marked and the corresponding EEG signal is selected as candidate waveform. The starting and ending points (t_{start} and t_{final}) are the position of the nearest local minimum points from the left and right of t_p whose instantaneous amplitude is smaller than the *mean*.

Table 2. Parameters for sleep spindle detection

Characteristic parameters	Judgments
peak[μv]	$A(t_p) \geq 3\mu v$
duration[s]	$0.5s \leq t_{final}-t_{start}-0.5 \leq 2s$
rising speed[$\mu v/s$]	$4\mu v/s \leq 0.5peak/(t_p-t_1) \leq 10\mu v/s$
falling speed[$\mu v/s$]	$4\mu v/s \leq 0.5peak/(t_2-t_p) \leq 10\mu v/s$

After selecting the candidate waveforms, the characteristic parameters are calculated as illustrated in Table 2. There are totally four characteristic parameters. *Peak* is the instantaneous amplitude of 13Hz signal at t_p. *Duration* equals to the time difference between starting and ending positions minus 0.5 seconds which is the delay time caused by CDM. *Rising speed* is the average speed when the instantaneous amplitude increased from 0.5**peak* to *peak*, where t_1 is the nearest point from the left of t_p whose amplitude equals to 0.5**peak*. *Falling speed* is the average speed when the

instantaneous amplitude decreased from *peak* to 0.5**peak*, where t_2 is the nearest point from the right of t_p whose amplitude equals to 0.5**peak*.

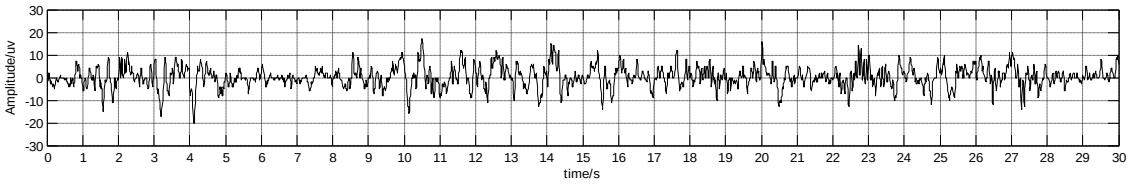
Sleep Spindle Detection

For each candidate waveform, the character parameters are compared with a set of defined threshold as in Table 2. The *peak* should be larger than 3*μv*, which means the amplitude is large enough corresponding to the appearance of sleep spindle. According to the definition of sleep spindle, the *duration* should be within 0.5-2 seconds. Additionally, the *rising speed* and *falling speed* are evaluated with the range from 4*μv/s* to 10*μv/s*, which corresponding to the sharp waveform of instantaneous amplitude in the CDM. Either the *rising speed* or *falling speed* meets the requirement, this condition is satisfied. Finally, when all the conditions are satisfied, the candidate waveform is judged as a detected sleep spindle.

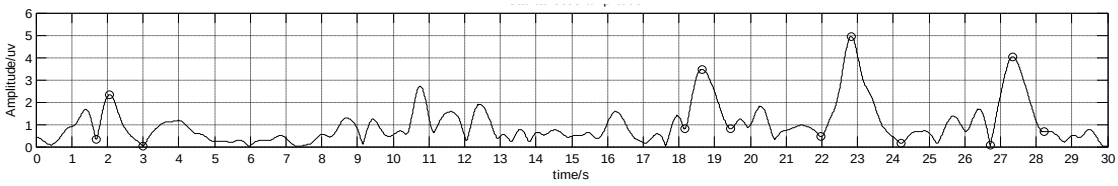
Result

Complex Demodulation

After pre-processing, the epochs which contained alpha activity and active eye movement of muscle artifacts were excluded for further analysis. CDM was applied for each remained epoch. In Fig.1, the raw EEG of C4/A1 of one epoch was shown in (a) and its instantaneous amplitude by CDM was in (b). Several sharp waveforms were detected in Fig.1 (b). The frequency components around 13 Hz can be observed at the same positions in Fig.1 (a). Those waveforms were selected as the candidate waveforms which are marked by empty circles in Fig.1 (b).



(a) Raw EEG of C4/A1 channel



(b) Instantaneous amplitude of frequency components around 13 Hz by CDM

Figure 1 CDM result for a 30s epoch

Totally, there are four candidate waveforms selected. The characteristic parameters of the candidate waveforms were shown in Table 3. Comparing with the judgment conditions in Table 2, the first candidate waveform does not meet the requirement as its value of *peak* is smaller than 3*μv*. The latter three candidate waveforms were satisfied with the requirements. Finally, the sleep spindles were detected at 18s, 23s and 27s for the epoch shown in Fig.1.

Table 3. Characteristic parameter values of candidate sleep spindles

t_p[s]	*Peak*[μv]	*Rising speed*[$\mu v/s$]	*Falling speed*[$\mu v/s$]	*Duration*[s]
2.06	2.33	4.66	3.53	0.82
18.64	3.47	5.26	3.40	0.79
22.82	4.93	7.25	4.93	1.76
27.34	4.03	5.30	4.11	1.01

Sleep Spindle Detection

The overnight sleep data of three subjects were tested. In Table 4, the epoch numbers with detected sleep spindles were counted and compared with the visual inspection of sleep stages. The epochs were classified into six sleep stages of awake, stage 1, stage 2, stage 3, stage 4 and REM (Rapid eye movement) according to the visual inspection.

Sleep spindle is the characteristic waveform for stage 2. Totally, subject 1 has 489 epochs inspected as stage 2, while subject 2 and subject 3 have 348 and 422 epochs correspondingly. The sleep spindle detection result in Table 4 showed that, to all subjects, nearly half of the epochs of stage 2 were detected with sleep spindles. Stage 3 and 4 are deep sleep where sleep spindle can also be observed. About 30% of the epochs of stage 3 and 4 were detected with sleep spindles. In stage awake, large amount of alpha components can be observed when the subject closed eyes and began to sleep. Subject 1 has totally 197 epochs of stage awake and 16 epochs were detected with sleep spindle. Subject 3 has totally 135 epochs of stage awake and 12 epochs were detected with sleep spindle. There was no spindle detected in stage awake in subject 2. Stage 1 is the transit stage from awake to sleep. To all subjects, there were also a few spindles detected in stage 1. To subject 1, there was no spindle detected in stage REM. 16 epochs of subject 2 and 30 epochs of subject 3 of stage REM were detected with spindles. The obtained results were fairly well compared with occurrence of sleep spindle and sleep stages.

Table 4. Detected sleep spindle and sleep stages

	Awake	Stage 1	Stage 2	Stage 3	Stage 4	REM
Subject1	16(197)	4(51)	220(489)	28(94)	5(45)	0(108)
Subject2	0(132)	43(149)	103(348)	6(48)	7(101)	16(137)
Subject3	12(135)	48(101)	378(422)	27(95)	4(53)	30(177)

Summary

In this study, an automatic sleep spindle detection algorithm based on CDM was introduced. Pre-processing is utilized to exclude the contaminated epochs by alpha, eye movement and muscle artifacts which is efficient to decrease the error of spindle detection. The instantaneous amplitude of frequency components around 13Hz by CDM reflected the instantaneous characteristics of spindle. The overnight sleep data were analyzed. The obtained results were quite satisfied comparing with the visual inspection of sleep stage. The detected sleep spindle were mostly in stage 2 and deep sleep stages which is consistent with the definition of sleep spindle in R&K sleep criteria. The presented method can be an assistant tool for sleep spindle detection and automatic sleep stage determination.

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