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Sleep Apnea Syndrome Detection Based on Degree of Convexity of Logarithmic Spectrum Calculated from Overnight Bio-vibration Data of Mattress Sensor

Iko Nakari[1] and Keiki Takadama[2]

Abstract— **This paper proposes the novel Sleep Apnea Syndrome (SAS) detection method based on the frequency analysis of the overnight bio-vibration data acquired from mattress sensor. Concretely, this paper designs the index called Degree of Convexity of the Logarithmic Spectrum (DCLS), which quantifies the degree of convexity by computing the difference between the waveform of the averaged logarithmic spectrum and the waveform of its approximation formula, and employs it to detect SAS. Through the human subject experiment on the SAS detection, the following implications have been revealed: (1) the SAS subjects tend to have the large density around 3Hz, and the average of DCLS in SAS subjects and healthy subjects are 98.6±10.1 and 48.2±6.8 respectively, which succeeds to correctly separate the nine SAS subjects and the nine healthy subjects; and (2) the characteristics of the WAKE stage are different between the SAS and healthy subjects.**

I. Introduction

The accumulation of sleep debt affects concentration in our daily life and increases the risk of industrial and traffic accidents [1], [2]. It also increases the risk of developing lifestyle-related diseases such as depression and dementia [3], [4]. For these reasons, it is necessary to have a sufficient sleep for reducing the above risk of accidents and diseases. However, it is hard for sleep apnea syndrome (SAS) patients to have their sufficient sleep due to sleep disorders. SAS causes hypopnea (weakening of breathing) and apnea (stopping of breathing) during sleep, both of which worsen the quality of sleep. According to the global survey of the obstructive sleep apnea syndrome (OSAS) as the main syndrome in SAS, the population of the OSAS patients is estimated as 78 million in USA, 242 million in China, and 31 million in Japan [5]. Even though the estimated number of patients is large, many of them are unaware of their suffering from SAS because of unconscious during sleep [6]. From these facts, it is important to detect SAS earlier and to give them appropriate treatment not for worsening their symptoms and for decreasing national healthcare costs.

For early detection of SAS, the simple monitoring system as the non-contacted system have been developed. For example, the methods based on mattress sensor can detect apnea according to the respiration amplitude computed from the bio-vibration data which filtered in the frequent range of respiration [7], [8]. These methods are effective for detecting apnea but are difficult to detect hypopnea, which are often found in SAS patients in early or middle stage of SAS patients. To tackle this issue, Hwang et al. proposed the method that can detect both apnea and hypopnea with mattress sensor in the case of "abnormal" respiration by applying the principal component analysis to detect it [9]. However, it is difficult to detect the hypopnea and apnea in the case of "forced" breathing (i.e., breathing with thoracic and abdomen movement) which are very similar to the "normal" respiration. What should be noted here is that the "forced" breathing is a main symptom in addition to the "abnormal" respiration, which means that the "abnormal" respiration detection in the conventional method is insufficient to detect SAS.

To tackle this the problem, this paper aims to propose the novel SAS detection method that can detect SAS even in the case of the "forced" breathing which are hard to be detected by the conventional methods. For this issue, this paper employs the bio-vibration data of a wide range of the frequent waves which cover not only the respiration but also the other waves. Through a comparison of the overnight bio-vibration data between SAS patients and healthy subjects, this paper also clarifies the characteristic difference of the WAKE stage between SAS patients and healthy subjects to explore a new symptom of SAS patients except for apnea/hypopnea.

This paper is organized as follows. The next section describes SAS. Section 3 proposes our SAS detection method based on the frequency analysis of the bio-vibration data acquired from mattress sensor. The human subject experiment is conducted and the results are analyzed in section 4. Finally, our conclusion is given in Section 5.

II. Sleep Apnea Syndrome

Sleep Apnea Syndrome (SAS) is one of the sleep disorders that causes the long-term sleep dept by apnea/hypopnea during sleep. Since apnea/hypopnea decreases oxygen saturation, the brain senses danger and sleep becomes shallow in order to return to normal breathing. As the definition, apnea occurs when breathing stops more than 10 seconds, and hypopnea occurs when the airflow of breathing becomes less than the half of the normal breathing and SpO_2 (oxygen saturation degree in the blood) decreases by more than 4%. To diagnos SAS, the international standard method called Rechtschaffen & Kales (R&K) method [10] is employed

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[1]Iko Nakari is with the Dept. of Informatics, the University of Electro-Communications, Tokyo, Japan (iko0528@cas.lab.uec.ac.jp)

[2]Keiki Takadama is a professor at the University of Electro-Communications, the Department of Informatics, Tokyo, Japan (keiki@inf.uec.ac.jp)

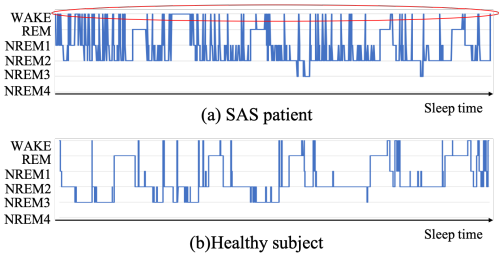


Fig. 1. Comparison of sleep stage between (a) SAS patient and (b) healthy subject.

in Polysomnography (PSG) test and classifies the sleep stages into the following six levels: WAKE, Rapid-Eye-Movement (REM), Non-REM (NREM) 1 to 4 (from shallow sleep to deep sleep). In the PSG test, electroencephalogram (EEG), electrooculogram (EOG), electrogram (EMG), and respiration of patients during sleep are measured, and these biological data are analyzed by the R&K method to estimate sleep stage. Fig. 1 shows the example of the sleep stage, where the vertical axis indicates the sleep stage while the horizontal axis indicates the sleep time. Figs. 1(a) and 1(b) show the sleep stage of the SAS patient and the healthy subject, respectively. As indicated by the red circle in Fig. 1, the SAS patient causes the frequent WAKE stage.

The severity of symptoms of SAS is classified by Apnea Hypopnea Index (AHI). It indicates the total number of apnea/hypopnea events per hour of sleep. The severities are summarized as follows: mild ($5 \leq AHI < 15$); moderate ($15 \leq AHI < 30$); and severe ($30 \leq AHI$).

III. Frequency Analysis of Bio-vibration Data

A. Overview

To discover the SAS characteristics from the bio-vibration data during sleep, this paper focuses on the differences among the multiple frequencies of the vibration waves in the bio-vibration data. In this paper, TANITA sleep scan SL-511 (Tokyo, Japan) was employed as the mattress sensor for acquiring bio-vibration data, and places it under the mattress in the bed. The sensor outputs one channel signal and the sampling rate is 16Hz. The procedure of the SAS detection method shown in Fig. 2 is summarized as follows: 1) measuring the overnight bio-vibration data; 2) applying the short-time Fourier transform (STFT) into the overnight bio-vibration data to calculate the average of the spectrum over the night; and 3) detecting SAS according to the SAS detection which is based on the averaged spectrum. In particular, Fig. 2 1) shows the overnight bio-vibration data acquired from the mattress sensor, where the vertical axis indicates the vibration value while the horizontal axis indicates the time. The larger the absolute sensor value, the larger the body movement (e.g., the absolute sensor value becomes large in the case of turning over). Fig. 2 2) shows that an application of STFT into the overnight bio-vibration data enables us to analyze what frequency of vibrations in a short period of time are strongly included in the bio-vibration

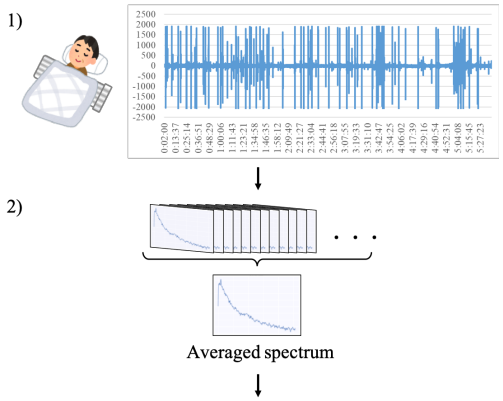


Fig. 2. Overview of the proposed SAS detection method.

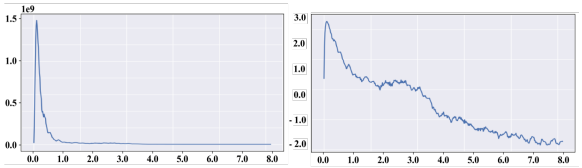
data during sleep. The reason for calculating the averaged spectrum is to eliminate the effect of accidental changes in the spectrum. Note that STFT is often employed to analyze the frequency of time-varying signals such as voices by a Fourier transform (FT) while shifting the time window. In this paper, Fast Fourier Transform (FFT) is employed instead of FT for reducing computing time.

The above analysis of the bio-vibration data covers not only the frequent range of the respiration and but also other frequent range to clarify the characteristic of SAS patients found in other than respiration.

B. Applying the STFT into Bio-vibration Data

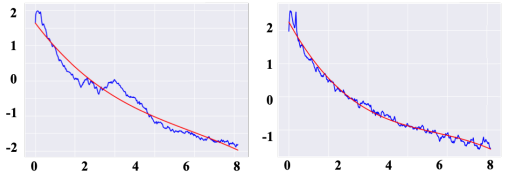
The specific steps of the STFT process in the proposed method are summarized as follows:

1) Applying FFT into the bio-vibration data with the 64 second window (note that the sampling rate of the mattress sensor in our study is 16Hz, so that the data size is $64 \times 16 = 1024$) to convert the bio-vibration data to the power spectrum. In this case, the bio-vibration data is represented in 512 dimensions from 0 to 8Hz. Fig. 3(a) shows the example of the power spectrum computed from bio-vibration data, where the vertical axis indicates the density of power spectrum while the horizontal axis indicates the frequency. The frequency band between 0.1Hz and 0.2Hz is related to respiration, and the frequency band between 0.6Hz and 1.5Hz is related to heartrates. As shown in the Fig. 3(a), the mattress sensor is easy to capture the large densities of the frequencies related to respiration, but is hard to capture the densities of other frequencies because of the small densities.
2) Converting the power spectrum into the logarithmic spectrum (log10) to make it easier to analyze the small densities of frequencies. Fig. 3(b) shows the example of the logarithmic spectrum converted from the power spectrum, where the vertical axis indicates the density of the power spectrum and the horizontal axis indicates the frequency. The only difference between Figs. 3 (a) and (b) is the representation of the vertical axis, i.e.,



(a) power spectrum (b) logarithmic spectrum

Fig. 3. Examples of (a) power spectrum and (b) logarithmic spectrum.



(a) SAS patient (b) Healthy subject

Fig. 4. Examples of averaged logarithmic spectrum

the normal value in Fig. 3 (a) and the logarithmic value in Fig. 3 (b).

3) The steps 1) and 2) are repeatedly conducted by shifting the bio-vibration data every second. After computing the logarithmic spectrum from the overnight bio-vibrations data, they are averaged to analyze the overnight trend of the bio-vibration data of a subject.

C. Differences in the Spectrum between SAS Patients and Healthy Subjects

Figs. 4(a) and 4(b) respectively show the examples of the averaged logarithmic spectrum of the SAS patient and healthy subject, where the vertical axis indicates the density while the horizontal axis indicates frequency. The blue and red lines represent the averaged logarithmic spectrum and its approximation formula (described later), respectively. As the common tendency of the SAS patient and healthy subject shown in Fig. 4, the density decreases as the frequency increases. What should be noted here, however, is that the SAS patient tends to have a larger density around 3Hz (like a convex shape) which is not found in the healthy subject.

To extract this difference, this paper quantifies the degree of convexity by computing the difference between the waveform of the logarithmic spectrum and its approximation formula. Here, it is defined as Degree of Convexity of the Logarithmic Spectrum (DCLS). The approximation formula is represented as follows,

$$\hat{y} = ax^3 + bx^2 + cx + d \tag{1}$$

where a, b, c and d are the coefficients to be estimated by least squares method, $\hat{y}$ represents the estimated density, and x represents the frequency. DCLS is computed as follows,

$$DCLS = \sum_{i=3}^{N} |y_i - \hat{y}_i| \tag{2}$$

where y_i indicates the density of the i-th frequency of the averaged logarithmic spectrum, and $\hat{y}_i$ indicates the value of the approximation formula (1) when $x = i$. Note that the densities of the averaged logarithmic spectrum of the first and second frequencies (i.e., 8/512Hz and 16/512Hz) are excluded when computing the approximation formula because they are susceptible to noise. The values of DCLS in Figs. 4(a) and 4(b) are 85.22 and 51.83, respectively. As shown in this example, the DCLS value in SAS patients is sufficiently larger than that in healthy subjects, which difference is employed to detect SAS in the proposed method.

IV. Experiments

To investigate the effectiveness of the proposed SAS detection method based on DCLS, this paper conducted the human subject experiment of the nine of SAS subjects (including the five moderate and four mild patients. Age information are not disclosed.) and the nine of the healthy subjects (age from 20 to 60). The average number of epochs (30 seconds) of sleep in SAS subjects are 934±57 and that in healthy subjects are 665±130. PSG data of all subjects is also measured to investigate relationship with the relationship between sleep stage and bio-vibration data, in addition to the bio-vibration data acquired from the mattress sensor value (required to compute DCLS). The ethics community of Ota General Hospital approved this study in agreement with Helsinki's declaration, and all the subjects signed their consent.

A. Results and Discussions

Figs. 5 and 6 show the averaged logarithmic spectrum (represented by the blue line) and its approximation formula (represented by the red line) of the SAS and healthy subjects, respectively. The alphabet in the upper right corner of each graph, "A to I" and "a to i" represent the IDs of the SAS subjects and healthy subjects, respectively. As shown in Figs. 5 and 6, the averaged logarithmic spectrums of the SAS subjects tend to have convex shape around 3Hz while the healthy subjects have the smoother waveform than that of SAS subjects.

Fig. 7 shows the DCLS values of all subjects, where the vertical axis indicates the DCLS value, the horizontal axis indicates the IDs of the subjects, and red line (manually determined) indicates the threshold for the SAS detection. The average of DCLS value in SAS subjects and healthy subjects are 98.6±10.1 and 48.2±6.8, respectively. As shown in Fig. 7, the SAS and healthy subjects are completely separated with the threshold. From the results, the proposed index, DCLS, has the potential of detecting SAS by just sleeping on a mattress sensor.

To analyze the high density around 3Hz (2.5Hz to 3.5Hz), the total density accumulated from the density of 2.5Hz to 3.5Hz (represented by the blue line) is added in the graph of the overnight sleep stages (represented by the orange line) in Fig. 8, where the left vertical axis indicates the sleep stage, the right vertical axis indicates the accumulated density, the horizontal axis indicates the time, and the arrows on the upper side represent where apnea/hypopnea occurred. As shown in Fig. 8, the SAS subject tends to have

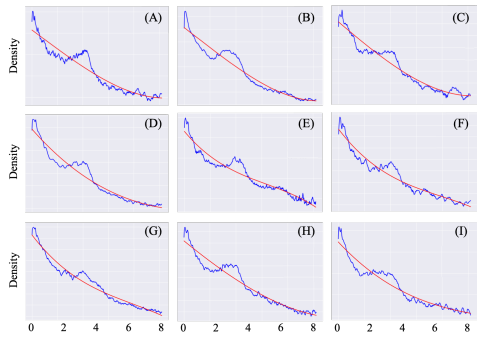


Fig. 5. Results of SAS subjects: blue line indicates averaged logarithmic spectrum and red line indicates approximation formula.

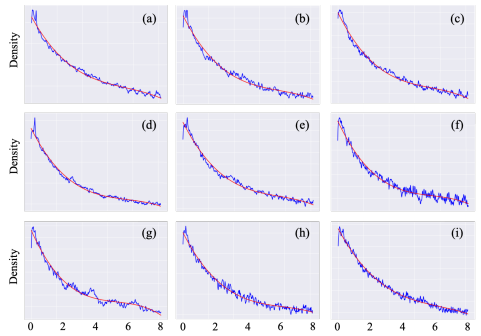


Fig. 6. Results of healthy subjects: blue line indicates averaged logarithmic spectrum and red line indicates approximation formula.

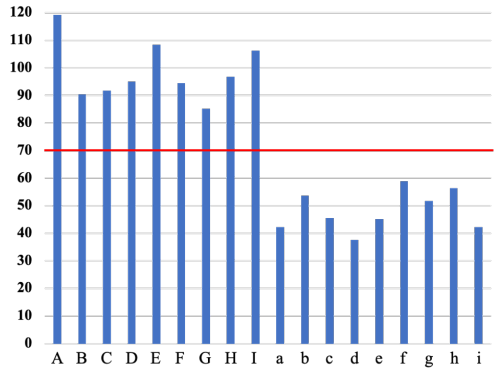


Fig. 7. Results of DCLS computed from SAS subjects (A to I) and healthy subjects (a to i).

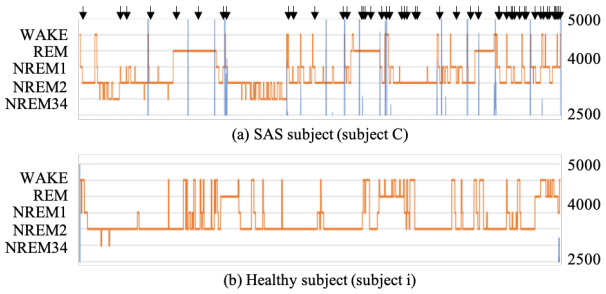


Fig. 8. The analysis of the relationship between sleep stages and around 3Hz.

the large accumulated density in the WAKE stage, while healthy subject has the large accumulated density only when falling asleep and waking up. This analysis suggests that the characteristics of the WAKE stage are different between the SAS and healthy subjects. More importantly, the WAKE stages with the large accumulated density do not always occur before/after apnea/hypopnea but many of them are found without the time of apnea/hypopnea. This implies that the SAS subjects generate 3Hz waves in the WAKE stages, which has a potential of being new symptom of the SAS patients except for the apnea/hypopnea. The 3Hz wave may deteriorate the quality of sleep and leads to have frequent WAKE stage.

V. Conclusion

This paper proposed the novel SAS detection method, which detects SAS patients according to the Degree of Convexity of the Logarithmic Spectrum (DCLS) based on the frequency analysis of the overnight bio-vibration data, and investigated the effectiveness of DCLS through human subject experiment by revealing the following implications: (1) the SAS subjects tend to have the large density around 3Hz and the proposed method based on DCLS succeeded to correctly separate the nine SAS subjects and the nine healthy subjects; and (2) the characteristics of the WAKE stage are different between the SAS and healthy subjects.

The future work is that it should be clarify the phenomenon around 3Hz represents.

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