Cardiopulmonary Analysis of Sleep Apnea Based on Weighted Limited Penetrable Visibility Graph

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Abstract

Cardiopulmonary coupling (CPC) has been recognized as an important and low-cost technique for in-home sleep monitoring. Clinically, sleep staging is a prior for evaluation of sleep state, especially for the sleep disorders, such as sleep apnea. However, there are few studies on CPC-based characteristic parameters that could be applied to sleep staging.

In this study, inspired by the Visibility Graph and complex networks, we realized CPC analysis using ECG-derived respiration (EDR) technique and mapped the EDR time series of different sleep stages for 16 sleep apnea patients into networks and calculated characteristic parameters using Weighted Limited Penetrable Visibility Graph (WLPVG), including the characteristic path length L, the weighted clustering coefficient entropy $E_{c\omega}$ and the weight distribution entropy E_{ω}. Each characteristic parameter was evaluated among different sleep stages.

Results showed the significant variation of characteristic parameters during different sleep stages. In particular, the characteristic path length L out of three parameters presented high sensitivity for capturing the difference in different stages.

This study explored the mechanism of the cardiorespiratory dynamic system during sleep and supported an interpretable basis for subsequent characterization and differentiation of sleep stages.

1. Introduction

Sleep apnea is recognized as a sleep disorder that the respiration repeatedly stops and starts during the sleeping process [1]. As a common type of sleep apnea, obstructive sleep apnea (OSA) affects up to 38 % of the general population [2]. The caused health risk includes sleep fragmentation, high blood pressure, depression, memory loss and anxiety, and cardiovascular system instability (increased levels of hypertension, coronary arterial disease, and arrhythmias) [3]. Although apnea significantly impacts health and sleep quality, the public's awareness of this disorder is low. Therefore, the development of sleep analysis of sleep apnea attracts more researchers' attention.

Sleep staging is a measure to assess sleep characteristics and determine total sleep time, which is highly related to evaluating sleep apnea severity. As a gold standard, Polysomnography (PSG) collects multimodal signals, such as electroencephalograms (EEGs), electromyograms, electrooculograms, electrocardiogram (ECG), pulse oximetry, airflow, and respiratory effort, and realizes the sleep analysis in the sleep laboratory. However, the PSG device is cumbersome, and professionals should supervise the operation. Therefore, sleep analysis should explore more convenient and cost-effective techniques.

Electrocardiogram (ECG) and respiration are two physiological signals widely used to analyze sleep characteristics in wearable monitoring. As two dynamic and complex systems of the human body, investigation of the dynamic behaviors of both systems during sleeping is essential [4]. Complex network theory has been employed in the dynamic analysis of complex physiological systems. The visibility graph (VG) proposed in [5] contributed to the analysis of EEG signals [6] and human heartbeat dynamics [7]. [8] applied VG on the cardiorespiratory coupling series during sleeping. To further increase the calculation efficiency, the improved method based on the weighted limited penetrable horizontal visibility graph (WLPHVG) was proposed in [9]. However, little research has been performed on the feature analysis of cardio-respiratory time series over the sleeping process.

Therefore, this study aims to employ the WLPHVG-based method on the cardiorespiratory interaction time series to build complex networks for analyzing dynamic characteristics across sleep stages of sleep apnea subjects.

2. Data

MIT-BIH Polysomnographic Database: The MIT-BIH polysomnographic database [10] collects overnight multiple physiological signals of subjects with sleep apnea in

 ISSN: 2325-887X DOI: 10.22489/CinC.2022.194

the Boston's Beth Israel Hospital Sleep Laboratory. A total of 16 subjects participated, and the recording duration varies from 6 to 8 hours. Each physiological signal is sampled at 250 Hz. Followed by the criteria of RechtschaHen and Kales, the sleep stages are annotated each 30 s with six labels (wake, stage 1,2,3,4, rapid eye movement (REM)). In our study, we combined stages 1 and 2 as the light sleep stage (LS) and stages 3 and 4 as the deep sleep stage (DS). The ECG data was broken into 30 s epochs based on the corresponding sleep stages.

3. Methods

3.1. Preprocessing and R peak detection

First, the raw ECG signal was low-pass filtered at a 35 Hz cutoff frequency to eliminate the high-frequency impacts [11]. Then, the Pan and Tompkins algorithm [12] was employed to detect R-peak locations.

3.2. ECG-derived respiration

The modulation of respiration on ECG is reflected in two aspects: morphology and rhythm. During the respiratory cycle, the chest movements due to the air filling and emptying of the lungs lead to the rotation of the heart's electrical axis, which causes respiration's influence on the ECG morphology. On the other hand, the heart rate increases during the inspiration and decreases during the expiration. The cyclic variation of heart rate shows the respiratory modulation of the rhythm of ECG. In this study, the ECG-derived respiration (EDR) technique in [13] is employed to extract respiration from ECG. Figure 1 showed the example of a 30 s ECG waveform, synchronously collected respiratory waveform and EDR waveform. It is noted that the EDR waveform is highly similar to the collected respiration both in morphology and rhythm.

3.3. Weighted limited penetrable horizontal visibility graph

The weighted limited penetrable horizontal visibility graph is proposed in [9], which defined each data point of the time series as the nodes in the network. The histogram is obtained by the amplitude of each point. According to the visibility rule, the two nodes connect if they can "see" each other, which means an intermediate node blocks the visible line between corresponding histograms of two nodes at a distance no greater than limited penetrable visual distance L_p. Compared to visibility graph (VG) [5] and limited penetrable horizontal visibility graph (LPHVG) [14], the weight is introduced in WLPHVG. The weight ω_{ij} of the edge between two nodes i and j is defined as:

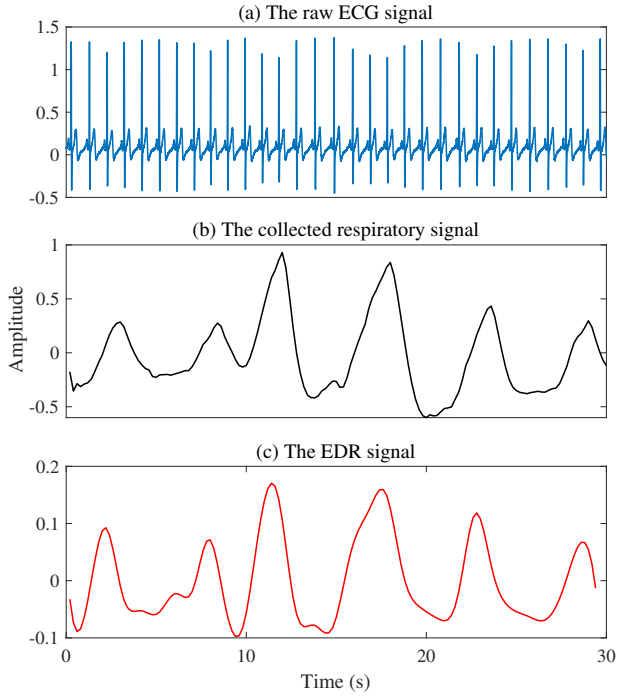

Figure 1. The example of (a) 30 s raw ECG waveform, (b) the synchronously collected 30 s respiratory waveform and (c) 30 s EDR waveform.

$$\omega_{ij} = \begin{cases} 1 + |(i-j)(x_i - x_j)|, & \text{i and j are connected} \\ 0, & \text{i and j are unconnected} \end{cases} \tag{1}$$

where x_i and x_j are amplitudes of node i and j, respectively.

The network characteristics are extracted through three parameters (the characteristic path length L, the weighted clustering coefficient entropy $E_{C\omega}$ and the weight distribution entropy E_ω to reflect dynamics of complex system. The detailed definitions of three parameters are described as follows:

(1) The characteristic path length

$$L = \frac{1}{N(N-1)} \sum_{i,j \in V, i \neq j} d_{ij} \tag{2}$$

where V is the set of nodes, N is the number of nodes, and d_{ij} is the lowest path length between node i and j.

(2) The weighted clustering coefficient entropy

$$E_{C\omega} = -\sum_{i=1}^{N} P_{C\omega,i} log(P_{C\omega,i}) \tag{3}$$

where

$$P_{C\omega,i} = \frac{C_{\omega,i}}{\sum_{i=1}^{N} C_{\omega,i}} \tag{4}$$

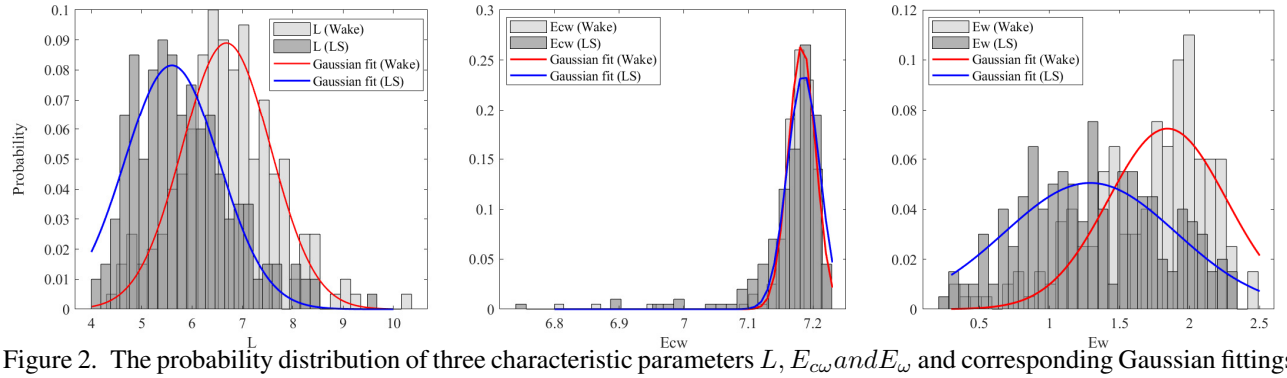

Figure 2. The probability distribution of three characteristic parameters L, $E_{c\omega} and E_{\omega}$ and corresponding Gaussian fittings.

$$C_{\omega,i} = \frac{\sum_{j,k} \omega_{ij}\omega_{jk}\omega_{ki}}{\sum_{j,k} \omega_{ij}\omega_{ki}} \tag{5}$$

(3) The weight distribution entropy
The histogram is constructed to exhibit the weight distribution of each edge and the number of intervals is M. The probability distribution of ith weight interval is $P_{\omega,i}$. Then, the weight distribution entropy could be written as:

$$E_{\omega} = -\sum_{i=1}^{M} P_{\omega,i} log(P_{\omega,i}) \tag{6}$$

4. Results

Figure 2 showed the probability distribution of three parameters (the characteristic path length L, the weighted clustering coefficient entropy $E_{c\omega}$ and the weight distribution entropy E_{ω}) between wake and light-sleep stages. To better visualize, we performed the Gaussian fitting on the distribution of each parameter. Compared with $E_{c\omega}$, the obvious difference could be distinguished in the distribution of L and E_{ω} in wake and light sleep stages. For both L and E_{ω}, the value exhibited a decreased trend from the wake to the light sleep stage. In other words, the mean value of Gaussian fitting decreased from around 7 to 5 for L and 2 to 1 for E_{ω}.

Figure 3 provided the detailed information of parameter (a) L, (b) $E_{c\omega}$ and (c) E_{ω} during whole sleep cycle, which involved four stages with wake to light sleep to deep sleep to rapid eye movement. During the transfer of sleep stages, L showed a continuous decreased trend, especially significant between the wake stage and light sleep. From figure. 3(b) and 3(c), the $E_{c\omega}$ and E_{ω} showed a similar variation among different sleep stages, which obviously decreased between wake to light sleep and then increased to deep sleep and rapid eye movement.

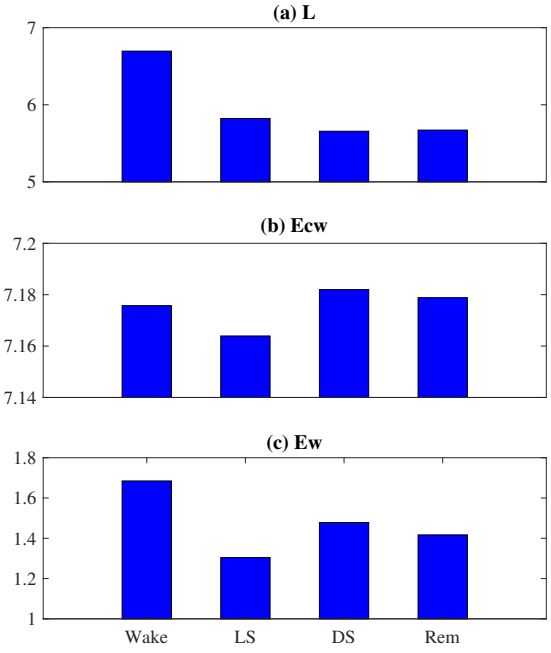

Figure 3. The values of three characteristic parameters (a) L, (b) $E_{c\omega}$ and (c) E_{ω} for different sleep stages.

5. Discussion and Conclusion

In this study, we investigated the dynamic characteristics of the cardiopulmonary system based on parameters (the characteristic path length L, the weighted clustering coefficient entropy $E_{c\omega}$ and the weight distribution entropy E_{ω}) of the weighted limited penetrable visibility graph during sleeping of sleep-apnea subjects.

The cardiopulmonary system is complex and controlled by the autonomic nervous system (ANS). The parameters of the complex system built by the EDR series during sleep are affected by the modulation of ANS during the sleep stages [15]. However, the sleep structure is disordered for those suffering from sleep apnea. Even though some re-

lated research was proposed, the focus is on cardiorespiratory interaction (CRI) analysis during normal sleep using complex networks. Few studies reported the dynamic characteristics of CRI with sleep apnea. [8] analyzed the CRI time series through the visibility graph method. The property of assortative mixing of the network during several sleep stages was investigated. The result showed the largest assortativity coefficient at the deep sleep stage and the lowest at the wake stage, indicating that deep sleep exhibited a more regular CRI pattern. This discovery is consistent with our results in figure.3(b) and 3(c). In the asleep stage, the entropy-based parameters $E_{c\omega}$ and E_{ω} achieved the maximum value at the deep sleep, which meant the CRI pattern is more stable than light sleep and rapid eye movement. This result is reasonable since the entropy is higher in the regular system. When sleep apnea occurs, the disrupted sleep leads to the irregularity of the heart rate and respiration, which explains the maximal value of E_{ω} at the wake stage.

In general, the weighted limited penetrable visibility graph provided a novel method for analyzing the cardiopulmonary interaction of sleep apnea and an opportunity of understanding the dynamic characteristics of complex networks and physiological mechanisms

Acknowledgments

The study was partly supported by the National Key Research and Development Program of China (2019YFE0113800), the National Natural Science Foundation of China (62171123, 62071241, 62001105 and 81871444), the Natural Science Foundation of Jiangsu Province (BK20190014 and BK20192004).

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