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Evaluating the sleep quality of obstructive sleep apnea patients after continuous positive airway pressure treatment

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ABSTRACT

Continuous positive airway pressure treatment (CPAP) is administered to treat the common disorder of obstructive sleep apnea. However, patients receiving CPAP treatment without a sleep assessment and clinical diagnosis often do not feel or understand the improvement in their condition, necessitating a sleep quality improvement index for physicians to analyze improvements in patient treatment rapidly. This work presents a novel sleep quality evaluation system that calculates the improvement value for sleep quality using electroencephalogram and electrocardiogram signal features, as well as fuzzy inferences. Experimental results indicate that the sleep quality improvement rating of the proposed system and that of the apnea–hyponea index correlate with each other. Importantly, the proposed system can identify considerable levels of improvement in the physiological signals of patients having undergone CPAP treatment.

1. Introduction

Obstructive sleep apnea (OSA), a sleep breathing disorder, happens in more than 2–4% adult general population. It is characterized by complete or incomplete airway collapse during sleep. The repeated collapses of the airway cause airflow limitation, oxygen desaturation, sleep fragmentation or both [1]. Sleep apnea is often diagnosed by capturing and analyzing physiological signals from polysomnogram (PSG), including an electroencephalogram (EEG), electrocardiogram (ECG), electromyogram (EMG), and oxygen saturation (SaO_2) [2,3].

Sleep apnea treatment methods include mouthpieces [4,5], upper airway reconstruction, medication [6–10], and continuous positive airway pressure (CPAP) therapy [11–13]. The treatment mouthpiece is a repositioning dental fitting that supports relaxed muscles. However, this treatment is only effective for patients with mild to moderate sleep apnea and fails to improve the condition of severe apnea patients. In contrast, upper airway reconstruction and CPAP therapy benefit patients to a certain extent. Although Robinson found that upper airway reconstruction and CPAP do not significantly differ in treatment outcome, upper airway reconstruction more adversely impacts patients [12]. CPAP therapy is thus a more common option than upper airway reconstruction. CPAP therapy involves fitting patients with a face mask treatment device that delivers air pressure into their airway at designated times. The pressure titration is adjusted according to the patient's adaptability and severity [13]. In addition to treating and improving the conditions of OSA patients, CPAP therapy also benefits cardiovascular disease patients. Owing to its non-invasiveness, CPAP has fewer side effects than upper airway reconstruction, and alleviates the symptoms of heart disease, cardiovascular disease, and hypertension patients. While considering CPAP as the most effective treatment method, Peled et al. found that long-term CPAP treatment improves the conditions of heart disease patients [14]. Furthermore, Butler et al. noted that CPAP treatment increases heart rate variation and parasympathetic nervous system activity of congestive heart failure patients [15]. Finally, Shinjuku et al. found that CPAP therapy alleviates hypertension [16].

Despite the effectiveness of CPAP as a treatment method, most patients are unaware of the subsequent improvement in or improvement levels for sleep quality. Treatment occurs mainly at night, after patients have fallen asleep. Therefore, patients who do not experience day time sleepiness or those with cardiovascular diseases often fail to subjectively recognize changes in sleep conditions. Therefore, the work develops a novel sleep quality evaluation system by using non-invasive physiological signals to analyze the pre- and post-treatment sleep quality of patients who received CPAP therapy and determine whether sleep quality has improved.

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Meaningful characteristics or features are selected and recorded, along with the sleep quality evaluation value (SQEV) estimated using the fuzzy method. Experimental results demonstrate the effectiveness of the proposed system in detecting improvements in sleep quality of patients after CPAP therapy.

The rest of this paper is organized as follows. Section 2 describes related work. Section 3 then introduces the system architecture. Next, Section 4 compares the experimental results of this work with those of previous works. Finally, Section 5 gives discussion and conclusions.

2. Related work

2.1. OSA disease signal analysis

Numerous methods can detect OSA. In addition to adopting different signals, these methods can be broadly classified into time, frequency, and time–frequency domains [17]. Time domain processing typically involves using the wavelet transform [18,19] and Hilbert–Huang transform (HHT) to extract and analyze signal features [20]. By using a discrete wavelet transform and continuous wavelet transform, Tagluk et al. captured wavelet coefficient features, incorporating them into an artificial neural network for training and classification [21]. According to those results, patients were classified as having one of following three types: obstructive sleep apnea, central sleep apnea, and mixed sleep apnea. Hsu et al. captured sleep-related delta wave frequency bands by using HHT from EEG signals; OSA was also detected using the variance [22]. Similarly, based on a wavelet transform and artificial neural network, Romero et al. classified the apnea type [23].

The frequency domain focuses on specific time intervals and, within these time frames, calculates the size or relationship of each frequency. Among the most common approaches include the Fourier transform [24,25] and calculation of power spectral densities (PSD). Yildiz et al. used an ECG as a diagnostic procedure for OSA patients [26]. The ECG waveform consist of three fundamental waveforms: P, QRS, and T. ECG-derived respiratory (EDR) signals are alternative respiration signals obtained from heart rate variability (HRV). By using a fast Fourier transform, that work also obtained the PSD features from HRV and EDR; OSA patients were then classified by using least squares support vector machines on the features. Moreover, based on the Fourier transform, Zywietz et al. classified ECG recordings into four portions: ultra-low frequency (i.e. 0–0.013 Hz), very-low frequency (i.e. 0.013–0.0375 Hz), low frequency (i.e. 0.0375–0.06 Hz), and high frequency (i.e. 0.17—0.28 Hz) [27]. Whether the participants were experiencing OSA on a minute-by-minute basis was evaluated using multiresolution analysis. Based on the Fourier transform to EEG recordings, Bandla et al. captured delta waves and observed changes during an OSA episode and without OSA [28]. Kim analyzed how patients with various levels of OSA differ, as well as their changes before awakening by performing a PSD transformation of the R wave to R wave (RR) interval in ECG signals [29]. Finally, based on frequency spectrum analysis of EEG recordings, Grenèche et al. examined how OSA patients and individuals without OSA differ in alpha, beta, delta, and theta waves [30].

The time–frequency domain combines the transformation or transforms methods of the previously mentioned domains [31]. In particular, time domain transformations are performed initially before applying frequency domain transformations to the data obtained. Based on a wavelet transformation of EEG signals, Álvarez et al. filtered four frequency bands (i.e. alpha, beta, delta, and theta) [32]. These four frequency bands and SaO_2 signals were processed with a discrete Fourier transform to achieve PSD transformation. The peak amplitude of the post-transformed SaO_2 signal, power corresponding to the SaO_2 peak amplitude range for the EEG, and power corresponding to the four wave bands of the EEG were subsequently used as the frequency spectrum density features values. Finally, the frequency median and spectral entropy were obtained. Also, the features were calculated using the Kolmogorov–Smirnov and Shapiro–Wilk tests to differentiate between patients with and without the disorder. By applying a short-time Fourier transform to ECG signals, Manrique et al. extracted 10 characteristics each from the spectral centroids, spectral centroids energy, and cepstral coefficients [33]. Moreover, the average person and sleep apnea patients were compared by using the time domain and frequency domain as the horizontal and vertical axes.

2.2. Sleep quality evaluation

Sleep quality evaluation methods are generally classified into questionnaires, sleeping posture and position measurements, and physiological signal analysis. Questionnaires involve the self reporting of participants regarding their records of sleeping conditions and sleeping durations. Buysse et al. used questionnaires, where each response yielded different scores, to calculate the Pittsburgh sleep quality index (PSQI) in order to evaluate the sleep quality of participants [34,35]. Buysse et al. compared how PSQI and the Epworth sleepiness scale (ESS) differ from each other, indicating that PSQI can more accurately reflect all-night sleeping conditions, whereas ESS reflects only the wakefulness and sleepiness of patients during the day time. Aloba et al. analyzed the feasibility and applicability of employing the PSQI to students by comparing PSQI and the diagnosis of each student [36]. According to their results, PSQI scores and sleep disorders correlated well with each other. Sleeping posture and position measurements involve either installing sensors on a bed to detect the frequency of all-night body movements or using image signal detection of body movement data to evaluate all-night sleep conditions. Gaddam et al. designed a home sleep quality assessment system, in which sensors were placed at the four corners of a bed; weights detected by the four sensors were recorded as well [37]. This method evaluates sleep quality by determining the frequency of postural and position changes during sleep. Majoe et al. calculated PSD by using ECG signals and detecting RR intervals [38]. All-night sleep conditions were then evaluated using these features and body movement data captured by a video camera.

Evaluating all-night sleep based on physiological signals generally involves processing and capturing features from various signals, including all-night EEG, ECG, and SaO_2 signals. Bsoul et al. placed a heart rate sensing device on participants and, then, transmitted the data to a cell phone via Bluetooth transmission for initial pre-processing [39]. Data was then sent to a server via wireless Internet for instant classification and determination, where signal features (e.g., mean, standard deviation, and standard deviation root mean square of the RR sequence) were captured. Alternatively, EDR can extract the amplitude means and standard deviations. The very-low frequency, low frequency, and high frequency feature values in these two sequences were captured using a fast Fourier transform. These values were then input into the support vector machine to classify and evaluate sleep quality. In contrast, Peng et al. extracted features from heart rate, sound, and image signals; a support vector machine was also used to calculate sleep duration and latency or delay to evaluate sleep efficiency [40]. Donahue et al. evaluated sleep conditions by monitoring electro-oculogram signals to determine all-night sleeping cycles and periods [41].