Computers in Biology and Medicine 88 (2017) 32–40

Contents lists available at ScienceDirect

Computers in Biology and Medicine

journal homepage: www.elsevier.com/locate/compbiomed

A novel method to precisely detect apnea and hypopnea events by airflow and oximetry signals

Wu Huang [a], Bing Guo [a,*], Yan Shen [b], Xiangdong Tang [a]

[a] Sichuan University, Chengdu, SC, China
[b] Chengdu University of Information Technology, Chengdu, SC, China

ARTICLE INFO

Keywords:
Apnea
AHI
Baseline amplitude
Hypopnea
OSAS
Respiratory event
SAHS

ABSTRACT

Sleep apnea hypopnea syndrome (SAHS) affects people's quality of life. The apnea hypopnea index (AHI) is the key indicator for diagnosing SAHS. The determination of the AHI is based on accurate detection of apnea and hypopnea events. This paper provides a novel method to detect apnea and hypopnea events based on the respiratory nasal airflow signal and the oximetry signal. The method uses sliding window and short time slice methods to eliminate systematic and sporadic noise of the airflow signal for improving the detection precision. Using this algorithm, the sleep data of 30 subjects from the Huaxi Sleep Center of Sichuan University (HSCSU) and the Teaching Hospital of Chengdu University of Traditional Chinese Medicine (THCUTCM) were auto-analyzed for detecting the apnea and hypopnea events. The total predicted apnea and hypopnea events were 8470. By manual investigation, the sensitivity and positive predictive value (PPV) of detecting apnea and hypopnea events were 97.6% and 95.7%, respectively. The sleep data of 28 subjects form HSCSU were auto-diagnosed SAHS according to the AHI. The sensitivity and PPV were 92.3% and 92.3%, respectively. This is an effective and precise method to diagnose SAHS. It can fit the home care SAHS screener.

1. Introduction

Approximately 2–4% of the adult population worldwide suffered from sleep apnea hypopnea syndrome (SAHS) in 1993 [1]. The estimated prevalence rates of the SAHS had increased over the last 2 decades since 1993; it relatively was increased between 14% and 55% depending on the subgroup in 2013 [2]. SAHS is related to cardiac disease, diabetes, hypertension and many other major diseases [3–12]; it is a risk factor for sleep stroke also [13]. Some studies indicate that there is a relationship between obstructive sleep apnea syndrome (OSAS) and cancer mortality [14]. In general, OSAS is accompanied by daytime sleepiness and tiredness; thus, this disease is associated with the incidence of traffic accidents [15–18].

A recent study has pointed out there is uncertainty about the accuracy or clinical utility of all potential screening tools [19]; however, so far the gold standard for SAHS disease diagnosis is polysomnography (PSG). Except to PSG diagnosis, more simple equipment is used to screen the disease based on different methods; moreover, the home care device for diagnosing OSAS is meaningful [20]. Some methods have depended on a single oxygen signal [21–23]; some algorithms have relied on a single airflow signal [24–26]. An algorithm depended on nighttime snoring [27]. Another method based on a nasal pressure signal [28]. Recently, more studies have focused on detecting respiratory events from the ECG signal [29–32]. Home care OSAS screening is becoming increasingly important. However, more effective, robust and precise algorithms are the focus of current efforts in the design of an OSAS screener [33].

The algorithm in this paper is based on the 2012 American Academy of Sleep Medicine (AASM) criteria [34]. It scores the respiratory events using nasal airflow and oximetry signals. It improves the scoring accuracy by eliminating the impact of systematic and sporadic changes of the baseline amplitude of the nasal airflow signal.

In the algorithm, the systematic and sporadic changes of the nasal airflow baseline are eliminated by a sliding window and a series of short time slices of the respiratory signal. At first, the whole recorded airflow signal is divided into a series of short time slices. Then, a width limited sliding window slides over all of the short time slices for analyzing the time slice state. Next, unclassified respiratory events are obtained according to the adjacent time slice state. Then, the unclassified events were classified as apnea or hypopnea events by the Bayesian criterion. Finally, the hypopnea events must be filtered by the oxygen desaturation event of the corresponding period.

* Corresponding author.
E-mail address: guobing@scu.edu.cn (B. Guo).

http://dx.doi.org/10.1016/j.compbiomed.2017.06.015
Received 26 February 2017; Received in revised form 7 June 2017; Accepted 14 June 2017

All original sleep data used by the algorithm were recorded by a SR20C portable sleep screener (SR20C) manufactured by Chengdu Easyhealth Technology Co., Ltd, Chengdu city, Sichuan province of China. The SR20C simultaneously records seven types of signals, including nasal airflow, thoracic and abdominal respiratory motion, pulse oximetry, heart rate, snores and sleep posture. The nasal airflow and oximetry signals among the seven signals were used by the algorithm for analyzing the respiratory events. The hardware parameters of the nasal airflow are as follows: sample rate is 50 Hz; filter band is from 0.05 Hz to 5 Hz; and ADC resolution is 12 bits. The pulse oximetry probe is a digital SpO2 probe. The sample rate is 1 Hz, with a range from 40% to 99% and a resolution of 1%. SR20C itself uses the algorithm.

Two groups of analyzed sleep datasets recoded by SR20C came from the Huaxi Sleep Center of Sichuan University (HSCSU) and the Teaching Hospital of Chengdu University of Traditional Chinese Medicine (THCUTCM). Among them, 28 sleep datasets came from HSCSU and 30 sleep datasets came from THCUTCM. The 58 sleep datasets achieved patient consent for the study. The demographics of 58 sleep data see Table 1. The 28 sleep datasets were selected randomly from two groups of sleep datasets from HSCSU and THCUTCM were taken as the training data used to get the priori and conditional probability for a Bayesian classifier. The remaining 30 sleep datasets from HSCSU and THCUTCM were used as testing data to verify the effectiveness and accuracy of the algorithm for classifying the apnea and hypopnea events. The 30 sleep datasets were automatically analyzed by the algorithm; a total of 8470 respiratory events were detected. The all apnea and hypopnea events auto analyzed by the algorithm were validated independently by two trained technician according to 2012 AASM criteria. The specificity and PPV of respiratory event detection were 97.6% and 95.7%, respectively.

PSG is taken as a diagnosing gold standard. The 28 sleep datasets from HSCSU were simultaneously recorded by the Alice5 PSG that was manufactured by Philips Respironics Company. The Alice5 PSG equipment belonged to HSCSU. The AHI of 28 simultaneously recorded datasets were independently auto analyzed by the Alice5 PSG and the algorithm. The correlation coefficient of the two groups of AHI results is 0.94.

This paper is divided into six sections. The first section contains the introduction. The second section analyzes the factors that affect the determination of respiratory events. The third section introduces the main algorithm. The fourth section provides the results. The fifth section presents the discussion. The last section presents the conclusions.

2. Factors that affect determination of respiratory events

There are many factors that affect the determination of the respiratory event; for example, the quality of the sampling signal, the judging criteria, and the dynamic changes in the respiratory amplitude and morphology.

2.1. Criteria for determining apnea and hypopnea events

The apnea and hypopnea events are scored in this paper according to the 2012 AASM criteria. Scoring a respiratory event in adults as apnea requires meeting two conditions: 1) there is a decrease in the peak signal excursion by $\geq$ 90% of the pre-event baseline; and 2) the duration of the $\geq$90% drop is $\geq$ 10 s. The respiratory event is scored as hypopnea if all of the following were met: 1) the peak signal excursions decrease by $\geq$ 30% of the pre-event baseline; 2) the duration of the $\geq$30% decrease in signal excursions is $\geq$ 10 s; and 3) there is $\geq$ 3% oxygen desaturation from the pre-event baseline or the event is associated with an arousal [34].

2.2. Systemic change in baseline amplitude

The baseline amplitude is the respiratory amplitude in the normal respiratory condition, the basis for determining the respiratory event. The baseline amplitude is not always stable. A systemic change typically occurs based on the following description. In a long period, such as 10 min or more, the baseline amplitude remained stable with subsequent quick increases or decreases greater than 50% relative to the previous baseline amplitude and then remains stable for another long period. The baseline amplitude may be changed by more than 50%; however, the amplitude in the next long period continuously maintains the relative stability. Moreover, it does not accompany oxygen desaturation events; thus, it is also considered to be normal breathing. The systemic change in the baseline amplitude may indicate a natural respiratory slowdown during sleep or it may indicate that the nasal catheter position changed or even fell off (see Fig. 1).

Table 1
The demographics of 58 sleep data came from HSCSU and THCUTCM.

Subject	Male	Female	Average Age	Range of age
Number	41	17	45 ± 15	19–75
Proportion	70.7%	29.3%		

The systemic change in the baseline amplitude may be classified into reversible and irreversible changes. Reversible systemic changes include a decrease or increase in the baseline amplitude. These changes may be caused by a change in the nasal airflow catheter position. The baseline amplitude increases when the catheter is close to the nostrils. However, the amplitude decreases when the catheter is away from the nostrils. If the nasal airflow catheter falls off or the recording device is abnormal, the amplitude change is irreversible. In this condition, the respiratory amplitude may be close to zero; the process of analyzing the respiratory event is typically stopped when there is an irreversible change in this algorithm.

2.3. Sporadic change in respiratory amplitude

In addition to systemic changes, there are many factors that may cause sporadic changes in the respiratory amplitude, e.g., the user turned over or coughed. This sporadic change may cause a significant change in the respiratory amplitude in a short duration (see Fig. 2).

3. Algorithm

The algorithm is referred to as short time slice event state (STSES) detection, and the state flow of short time slice (SFSTS) generates the respiratory events algorithm. The purpose of the algorithm is to eliminate the influence of systemic or sporadic changes in the respiratory amplitude to more accurately identify respiratory events.

The core idea of the algorithm is to dynamically track and decrease the influence of systematic changes in baseline amplitude using a sliding window and filter out the influence of sporadic change in the respiratory amplitude using the short time slice method.

According to the idea, the algorithm mainly contains two basic processes:

1) Converting the original respiratory signal into the SFSTS
2) Generating different respiratory events from the SFSTS

In the first step, a sliding window including many short time slices slides over the whole original respiratory signal; then, all short time slices are converted into the SFSTS. There are three basic states: normal, apnea and hypopnea states. In the second step, the multi adjacent STSES are merged into a respiratory event according to the 2012 AASM criteria until the whole SFSTS is converted into respiratory events. The process is illustrated in Fig. 3.

In Fig. 3, N is the normal state, A is the apnea state, and H is the hypopnea state.