Recognizing Central and Obstructive Sleep Apnea Events from Normal Breathing Events in ECG Recordings

AH Khandoker, J Gubbi, M Palaniswami

The University of Melbourne, Victoria, Australia

Abstract

Obstructive sleep apnea (OSA) causes a pause in airflow with continuing breathing effort. In contrast, central sleep apnea (CSA) event is not accompanied with breathing effort. The aim of this study is to differentiate CSA and OSA events from normal breathing events using wavelet based features of ECG signal over 5 second period. Total 164880 epochs(each of 5-second duration) from normal breathing events, 196 epochs from 116 CSA, 5281 epochs from 2173 OSA and 3073 epochs from 1563 hypopnea events were selected from single lead ECGs (sampling rate=250 Hz). At the first stage of classification, apnea events were classified from normal breathing events and at the second stage, hypopneas were identified from all apnea events and at final stage, CSA and OSA types were recognized at 98.96% accuracy. Results indicate the possibility of recognizing OSA/CSA events based on shorter segments of ECG signals.

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1. Introduction

Obstructive sleep apnoea (OSA) is a temporary closure of the upper airway during sleep when air is prevented from entering lungs. The onset of each OSA is associated with inspiratory efforts against a closed airway which increase parasympathetic activity leading to a bradycardia, but as the physiological stress builds up during the apnea the sympathetic activity predominates. This peaks shortly after the moment of arousal at which time there is systemic vasoconstriction, hypertension and a tachycardia. Termination of OSA requires arousal from a deeper to lighter stage of sleep or wakefulness [1].

On the other hand, observation during central sleep apnoea (CSA) reveals an absence of respiratory movements, which differentiate these apnoeas from OSA. The arousals are less frequent than in OSA because of the absence of any increased inspiratory effort as an arousal stimuli. During CSA the Pco_2 gradually rises and when it reaches the apnoeic threshold, a period of hyperventilation then begins to lower the Pco_2 again [1].

Approximately 50% of heart failure patients experience sleep-disordered breathing [2], with either central sleep apnoea (CSA) or obstructive sleep apnea (OSA) usually predominating but both often present. Different algorithms on cheaper ambulatory ECG monitoring technology have recently been proposed to detect OSA [3]. However, the reported methods can detect if there is an OSA event during any given minute.

This study aims to automatically recognize actual OSA/CSA events from normal breathing events using wavelet based features of ECG signal over 5 second sliding window (onset, maximum and termination of the event) and two-stage feed forward neural network. Automated scoring results have been compared with original scoring for the events.

2. Methods

2.1. Subjects and sleep studies

The polysomnograms of 33 sleep apnoea patients [(mean ±SD) age 54±9 yrs, body mass index (BMI) 30±2 kg/m2] were analysed. All subjects were free of any cardiac history. Diagnosis was based on clinical symptoms and polysomnographic (PSG) outcomes. Respiratory events were scored using criteria proposed by the AASM[4]. Hypopneas were defined as a >50% reduction in airflow from the baseline value lasting for >10 s and associated with a 3% desaturation or an arousal. Obstructive apnoea was defined as the absence of oronasal airflow for >10 s in the presence of persistent respiratory efforts. The range of apnoea-hyponea index (AHI) was 0.3~43.

2.2. Feature extraction and model selection

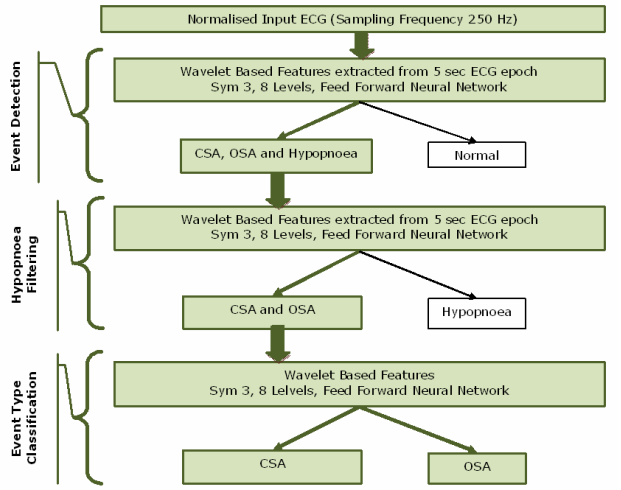

Figure 1. Flow chart of the proposed method to detect apnea events and classify apnea type.

Figure 1 shows the schematic of the proposed approach for which the input is ECG and the output are CSA, OSA, Hypopnoea and Normal. The input ECG (sampling frequency ≥ 250 Hz) signal is divided into 5 sec epochs and are down sampled to 250 Hz if sampling frequency is higher. The signal was band pass filtered with lower cut off of 1 Hz and a higher cut off frequency of 100 Hz. The process is divided into three stages – event detection, hypopnoea filtering and event type classification.

Total 164880 epochs(each of 5-second duration) from normal breathing events, 196 epochs from 116 CSA, 5281 epochs from 2173 OSA and 3073 epochs from 1563 hypopnea events were selected from single lead ECGs (sampling rate=250 Hz) collected.

2.2.1. Stage 1-Event detection

In the first stage of event detection, all ECG epochs during normal breathing were filtered out and the events including hypopnoea, central sleep apnoea and obstructive sleep apnoea were retained.

Each ECG epoch was decomposed to eight levels of detailed coefficients using mother wavelet Symlet (sym8). From each level of approximate and detailed coefficients, Shannon's entropy [6], mean, variance, skewness and kurtosis were extracted. In total 45 features were extracted. Using all features, a feed forward single layer neural network with 33 hidden nodes (heuristically chosen) was used for event detection. Before the features were used as input to the classifier a median filtering was performed. The feature value output of the smoothing operation or an epoch was the average of the feature values for that epoch with the surrounding epochs.

2.2.2. Stage 2-Hypopnea filtering

In the second stage, the features extracted in the first stage are used again for filtering hypopnoea from CSA and OSA. Again, sym8 wavelet was used for 8 level wavelet decompositions. However, in order to select best features of discrimination capability for hyponea and full apnea (OSA+CSA) events, the area under receiver operating characteristics (ROC) curve was estimated for each individual features. This resulted in 27 best features (ROCarea> 0.6) containing mean, variance and Shannon entropy values of wavelet approximate and detailed coefficients at all levels. Feed forward single layer neural network with 23 hidden nodes (heuristically chosen) was used for classifying hypopnea events from full apnea (OSA+CSA) events.

2.2.3. Stage 3-Event type classification

For event type classification, Shannon entropy, log energy entropy, arithmetic mean and geometric mean were calculated for approximate and detailed coefficients at 8 levels using sym8 wavelet. This resulted in 36 features. Among them 9 best features were selected by add-remove method with Mahalanobis distance measures showing ROC area 0.92. Based on the results, 9 Shannon entropy features were retained. The highest ROC area for Shannon entropy value of detailed coefficients at level 3 (16-32 Hz) was found to 0.91. Feed forward single layer neural network classifier with 7 hidden nodes (heuristically chosen) was used for classification (OSA/CSA).

3. Results

Table 2. Summary of the results of Neural Networks classifiers' performances at three stages.

Stage	Sensitivity	Specificity	Accuracy
1	87.64	95.45	95.10
2	86.12	78.72	83.40
3	93.72	99.16	98.96

Stage 1: Event detection. Sensitivity for 5 sec ECG epochs during CSA/OSA/hypopnoea events; Specificity for epochs during normal breathing.
Stage 2: Hypopnoea filtering. Sensitivity for 5 sec epochs during CSA/OSA and specificity for epochs during hypopnoea.

Stage 3: Event type classification cross validation results. Sensitivity for 5 sec epochs during CSA and Specificity for epochs during OSA.

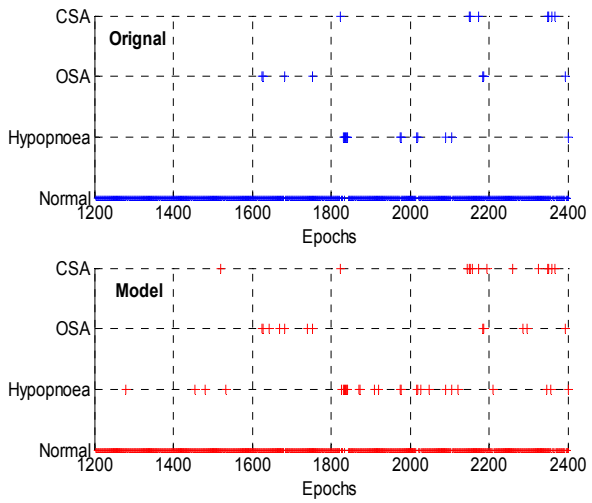

Figure 2. Original and model based apnoea event scoring for the Patient ID 17 with $AHI_{original}$=12.27 (AHI_{model}= 15.63). The events between 1200 to 2400 epochs (epoch length=5 second) from the start of the recording are shown.

4. Discussion and conclusions

Three-stage Feed forward Neural network(NN) models was trained using the selected best features. Ten-fold cross validation (randomly 70% for training and remaining 30% for testing events by combining epochs) results of the first stage NN model show the average accuracy of 87.64% in recognizing apnea epochs from all epochs. As for the performance of third stage NN model using shannon's entropy values of wavelet coefficients, average accuracy of 98.96% in classifying OSA and CSA epochs was obtained. These results indicate the possibility of noninvasively recognizing OSA/CSA events from normal breathing events based on shorter segments of ECG signals.

The highest ROC area for Shannon entropy value of detailed coefficients at level 3 (16-32 Hz) was found to be 0.91 in discriminating OSA/CSA epochs. In ECG signal, power in the frequencies higher than 20 Hz reflects EMG from respiratory muscle activity [5]. We speculate that difference in the intensity of respiratory effort during OSA and CSA events are reflected in 16-32 Hz band of ECG signals.

Table 1. Comparisons on original apnoea/hypopnoea index ($AHI_{original}$) and the model based AHI_{model} at stage 1.

Patient ID	Original		Model	
	Number of Events	AHI	Number of Events	AHI
1	3	0.39	4	0.53
2	98	13.63	112	15.57
3	184	25.89	285	40.09
4	188	26.32	346	48.45
5	91	10.92	105	12.6
6	166	19.94	234	28.11
7	143	20.33	101	14.36
8	82	11.04	58	7.81
9	255	38.93	271	41.37
10	0	0	3	0.38
11	38	4.6	36	4.35
12	243	30.12	414	51.32
13	109	13.91	164	20.94
14	17	1.75	30	3.09
15	236	35.44	362	54.37
16	121	16.24	207	27.79
17	58	7.49	121	15.63
18	168	20.53	273	33.36
19	123	18.5	140	21.05
20	38	4.65	73	8.94
21	23	3.24	49	6.89
22	64	8.08	115	14.53
23	55	8.53	124	19.22
24	62	8.97	114	16.5
25	131	19.29	188	27.68
26	31	4.44	42	6.02
27	63	8.62	69	9.44
28	24	3.19	22	2.92
29	244	36.51	312	46.68
30	1	0.14	0	0
31	1	0.14	1	0.14
32	150	24.39	233	37.89
33	4	1.09	5	1.36

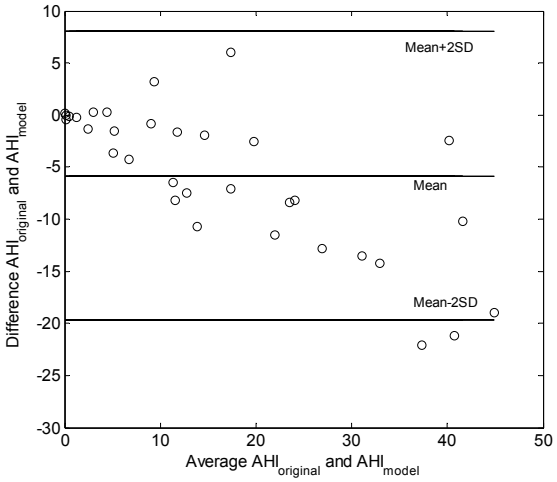

Figure 3. Bland-Altman plot of the relationship between the difference between the original apnoea/hypopnoea index ($AHI_{original}$) and the model based AHI_{model} score versus their mean value. Mean bias (—), +2SD and -2SD lines are shown.

Bland-Altman plot shows the paired difference between two observations on each subject against the mean of these two observations. For AHI_{model} measures, we get the bias of -5.82 with limits of agreement 8.01 and -19.65. Whether this is acceptable agreement needs to be judged from a clinical viewpoint. However, it is obvious that neural network based model overestimates the severity of the apnoea. The range of AHI_{model} is (min=0 and max=54.37). For a new test subject, AHI_{model} is likely to give a value between 20% and 150% of that obtained by $AHI_{original}$. Possible reasons for overestimation cannot be systematically explained. However, respiratory events of all subjects were later examined and found that respiratory events of the subjects with higher AHI but lower posterior probability contained more than 50% hypopneas. Although an apnoea is a near complete cessation of airflow, a hypopnea is partial reduction in the airflow amplitude caused by airway narrowing (but not total collapse). Another reason may be the heuristic rule to define the events that was set at 10 second (two consecutive 5 second epochs). For example, two 10 second events separated by a 5-second normal epoch could have been combined to one event.

Future research is required to reduce the overestimation of apnoea events and thereby the AHI. De Chazal [7] reported that apnea classifier accuracy depends on the ECG epoch length and the shortest as 15 second ECG epoch showed lowest accuracy. In this study, we extracted the features from broadband ECG signals (only 5 second epoch length) containing the influence of chest muscle effort.

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Address for correspondence

Ahsan Khandoker
Dept. of Electrical & Electronic Engg. The University of Melbourne, VIC -3010, Australia.
E-mail: a.khandoker@ee.unimelb.edu.edu.au