A Snoring Classifier based on Heart Rate Variability Analysis

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Abstract

The effect of snoring on the cardiovascular system is not well-known. In this study we analyzed the Heart Rate Variability (HRV) differences between light and heavy snorers. The experiments are done on the full-whole-night polysomnography (PSG) with ECG and audio channels from patient group (heavy snorer) and control group (light snorer), which are gender- and age-paired, totally 30 subjects. A feature Snoring Density (SND) of audio signal as classification criterion and HRV features are computed. Mann-Whitney statistical test and Support Vector Machine (SVM) classification are done to see the correlation. The result of this study shows that snoring has close impact on the HRV features. This result can provide a deeper insight into the physiological understand of snoring.

1. Introduction

Sleep medicine is the science of the study of sleep and its processes, and also refers to the diagnosis and therapy of sleep disturbances and disorders. A common disorder during sleep is the respiratory-related disorders (SRRD) including Obstructive Sleep Apnea (OSA), Central Sleep Apnea (CSA) and snoring. With OSA the patient's upper airway is repeatedly obstructed during sleep, which reduces (hypopnea) or stops (apnea) the airflow. CSA is without airway obstruction but is thought to be caused by a periodic cessation of respiratory drive [1]. The OSA or CSA patient often stops breathing during sleep several hundreds of time throughout the night. This causes depletion in oxygen levels as well as changes in blood pressure, heart beat, and brain functions.

Snoring is a common respiratory event in the general population, especially from older people [2]. It often associated to SRRD as precursor and its main known effect is loud noisy breathing. There are publications showing that OSA and CSA have relationship to the Heart Rate Variability HRV features [3-6], but the relationship between snoring and HRV features are still unknown. This paper is to validate the effect of snoring on HRV features with experimental data, statistical analysis and classification. The result of this paper is expected to provide deeper insight to the physiological understanding of snoring.

2. Materials and methods

In this session, the materials and methods for data analysis are described. The interest is to find the correlation between HRV features and snoring severity.

2.1. Patients and signals

The study is composed by 30 subjects in total. The selection criteria are: Apnea-hypopnea Index (AHI) lower than AHI 5/hour, Limbs Movements(LM) lower than 2 LM/hour, Body Mass Index (BMI) lower than 40 BMI, number of Oxygen desaturation SaO2 < 92% is less than 1/hour. The subjects are divided in two groups according to number of manually scored snoring events. The Low incidence group with 15 subjects (6F, 9M) age between 26~67 years (mean 44.47 +/- 11.64) has Snoring Index (SI), number of snores per hour lower than 100/h. High incidence group with 15 subjects (5F, 10M) age between 29~65 years (mean 46.06 +/- 11.86), has more than 300 SI/h.

Whole-night Polysomnography (PSG) are recorded for subject selection and analysis, with the standard 6 EEG, chin EMG, asymmetric outer cantus EOG, 3-lead ECG, Cannula, Thermistor, contact microphone, body position, Leg EMG, Thorax and Abdominal strain-gauge and oximetry. The bio-amplifier for signal acquisition is model Sommeil 800 of Meditron Lda. The processing algorithms are implemented as plug-in on the Somnium software platform from Cognitron, SP., Br. The patient data collection has been approved by the ethical committee of University Hospital of UNESP, Botucatu, SP., Br.

2.2. Computation of features

The HRV features are computed from Normal RR (NN) intervals of the digitized ECG signal with 256-Hz sampling rate. The temporal locations of QRS complexes are detected with Hamilton-Tompkins method [7]. Validated with MIT-BIH Arrhythmia database, the QRS detection accuracy is reported 99.46%. Then the NN intervals are obtained by computing the time differences of consecutive normal QRS complexes and re-sampling for alignment to every second of time. The time domain HRV features are computed based on the QRS complex detection result. The frequency domain HRV features are computed from the re-sampled NN interval series. Both time domain and frequency domain HRV features and their means are shown in Table I. The HRV features are computed for each 10-min intervals (epochs). So there are dozens of sets of features for a whole-night record.

HRV Feature SD1 and SD2 are computed by applying an ellipse fitting technique of quantitative analysis of Poincaré HRV plots. The Poincaré HRV plot is a graph in which each RR interval (in ms) is plotted against next RR interval [8].

SD1 and SD2 can be estimated with Equation (1) and (2).

$$\mathrm{SD1} = \mathrm{Var}\left(\frac{1}{\sqrt{2}}\mathrm{RR_n} - \frac{1}{\sqrt{2}}\mathrm{RR_{n+1}}\right) = \frac{1}{2}\mathrm{SDSD}^2 \quad (1)$$

$$\mathrm{SD2} = 2\mathrm{SDRR}^2 - \frac{1}{2}\mathrm{SDSD}^2 \quad (2)$$

where SDRR is standard deviation of the RR intervals and SDSD is standard deviation of the successive differences of the RR interval [9].

Since the heart rate signal is highly non-linear, non-stationary and non-equilibrium in nature, Detrended Fluctuation Analysis (DFA) is applied to the NN interval series. DFA calculates the root-mean-square fluctuation of integrated and detrended NN interval, which permits the detection of intrinsic self-similarity embedded in this time series [10].

Normally, the resulted scaling exponent α on log-log plot is not strictly linear when applied DFA on HRV signal. Therefore, a short range scaling exponent α0 and long range scaling exponent α1 is employed in this research. The range of α0 and α1 is selected base on the suggestion from previous work [11].

For audio signal, a feature called Snoring Density (SND) is introduced by the authors and computed. It is the percentage of snoring calculated from the audio signal within the analysis interval (10 min). It is computed by firstly estimating the smoothed envelope of audio signal and then comparing the samples in the time series of smoothed envelop to a threshold. If the amplitude of a sample in this smoothed envelop time series is larger than the threshold, then this sample is counted as a snoring sample. The SND can be computed from total number of snoring samples divided by the total number of samples in one analysis interval.

Table 1. Meaning of HRV features.

Feature	Meaning
MNN	Mean of all NN intervals
SDNN	Standard deviation of all NN intervals
RMSSD	Root mean square successive difference
MSD	Mean successive difference
SDSD	Standard deviation of the successive differences
NN50	Number of consecutive NN intervals changing more than 50 ms
pNN50	pNN50 = (NN50 count)/(total NN count)
RRTI	RR Triangular Index
TINN	Triangular Interpolation of NN
maxNN	Maximum NN interval
minNN	Minimum NN interval
maxSD	Maximum successive difference
minSD	Minimum successive difference
SD1	Standard deviation of points perpendicular to the axis of line-of-identity in Poincare plot
SD2	standard deviation of points along the axis of line-of-identity in Poincare plot
DFAα0	Short range scaling exponent of DFA
DFAα1	Long range scaling exponent of DFA
VLF	Very Low Frequency total spectral power (0.003-0.04 Hz)
LF	Low Frequency total spectral power (0.04-0.15 Hz)
HF	High Frequency total spectral power (0.15-0.4 Hz)
TPW	Whole band total spectral Power
LF/HF	Ratio of low to high freq. power
LFmx	Peak Amplitude in LF band
LFfx	Frequency of LF band peak
HFmx	Peak Amplitude of HF band
HFfx	Peak frequency of HF band
LF nu	The normalized LF power
HF nu	The normalized HF power
VLFmx	Peak amplitude of VLF band
VLFfx	Peak frequency of VLF band
TPWmx	Peak amplitude of TPW band
TPWfx	Peak Frequency of TWP band

Note: All the computations are to NN intervals within the analysis interval

Table 2. Classification Criteria defined by Authors.

Feature	Meaning
SI	Number of snoring per hour
SND	Percentage of the time of snoring to the time of the whole analysis interval

The smoothed envelope of snoring signal is estimated as below. First, Hilbert transform (HT) of the audio samples is computed to obtain the complex envelop. Then, the real envelope of the signal can be obtained by calculating the absolute value of the HT result. Finally, a 25-point moving average filter is applied on real envelop for smoothing this signal.

2.3. Statistical analysis and classification

Mann-Whitney statistical analysis is employed to find the significances of HRV features. If a HRV feature is

Table 3. Mann-Whitney Analysis (Experiment A. Time Domain).

Feature	Low SI	High SI	M-W P Value
MNN	874.9± 112.8	924.6± 101.6	0.25
SDNN	62.1± 19.6	67.8± 23.3	0.683
RMSSD	37.7 ±15.6	46.7± 16.6	0.389
MSD	24.2±10.6	29.8 ±14.0	0.389
SDSD	37.7 ±15.6	46.7± 16.6	0.389
NN50	74.2±64.4	91.3 ±75.5	0.624
pNN50	11.4±10.2	15.04± 13.8	0.595
RRTI	19.3±5.5	20.2± 5.8	0.967
TTIN	165.9±39.5	153.8± 37.5	0.412
maxNN	1051.1±145.5	1135.8± 127.9	0.137
minNN	612.8±107.8	612.4± 128.7	0.87
maxSD	218.3±95.8	272.4± 110.1	0.267
minSD	-188.2±90.9	-257.3± 122.9	0.161
SD1	23.3±8.8	27.7 ±8.8	0.367
SD2	75.0±23.5	82.9 ±26.5	0.624
DFAα0	1.1±0.34	0.97 ±0.36	0.345
DFAα1	0.89±0.07	0.89± 0.04	0.87

Table 4. Mann-Whitney Analysis (Experiment A. Freq. Domain).

Feature	Low SI	High SI	M-W P Value
VLF	788.5±413.9	904.7± 515.1	0.713
LF	313.4±212.8	309.2±206.5	1
HF	174.8±113.2	259.8±237.4	0.285
TPW	1459.5± 730.1	1764.5± 976.3	0.412
LF/HF	3.3±2.2	1.9±0.9	0.187
LFmx	28.9±19.5	30.5±19.9	0.806
LFfx	0.059±0.007	0.059±0.007	0.624
HFmx	13.3±10.8	25.2±34.3	0.285
HFfx	0.242±0.035	0.258±0.039	0.345
LF nu	47.8±11.9	41.6±10.8	0.148
HFnu	28.8±13.7	33.7±10.9	0.285
VLFmx	160.0±83.98	186.8±113.6	0.713
VLFfx	0.01±0.004	0.011±0.002	0.713
TPWmx	211.69±130.01	287.86±241.82	0.744
TPWfx	0.025±0.033	0.036±0.028	0.126

found significant, it is believed with high correlation to snoring, otherwise low correlation to snoring. The significance level is defined as $p<0.05$ during the test.

Support Vector Machine (SVM) is also applied as an attempt to classify snoring level (heavy and light) with HRV features. SVM is a non-probabilistic binary linear classifier which recognize patterns by constructing a hyperplane in infinite dimensional space and then a good separation is achieved by the hyperplane that has the largest distance to the nearest training data points. HRV features are divided into training set and test set and then normalized to the region from 0 to 1. To increase classification accuracy, Principal Component Analysis (PCA) is applied on the normalized data to reduce the dimension. Since parameter selection for SVM has large impact on classification accuracy, in the training section, an automatic parameter adjustment based on search grid is employed. Finally, the test set is feed into the parameter optimized SVM model for classification.

Two experiments are performed. In experiment A, the analysis features are the whole-night HRV features characterizing the global cardiovascular condition of a subject throughout the night. The classification criterion is SI value of the subject. There are 30 sets of features corresponding to 30 subjects in this experiment. In experiment B, every 10-min epoch is labeled as automatic high snores (AHS) and automatic low snores (ALS) by comparing the SND to an empirical threshold value 13%. The label and HRV features form a data set. There are 919 data sets from the 30 subjects.

3. Results and discussion

3.1. Statistical analysis result

The statistical results from table III (Time domain HRV features analysis) and table IV (Frequency domain HRV features analysis) show that no features has significant difference between low SI and high SI in experiment A. However, table V and table VI show that SDNN, RMSSD, MSD, SDSD, NN50, Pnn50, RRTI, TTIN, maxSD, minSD, SD1, DFAα0 and DFAα1 in time domain and LF, HF, LF/HF, LFmx, HFmx, LFnu and HFnu in frequency domain have significant differences ($p<0.05$) between ALS and AHS groups in experiment B.

3.2. Classification result

SVM training and classification are performed on both experiments. Results showed that the classification accuracy of the previous one is lower than 50%, which means that no significant difference between the two groups. This result is obtained by 15 sets used as training set and the other 15 used as test set, as shown in table VII.

On the other hand, positive result is obtained on experiment B, in which there are 460 epochs are employed for training and 459 epochs are employed as test set. Result of experiment B is listed in table VIII, where the overall classification accuracy is 75.82%.

4. Conclusion

SVM and statistical analysis are applied to two sets of experimental data with different outcomes. Experiment A using global features and visual scoring criteria concludes wrongly that snoring do not have much impact on the HRV features. In experiment B, where features are calculated locally, highly significant features are found and SVM gives promising results.

The main conclusion that can be draw from this study is that using global density index maybe not able to classify snoring severity. A more accurate and probably better index in terms of real impact on the HRV system should be drawn from the proportion of AHS epochs.

Table 5. Mann-Whitney Analysis (Experiment B. Time Domain).

Variable	AHS	ALS	M-W P Value
MNN	874.9± 139.85	906.40±97.15	0.366
SDNN*	60.67± 30.25	68.65±31.34	0.002
RMSSD*	38.55±19.55	46.70±22.61	<0.001
MSD*	25.09±11.90	31.68±13.14	<0.001
SDSD*	38.55±19.55	47.69±22.60	<0.001
NN50*	73.50±73.06	110.61±89.16	<0.001
pNN50*	11.81±12.10	17.57±14.91	<0.001
RRTI*	19.24±7.48	21.35±7.13	0.001
TTIN*	159.32±62.49	175.05±61.99	0.001
maxNN	1089.35±175.40	1110.09±154.14	0.272
minNN	652.88±193.59	630.66±201.90	0.625
maxSD*	210.97±166.04	232.97±175.51	0.025
minSD*	-186.29±156.44	-208.04±173.32	0.015
SD1*	22.69±11.04	27.77±11.53	<0.001
SD2	74.60±39.08	80.02±38.55	0.078
DFAα0*	1.09±0.4	1.06±0.28	0.001
DFAα1*	0.89±0.20	0.84±0.20	0.011

Here * means significant with p<0.05

Table 6. Mann-Whitney Analysis (Experiment B. Freq. Domain).

Variable	AHS	ALS	M-W P Value
VLF	789.52±978.75	739.4±927.89	0.567
LF*	308.52±341.90	361.25±402.40	0.008
HF*	174.85±191.19	281.62±360.98	<0.001
TPW	1485.67±1846.81	1601.01±1812.79	0.121
LF/HF*	2.72±2.96	1.89±2.29	<0.001
LFmx*	30.22±35.73	35.74±44.31	0.031
LFfx	0.06±0.02	0.06±0.02	0.352
HFmx*	13.47±16.13	27.63±29.21	<0.001
HFfx	0.24±0.05	0.25±0.05	0.098
LF nu*	30.71±18.55	35.45±17.09	0.037
HFnu*	157.15±13.7	112.17±183.36	<0.001
VLFmx	160.0±254.77	30.96±118.62	0. 4
VLFfx	221.37±735.80	169.05±438.13	0.493
TPWmx	5.18±40.17	39.00±137.05	0.355
TPWfx	0.03±0.07	0.08±0.11	0.11

Here * means significant with p<0.05

Table 7. Confusion table for SVM test set (N=15).

	High SI (Predict)	Low SI (Predict)
High SI (Label)	5 (33.33%)	2 (13.33%)
Light (Label)	7 (46.67%)	1 (6.67%)

Table 8. Confusion table for SVM test set (N=459).

	AHS (Predict)	ALS (Predict)
AHS (Label)	30 (6.54%)	63 (13.73%)
ALS (Label)	48 (10.45%)	318 (69.28%)

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