Classification of Sleep Disordered Breathing in the Evaluation of Acoustic Sound in Correlation with the ECG Signal

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Abstract

Current trends in patient care emphasize the overall quality of life as a goal for treatment outcome, therefore various ways of continuous patient monitoring have become increasingly popular in healthcare. Since an average human spends one third of his life asleep, it is apparent that the quality of sleep has an important impact on the overall life quality. The aim of the study was to investigate the predictive capability of a dual-modality analysis scheme for the detection of sleep disordered breathing, specifically for automatic detection of sleep disorders such as snoring, wheezing or sleep apnea in the evaluation of acoustic sound in correlation with the electrocardiography (ECG) signal during sleep.

1. Introduction

Acquisition of bioelectrical signals and the development of new processing techniques continue to excite physicians and engineers alike, as over the years these have helped uncover new information regarding various diseases. Cardiology is an excellent example of a medical field in which bioelectrical signals from the heart are indispensable in the diagnostic process. ECG signal is one of such diagnostic tools which became standard in clinical practice. Researchers have previously looked at various aspects of analyzing ECG patterns in order to diagnose cardiac disorders. Interestingly, sleep disorder patients were found to have a high prevalence of heart disease [1,2] and it was proven that sleep monitoring may often lead to the diagnosis of cardiac disorders e.g. sleep apnea may be associated with cardiovascular problems. Also stress, congestive heart failure, and chronic lung disease may result in cardiac abnormalities. Therefore, simultaneous observation of the ECG and the respiratory cycle over periods of sleep can often be clinically useful [3, 4]. Nevertheless research has been previously focused on either sleep acoustic signal or ECG analysis. This work was aimed at finding a correlation between and define the predictive value of two specific physiological signals: acoustic signal of breathing and ECG signal represented by heart activity parameters at the same period of breathing during sleep. Evaluation of these simultaneously recorded signals using different methods enabled the assessment of variability parameters during sleep.

The first requirement was to derive a set of descriptors (features, measurements) of measured signals using relevant methods of analysis of biomedical signals. Each feature should be sensitive to the tonality of the signal and also to different properties of the signal.

The second goal was to select a specific set of features, resistant to various types of background noise. This allowed an analysis of sound recordings, as well as the detection of snoring and other sounds that occur during the night, arising in different types of breaths, regardless of differences between individuals in correlation with the ECG signal. Designed set of features should provide high efficiency of recognition of the tonal components, regardless of the shape of the spectrum of the background noise.

The third and final requirement was to increase the sensitivity of weak tone detection. Detection algorithms should identify the disorder, the presence of which is difficult or even impossible to unambiguously distinguish by human ear - weak signals may be audible by one doctor, and not heard by the other, which leads to different diagnoses. Therefore the algorithm should also eliminate differences in the diagnosis ranking, due to subjective feeling or physiological precondition of the interpreting doctor.

2. Materials and methods

Breathing sounds and ECGs of 15 study subjects with different degrees of disordered breathing were captured and analyzed. The sounds were recorded using a small microphone hung in front of the patient's mouth at a distance of about 5cm. The signal was recorded and sent through the analog-to-digital converter directly to the computer system (44100 Hz sampling rate, captured with Cool Edit Pro software) and subsequent analysis was performed. Simultaneously, ECG placed on the thorax and limbs was used for acquisition of the electrocardiographic recording over the entire night. This was carried out using a three-lead (III, V1 and V5), battery operated personal recorder with 12-bit 128Hz acquisition parameters (Apekt 702, Aspel).

The resulting sample database of acoustic signal sound of snoring and breathing and co-registered ECG signals were analyzed, with details described in the following sections. The simultaneous measurement of these vital signs was used to quantify the respiratory obstruction and/or disorders during sleep [5, 6,7].

2.1. Electrocardiogram based sleep pattern analysis

The Holter ECG method, most common for monitoring long-term heart activity, was used to acquire ECG signal during the night. The device continuously monitored various electrical activity of the cardiovascular system. Its extended recording period is primarily useful for observing occasional cardiac arrhythmias or other abnormalities connected with the cardiovascular system. This method helped to find sleep disorders and its correlation with other biomedical signals during entire night sleep in study subjects. Based on ECG signals, statistical parameters were derived and used to define a vector of features to evaluate the different states during sleep [8]. There are a number of factors carrying potentially valuable diagnostic information, which may include the following: the average length, standard deviation and variance of the RR interval, etc. This approach is characterized by simplicity and relatively low computational complexity, but it is also characterized by a high sensitivity to noise and artefacts present in the signal, which in turn may contribute to errors during detection.

2.2. Acoustic signal based sleep analysis

Sounds occurring during the night are produced in the vocal tract, similarly to speech. Thanks to that analogy, existing techniques for speech analysis have been applied to evaluate snoring. Acoustic analysis was performed at time periods where different types of sounds were observed e.g. snoring, wheezing, stopped breathing etc. Analysis techniques of the information contained in the acoustic signals were variants of the audio signal processing methods. Usually at least one method is used in each step of the signal processing procedure. Acoustic analysis techniques used in the study gave information on the mechanism, loudness, intensity and allowed extraction of relevant parameters to describe the signal. Two stages of data processing were used to recognize the acoustic signal: creation of patterns to be identified, followed by their identification. The technique recognized the sound categories on the basis of previously registered patterns.

2.3. Acoustic and ECG signal integration for identification of sleep breathing events

Two methods described above provided a database of parameters that, after the statistical analysis and supported by the subjective sleep evaluation made by tests subjects, guided the system-supported sleep evaluation. In this case, derived values of parameters used for statistical analysis are listed in Table 1.

Table 1. Parameters derived from ECG/audio recordings

Recording type	Parameters
Electrocardiogram	SDNN, RMSSD, p50nn, SDi, SDANN
Audio recordings	M0, M1, M2, F1, F2, F3, F4, FF1, FF2, FF3, FF4, W1, W2, W3, C1, C2, C3, C4, C5, C6, C7, C8, C9, C10, C11, C12, f01_sr, jitter, shimmer

In order to be able to process the variety of data provided by the used methods, the following features had to be developed:

- sensor-specific software translating the acquired signal into a mode specific message of unified format,
- system-specific data structures and exchange rules considering the informative properties of particular sources,
- data mining and/or artificial intelligence based decision methods.

Since the contribution of specific parameters were not known and major intersubject variability was expected, a decision system allowing adaptation for subject and environment conditions had to be designed for this study. Such system had to be trained its desirable functionality prior to be used for sleep evaluation.

2.4. Statistical data analysis

One-way ANOVA and/or Kruskal–Wallis test was used to compare continuous data between more than two samples. One-way ANOVA was used when independent samples were normally distributed and their variances were equal. The equality of variances was tested with Levene’s test. Normally distributed values were presented as mean with standard deviation. Non-normally distributed values were presented as median with 1st and 3rd quartile (interquartile range, IQR). P-value below 0.05 was considered significant, indicating that the observed result would be highly unlikely under the null hypothesis. Two logistic regressions were proposed to show types of probabilistic statistical classification models:

1) First logistic regression
   The breathing events were divided in two groups (normal breathing vs. all breathing events)
2) Second logistic regression
   Only disordered breathing events were divided in two groups (severe snoring vs. other breathing events)

This was used to foresee a response from a predictor, used to anticipate the outcome of a categorical dependent variable (i.e., a class label) based on parameters listed in Table 1. In both logistic regressions, the Akaike information criterion (AIC) was used. This criterion is a measure of the relative quality of a statistical model, for a given set of data, and was used to select only the parameters best describing the model. Next, these classifiers were evaluated using a receiver operating characteristic (ROC) curve and the area under the graph. In this study the ROC curves were used to evaluate the goodness of fit for binary classifiers, specifically the rate of events that were correctly predicted as events:

a) in first regression correctly predicted normal breathing and other types of disordered breathing,

b) in second regression correctly predicted severe snoring and other types of disordered breathing.

This was compared against the false positive rate (rate of nonevents predicted to be events) for the different possible cut-off points. The closer the curve follows the left border and then the top border of the ROC space, the more accurate the classification. The closer the curve comes to the 45-degree diagonal of the ROC space, classification tends towards random. Classification quality was measured by the area under the ROC curve, where an area of 1 represents a perfect test; and area of 0.5 represents a worthless classification.

3. Results

The acoustic analysis indicated that characteristics of inspiration and expiration could vary significantly even for the same test subject. Since it is possible to observe changes in the acoustic characteristics, treating the two phases similarly was avoided. Collected data was divided into the following classes, based on breathing events:

1- Normal breathing
2- Severe snoring
3- Moderate snoring with slow breath
4- Moderate snoring with fast breath
5- Mild snoring
6- Gasping
7- Whizzing

Entire dataset for statistical analysis consisted of over 30 different parameters listed in Table 1. Descriptive statistics and statistical analysis of significance was performed in and between classes 1-7. Table 2 presents select few parameters where strongly significant (p-value <0.0001) differences between at least two classes were recognized with their variability.

Table 2. Variability of select parameter divided into defined classes, expressed as median (IQR).

Class	SDNN	RMSSD	M0	FF3
1	131 (102-56)	161 (86-208)	1284 (1172-1517)	24 (21-26)
2	22 (16-89)	14 (12-71)	940 (845-989)	17 (14-18)
3	30 (24-35)	10 (9-11)	1393 (720-1564)	29 (15-30)
4	41 (26-98)	14 (10-137)	1624 (1450-1703)	31 (28-33)
5	45 (34-56)	47 (36-57)	520 (462-739)	6 (5-13)
6	13 (11-15)	7 (6-8)	1808 (1610-1958)	37 (34-38)
7	16 (12-22)	8 (7-8)	1725 (1587-1870)	34 (32-37)

For performing the statistical analysis using methods described in the previous section, it was assumed that there are two groups of breathing:

1) normal breathing and disordered breathing
2) severe snoring and other disordered breathing.

The following two cases where considered:

1) first group is known to be normal (negative), not having disordered breathing and the other is known to have disordered breathing (positive);
2) second group was known to be normal (negative), not have severe snoring and the other is known to have severe snoring (positive).

All parameters listed in Table 1 for all subjects were used to test for the disordered breathing. The test was bound to find some, but not all, abnormals to have the disordered breathing - the ratio of the abnormals found by the test to the total number of abnormals known to have the disordered breathing is the true positive rate (also known as sensitivity). Similar holds true for the second scenario, where the test would find some, but not all, normals to not have the disease - the ratio of the normals found by the test to the total number of normals (known from the 'gold standard' technique) is the true negative rate (also known as specificity).

Results of such analysis in both cases showed the areas under the ROC curves are close to 1. This means that the selected parameters can discriminate normal vs. abnormal events (Figure 1) during the night with high sensitivity and specificity. Figure 2 shows similar holds true for deciding, whether these events were incidents of severe snoring or have a different background.

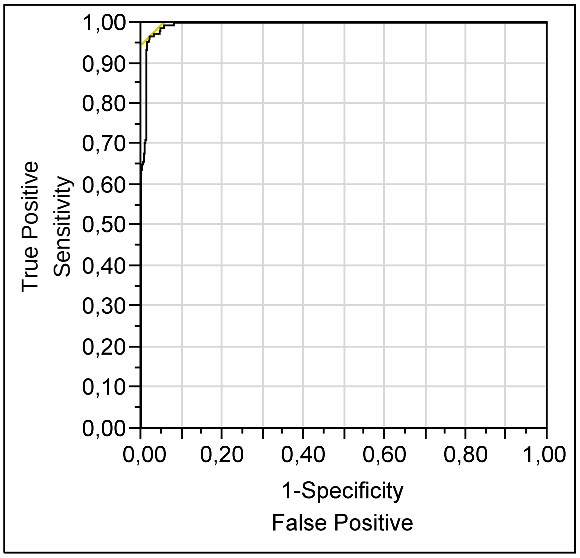

Fig. 1. ROC curve - normal breathing vs. all observed events. Area Under Curve = 0, 99453. Cut off point - 0.37.

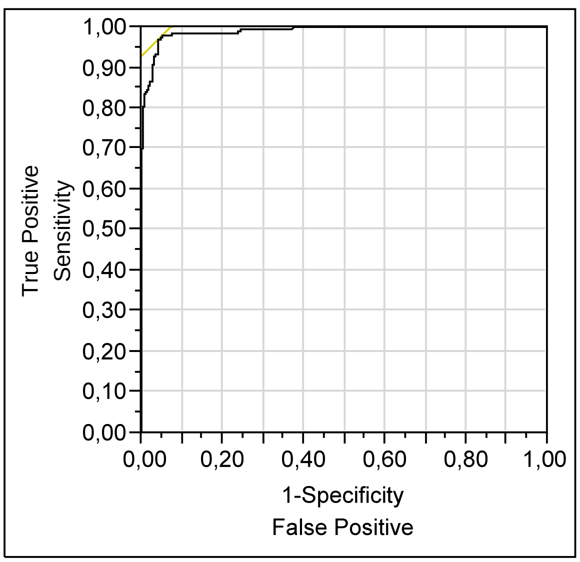

Fig. 2. ROC curve - severe snoring vs. all other observed events. Area Under Curve = 0,99025. Cut off point - 0.35.

4. Summary

The measurement of breathing through simultaneously acquired acoustic and ECG signals was used to quantify the respiratory obstruction during sleep and discriminate the source of such events. In the case of patients described in the study, it can be observed that selected acoustic and ECG parameters are changing in the presence of breathing events. Statistical analysis of ROC curves yielded very good results with visible strong association between parameters. This suggests the proposed parameters have a very high predictive value in differentiating causes and severity of respiratory events during sleep. Results can be used as an introduction for designing a system for automatic analysis of breath based on acoustic and cardiac parameters and show perspectives in use of data mining, i.e. random forests [9, 10].

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