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Building a Cepstrum-HMM kernel for Apnea identification

Carlos M. Travieso [a,b,*], Jesús B. Alonso [a,b], Marcos del Pozo [a], Jaime R. Ticay [a], Germán Castellanos-Dominguez [c]

[a] Institute for Technological Development and Innovation in Communications (IDETIC), Universidad de Las Palmas de Gran Canaria, E-35017, Spain
[b] Signals and Communications Department, Universidad de Las Palmas de Gran Canaria, Campus de Universitario Tafira s/n, E-35017 Las Palmas de Gran Canaria, Spain
[c] Pattern and Signal Recognition Group, Universidad Nacional de Colombia, sede Manizales, Colombia

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ABSTRACT

Authors present an approach based on the transformation of the Cepstral domain on Hidden Markov Model, which is employed for the automatic diagnosis of the Obstructive Sleep Apnea syndrome. The approach includes an Electrocardiogram artefacts removal and R wave detection stage. In addition, the system is modeled by a transformation of the Cepstral domain sequence using Hidden Markov Models (HMM). Final decisions are taken with two different approaches: A Hidden Markov Model and Support Vector Machine classifiers, where the parameterization is based on the transformation of HMM by a kernel. Two public databases have been used for experiments. Firstly, Physionet Apnea-ECG Database for building algorithms, and finally, The St. Vincent's University Hospital/University College Dublin Sleep Apnea Database for testing out with a blind independent dataset. Achieved results were up to 99.23% for Physionet Apnea-ECG Database, and 98.64% for The St. Vincent's Database.

1. Introduction

Obstructive Sleep Apnea (OSA) is a disorder characterized by repetitive and intermittent occlusion of the upper airway during sleep. Since it affects the quality and quantity of sleep, it is linked to cardiovascular, respiratory or metabolic diseases. Also, due to its high morbidity and mortality [1], it constitutes a big problem for the health. The estimated prevalence of adult population in the industrialized world is between 2% and 4% [2]. In US and Japan [3], rates are between 1 and 2%, although it has been suggested that there are many undiagnosed cases.

Due to the importance of the disease, the research to detect and quantify OSA, mainly, has been encouraged to use the electrocardiogram (ECG) [4]. Also the ECG analysis is minimally intrusive, inexpensive, and may be particularly well-suited for screening. These methods might exploit respiratory sinus arrhythmia, beat-to-beat variations in waveform morphology related to the displacement of the ECG electrodes, or both of these phenomena [4]. The results achieved in [4] were very satisfactory and opened new horizons in this area.

In that respect, the authors in [5] applied PCA transform to Chazal and Yilmaz features on sleep Apnea detection using ECG signal, employing RBF kernel SVM. The best classification accuracy was obtained with an error rate up to 0.7814%, using the MIT Apnea Database.

In [6], the MIT OSA Database is used, for which data are obtained from the nasal, abdominal, and chest based respiratory signals being derived from simultaneously recorded ECG of the polysomnography recordings related to the 5 different patients. Then, the performances of the 6 different ECG-derived respiration (EDR) methods are evaluated by the average of the Mean Respiratory Rates (MRRs) and the correlations of the homogeneous respiratory signals produced by cubic interpolation of the derived time series from the instantaneous respiratory rates (IRRs). Due to the MRRs based evaluations, average MRR values of the chest and abdomen based MRRs have 97% and 90% accuracy, respectively. Referring to the absolute error related to the chest and abdomen based average, MRRs are 3.3% and 9.8%, respectively. However, the absolute errors related to EDR from EDR1 to EDR6 are 29%, 25%, 6.5%, 9.7%, 15.4% and 4%, respectively.

In [7], a new concept called "sleep effectiveness" is proposed that is conceptualized as a sleep state allowing the normal functions of sleep for brain and body. The method uses ECG signals from the MIT Apnea Database to extract autonomic and respiratory influences, both of which are intensely modulated by state (either sleep or awake). The resulting "sleep spectrogram" is a map of coupled oscillations during sleep, which yields unique insights

* Corresponding author at: Signals and Communications Department, Institute for Technological Development and Innovation in Communications (IDETIC), Universidad de Las Palmas de Gran Canaria, Spain. Tel.: +34 928 452 864; fax: +34 928 451 243.
E-mail addresses: carlos.travieso@ulpgc.es, ctravieso@dsc.ulpgc.es (C.M. Travieso).

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into physiological and pathological sleep. The method is a non-linear approach to amplify the spectral peaks. If one signal is weak, e.g., the Heart Rate Variability (HRV) can be reduced with age, beta-blockers, sleep Apnea or congestive heart failure, and then EDR component is sufficient for analysis. Similarly, if an EDR is noisy but being computed using the HRV, the dominant frequencies might emerge through cleanly.

In [8], common tests, like ECG and blood oxygen level, have been used aimed to detect Apnea. Classification accuracy has also been calculated for each step individually, along with system overall accuracy. Thus individually, EDR (ECG derived respiration), HRSV (Heart Rate Statistical Variability) and O_2 (blood oxygen level) provided an accuracy of 97.4%, 98% and 97.2% for the same set of data comprising overall 8 h of recordings from MIT Apnea Database. Overall classification accuracy, utilizing a set of logic gates, was 99.20%.

In [9], a low-cost, real-time sleep Apnea monitoring system called "Apnea MedAssist" is used for recognizing OSA episodes [9]. It is implemented on smarthphones using the Android operating system, and uses an adult subject-independent support vector or a subject-dependent classifier model. With the former classifier, it achieves a classification up to 90% and a sensitivity of 96% employing the MIT Apnea Database.

In [10], OSA detection was performed by using QRS complex (waves from ECG) caused by Apnea and spectral abnormalities in the HRV, which are related to recurrent respiratory events. The system achieves 14788/17262 correct classifications on a minute-by-minute basis. In [11], the detection was accomplished by visually inspecting spectrograms of various features of the ECG such as the heart rate, S-pulse amplitude, and pulse energy. Another interesting approach is found in [12], where the frequency analysis was performed by the use of Fourier transform.

A wide variety of features based on heartbeat intervals and an ECG-derived respiratory signal were considered in [13], where linear and quadratic discriminant classifiers were compared. In a recent work [14], dynamic features were extracted from time frequency distributions. A methodology to measure the relevance of each dynamic feature was applied before the implementation of a k-nearest neighbor (k-NN) classifier to recognize between normal and pathologic signals.

Other authors have used different databases, in particular, The St Vincent's University Hospital/University College Dublin (SVUH/UCB) Sleep Apnea Database. In [15], the analysis methodology consists of four basic steps: first, Heart rate signal extraction; next, artefact rejection; third, interpolation of the heart rate signal; and finally, power spectral analysis. In the last step, the power in six bands was obtained, where the following ratios were calculated: (a) R_C: defined as the ratio of the classical Low Frequency (0.04–0.15 Hz) to High Frequency (0.15–0.4 Hz) bands. (b) R_O: the ratio of the Low Frequency (0.06–0.026 Hz) to High Frequency (0.06–0.25 Hz) bands. (c) R_D: the ratio of the Low Frequency (0.005–0.01 Hz) to High Frequency (0.01–0.05 Hz). In particular, the used datasets were Apnea-ECG database, MIT-BIH database, SVUH/UCB sleep apnea database, CHUS database, and Fantasia database. The best performance was achieved by using R_D (provided a threshold of 3.15%), for which the following accuracy values were achieved: 100%, 100%, 72%, 100%, and 75% for above databases, respectively. Results suggest that researchers must strongly consider the database used when quoting their results, since selected cases are highly database dependent and would bias the conclusions. In [16], authors derive the respiratory waveform as follows: (a) measure peak-to-trough QRS amplitude in a single-channel ECG, (b) remove the outliers introduced by noise and artifacts, (c) interpolate the derived values, and (d) filter the values within the respiration rates of 5 and 25 cycles per minute. By applying a feature selection scheme on the learning data set, 3 features were chosen for being used in the classification: (a) the number of events for which breath swings signal passes a threshold, (b) the percentage of time that the breath swing signal is below that threshold, and (c) respiration rate. The database used for developing the EDR-based algorithm was The SVUH/UCB sleep apnea database. The accuracy rates achieved was 88% of sleep-disordered breathing detection.

Another approach was presented in [17]. The features extracted from successive wavelet coefficient levels (after signal wavelet decomposition due to HRV from RR′ intervals and EDR from R waves of QRS amplitudes) were used as inputs to the SVMs to recognize OSA+/− subjects. The employed databases were: The Sleep Research Unit (SRU), Physionet Apnea-ECG and the SVUH/UCB Sleep Apnea. From these used databases, 83 training sets holding 65 OSA and 18 OSA subjects from Sleep Research Unit (SRU) Database [17] were taken, along with 42 test subjects having different degrees of OSA, of the other two databases. Using the leave-one-out technique for validation, the maximum accuracy of the training set was 100%, employing SVMs and using a subset of a selected combination of HRV and EDR features. Test results present a correctly recognizer for 24 out of 26 OSA analyzed subjects; and 15 out of 16 OSA subjects, i.e., an 92.85% classification accuracy.

In this work, therefore, the proposal is based on the use of Cepstral coefficients that are transformed by a Hidden Markov Models (HMM) to be finally classified by Support Vector Machines (SVM). So, this approach uses information from ECG and gives a new point of view regarding the usage of an HMM kernel, since to the best of the author's knowledge another different kinds of system had been proposed. An important aspect to consider when performing analysis of ECG signal, concerns the removal of artefacts, because they corrupt the information content and reduce the effectiveness of the classification and recognition tasks. Artefacts are mainly caused by the disconnection of electrodes or due to patient movements. To cope with this issue, a novel specific block is proposed so that such artefacts are removed and hence more reliable results are obtained. Our proposal also considers a parameter Cepstral coefficients and classification using HMM. We also test an approach based on SVM classifiers employing a kernel based derived for HMM and Cepstral coefficients (see Fig. 1).

This paper is organized as follows. Section 2 presents the theoretical background that is composed by the introduction of the artefact removal, the proposed feature extraction and the classification step. Section 3 details the experimental setup and databases. In Section 4, we provide a comparison of the obtained

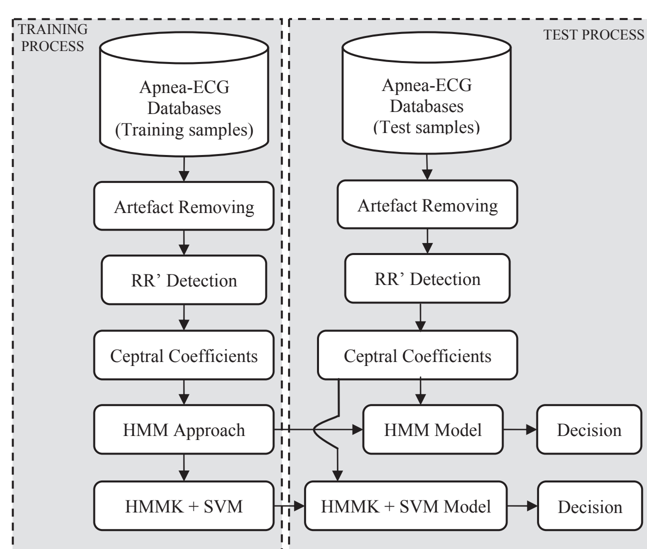

Fig. 1. Our functional flow diagram for automated detection of OSA.