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Technical note

Computer-aided obstructive sleep apnea detection using normal inverse Gaussian parameters and adaptive boosting

Ahnaf Rashik Hassan

Department of Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology, Dhaka 1205, Bangladesh

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ABSTRACT

Automatic sleep apnea detection using single lead ECG is a precondition for the implementation of a sleep apnea monitoring device. Computerized sleep apnea screening is also essential for expediting sleep apnea research and alleviating the onus of physicians of analyzing a large volume of data by visual inspection. However, most of the state-of-the-art works on automated sleep apnea identification are either based on multiple leads and multiple physiological signals or yield poor performance. In this article, normal inverse Gaussian (NIG) pdf modeling in the recently proposed tunable-Q factor wavelet transform (TQWT) domain is introduced for computer-assisted sleep apnea diagnosis from single-lead ECG signals. First, ECG signal segments are decomposed into sub-bands using TQWT. Afterwards, the corresponding NIG parameters are computed from each of the sub-bands. These parameters are used as features in the proposed apnea detection algorithm. Adaptive boosting (AdaBoost), an eminent ensemble learning based classification scheme is employed to perform classification. The suitability of TQWT is analyzed. The effectiveness of the selected features is validated by intuitive, statistical, and graphical analyses. The performance of the proposed feature extraction scheme is evaluated for various choices of classifiers. Optimal choices of TQWT and AdaBoost parameters are also determined. The performance of the proposed method, as compared to the state-of-the-art algorithms, is comparable or superior in terms of various performance metrics.

1. Introduction

Obstructive sleep apnea (OSA) is a sleep disorder that is characterized by repetitive and cyclic pharyngeal airway collapse. It affects approximately 10% of the general population, the majority of which are obese or overweight persons [1]. Nearly 4% of middle-aged men and 2% of middle-aged women are affected by OSA and the quality of lives of the patients are deteriorated [2]. OSA patients suffer from multifarious problems such as somnolence, poorer daytime cognitive performance, and cardiovascular morbidity and mortality. Traditionally, OSA diagnosis is performed by experts physicians based on visual observation of polysomnography (PSG) signals.

OSA identification on the basis of visual examination is problematic for multifarious reasons. Assessment of sleep apnea by trained experts is reliant on expensive human resources, rater's level of expertise and experience. Furthermore, the large volume of data that have to be analyzed per examination make manual sleep apnea onerous and prone to errors due to fatigue. Urgent clinical cases may also demand quick diagnosis. Manual screening, owing to its time-consuming nature, is bound to fail in such situations. This, in turn, will lead to belated diagnosis of OSA. Again, given the gargantuan amount of time it consumes, OSA screening based on visual inspection cannot scale to handle large data-sets. This particularly hinders large-scale population studies in sleep apnea research. So, from the foregoing discussion, it is evident that there is a dire need of an automatic sleep apnea screening method. Now question arises – why must the OSA detection scheme be single-lead based?

The development of a non-invasive, wearable, portable, yet low-power sleep apnea auto-diagnostic device is essential for in-home care. Such a device that will allow the user to carry out a preliminary test at home without the intervention of a physician, has garnered the interest of sleep research community. Such sleep apnea monitoring device can play a vital role in early diagnosis and the subsequent timely treatment of OSA. In order to ensure portability and wearability, the use of only one channel of physiological signal is essential for devising an automated OSA detection scheme. This will ensure enhanced battery life while keeping the size of the device comfortable for the user. The feasibility of such device, thus, solely depends on a single-lead based computerized OSA identification scheme.

E-mail address: ahnaf.hassan0@gmail.com

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Albeit the number of computer-assisted OSA detection algorithms using single lead ECG is limited, various multichannel or multiple physiological signal based schemes have been propounded in the literature for automatic OSA screening. Yildiz et al. [3] utilized discrete wavelet transform (DWT), fast-Fourier transform (FFT) and LS-SVM for computerized OSA classification. Bsoul et al. [4] implemented a real-time sleep apnea and hypopnea syndrome detection system using 111 features in spectral and time domains extracted from ECG data. Al-Angari and Sahakian [5] heart rate variability, oxygen saturation, and respiratory effort signals to classify OSA events using SVM. Hassan and Haque [6] proposed a computerized OSA detection scheme using spectral features in the dual-tree complex wavelet transform domain. Nguyen et al. [7] employed heart rate complexity as measured by recurrence quantification analysis statistics of heart rate variability data to classify OSA events. Chen et al. [8] propounded a single lead based scheme that utilizes an OSA severity index and support vector machine for OSA diagnosis. Hassan and Haque [9] extracted statistical and spectral moments directly from the ECG signals and performed classification using Bagging. Varon et al. [10] used principal components of the QRS complexes as features and classified using least-squares support vector machine.

In this study, we tackle the problem of computer-assisted OSA detection using a newly proposed signal processing technique, namely tunable-Q factor wavelet transform (TQWT). First, we decompose the ECG signals in 1 min. basis. Afterwards, we decompose the ECG signal segments into sub-bands using TQWT. We then model the TQWT sub-bands using symmetric normal inverse gaussian (NIG) pdf. In this work, we use NIG parameters as features to capture the underlying differences of apneic and non-apneic ECG signal segments in the TQWT domain. Until now this is the first time TQWT in conjunction with NIG modeling is employed for automated OSA screening. The validity and the efficacy of NIG parameters in the TQWT domain are inspected. Adaptive boosting (AdaBoost) is introduced for computerized OSA identification. We also investigate the optimal choices of TQWT and AdaBoost parameters. The performance of the scheme proposed herein, as compared to the that of the state-of-the-art ones, is also promising in terms of various performance metrics. Besides aiding clinicians, various advantages of the proposed scheme makes it suitable for device implementation as well.

The rest of the article is organized as follows. Section 2 describes the experimental data used in this work. We then present the proposed feature extraction scheme, investigate its effectiveness, and the classifier used in our method in Section 3. Section 4 presents the results of our experiments and explicates their significance. Finally, Section 5 brings the article to conclusion.

2. Materials

The experimental data used in this study can be accessed in Physionet's apnea-ecg Database [11]. The reason for using the database is its availability in the public domain and its widespread use in the contemporary literature [7,10,8,12]. A total of 35 subjects with OSA are used. In Physionet's apnea-ecg data-set, there are recordings of three subsets, namely apnea group (class a, containing 100 min or more in apnea), borderline group (class b, containing 5–99 min in apnea) and normal group (class c, with 5 min or less in apnea). The mean ages of class a, b, and c are 50, 46, and 33 years respectively. The range of age of the subjects of class a, b, and c are 29–63, 39–53, and 27–47 year respectively. Apnea Hypopnea Index (AHI) of these subjects ranges between 0 and 83. The age of those subjects is between 27 and 63 years (mean: 45 ± 10 years) with body mass index (BMI) between 19.2 and 45.33 kg m^2 (mean: 28.01 ± 6.49 kg m^2). The weights of the subjects are between 53 and 135 kg (86.3 ± 22.2 kg). Each of the recordings is about 7–10 h long. The records were labeled and scored by an expert for sleep apnea/hypopnea events on a 1-min basis. Each recording contains annotations by experts on 1 min basis which evinces the presence or absence of apnea during that minute. ECG signals are sampled at 100 Hz with 12-bit resolution. Thus, the length of each 1-min signal segment is 60 s or 6000 samples. Fig. 1 shows a normal and an apneic ECG signal segments. More details on the data can be found in [11].

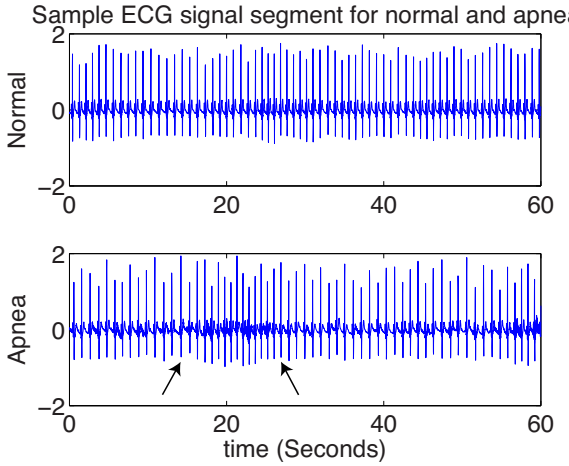

Fig. 1. Sample apneic and normal ECG signal segments. The duration of sleep apnea in the signal segment is highlighted with arrows.

To conduct the experiments, half of the apnea-ecg data-set has been randomly chosen as training data and the rest of the data as testing set. In this way, it has been ensured that the entire apnea-ecg can be used either for training or for testing, but never at the same time. This data-setting also reduces the chance of overfitting. The aforementioned process of forming train and test data has been repeated 20 times and the average performance metrics are reported in this article.

3. Methods

3.1. Tunable-Q factor wavelet transform

Tunable-Q factor wavelet transform, a recently proposed flexible and fully discrete wavelet transform, has emerged as a useful tool to analyze oscillatory signals [13]. It achieves flexibility by adjusting its input parameters – Q-factor Q, over-sampling rate or redundancy denoted as r and number of levels of decomposition J. Q controls the number of oscillations of the wavelet and is expressed mathematically as follows.

$$Q = \frac{f_c(j)}{BW(j)} \tag{1}$$

where

$$f_c(j) = \alpha^j \frac{2-\beta}{4\alpha} \tag{2}$$

$$BW(j) = \frac{1}{2}\beta\alpha^{j-1}\pi \tag{3}$$

and $j = 1, 2, \ldots, J$. So, for fixed Q, $f_c(j)$ decreases with the increase of j and the associated BW also get reduced. Besides, the time-domain duration of the wavelets become wider. r ensures that the undesired excessive ringing is in control with a view to localizing the wavelet in time, yet it does not alter its shape. For fixed Q, increasing the value of r leads to increase the overlap between