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Automatic sleep staging using empirical mode decomposition, discrete wavelet transform, time-domain, and nonlinear dynamics features of heart rate variability signals

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ABSTRACT

The conventional method for sleep staging is to analyze polysomnograms (PSGs) recorded in a sleep lab. The electroencephalogram (EEG) is one of the most important signals in PSGs but recording and analysis of this signal presents a number of technical challenges, especially at home. Instead, electrocardiograms (ECGs) are much easier to record and may offer an attractive alternative for home sleep monitoring. The heart rate variability (HRV) signal proves suitable for automatic sleep staging. Thirty PSGs from the Sleep Heart Health Study (SHHS) database were used. Three feature sets were extracted from 5- and 0.5-min HRV segments: time-domain features, nonlinear-dynamics features and time–frequency features. The latter was achieved by using empirical mode decomposition (EMD) and discrete wavelet transform (DWT) methods. Normalized energies in important frequency bands of HRV signals were computed using time–frequency methods. ANOVA and *t*-test were used for statistical evaluations. Automatic sleep staging was based on HRV signal features. The ANOVA followed by a post hoc Bonferroni was used for individual feature assessment. Most features were beneficial for sleep staging. A *t*-test was used to compare the means of extracted features in 5- and 0.5-min HRV segments. The results showed that the extracted features means were statistically similar for a small number of features. A separability measure showed that time–frequency features, especially EMD features, had larger separation than others. There was not a sizable difference in separability of linear features between 5- and 0.5-min HRV segments but separability of nonlinear features, especially EMD features, decreased in 0.5-min HRV segments. HRV signal features were classified by linear discriminant (LD) and quadratic discriminant (QD) methods. Classification results based on features from 5-min segments surpassed those obtained from 0.5-min segments. The best result was obtained from features using 5-min HRV segments classified by the LD classifier. A combination of linear/nonlinear features from HRV signals is effective in automatic sleep staging.

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Moreover, time–frequency features are more informative than others. In addition, a separability measure and classification results showed that HRV signal features, especially nonlinear features, extracted from 5-min segments are more discriminative than those from 0.5-min segments in automatic sleep staging.

1. Introduction

Sleep disorders deteriorate quality of life and cause negative effects on human health. Generally speaking, sleep is divided into two main states: non-rapid eye movement (NREM) and rapid eye movement (REM.) NREM sleep is divided into 3 stages: stage1, stage2 and slow wave sleep (SWS) [1,2]. Sleep staging is usually performed manually by a sleep specialist or a technician according to some established rules. Visual classification of sleep stages is difficult and time intensive due to the complex interpretation based on detailed analysis of a large number of polysomnographic traces. Computer-aided sleep staging could facilitate this task.

The electroencephalogram (EEG) is one of the most important and frequently used signals for automatic sleep staging [1]. Therefore, most of the efforts made to date have been based on using this signal. However, recording and analysis of the EEG signal presents a number of technical challenges, especially at home. Instead, electrocardiographic (ECG) signals are much easier to record and may offer an attractive alternative for home monitoring of sleep. As such, the use of ECG-derived signals with favorable characteristics in terms of recording and noise immunity, rather than an array of signals, as required for clinical polysomnography is of research interest.

It has been shown that autonomic nervous system (ANS) activity differs during waking and sleeping states. During NREM sleep, sympathetic input is reduced and parasympathetic activity predominates, resulting in relative stability in ANS function. REM sleep, in contrast, is characterized by highly variable sympathetic activation (which can be comparable to or higher than awake levels) punctuated with phasic parasympathetic discharge, which results in fluctuating cardiovascular and respiratory behaviors. Accelerations and pauses in heart rate and irregular ventilation are therefore characteristic of REM sleep [3]. In addition, by directly recording sympathetic nerve activity for several hours, investigators have provided solid evidence that sympathetic activity reduced by more than half from wakefulness to SWS but increased to levels above waking value during REM sleep [4].

The spectral components of the heart rate variability (HRV) signal produce quantitative markers of sympathetic and parasympathetic activities of the ANS, which differ significantly from each other during wake and different sleep stages [3]. As such, using HRV signals to extract information for automatic sleep staging is a promising exploration. The spectral components of the HRV signal are divided into 4 frequency bands: ultra low-frequency (ULF): 0–0.0033 Hz, very low-frequency (VLF): 0.0033–0.04 Hz, low-frequency (LF): 0.04–0.15 Hz, and high-frequency (HF): 0.15–0.4 Hz [5].

Penzel et al., by using detrended fluctuation analysis (DFA), showed that the dynamics of HRV signals are different in wake and sleep stages [6]. They also used spectral analysis and DFA in order to extract information from HRV signals separately for automatic sleep staging and showed that DFA is a better measure than spectral analysis [7]. Redmond et al. used cardiorespiratory signals to classify wake, NREM sleep and REM sleep [8]. They also performed similar analysis to distinguish between wake and sleep stages in a subject group in which Sleep Disordered Breathing (SDB) was absent [9]. Spectral analysis and time-domain methods have been used for feature extraction in previous research. Mendez et al. separated REM and NREM sleep by using HRV signals [10]. They used time varying autoregressive models for feature extraction and a hidden Marko model (HMM) for classification. Recently, Adnane et al. used HRV signals to separate wake and sleep stages. A combination of spectral analysis, time-domain and DFA methods were used for feature extraction in their research [11]. In all of the previous research, 0.5-min (30-s) epochs of HRV signals were selected for analysis. Additionally, except for the DFA method, linear methods were used in order to extract features.

In HRV signal analysis, it has been shown that better results can be obtained by combining linear and nonlinear feature extraction methods [12–14]. Generally, time–frequency methods are more suitable for the analysis of non-stationary signals such as HRV signals. Therefore, discrete wavelet transform (DWT) and empirical mode decomposition (EMD) methods were deployed in this study. In a comprehensive article, Huang et al. presented the EMD method and the associated Hilbert spectra for time–frequency adaptive analysis of nonlinear and non-stationary time series [15]. The advantages of DWT and EMD methods in HRV signal analysis have been studied in separate investigations [16,17].

Using this background, DWT and EMD methods were used in our study to extract features from HRV signals for automatic sleep staging. Also, a number of features were extracted by using time-domain and nonlinear dynamics analyses methods. First, these methods were used for feature extraction. Then the importance of each feature was evaluated by a statistical analysis such as the Analysis Of Variance (ANOVA) test. Subsequently, the extracted features in 5-min segments of HRV signals were compared with those extracted from 0.5-min segments of these signals by performing a two-tailed t-test and calculating a parameter called "separability measure." Finally, the extracted features were fed into linear discriminant (LD) and quadratic discriminant (QD) classifiers for further classification.

The rest of the paper is organized as follows. Section 2 provides the materials and methods used in this work. The results of the application of the proposed algorithms to the