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Computer-aided sleep staging using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise and bootstrap aggregating

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ABSTRACT

Computer-aided sleep staging based on single channel electroencephalogram (EEG) is a prerequisite for a feasible low-power wearable sleep monitoring system. It can also eliminate the burden of the clinicians during analyzing a high volume of data by making sleep scoring less onerous, time-consuming and error-prone. Most of the prior studies focus on multichannel EEG based methods which hinder the aforementioned goals. Among the limited number of single-channel based methods, only a few yield good performance in automatic sleep staging. In this article, a single-channel EEG based method for sleep staging using recently introduced Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN) and Bootstrap Aggregating (Bagging) is proposed. At first, EEG signal segments are decomposed into intrinsic mode functions. Higher order statistical moments computed from these functions are used as features. Bagged decision trees are then employed to classify sleep stages. This is the first time that CEEMDAN is employed for automatic sleep staging. Experiments are carried out using the well-known Sleep-EDF database and the results show that the proposed method is superior as compared to the state-of-the-art methods in terms of accuracy. In addition, the proposed scheme gives high detection accuracy for sleep stages S1 and REM.

1. Introduction

Sleep is a rapidly reversible state that is characterized by loss of consciousness and reduced responsiveness to external stimuli [1]. In humans, sleep related ailments deteriorate the quality of lives of the patients and are the second most causes of complaints requiring medical attention. [2]. The purpose of sleep staging is to classify sleep stages which is essential for sleep disorder diagnosis and sleep research. Traditionally, all night polysomnographic (PSG) recordings are visually scored by experts based on Rechtschaffen and Kales's (R&K) recommendations [3] or a new guideline developed by the American Academy of Sleep Medicine (AASM) [4]. The major changes of AASM standards comprise EEG derivations, the merging of stages S3 and S4 into N3, the abolition of stage "movement time", the simplification of many context rules as well as the recommendation of sampling rates and filter settings for PSG reporting and for user interfaces of computer-assisted sleep analysis [5]. According to R&K standard, there are six sleep stages, namely – Awake (AWA), Non-Rapid Eye Movement stages 1–4 (S1–S4) and Rapid Eye Movement (REM).

PSG recording involves a minimum of 11 channels, including electroencephalogram (EEG), electromyogram (EMG), electrooculogram (EOG), oxygen saturation (SpO2), electrocardiogram (ECG), etc. Manual scoring requires sleep scorers to apply visual pattern recognition of a huge amount of signals. The classification of 8-h (whole night) recording requires approximately 2–4 h [6]. Also, the process's onerous and subjective nature makes it error-prone. Currently, PSG examination requires the patient to undergo overnight sleep studies in a specially equipped sleep laboratory. As a result, the sleep quality of the subject can be reduced due to the unfamiliar environment. An automatic sleep staging scheme can assist the clinical staff and speed up the diagnosis of various sleep disorders. Again, automatic sleep scoring with reduced channel requirement is essential for a portable sleep quality evaluation device [7]. In this respect, the use of only EEG signals for computerized sleep scoring has been explored by various researchers for a feasible sleep quality evaluation device. However, most of these methods use multiple EEG channels which prohibit portability and wearability of the device [8]. An automatic sleep scoring algorithm using single channel EEG can ensure wearability and portability of sleep quality evaluation at home. Moreover, excessive wire connections for PSG cause sleep disturbance, whereas automatic sleep scoring based on single channel EEG reduces sleep disturbance caused by recording wires [8].

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Various single or multichannel based methods for automated sleep scoring have been reported in the literature [9]. Agarwal and Gotman [10] segmented five-channel PSG data in quasi-stationary components, computed features such as amplitude, dominant rhythm, spindles, frequency weighted energy, etc. and used k-means clustering to classify sleep stages. Held et al. [11] presented a neuro-fuzzy classifier to classify sleep stages of healthy infants from four-channel PSG recordings. Karkovská et al. [12] extracted many features such as average amplitude, variance, spectral powers, coherence, fractal exponent, etc. from data collected from six EEG channels, two EOG channels and one EMG channel and classified using quadratic discriminant analysis. Liang et al. [8] used multiscale entropy and autoregressive model parameters as features and linear discriminant analysis as classifier for single-channel automatic sleep scoring. Ronzhina et al. [13] used the power spectrum density of single channel EEG in an artificial neural network for sleep staging. In [14], six energy features obtained from single channel EEG were fed into an Elman neural network classifier for sleep classification. Zhu et al. [15] generated difference visibility graph (VG) and horizontal VG from single channel EEG signal and extracted nine features from them to classify using support vector machine. Imtiaz [16] utilized spectral edge frequency, absolute and relative power of the signal for only REM detection from single channel EEG. Koch et al. [17] put forward a Latent Dirichlet Allocation topic model based method using four-channel multiple physiological signals (EEG and EOG) for sleep staging.

In this article, an automatic method for sleep stage classification using single channel EEG is proposed. At first, EEG signal segments are decomposed into intrinsic mode functions using Complete Ensemble Empirical Mode Decomposition with Adaptive Noise (CEEMDAN). Higher order statistical moments such as mean, variance, skewness and kurtosis are then computed from the intrinsic mode functions. As compared to its predecessors such as Empirical Mode Decomposition (EMD) and Ensemble Empirical Mode Decomposition (EEMD), CEEMDAN gives an exact reconstruction of EEG signal without mode mixing and with a better spectral separation of the mode functions. Moreover, like EMD or EEMD it is data-driven and requires no prior basis function. Although EMD and EEMD have been used in various physiological signal analysis, CEEMDAN has been applied only recently for processing such signals [18]. Classification of sleep stages is performed using an ensemble learning based classifier, namely Bootstrap Aggregating (Bagging). It should be mentioned that to the best of our knowledge, classification of sleep stages in the CEEMDAN domain is yet to be reported in the literature. In addition, the application of Bagging in sleep stage classification is introduced in this work. The rest of the paper is organized as follows. Section 2 describes the experimental data that are used in this work. Section 3 gives a brief description of CEEMDAN along with its predecessors – EMD and EEMD. Description and statistical analyses of the features used are also provided. Bagging is described briefly in Section 4. Experimental results of this work are discussed in Section 5. Finally, some concluding remarks are given in Section 6.

2. Materials

The recordings used for evaluation of the proposed scheme were obtained from Caucasian males and females (21–35 years old) without any medication. The data can be accessed in Physionet Data Bank's [19] Sleep-EDF Database [20,21]. The first four recordings (marked as sc^*) were obtained in 1989 from ambulatory healthy volunteers during 24 hours in their normal daily life. The last four data recordings (marked as st^*) were obtained in 1994 from subjects who had mild difficulty falling asleep but were otherwise healthy. They contain horizontal EOG, Fpz–Cz and Pz–Oz EEG data, each sampled at 100 Hz. EEG signal from Pz–Oz channel yields better classification performance than that of the Fpz–Cz channel [8,13,15,22]. So in our study Pz–Oz channel EEG signal is used.

Table 1
Description of train and test epochs.

	AWA	S1	S2	S3	S4	REM	Total
Train Epochs	4027	302	1810	336	313	804	7592
Test Epochs	4028	302	1811	336	314	805	7596

Experts already scored each 30 s of EEG data and generated the hypnogram in accordance with the R&K recommendations [3]. So the interval of each epoch in this study is defined as 30 s or ($30 \times 100 =$) 3000 data points. Each epoch was scored by expert scorers in one of the eight classes: AWA, S1, S2, S3, S4, REM, MVT (Movement Time) and 'Unscored'. The entire data-set is divided into two halves – the odd numbered epochs are chosen as the training data and the rest of them are used as test data. Table 1 summarizes the number of epochs of different classes that are used in this work.

3. Methods

3.1. Empirical Mode Decomposition

Empirical Mode Decomposition (EMD) [23] aims to generate highly localized time-frequency estimation of a signal in a data-driven fashion by decomposing it into a finite sum of intrinsic mode functions (IMF) or modes. Each mode must satisfy two conditions:

1 The number of extrema and the number of zero crossings must be the same or differ at most by one.
2 At any point the mean value of the envelope defined by the local maxima and the envelope defined by the local minima is zero.

EMD iteratively decomposes an N-point EEG epoch X into amplitude and frequency modulated oscillatory IMFs using the following steps:

1 Set $h_1 = X$.
2 Identify the local maxima and minima of h_1.
3 Obtain the envelope of local maxima v_{max} and that of local minima v_{min} using cubic spline interpolation.
4 Generate the local mean curve m by generating the upper and lower envelopes:

$$m = \frac{v_{max} + v_{min}}{2} \quad (1)$$

5 Compute h_2 by subtracting the local mean curve from h_1:

$$h_2 = h_1 - m \quad (2)$$

6 Repeat steps (2)–(5) until the difference between h_{k+1} and $h_k(SD(k))$ defined as follows reaches a predefined value ϵ.

$$SD(k) = \frac{\|h_{k+1} - h_k\|^2}{\|h_k\|^2} < \epsilon \quad (3)$$

where $\|.\|$ is the Euclidian L2-norm.
7 Set $c_1 = h_k$ as the first mode.
8 Find the residue, $r_1 = x - c_1$. Steps (1)–(7) are known as sifting.
9 Substitute X in 1) with r. Repeat steps (1)–(7) to find the rest of the IMFs $c_2, c_3, \ldots, c_L$.

Thus, the input signal can be decomposed into L IMFs until the residue becomes a monotonic function such that further extraction