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An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequency image

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ABSTRACT

Detection of the characteristics of the sleep stages, such as sleep spindles and K-complexes in EEG signals, is a challenging task in sleep research as visually detecting them requires high skills and efforts from sleep experts. In this paper, we propose a robust method based on time frequency image (TFI) and fractal dimension (FD) to detect sleep spindles in EEG signals. The EEG signals are divided into segments using a sliding window technique. The window size is set to 0.5 s with an overlapping of 0.4 s. A short time Fourier transform (STFT) is applied to obtain a TFI from each EEG segment. Each TFI is converted into an 8-bit binary image. Then, a box counting method is applied to estimate and discover the FDs of EEG signals. Different sets of features are extracted from each TFI after applying a statistical model to the FD of each TFI. The extracted statistical features are fed to a least square support vector machine (LS_SVM) to figure out the best combination of the features. As a result, the proposed method is found to have a high classification rate with the eight features sets. To verify the effectiveness of the proposed method, different classifiers, including a K-means, Naive Bayes and a neural network, are also employed. In this paper, the proposed method is evaluated using two publically available datasets: Dream sleep spindles and Montreal archive of sleep studies. The proposed method is compared with the current existing methods, and the results revealed that the proposed method outperformed the others. An average accuracy of 98.6% and 97.1% is obtained by the proposed method for the two datasets, respectively.

1. Introduction

Sleep scoring is a challenging task in sleep classification research due to the characteristics of the sleep stages vary [12,31,39]. According to the Rechtsaffen and Kales (R&K) guidelines [49], a human sleep cycle is divided into two main parts: the non-rapid eyes movements sleep (NREM) and rapid eyes movements sleep (REM), where the NREM includes four stages namely: Stage 1 (S1), Stage 2 (S2), Stage 3 (S3) and Stage 4 (S4).

The guidelines of the R&K have been modified by the American Academy of Sleep Medicine (AASM) in 2002. The AASM presented a different version of sleep scoring [28] by which the NREM is reduced to three stages, with S3 and S4 are combined into one stage as slow wave stage (SWS). Much clinical research have revealed that individual sleep stages exhibit unique electroencephalogram (EEG) patterns and characteristics that reflect human states whether he/she is awake or asleep. Those characteristics of sleep stages reflect the changes in brain neurons and muscles at each sleep stages [11]. Analyzing those brain waveforms is an important task for neurologists to score and analyse EEG sleep signals [17,29].

Two of the important transiting bio-signal waveforms in sleep stages are sleep spindles and k-complexes that are often used to score sleep stages [28]. Sleep spindles are the most important transient events to detect sleep stage 2 in EEG signals. They are defined as a series of distinct waves which are within a frequency range of 11–16 Hz with a minimum duration of 0.5 s (s) [60,28]. Some studies reported that, the minimum and maximum durations of sleep spindles are 0.5 s and 3s, respectively [30,60,13], with an amplitude from 5 μV to 25 μV [34]. The presence or absence of sleep spindles in EEG sleep signals has a high impact on the memory consolidation of humans [35,42]. From EEG recordings, it is observed that any change in the density of sleep spindles can result in some sleep disorders, such as insomnia and schizophrenia and autism [20,59]. Consequently, automatically detecting and analyzing sleep spindles can help experts in diagnosing sleep disorders.

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Traditionally, the detection of sleep spindles mainly depends on visual inspection that is carried out based on the knowledge of clinicians or sleep expert. The accuracy and reliability of the manual scoring are based on the experiences of experts. Visual scoring of sleep spindles is very time consuming, subjective and prone to errors due to there are typically thousands of sleep spindles occurred in each EEG recording [1]. Identifying sleep spindles in EEG signals visually requires high skills from experts. However, developing an automatic approach to identify those marked occurrences in the sleep stages is an ongoing challenge.

Various attempts were made in identifying sleep spindles based on Fourier, wavelet and hybrid transforms [16,27,54,26]. Machine learning methods, such as support vector machines, neural networks, and genetic algorithms, were also employed to classify the extracted features by those transformation techniques [2,3,38]. Yücelbaş et al. [61] used a short time Fourier transform (STFT) combined with an artificial neural network to detect sleep spindles in EEG signals. The STFT was also used as a feature extractor by da Costa et al. [14]. The extracted features were fed to a K-means to recognize the segments of sleep spindles from non-sleep spindles segments. Estévez et al. [18] propounded a merge neural gas model with the STFT to analyse EEG signals. A maximum sensitivity of sleep spindles detection was 62.9%. Güneş et al. [24] utilized the STFT to decompose an EEG signal. The most discriminating features were extracted from the frequencies of interest. The extracted features were forwarded to two machine learning methods: a support vector machine and a multilayer perceptron to detect sleep spindles.

Recently, many researchers reported the detection of sleep spindles based on a matching pursuit and filtering techniques. Ventouras et al. [58] utilized a bandpass filter with an artificial neural network to detect sleep spindles. The obtained results in terms of sensitivity and accuracy were reported. In that study, an average of 87.5% accuracy was achieved. Żygierewicz et al. [66] presented a matching pursuit method to detect sleep spindles. The maximum sensitivity reported in that study was 90%. Schönwald et al. [52] also employed the matching pursuit to detect sleep spindles based on the amplitude, frequency, and duration characteristics of the signals. An average of sensitivity and specificity of 80.6% and 81.2% were achieved, respectively.

According to the literature, we found that the fractal dimension has been proved to be an efficient approach to explore the hidden patterns in digital images and signals. It has been used to analyse EEG signals to trace the changes in EEG signals during different sleep stages, and also was employed to recognize different digital images patterns. Yang et al., [63] and Sourina et al. [56] applied a fractal dimension technique to analyse sleep stages in EEG signals. Ali et al. [7] also utilized a fractal dimension technique for voice recognition. Furthermore, a time frequency image (TFI) has been used to analyse different types of EEG signals, such as EEG sleep stages signals. Bajaj and Pachori [9] identified EEG sleep stages based on time frequency images. Fu et al., in [22] used a time frequency image as a features extractor for epileptic seizures classification. Bajaj et al., [8] also classified alcoholic EEGs based on time frequency images.

Although the existing methods have achieved some good results in sleep spindles detection, a considerable amount of further improvement on the existing methods are still in demand. In this paper, the fractal dimension combined with time frequency images is used to detect sleep spindles in EEG signals. Firstly, each EEG signal is partitioned into segments of 0.5s. Then, each segment is transformed into a time frequency image using a short time Fourier transform (STFT). Each TFI is converted into a binary image. The box counting technique is applied to each TFI and the statistical features are extracted from the FD. Different set of statistical features are extracted and tested from the FDs to figure out the best combination of features for detecting sleep spindles. Different classifiers are also used to validate the proposed method. The obtained results showed that the proposed method achieved a high accuracy for detecting sleep spindles in EEG signals.

The rest of this paper is organized as follows: Section 2 describes the EEG datasets used. Section 3 presents the methodology of the proposed method. The experimental results are explained in Section 4. Finally the discussions, conclusions and future work are provided in Section 5.

2. Experimental EEG data

In this study, two different datasets were used to evaluate the proposed method for detecting sleep spindles in EEG signals. Those databases that are publicly available are: the DREAMS datasets (Devusty) [15] and Montreal Archive Sleep Studies (MASS) (O'Reilly et al. [40]. The following section briefly explains the details of the two datasets.

2.1. The dream sleep spindles dataset (Datsaet-1)

The EEG data sets used in this paper were collected through the Dream Project at University of Mons-TCTS Laboratory (Devyust et al.). The sleep EEG data sets were recorded from eight subjects with various sleep diseases, such as dysomnia, restless legs syndrome, insomnia, and apnea/hypopnea syndrome. The subjects were aged between 30 and 55 years. The signals were recorded in 30 min intervals during a whole night. The recorded signals were scored, and the ending and starting time instances of the sleep spindles were marked. Six of the EEG recordings were sampled at 200 Hz, while the other two recordings were sampled at 100 Hz and 50 Hz. Each EEG recoding included with two EOG channels of P8-A1 and P18-A1, three EEG channels of CZ-A1 or C3-A1, FP1-A and O1-A1, and one EMG channel. The sleep spindles in the Dream database were detected manually by two experts. The first expert scored all the eight recordings, while the second expert annotated six recordings out of the eight EEG recordings. In this study, the CZ-A1 channel and the EEG recording sampled at 200 Hz were used. The subjects selected were subject IDs 2, 4, 5, 6, 7 and 8. Table 1 shows the number of the segments that were used in this research. The dataset along with additional information is publicly available from: http:\\www.tcts.fpms.ac.be/∼devuyst/Database/DatabaseSpindles.

2.2. Montreal archive of sleep studies (Dataset-2)

The database was recorded from 19 subjects: 8 males and 11 females. The age of the subjects was between 30–55 years. The EEG signals were recorded in 20 min intervals during a whole night. The EEG signals were sampled at 256 Hz. Each EEG recording included 19 EEG channels, four Electrooculography (EOG), electromyography (EMG) and Electrocardiography (ECG) channels. In this database the visual scoring of sleep spindles were carried out aslo by two experts. The first expert annotated 19 recordings, including sleep spindles according to the AASM rules, while the second only annotated 15 out of 19 recordings, including sleep spindles according to the R&K criteria. In this study, the EEG scoring from six subjects were chosen randomly. The subjects selected were subject IDs 1, 2, 7, 9, 14 and 18. Table 2 shows the number of segments that were used in this research. The datasets can be accessed through *http://www.ceams-carsm.ca/en/MASS*. Tables 1 and 2 included five columns: namely, subject ID, the number of segments with sleep spindles, the number of all segments in all EEG signals, minimum and maximum sleep spindles. The experiments were conducted using Matlab software (Version: R2015) on a computer with the