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Automatic detection of alertness/drowsiness from physiological signals using wavelet-based nonlinear features and machine learning

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ABSTRACT

Physiological signals such as electroencephalogram (EEG) and electrooculography (EOG) recordings are very important non-invasive measures of detecting a person's alertness/drowsiness. Since EEG signals are non-stationary and present evident dynamic characteristics, conventional linear approaches are not highly successful in recognition of drowsy level. Furthermore, previous methods cannot produce satisfying results without considering the basic rhythms underlying the raw signals. To address these drawbacks, we propose a system for drowsiness detection using physiological signals that present four advantages: (1) decomposing EEG signals into wavelet sub-bands to extract more evident information beyond raw signals, (2) extraction and fusion of nonlinear features from EEG sub-bands, (3) fusion the information from EEGs and eyelid movements, (4) employing efficient extremely learning machine for status classification. The experimental results show that the proposed method achieves not only a high detection accuracy but also a very fast computation speed. The proposed algorithm can be further developed into the monitoring and warning systems to prevent the accumulation of mental fatigue and declines of work efficiency in many environments such as vehicular driving, aviation, navigation and medical service.

1. Introduction

Increasing studies have explored the measurements of drowsiness due to its impact on public health, public safety and productivity (Baker et al., 1994; Boksem, Meijman, & Lorist, 2005; Dawson et al., 2014; Folkard & Tucker, 2003). The ability of a person to maintain alert and make decisions quickly decreases considerably during the drowsiness stage (Garcés Correa, Orosco, & Laciar, 2014). Fatigue driving under drowsy even sleepy state is an important determinant of traffic accidents (Azim, Jaffar, & Mirza, 2014; Cyganek & Gruszczyński, 2014; Forsman, Vila, Short, Mott, & Van Dongen, 2013; Hashemi, Saba, & Resalat, 2014; Hu & Zheng, 2009; Jagannath & Balasubramanian, 2014; Jo, Lee, Park, Kim, & Ki, 2014; Li & Chung, 2014). In addition to vehicular safety concern, drowsiness and fatigue are very important issues for workers and employees in the fields of industrial manufactories (Tucker, Folkard, & Macdonald, 2003), power plants (Baker et al., 1994), navigation, aviation (Borghini, Astolfi, Vecchiato, Mattia, & Babiloni, 2014) and medical service.

Physiological measurements such as EEG recordings, eyelid movement, galvanic skin response (GSR), heart rate and pulse rate provide insight into human activities directly and achieve relatively accurate quantification evaluation of drowsiness/alertness (Boksem et al., 2005; Borghini et al., 2014; Dissanayaka et al., 2015; Garcés Correa et al., 2014; Hashemi et al., 2014; Hu & Zheng, 2009; Jagannath & Balasubramanian, 2014; Lal & Craig, 2005; Lee et al., 2014; Li & Chung, 2014; Singh et al., 2013). Among these different measures, EEG is commonly viewed as the "golden standard" in the identification of states ranging from vigilant or alert to drowsy or asleep (Garcés Correa et al., 2014; Johnson et al., 2011).

However, the visual inspection of continuous physiological signals is very arduous and challenging work even for the trained neurologists (Nakamura, Chen, Sugi, Ikeda, & Shibasaki, 2005) since physiological signals are easy to be contaminated by the excessive presence of artifacts and present extensive individual difference. Hence, it is significant to develop the automatic system to liberate the neurologists from long-term EEG interpretation. The goal of this research is to develop an efficient system to detect drowsy/alert epochs which will be applied in: (1) assistance of neurologists to review potential segments of alert and drowsy states for further

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inspection (Nakamura et al., 2005; Shibasaki et al., 2014); (2) monitoring and warning systems for detecting the drowsy states to prevent the accumulation of mental fatigue and declines of work efficiency in real-world operation and living environments (Lin et al., 2008).

Researchers have attempted to develop various algorithms for the automatic detection of drowsiness/alertness based on physiological signals and those studies mainly focus on techniques for feature extraction and classification. Some of the efficient feature extraction methods based on EEG signals are as follows: waveform and statistics from time series (Garcés Correa et al., 2014), power spectral density (Chen et al., 2010; Lal & Craig, 2005), cross spectral density (Vuckovic, Radivojevic, Chen, & Popovic, 2002), wavelet coefficients (Lee et al., 2014; Subasi, 2005), functional coherence (Dissanayaka et al., 2015) and visually evoked potentials (VEP) (Hashemi et al., 2014). Besides, ocular measures, such as eye movement and blink tracking are considered as promising ways for monitoring drowsiness (Hu & Zheng, 2009; Li & Chung, 2014). Some of these studies have been tested on practical systems such as brain-computer interface for monitoring and warning of driver's drowsiness (Azim et al., 2014; Hashemi et al., 2014; Lal et al., 2003; Lin et al. 2008).

Since EEG signals are non-stationary and present evident dynamic characteristics, conventional linear approaches are not highly successful in recognition of drowsy level. Nonlinear methods obtained more popularity in the recent years and the summary of such studies is given in the discussion part of the paper. In this study, we assess and compare four nonlinear methods, i.e., approximate entropy (ApEn), sample entropy (SampEn), renyi entropy (RenEn) and a novel graphic method named recurrence quantification analysis (RQA). Furthermore, recent investigations indicate that some nonlinear measures cannot achieve satisfying performance without considering the basic rhythms of physiological signals (Chen, Zhang, Zou, Zhao, & Wang, 2014). In some cases, EEG separate sub-bands may present more accurate information about constituent neuronal activities underlying EEG signals. The characteristics which are not evident in the original full-spectrum EEG may be distinct in separate sub-bands (Chen et al., 2014). Hence, our proposed system implemented the wavelet decomposition to extract the nonlinear features with different time and frequency scales.

Another important task for the design of an automatic system is to develop a highly sensitive classifier with a low false detection rate. To improve the overall performance of a detection system, the designers must confront a steep tradeoff between detector sensitivity and specificity and make a compromise between detector efficiency and specificity. Some of the reported systems such as driving fatigue detection system (Li & Chung, 2014) was based on the estimation of eye close degree (ECD) using EEG sensors and constructed a support vector machine (SVM) for classification. Garcés Correa et al. (2014) developed an automatic method to detect the drowsy status in EEG records based on time, spectral and wavelet analysis and the selected features were fed to a neural network classifier. Artificial neural network (ANN) (Garcés Correa et al., 2014; Singh et al., 2013; Subasi, 2005; Vuckovic et al., 2002) and support vector machine (SVM) (Hu & Zheng, 2009; Jo et al., 2014; Lal & Craig, 2005; Lee et al., 2014; Yeo et al., 2009; Zhao, Zheng, Zhao, Tu, & Liu, 2011) have been widely explored as the detector for classification. However, when the sample size is large, the learning speed of both methods is too slow to meet the requirements for real-time applications. SVM may perhaps tend to achieve suboptimality in classification applications due to some optimization constraints. A novel learning algorithm named extreme learning machine (ELM) (Huang, Zhu, & Siew, 2006) can not only avoid falling into local optima but also largely improve the learning speed. In this research, the wavelet-based nonlinear features were fed to the ELM classifier for detecting drowsy/alert states with overall consideration of detector sensitivity, specificity and efficiency.

2. Materials

2.1. Participants and experiment task

Sixteen healthy male students participated in this experiment, ranging in age from 22 to 25 years old. Subjects were required to keep a sleep diary one week prior to the experiment to ensure that they had at least 7 h of continuous sleeping time and regular sleeping hours. Thirteen subjects who reported good and regular sleep were finally selected for this study. Subjects were instructed to abstain from prescription medication, alcohol and caffeine 24 h before experiments. The experiments were performed according to the Declaration of Helsinki. The project protocol was approved by the local Institutional Review Board (IRB) of East China University of Science and Technology. The subjects gave their informed consent prior to the experiments.

The experiment task started around 3:00 p.m., which corresponded to the afternoon sleepiness peak in the human circadian rhythm (De Gennaro et al., 2001; Yeo et al., 2009). Subjects performed mental calculation for continuous two hours in which the subject's attempts at maintaining vigilance were dependent on their own determination to stay awake. During the experiment subjects were settled in a separate cubicle and no feedback of calculation performance was presented to the subjects, thereby reducing external disturbances and providing an environment conducive to sleep.

2.2. Data acquisition

Night-channel EEG signals were recorded by a digital EEG machine (Nihon-Koden EEG 2110) with the sampling frequency of 256 Hz. Electrodes were positioned at Fp1, Fp2, F3, F4, Fz, Cz, O1, O2 and Oz against ipsilateral earlobe electrode (A1, A2 or the average of A1 and A2) according to the standard 10–20 system. Additionally, two-channel EOG signals were recorded to analyze blink activities as part of the classification criteria for both visual inspection and automatic detection.

2.3. Data preparation

The artifact was removed from the recording by visual inspection. Two neurologists manually selected the segments used in this study. Each of them inspected the EEG/EOG recordings according a detailed criterion using three identifiers: (1) eye blink patterns (2) dominant EEG activity (3) frontal midline theta rhythm.

The 'alert' state refers to relaxed wakefulness with the presence of dominant beta rhythm (13–25 Hz) (Yeo et al., 2009) and quick blink activities (Doughty, 2002). The 'drowsy' state is recognized when EEG showing the presence of slow eye movement with occipital alpha rhythm (9–13 Hz), a decrease in the amplitude and/or frequency of the alpha rhythm (alpha dropout) (Yeo et al., 2009). The frontal midline (Fm) theta rhythm appears when some healthy subjects are under light drowsiness engaged in a mental task (Takahashi, Shinomiya, Mori, & Tachibana, 1997). Fm theta is induced not only during mental tasks but also during sleep stages and it appears during rapid eye movement (REM) and stage 1 of non-REM (NREM) sleep (Inanaga, 1998). Individual difference should be taken into account during the usage of dominant rhythm and Fm theta. Each of the neurologists inspected the EEG recordings using the above criteria and then agreed which EEG sequences clearly indicated a drowsy or alert state. The segments with