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Investigating the interaction between heart rate variability and sleep EEG using nonlinear algorithms

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HIGHLIGHTS

- A new model for monitoring the sleep stages is built based on Hilbert Huang transform.
- Two main oscillations were defined to depict the feature of sleep EEG based on HHT.
- Slow- and fast-waves oscillations correspond to fluctuations in the delta and high frequency band.
- DFA $\alpha 1$ was used to reflect the ANS activity during sleep.
- The relationship between sleep EEG and HRV was significantly confirmed in this study.

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ABSTRACT

Background: The multi-mode modulation is a key feature of sleep EEG. And the short-term fractal property reflects the sympathovagal modulation of heart rate variability (HRV). The properties of EEG and HRV strongly correlated with sleep status and are interesting in clinic diagnosis.
New method: 19 healthy female subjects were included for over-night standard polysomnographic study. Hilbert Huang transform (HHT) was used to characterize the temporal features of slow- and fast-wave oscillations decomposed from sleep EEG at different stages. Masking signals were used for solving the mode-mixing problem in HHT. On the other hand, detrended fluctuation analysis (DFA) was used to assess short-term property of HRV denoted as DFA $\alpha 1$, which reflects the temporal activity of autonomic nerve system (ANS). Thus, the dynamic interaction between sleep EEG and HRV can be examined through the relationship between the features of sleep EEG and DFA $\alpha 1$ of HRV.
Results: The frequency feature of sleep EEG serves as a good indicator for the depth of sleep during non-rapid eye movement (NREM) sleep, and amplitude feature of fast-wave oscillation is a good index for distinguishing rapid eye movement (REM) from NREM sleep.
Comparison with existing method: The relationship between DFA $\alpha 1$ of HRV and the mean amplitude of fast-wave oscillation of sleep EEG affirmed with Pearson correlation coefficient is more significant than the correlation verified by the traditional spectral analysis.
Conclusion: The dynamic properties of sleep EEG and HRV derived by EMD and DFA represent important features for cortex and ANS activities during sleep.

1. Introduction

Clinical studies have shown that acute stress affects heart rate variability during sleep (Hall et al., 2004), particularly slow-wave sleep, which is thought to be associated with a “restorative” or “refreshing” sensation (Tasali et al., 2008). The dynamic interactions between EEGs and cardiac autonomic function during sleep have only been explored and reported using fast Fourier transform

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based (FFT-based) analysis (Jurysta et al., 2003). Those properties of sleep electroencephalogram (EEG) and heart rate variability (HRV) have been used in many clinical diagnoses, such as sleep apnea syndrome (Roche et al., 1999; Jurysta et al., 2006), depressive disorder (Jurysta et al., 2010), and acute schizophrenia (Boettger et al., 2006).

In traditional sleep medicine, human sleep is polygraphically defined by stages 1, 2, 3, 4 of non-rapid eye movement (NREM) sleep and rapid eye movement (REM) sleep, according to the "Manual of Standardized Terminology, Techniques and Scoring System for Sleep Stages of Human Sleep" proposed by Rechtschaffen and Kales (R-K criteria) (Rechtschaffen and Kales, 1968). The four stages of NREM sleep are denoted as NREM1, NREM2, NREM3, and NREM4. Spectral analysis uncovers more detailed sleep fluctuations beneath the continuous fluctuating pattern of EEG signals during sleep (Uchida et al., 1992, 1994, 1999). On the other hand, the dynamics of HRV serves as a good assessment of autonomic nerve system (ANS) activity during sleep (Mina et al., 2003). Spectral analysis is commonly used in the investigations associated with sleep EEG and HRV (Mina et al., 2003; Otzenberger et al., 1997, 1998; Ehrhart et al., 2000; Brandenberger et al., 2001).

However, both sleep EEG and HRV are nonlinear and non-stationary signals. In this study, we aimed to re-investigate the features of sleep EEG and the dynamic properties of HRV based on two innovative analysis algorithms, which were particularly developed for analyzing nonlinear and non-stationary signals. Empirical mode decomposition (EMD) is the first nonlinear algorithm for decomposing a time series into a finite number of intrinsic mode functions (IMFs) (Huang et al., 1998). In addition, the frequency and amplitude modulations of an IMF can be derived by Hilbert transform. The association of EMD and Hilbert transform is named as Hilbert Huang transform (HHT). The second algorithm is detrended fluctuation analysis (DFA) (Peng et al., 1995a), which serves to quantify the fractal property of signals. The short-term (scales 4–11) fractal property of human heart beat time series denoted as DFA α_1 represents a state function of autonomic nerve system (ANS) during sleep (Tulppo et al., 2005; Penzel et al., 2003). A high value of DFA α_1 represents an active state of ANS, often observed during REM sleep. A low value of DFA α_1 represents an inactive state of ANS, often observed during slow wave sleep (SWS).

In this study, sleep EEG recordings were decomposed into a set of IMFs by EMD. Two major oscillations denoted as slow-wave (SW) and fast-wave (FW) oscillations were reconstructed using IMFs according to the averaged frequencies of IMFs. Both SW and FW oscillations were smoothed by moving average to represent two major oscillatory fluctuations of sleep EEG. Furthermore, Hilbert transform was used to derive the frequency and amplitude modulations of the smoothed SW and FW oscillations. Frequency and amplitude modulations of SW and FW oscillations represent the temporal features of sleep EEG at different stages. Thus, the sleep stages can be automatically verified based on the features of sleep EEG.

In clinic, sleep EEG reflects the activities of cortices and HRV reflects the activity of ANS. The interaction between sleep EEG and HRV can be verified as the relationship between the temporal features of sleep EEG and DFA α_1 of HRV in comparison with the association between the power of delta band of sleep EEG and the normalized HF power of HRV in spectral analysis (Jurysta et al., 2003, 2006, 2010). The relationship between the features of EEG and DFA α_1 of HRV was verified by Pearson correlation coefficient with value of 0.512 ± 0.171. The association between the power of delta band of sleep EEG and the normalized HF power of HRV was also verified by Pearson correlation coefficient with value of 0.261 ± 0.212. Both results reflect a correlation between the activities of cortices and ANS. The relationship between the features of sleep EEG and DFA α_1 of HRV is more significant than the relationship verified by FFT-based methods.

2. Material and methods

2.1. Subjects

Gender differences can be observed in sleep parameters; to prevent confounding effects due to gender, we recruited only women for the present study. In total, 19 healthy women (aged 30.5 ± 3.4 years) were recruited. All subjects provided their informed consent, and the study was approved by the local IRB.

2.2. Polysomnography (PSG)

Standard overnight PSG was performed using a computerized sleep-scoring system under the continuous monitoring of board-certificated sleep technicians (Sandman; Tyco Ltd. Ottawa, Canada) in the sleep lab of the teaching hospital. The subjects in the PSG study were asked to maintain their usual sleep schedule for one week prior to the study. To minimize the interference of menstruation on sleep and pain, the PSG was conducted 7–10 days after each subject's last menstrual period. The PSG recordings began at the subjects' usual bedtime and ended at their usual waking time in the morning. The PSG recordings included 21 channels: 6 channels for EEG (C3/C4/O1/O2/A1/A2 in 10–20 systems), 2 channels for electrooculogram (EOG), 6 channels for electromyogram (EMG) over the submental and bilateral anterior tibialis muscle, 2 channels for electrocardiogram (ECG), 1 channel for a nasal cannula flow meter, 2 channels for abdomen and chest movement, 1 channel for pulse oximetry, and 1 channel for a position sensor. The temperature of the recording room was maintained between 24 and 26 °C. A blinded, board-certified, experienced sleep technician manually performed the PSG scoring in 30-second epochs following the R-K criteria (Rechtschaffen and Kales, 1968). The parameters for sleep onset latency, sleep efficiency, total sleep time, sleep stage, and other sleep events were scored accordingly. The raw data of the PSG were stored digitally for further processing and analysis. The sampling rate for the EEG and ECG was 128 Hz.

2.3. Decomposing sleep EEG into slow- and fast-wave oscillations by EMD

The EMD decomposes a time series into a set of intrinsic mode functions (IMFs) (Huang et al., 1998). An IMF must satisfy a necessary condition that the numbers of zero-crossings and extrema must be equal or at most differ by 1, and it guarantees a well-behaved Hilbert transform of the IMF. The relationships among the original signal, IMFs and the residue can be expressed as:

$$X(t) = \sum_{k=1}^{n} C_k(t) + R(t) \tag{1}$$

where $X(t)$ is the original time series; $C_k(t)$ is the kth IMF; n is the number of IMFs; and $R(t)$ is the residue.

The averaged period and energy density of an IMF can be determined by the following equations provided by Wu and Huang (2004) and the averaged frequency is the inverse of averaged period.

$$E_n = \frac{1}{N} \sum_{j=1}^{N} [C_n(j)]^2 \tag{2}$$