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Research paper

A comparison study on stages of sleep: Quantifying multiscale complexity using higher moments on coarse-graining

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ABSTRACT

It is of great interests in identifying dynamical properties of human sleep signals using electroencephalographic (EEG) measures. Multiscale entropy (MSE) is effective in quantifying the degree of unpredictability of time series in different time scales. To understand the superior coarse-graining approach for the EEG analysis, we therefor use different moments to coarse-grain a time series, and examine their volatility as well as the effectiveness in quantifying the complexities of sleep EEG in different sleep stages. Both the simulated signals (logistic map) and the EEGs with different sleep stages are calculated and compared using three types of coarse-graining procedure: including MSE_{μ} (mean), MSE_{σ^2} (variance) and MSE_{skew} (skewness). The simulated results show that the generalized MSE (including MSE_{σ^2} and MSE_{skew}) can identify the differences in chaotic more easily with less fluctuation of entropy values in different time scales. As for the analysis of human sleep EEG, we find: (1) at small scales (<0.04 s), the entropy is higher during wakefulness and increasing time scales. (2) At large scales (0.25 s–2 s) in contrast, entropy is higher during deep sleep and lower with increasing time scales.

1. Introduction

It is well-known that a high-quality sleep can ensure the well-function in our daily lives, such as mental health, creative ability and working performance. Insufficient or ineffective sleep can cause daytime sleepiness, irritability, emotional distress, depressive or anxious mood, or even increased accident rates. In clinical, a variety of sleep measures are used in the identification and classification of sleep quality [1–4]. Unlike the Epworth Sleepiness Scale [5] which is subjective, polysomnographic (PSG), a multi-parametric test, is frequently used in sleep medicine and a popular diagnostic tool in the study of sleep. The PSG includes a comprehensive recording of the physiological changes, including electroencephalogram (EEG), electrooculogram (EOG), chin electromyogram (EMG), electrocardiogram (ECG), oxygen saturation (SpO2), and respiration (Resp.) [6]. Among them, EEG raises the most attention due to its representation as well as the rich information in

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brain activities [7]. In 1968, Rechtschaffen & Kales (R&K) [8] classified sleep/wake into three types of stages (epoch length = 30 s): Awake, non-rapid eye movement (including N-REM stage 1, N-REM stage 2, N-REM stage 3), and rapid eye movement (REM). Although the exact mechanisms of sleep, learning, and memory are not entirely understood, researchers believe that specific features of EEGs during different sleep stages are associated with the formation of particular types of memory. In particular, the relationship between the consolidation of different types of memories and the various sleep stages has raised a great deal of attention in recent years. Thus, it is essential to understand the changes in the sleep architecture during sleep cycles, numerous methods were therefore proposed in detecting the EEG features in each sleep stage in the last decades. For example, wavelet packet coefficients and artificial neural networks were deployed to classify sleep stages [9]; detrended fluctuation analysis was applied to analyze the fluctuation of EEG features in sleep apnea patients [10], the non-linear parameters: correlation dimension, fractal dimension, largest Lyapunov entropy, approximate entropy, Hurst exponent, phase space plot and recurrence plots were compared in quantifying the cortical function at different sleep stages [11].

However, it is still remains a challenge in identifying the sleep stages in sleep research society due to the highly complicated waveform of EEG; that is, both the amplitudes and frequencies are modulating in nonlinear and nonstationary patterns. Generally, EEG comprises the waves and events as: Delta waves (0.5–4 Hz), Theta waves (4–8 Hz), Alpha waves (8–13 Hz), Beta waves (13–35 Hz), Sleep spindles (12–14 Hz), and *K*-complexes (0.5–1.5 Hz) [6]. The complexity and changeability of EEG therefore bring about the necessity of applying dynamical and multiple time scales approaches in extracting the characteristics of sleep EEG, and let the temporal structure to tell its own story. To extract features in EEG signals, different methods are used in the calculation, such as standard deviation [12], power density [13], fractals [14] and information entropy [15–17]. Other than the above mentioned methods, sample entropy is excellent in quantifying the temporal structure of complex systems [18,19]. The MSE method [20], employing sample entropy as a measure in quantifying the degree of unpredictability of time series in different time scales, can be particularly informative and straightforward in describing the dynamic changes of physiological status. The application scopes of this method involve quantifying brain signal variability [15], illustrating the feasibility and well performance in the brain death diagnosis [21] and so on. Besides, Bell et al. [22] also showed that MSE can provide sensitive measures in nonlinear and dynamical systems and evaluate homeopathic remedy effects on human sleep EEG patterns.

Coarse-graining, an essential operation in the realization of MSE, is a procedure that obtains a new series using the mean value in each non-overlapping segments of equal length as the new variable. An interesting question is whether we will discard important information in using the first moment (mean value) in deriving copies of the original signal in different time scales. In 2015, Costa et al. used variance in the coarse-graining procedure with its application to heart beat time series [23]. However, the availability of using skewness in coarse-graining is remained unvalidated, nor its possibility in telling the distinction of the sleep stages. In our study, we compare the MSE results using multiscale entropy with generalization to higher moments (MSE_n) to coarse-grain the original time series. The previously MSE method is represented as MSE_μ, here μ stands for the first moment (mean). On the other hand, we also study the performances of MSE using second moment MSE_{σ^2} (variance) and third moment MSE_{Skew} (skewness). In order to examine the effectiveness and reliabilities in identifying the complexities between the three coarse-graining approaches, the logistic map, a family of nonlinear dynamical series with different degree of chaotic behavior is analyzed at first. After that, we apply MSE_n to identify the differences of temporal structure with different time scales into EEG derivation in healthy human during sleep.

In Section 2, we elaborate the detail methodology in quantifying multiscale entropy with higher moments. After the verification of the effectiveness in different methods using simulated signals in Section 3.1. Section 3.2 describes the data collection and the experiment protocols. The MSE_n results of the real data are shown in Section 3.3. At last, Section 4 concludes our findings.

2. Methodology

2.1. Sample entropy

Sample entropy (SampEn) quantifies the regularity of a time series. Mathematically, the procedure goes as follows.

For a time series $\{x_1, x_2, \ldots, x_N\}$, with the data length N, $N-m+1$ template vectors $\mathbf{x}_m(i) = (x_i, x_{i+1}, \ldots, x_{i+m-1})$ with $\{i | 1 \le i \le N-m+1\}$ are considered, where m is the embedding dimension, and r stands for the tolerance for the accepting matches. The distance between each pair of vectors is defined as the maximum difference between the two vectors

$$d[\mathbf{x}_m(i), \mathbf{x}_m(j)] = \max |x_{i+k} - x_{j+k}| : \ 0 \le k \le m-1 \tag{1}$$

Suppose B_i is the number of pairs with their distances smaller than r between $\mathbf{x}_m(i)$ and $\mathbf{x}_m(j)$, where $i \neq j$; and A_i is the number of pairs with their distances smaller than r between $\mathbf{x}_{m+1}(i)$ and $\mathbf{x}_{m+1}(j)$, where $i \neq j$. The probability that $\mathbf{x}_m(j)$ is within r of $\mathbf{x}_m(i)$ is

$$B_i^m(r) = \frac{B_i}{N-m-1}, \tag{2}$$

and the density is

$$B^m(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} B_i^m(r). \tag{3}$$