Automated Sleep Staging Using Detrended Fluctuation Analysis of Sleep EEG

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Abstract. An accurate sleep staging is crucial for the treatment of sleep disorders. Recently some studies demonstrated that the long range correlations of many physiological signals measured during sleep show some variations during the different sleep stages. In this study, detrended fluctuation analysis (DFA) is used to study the electroencephalogram (EEG) signal autocorrelation during different sleep stages. A classification of these stages is then made by introducing the calculated DFA power law exponents to a K-Nearest Neighbor classifier. Our study reveals that a 2-D feature space composed of the DFA power law exponents of both the filtered THETA and BETA brain waves resulted in a classification accuracy of 94.44%, 91.66% and 83.33% for the wake, non-rapid eye movement and rapid eye movement stages, respectively. We conclude that it might be possible to build an automated sleep assessment system based on DFA analysis of the sleep EEG signal.

Keywords: Electroencephalogram (EEG), Detrended fluctuation analysis (DFA), sleep, K-Nearest Neighbor (KNN).

1 Introduction

Sleep is not just a constant state controlled by metabolic needs for the body being at rest. Instead, sleep consists of different well-defined sleep stages, namely, wake (WK), rapid eye movement (REM) and non-REM sleep. In a normal restorative sleep, these stages follow a well-structured temporal order [1].

For more than 40 years, visual assessment of wakefulness and sleep in clinical sleep studies has been based on standard manual of Rechtschaffen and Kales (R&K) [2]. Although this manual is considered the gold standard inside sleep research community, a considerable amount of research has been carried to define methods that would give a more detailed and accurate sleep description of sleep macrostructure and overcome the known limitations of the R & K manual [3-5].

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During recent decades, multitude methods aiming at objective, continuous-scale quantification of sleep depth have been presented [4, 6, 7]. Most of the important early findings of clinical sleep medicine were based on period analysis, which makes it possible to carry out time–frequency analysis even visually for properly band-pass filtered data [4]. Hjorth parameters were introduced to characterize amplitude, time scale and complexity of the EEG through time-domain operations and were exemplified to be applicable in the analysis of objective sleep depth [8]. More recently, more studies on sleep staging have been conducted including: at least stochastic complexity measures [9], relations of certain spectral bands [10-12], models on EEG micro-continuity [13], Hidden Markov Models [14], segmentation approaches [15], k-means clustering based feature weighting combined with K-Nearest Neighbor and decision tree classifier [16], and Fuzzy logic combined with genetic algorithm [17].

The electrophysiological activities on the cortex reflected by EEG vary with the electrophysiological activities of the nerve cell in a special part of brain. When people are performing some mental tasks, the EEG signal shows highly non-stationary and non-linear characteristics. The detection of the mental EEG properties was studied using detrended fluctuation analysis (DFA) [18]. DFA is a new method recently introduced for analyzing power-law long-range correlations in a variety of non-stationary time series. DFA was used to characterize long-rang correlations between nucleotide sequences [19]. The advantage of the DFA method is that it systematically eliminates trends of various order caused by imperfect measurement [20].

Recently researchers applied the DFA for the analysis of the physiological time series as the heart rate variability (HRV) [21, 22] and breathing rate variability (BRV) intervals during sleep [23]. These studies revealed that both the HRV and BRV show high autocorrelation exponents during both WK and REM stages while they lose autocorrelation during NREM sleep stage.

In this paper, we used DFA to study the correlation properties of the EEG signal and its filtered components (Alpha, Beta, Delta and Theta) during various sleep stages. Our aim was to gain better understanding of the relative importance of the DFA-derived features for automated sleep staging. The DFA power-law exponents derived from a single EEG signal were then used to design a K-Nearest Neighbor- based classifier for sleep stages detection with a high degree of accuracy.

2 Subjects and Methods

2.1 Subjects and Sleep Recording

Twelve subjects aged 20-32 underwent one overnight polysomnographic recording which comprised EEG signal acquisition (4 channels, Ag/AgCl electrodes placed according to the 10-20 International System referred to linked earlobes: C3, C4, F3, F4). Recordings were carried out using Alice Polysomnogramic System (Respironics, Inc.). The signals were sampled at 100 Hz using 12-bit A/D precision and stored on hard disk for further analysis.

2.2 Sleep Scoring

Sleep stages were initially scored and labeled using the automated scoring algorithm of Alice Sleepware software then the scored signals were reviewed by a specialist for correction according to standard criteria (R&K) on 30-second epochs. For subsequent analysis, the labeled sleep stages were grouped into three classes: “NREM sleep”, “REM sleep” and “wakefulness”. Nine minutes for each sleep stage were extracted from each patient EEG record to be investigated. The first and last epochs of each sleep stage is excluded from our analysis in order to avoid the effect of transitions between sleep stages. Thus, the whole dataset is composed of 108 min/sleep stage or 324 min representing all the stages.

2.3 EEG Signal Analysis

The raw EEG signal was introduced to a filter bank as shown in Fig. 1 to separate known brain waves: Delta, Theta, Alpha and Beta waves. The filtered signals are shown in Fig 2. Each wave was then segmented by 1 minute long window and studied separately during each sleep stage using DFA to reveal the variations in the autocorrelation properties of each of these waves during various sleep stages.

2.4 Detrended Fluctuation Analysis(DFA)

DFA is a technique used to characterize the correlation structure of non-stationary time series. DFA reveals the properties of non-stationary time series by calculating the scaling exponents which index the long-range power-law correlations. The DFA procedure [19, 20] consists of four steps.

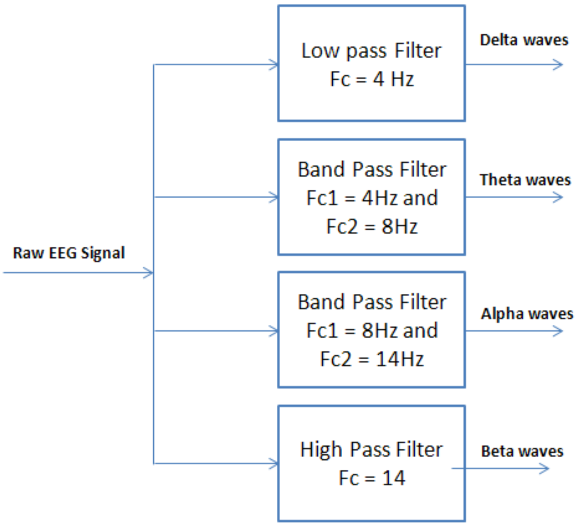

Fig. 1. Block diagram of the filter bank system

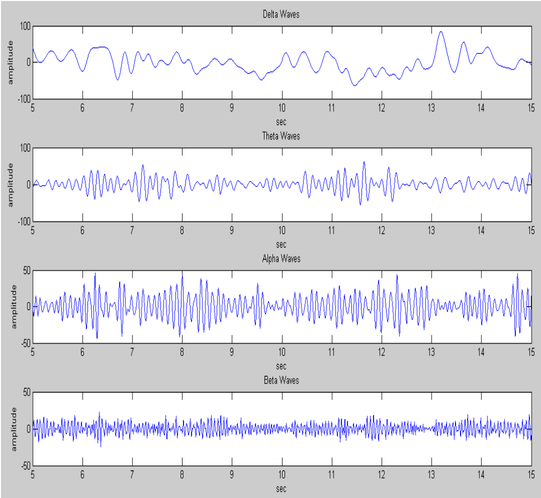

Fig. 2. The filtered EEG signals: Delta, Theta, Alpha, and Beta

- Step 1: Determine the "profile"

$$Y(i) = \sum_{k=1}^{i} \left(\tau_k - \langle\tau\rangle\right), \quad i = 1,\ldots\ldots,N \tag{1}$$

of the data series τ_k of length N and a mean $\langle\tau\rangle$.

- Step 2: we divide $Y(i)$ into $N_t = \mathrm{int}(N / t)$ non-overlapping segments of equal length t. Since the length N of the series is often not a multiple of the considered time scale t, a short part at the end of the profile may remain. In order not to disregard this part of the series, the same procedure is repeated starting from the opposite end. Thereby, $2N_t$ segments are obtained altogether.
- Step 3: Calculate the local trend for each of the segments by a least-square fit of the data. Then determine the variance

$$F_t^2(\upsilon) \equiv \frac{1}{t} \sum_{i=1}^{t} \left[Y\left((\upsilon-1)t + i\right) - p_\upsilon(i)\right]^2 \tag{2}$$

for each segment υ, $\upsilon = 1,\ldots\ldots\ldots, N_t$. Here, $p_\upsilon(i)$ is the fitting polynomial in segment υ. Linear, quadratic, cubic, or higher order polynomials can be used in the fitting procedure (conventionally called DFA1, DFA2, DFA3,…..) .

- Step 4: Average over all segments and take the square root to obtain the fluctuations function

$$F(t) \equiv \left[\frac{1}{2N_t} \sum_{\upsilon=1}^{2N_t} F_t^2(\upsilon)\right]^{\frac{1}{2}} \tag{3}$$

The logarithm of $F(t)$ is then plotted as a function of the logarithm of the time scale t. The slope, α, of the plot of $\text{Log}_2(F(n))$ versus $\text{Log}_2(n)$ is called the scaling or self-similarity exponent. If the time series shows self-similarity, this plot will display a linear scaling region and slope $\alpha > 0.5$. This exponent is 0.5 for white noise, where the values of the time series are completely uncorrelated. When the exponent is $\alpha < 0.5$, power-law anti-correlation is present, such that large values in the time series are more likely to be followed by small values and vice versa. When $\alpha > 0.5$, correlations exist but cease to follow a power-law form.

In order to determine how $F(t)$ depends on the time scale t, steps 2 to 4 were repeated 30 times with different time scales between t = 4 and 6000. The long range auto-correlation properties of the raw sleep EEG signal and the filtered brain waves of each sleep stage were investigated separately using DFA2 as shown in Fig. 3. The mean and standard deviation of the computed DFA2 parameters for the different sleep stages are given in Table 1.

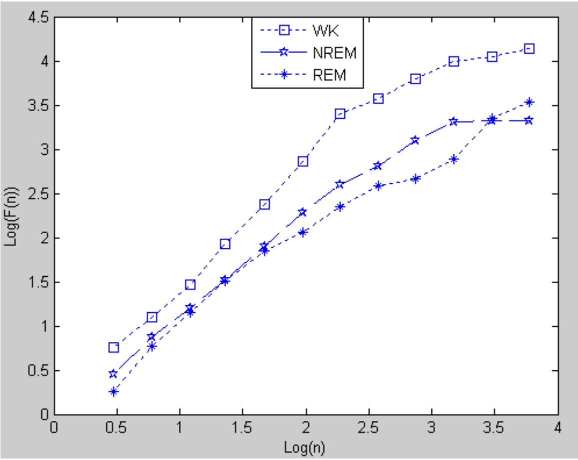

Fig. 3. DFA analysis of a 1-min long EEG record of a single subject corresponding to the WK, NREM and REM sleep stages

Table 1. The DFA characteristic values for each sleep stage

Sleep Stage	Raw EEG	Delta	Theta	Alpha	Beta
WK	0.858 ± 0.1003	1.0665 ± 0.0908	0.2853 ± 0.0203	0.1582 ± 0.013	0.0437 ± 0.0108
NREM	0.4099 ± 0.1675	0.9626 ± 0.0926	0.3021 ± 0.007	0.1566 ± 0.0095	0.0616 ± 0.0078
REM	0.8628 ± 0.0835	1.0128 ± 0.0809	0.2937 ± 0.0118	0.1597 ± 0.01	0.0551 ± 0.0095

Table 2. The significane levels for the group differences between sleep STAGES USING Bonferroni test. each line lists the results for the comparison of the stages named in coloumn 1 and 2

Stage 1	Stage 2	Raw EEG	Delta	Theta	Alpha	Beta
WK	NREM	P < 0.001	P < 0.001	P < 0.001	n.s	P < 0.001
WK	REM	n.s	P < 0.001	P < 0.001	n.s	P < 0.001
NREM	REM	P < 0.001	P < 0.001	P < 0.001	P < 0.05	P < 0.001

2.5 Statistical Analysis

In order to check the difference between individual groups, Bonferroni test was applied to DFA data sets. Statistical significance was stated for $p < 0.05$. The statistical test was performed by SPSS version 10 (SPSS Inc, Chicago, IL).

The results of the Bonferroni test are listed in Table 2. It can be seen that the Alpha waves showed no significance on comparing both the WK versus REM stages and the WK versus NREM stages. For this reason, the DFA2 parameters of the Alpha waves are excluded from the features vector construction to be used in sleep stages classification.

2.6 K-Nearest Neighbor Classifier (KNN)

The Nearest Neighbor Classification is the most straightforward in machine learning where examples are classified based on the class of their nearest neighbor. It is often useful to take more than one neighbor into account so a modified technique commonly referred to as K- Nearest Neighbor (KNN) classification uses the K nearest neighbors in determining the class of the unknown example [24]. Fig. 4 depicts the basic idea of a 5-Nearest Neighbor classifier applied for a two class problem in a two dimensional feature space.

In general, the distance d between q and x_i is calculated as :

$$d(q, x_i) = \sum_{f \in F} \omega_f \, \delta(q_f, x_{if}) \tag{4}$$

where q is unknown example, F is the training set, x_i is i-dimensional feature vector, ω_f is the class label and $\delta(q_f, x_{if})$ is defined as follows:

$$\delta(q_f, x_{if}) = \begin{cases} 0 & f \text{ discrete and } q_f = x_{if} \\ 1 & f \text{ discrete and } q_f \neq x_{if} \\ |q_f - x_{if}| & f \text{ continuous} \end{cases} \tag{5}$$

Hence, q is classified according to the majority class of the N-nearest neighbors.

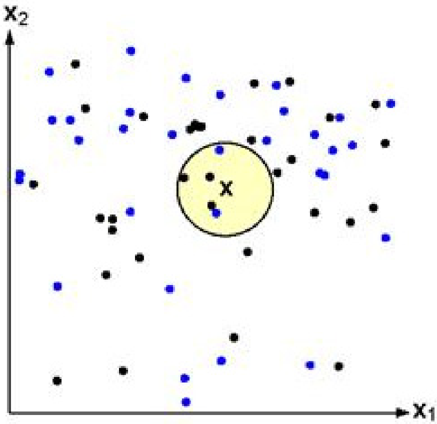

Fig. 4. A simple example of 3-Nearest Neigbour classification

In this study, the classification of the different sleep stages is done and compared using the DFA2 parameters of the raw EEG signal on one hand and the filtered signals on the other hand. The raw EEG parameters were used to construct a 1-D feature space. The parameters of the Delta, Theta and Beta waves were used to construct three sets of 2-D features spaces. Fig. 5 shows the 2-D feature space derived from the Theta and Beta waves. Also, a one 3-D features space is derived from the three filtered signals together as illustrated in Fig. 6. The whole dataset size composed of 324 stages is divided into a training set of 216 stages and a testing set of 108 stages.

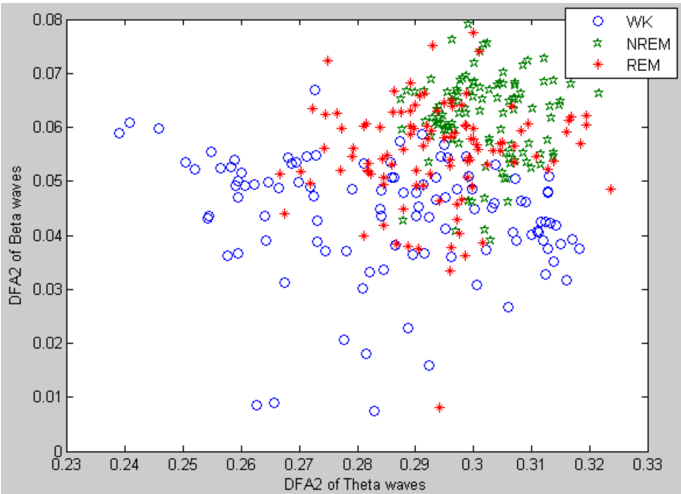

Fig. 5. The 2-D features space constructed from the DFA2 parameters of Theta waves versus BETA waves

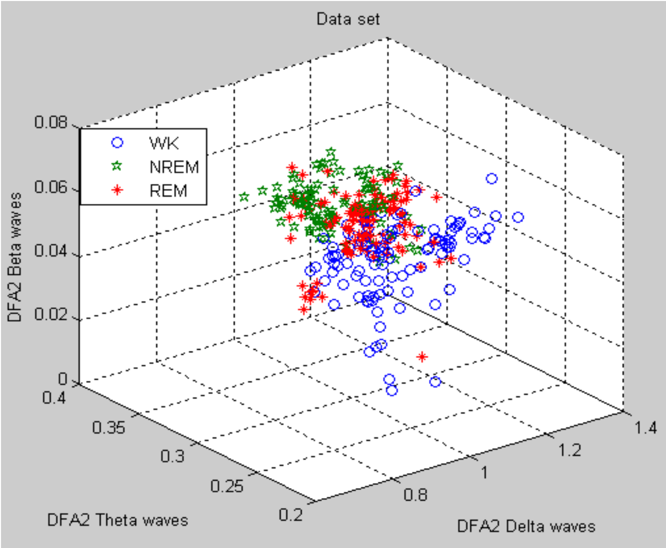

Fig. 6. The 3-D feature space constructed from the DFA2 parameters of Theta, Beta and Delta waves

Table 3. The accuracy of KNN classifier to classify varous sleep stages based on three different sets of 2-D feature spaces

Sleep Stage	Delta vs Beta		Delta vs Theta		Beta vs Theta	
	K	accuracy	K	accuracy	K	accuracy
WK	7	72.22%	5	55.55%	7	94.44%
NREM		50.00%		75.00%		92.66%
REM		55.55%		50.00%		83.33%

3 Results

The KNN classification using the raw EEG parameters resulted in an accuracy of 61.11%, 83.33% and 44.44% at K=7 for the WK, NREM and REM sleep stages, respectively. The 3-D feature space showed an accuracy of 55.55%, 58.33% and 55.55% at K=7 to separate the WK, NREM and REM sleep stages, respectively.

The introduced three sets of 2-D feature spaces to the KNN classifier showed the classification accuracies listed in Table 3. It can be seen that Beta versus Theta features showed the highest accuracy in differentiating between the different sleep stages.

4 Discussion

In our knowledge, this paper presents the first study which systematically investigates the autocorrelation properties of the sleep EEG signal and its extracted waves: Alpha, Beta, Theta, and Delta, using DFA. The study reveals that the EEG signal is almost uncorrelated during NREM ($\alpha \approx 0.5$) while long-range correlations ($\alpha > 0.5$) exist during the WK and REM stages. These results are consistent with the DFA analysis results for both the heart rate variability and the breathing rate variability during sleep [21, 22, 23]. The mechanism underlying such fluctuations may be related primarily to the different autonomic regulations during REM and NREM sleep stages. The extracted components, Theta, Beta, and Alpha, however, show anti-power-law correlation properties ($0 < \alpha < 0.5$) which indicates the high roughness inherent in these waves during the different sleep stages.

An attempt of separating the sleep stages using KNN classifier based on the feature space derived from the power-law exponents of the EEG signals and its filtered components is done. Results revealed that the Beta versus Theta features had superior ability to separate sleep stages than the other features.

The small number of subjects is considered as a limitation in our study as we think the accuracy of the classifier could be enhanced with increasing the training data set as the KNN classifier are considered as *Lazy* classifiers.

Our results do indicate that it might be possible to build a sleep assessment system based on EEG signal only to reduce the large number of electrodes that is mounted on the subject with a conventional polysomnogram method which obviously affects the comfort ability of the subject and may interfere with the accuracy of his sleep assessment.

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