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Nonlinear Dynamics Measures for Automated EEG-Based Sleep Stage Detection

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Key Words
Sleep apnea · EEG · REM sleep · NREM sleep · Nonlinear · Variability · Recurrence quantification analysis

Abstract
Background: The brain's continuous neural activity during sleep can be monitored by electroencephalogram (EEG) signals. The EEG wave pattern and frequency vary during five stages of sleep. These subtle variations in sleep EEG signals cannot be easily detected through visual inspection. ***Summary:*** A range of time, frequency, time-frequency and nonlinear analysis methods can be applied to understand the complex physiological signals and their chaotic behavior. This paper presents a comprehensive comparative review and analysis of 29 nonlinear dynamics measures for EEG-based sleep stage detection. ***Key Messages:*** The characteristic ranges of these features are reported for the five different sleep stages. All nonlinear measures produce clinically significant results, that is, they can discriminate the individual sleep stages. Feature ranking based on the statistical F-value, however, shows that the third order cumulant of higher order spectra yields the most discriminative result. The distinct value ranges for each sleep stage and the discriminative power of the features can be used for sleep disorder diagnosis, treatment monitoring, and drug efficacy assessment.

1. Introduction

Sleep is a naturally occurring state of meditation characterized by distorted consciousness and immobility of voluntary and sensory muscles, but the human brain is continuously processing during sleep. Sleep

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Table 1. The 5 stages of sleep [109–112]

Stages	Eye movement	EEG variation
Stage 0 (wake)	Eyes are open	EEG varies rapidly Prominent beta activity with 13–26 Hz frequency and low voltage of 10–30 μV Alpha activity with 8–12 Hz frequency and higher voltage of 20–40 μV
Stage 1 (drowsiness)	Slow movements of eye rolling	Alpha waves (8–12 Hz) disappear Theta waves (4–7 Hz) appear
Stage 2 (light sleep)	Eye movement stops	Burst of brain activity visible on EEG Sleep spindles (11–15 Hz) and K-complexes appear on the background of theta waves
Stage 3 (deep sleep)	–	Delta waves appear slowly with EEG amplitude >75 μV and 1–3 Hz frequency Sleep spindles and K-complexes also exist
Stage 4 (deep/slow wave sleep)	–	Prominent delta waves with frequency <2 Hz and high EEG amplitude
Stage 5 (REM sleep)	REM with sporadic muscular twitches	Mixed frequency and low voltage Occasional bursts of saw tooth wave

helps the cognitive development [1], increases the learning rate and nourishes the emotional and physical state of a living being [2]. Tarokh et al. [3] report continuity of cortical development in adolescents [4] using sleep electroencephalogram (EEG) signals. During sleep, an individual is physically at rest but mentally at work. Irregularity in sleeping habits can lead to sleep disorders, such as insomnia (lack of sleep), obstructive sleep apnea (OSA; disturbed sleep) and narcolepsy (excessive sleep) [5]. Sleep disorders tend to affect the normal lifestyle of an individual causing dizziness, chronic headache, restlessness and cardiac disorders [6–8]. The continuous brain activity during sleep can be studied through EEG signals. Detecting variation in the EEG amplitude, frequency and wave pattern can help in both the identification of different sleep stages and the sleep-related disorders [9, 10].

The EEG signals are recorded by scalp electrodes or an electrode cap. The measurements act as a brain state indicator. Hence, they are used for the quantitative analysis of different brain regions and its functional connectivity. EEG signals are highly irregular, nonlinear and non-stationary in nature. They are divided into different types of waves based on varying frequencies and wavelength: (a) gamma (30–128 Hz), (b) beta (13–30 Hz), (c) alpha (8–13 Hz), (d) theta (4–8 Hz) and (e) delta (below 4 Hz) [11, 12]. Kim et al. [13] used sleep EEG signals to determine the severity of OSA [14] using the brain recurrence analysis. They search for markers of sleep depth and fragmentation for classification of patients with mild and moderate OSA disorder.

Rechtschaffen and Kales [15] (R&K) divide sleep stages broadly into 2 streams: Non-Rapid Eye Movement (NREM) sleep and Rapid Eye Movement (REM) sleep. The NREM sleep is classified into 4 stages: Stage 1 (drowsiness), Stage 2 (light sleep), Stage 3 (deep sleep) and Stage 4 (deep, slow wave sleep) [16] (table 1). The REM sleep is Stage 5 (table 1). Another standard method of sleep stage division was developed by the American Academy of Sleep Medicine (AASM). According to the AASM, the third and fourth stages of R&K standard are coupled into one called the slow wave/deep sleep [17–19]. Figure 1 presents sample EEG signals of different sleep stages obtained from healthy individuals who have a basal sleep need of 7–8 h every night. Basal sleep need is the amount of sleep required on a regular basis by human body for optimal performance [20]. The EEG signals were collected from the repositories described in Section 2.

In recent years, a number of researchers and neuroscientists have analyzed the brain's activity during sleep using EEG and imaging data. Bajaj and Pachori [18] classified sleep EEG signals based on the time-frequency image (TFI) of EEG signals obtained by the Smoothed Pseudo Wigner-Ville Distribution method. Histogram-based features for each sub-images of EEG signals, corresponding to different frequency bands, are computed from TFI and classified by multiclass least squares support vector

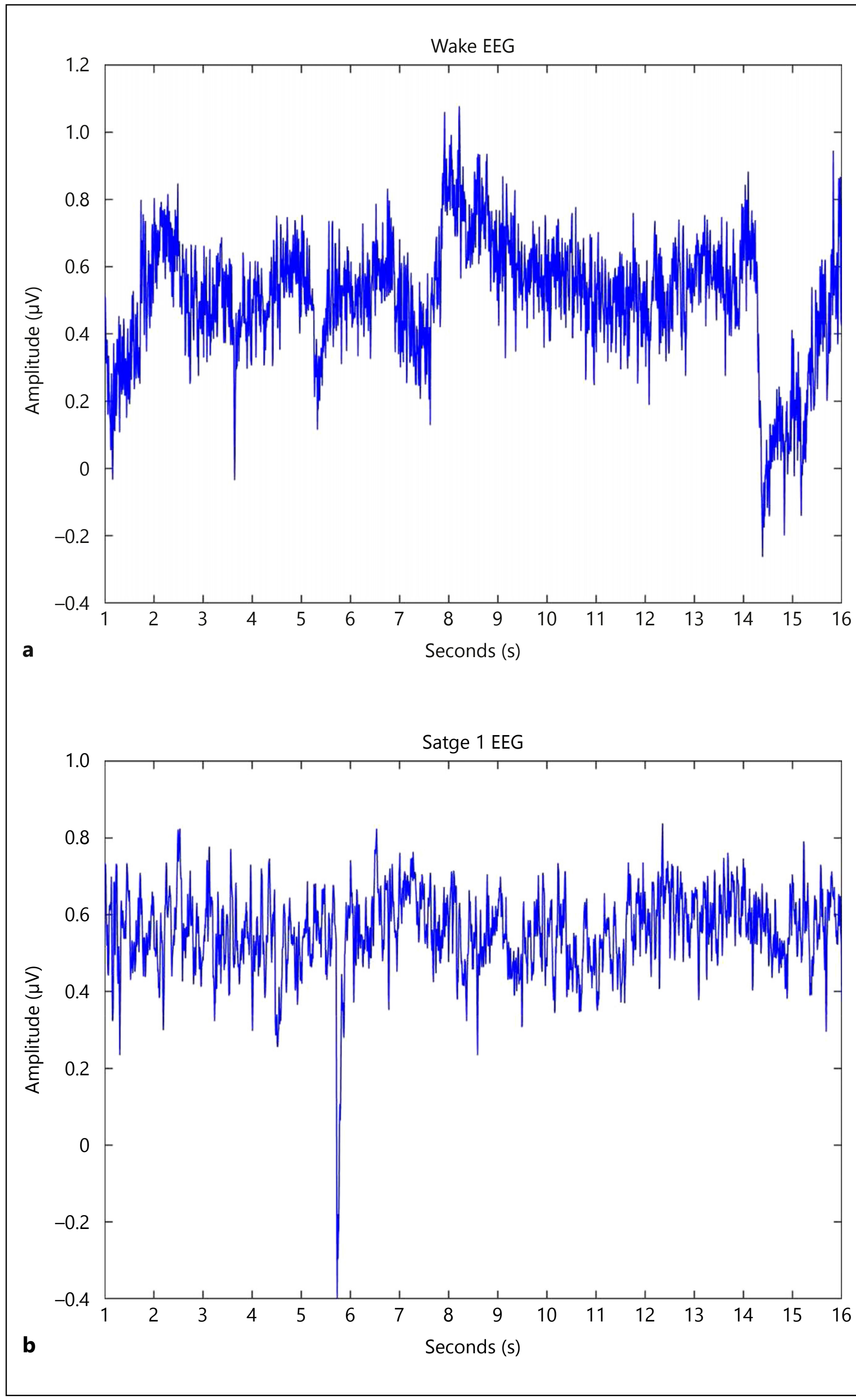


Fig. 1. Sample EEG signals of **a** Stage 0 (wake), **b** Stage 1 (drowsiness).

machines (SVMs) [21] with radial basis function [22, 23] and Mexican hat and Morlet wavelet kernel functions [24, 25]. Gunes et al. [26] describe a sleep stage recognition system using EEG signals and k-means clustering. The goal is to help physicians indicate different sleep stages and the occurrence of respiratory, cardiac and muscular events in the sleep scoring process [27]. Combinations of wavelet signal processing technique, chaos theory/non-linear science and neural network pattern recognition techniques have been reported in recent years for the

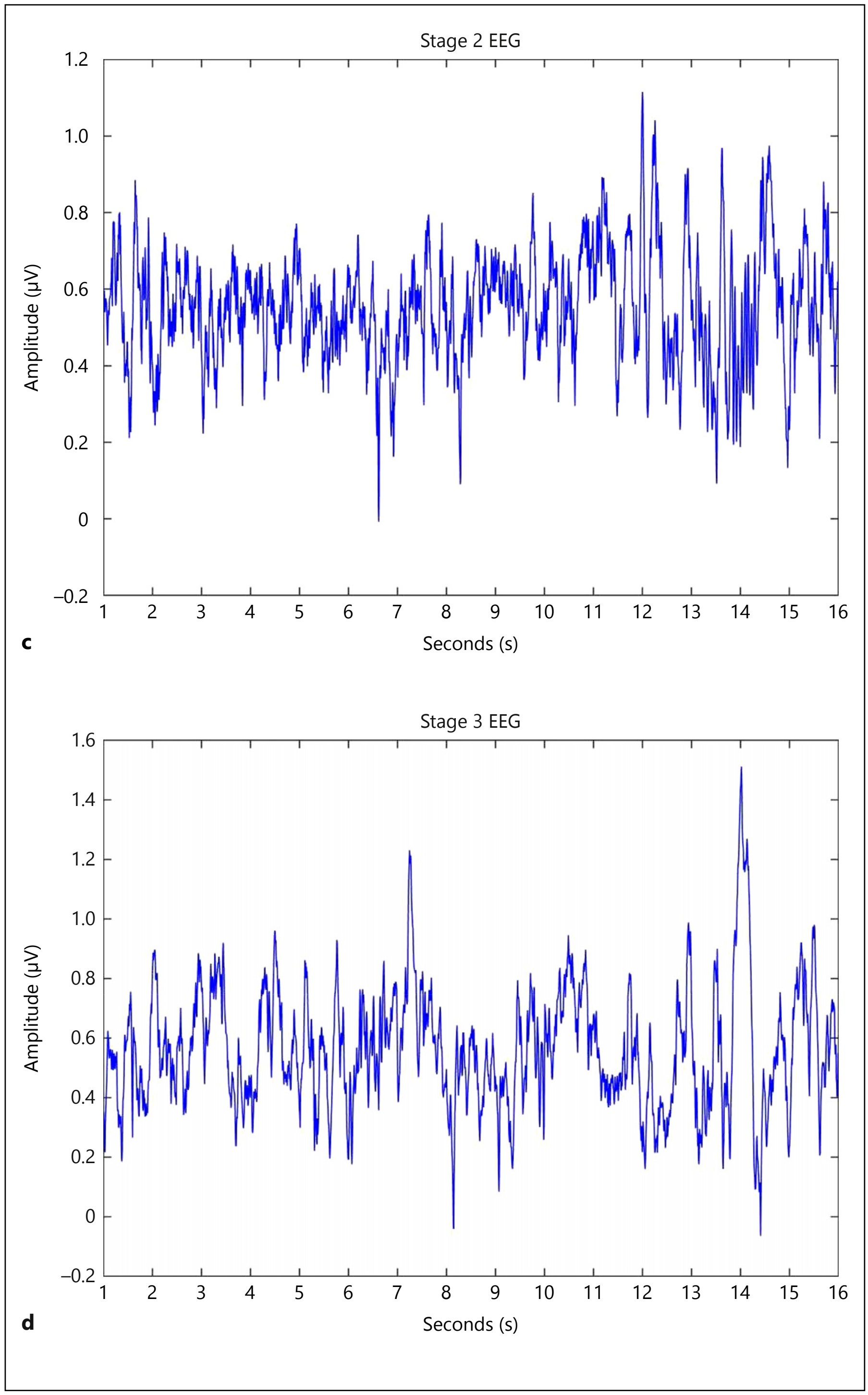


Fig. 1. Sample EEG signals of **c** Stage 2 (light sleep), **d** Stage 3 (deep sleep).

EEG-based diagnosis of varying disorders such as epilepsy [28–33], Alzheimer's disease [34, 35], attention deficit hyperactivity disorder [36, 37], autism spectrum disorder [38–40], major depressive disorder [29] and alcoholism [41].

Some of the most interesting sleep stage research is based on parameters extracted from EEG signals using nonlinear dynamics and the chaos theory. This paper presents a comprehensive review and comparative analysis of these nonlinear methods.

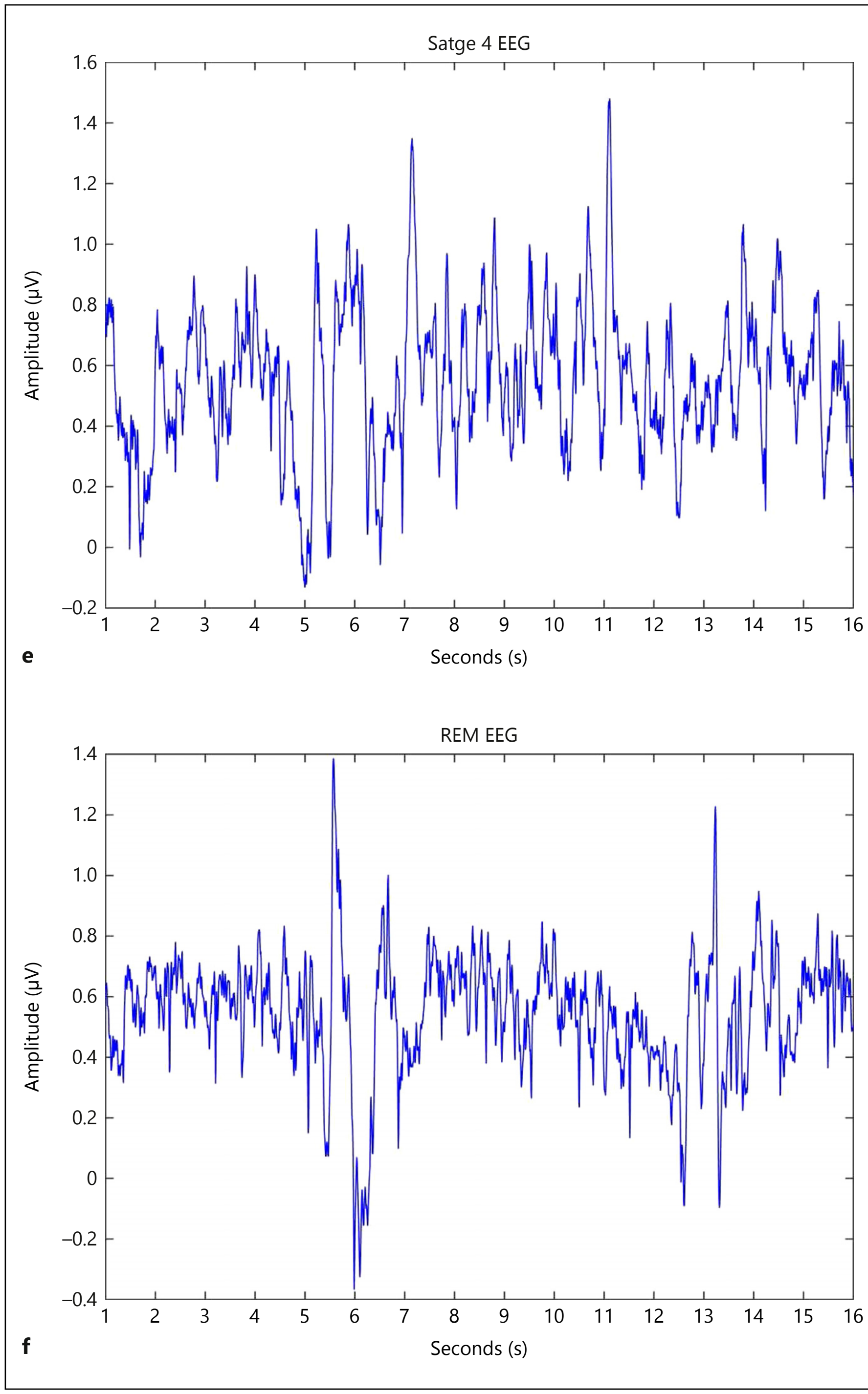


Fig. 1. Sample EEG signals of **e** Stage 4 (deep slow wave sleep), **f** Stage 5 (REM sleep).

2. EEG Data

PhysioNet provides free access to a large number of electrophysiological data sets. The sleep EEG data used in this study were collected from 2 different databases. The EEG signals of 25 subjects from St. Vincent's University Hospital/University College Dublin Sleep Apnea Database and 14 subjects from University College Dublin, Ireland, were obtained using a standard overnight polysomnography. The sleep stages were determined based on the R&K standard. The sampling frequency for St. Vincent's University Hospital data set was 128 Hz, digitized at 16-bits and filtered in the 0.3–35 Hz range whereas the sampling frequency for University College Dublin data set was 125 Hz, digitized at 16-bits and band pass filtered in the 0.3–30 Hz range. In this research, each of the 39 EEG data sets was divided into 2,000 samples.

3. Analysis of Sleep EEG Signals Using Nonlinear Dynamics Methods

The EEG signal variations cannot be perceived by mere visual inspection because of their highly random and chaotic nature. An automatic system capable of categorizing different sleep stages is developed using signal processing techniques based on the statistical analysis of linear and nonlinear characteristics of sleep EEG signals. Time and frequency analyses by themselves do not provide accurate results as these methods are unable to capture the minute information from the EEG signals due to their non-stationary and nonlinear nature [12]. Thus, nonlinear dynamics are applied to sleep EEG signals to differentiate diverse stages of sleep. Chouvarda et al. [42] have analyzed the sleep stages using fractal dimension, approximate and sample entropies. They have shown clear variations in these features at various sleep stages.

3.1 Commonly-Used Nonlinear Dynamics Method

Nonlinear methods have proven to be an efficient tool in understanding the complexities of the brain [43–49]. They help in the identification of underlying behavior of biological signals [11, 50, 51], such as electrocardiogram, EEG and magnetoencephalogram and thus, can be applied to all non-stationary signals. Various nonlinear algorithms can be used in the analysis of sleep EEG signals.

Approximate entropy (ApEn) is a complexity measure that quantifies the unpredictability of fluctuations in a time series signal [52–54], whereas sample entropy (SampEn) measures the regularity of a physiological time series signal and is independent of the pattern length [53, 55, 56]. Fuzzy entropy (FuEn) expresses the fuzzy information of a signal [57] using the concept of fuzzy logic [58–61]. Renyi' entropy (ReEn) is a generalized uncertainty measure [62]. Permutation entropy (PerEn) is a signal generating state-based uncertainty measure [63, 64]. Hurst exponent (H) constitutes an estimation of self-similarity and correlation properties found in physiological signals [65]. The largest Lyapunov exponent (LLE) is a nonlinear method employed to differentiate a chaotic signal from a periodic signal [66, 67] and correlation dimension (CD) measures the dimension of fractals [68]. Kolmogorov complexity (KC) is a measure of the computing resources required to specify a signal sequence [69]. Lempel–Ziv complexity estimates the complexity of discrete time signals. It can act as a scalar metric to compute the bandwidth of highly random processes and can also calculate harmonic variability in quasi-periodic signals [70]. Detrended fluctuation analysis quantifies the minute details of the physiological signals using the fractal property [71].

3.1.1 Higher Order Spectra

Second order measures, such as autocorrelation function or power spectrum, provide a partial explanation of a random process. The principles of power spectrum are extended to higher orders called higher order spectra (HOS) to determine the subtle changes and the shape of a waveform.

HOS detects the nonlinearity and deviations from Gaussianity and preserves the phase characteristics of a signal [72, 73]. Higher order cumulants (third order or more) are the functions of higher order moments of a random process. They are used to extract momentous information from the EEG signal to help with the diagnosis of several abnormalities and neural disorders [74–76]. The bispectrum is a third order statistic that can be used in the analysis of electrophysiological signals. Figures 2 and 3 present the magnitude plots of bispectrum and cumulants of sleep EEG signals. These plots describe the interaction between frequencies associated with the nonlinearities of EEG signals during sleep. The functional features (moments of bispectrum; H1, H2, H3, H4, H5 and normalized bispectral entropy (Ent1) [77], normalized bispectral squared entropy (Ent2), normalized bispectral cubic entropy (Ent3)) obtained from the bispectrum (table 2) and bicoherence can be used to determine the 5 stages of sleep [78, 79].

3.1.2 Recurrence Quantification Analysis

Recurrence quantification analysis (RQA) quantifies the irregular and non-stationary nature of a physiological signal. It determines the number of rhythmic patterns and its duration in a time series signal [80]. The nonlinearity of a signal is analyzed by calculating different features, such as determinism (det), laminarity (lam), recurrence rate (rr), recurrence time (t1, t2), entropy (ent), longest vertical line (vmax), largest diagonal line (lmax), mean diagonal length (meanlen) and trapping time (Tt) [81] listed in table 3. The recurrence plot is a 2D plot of dotted arrays that helps in the detection of masked periodic nature and

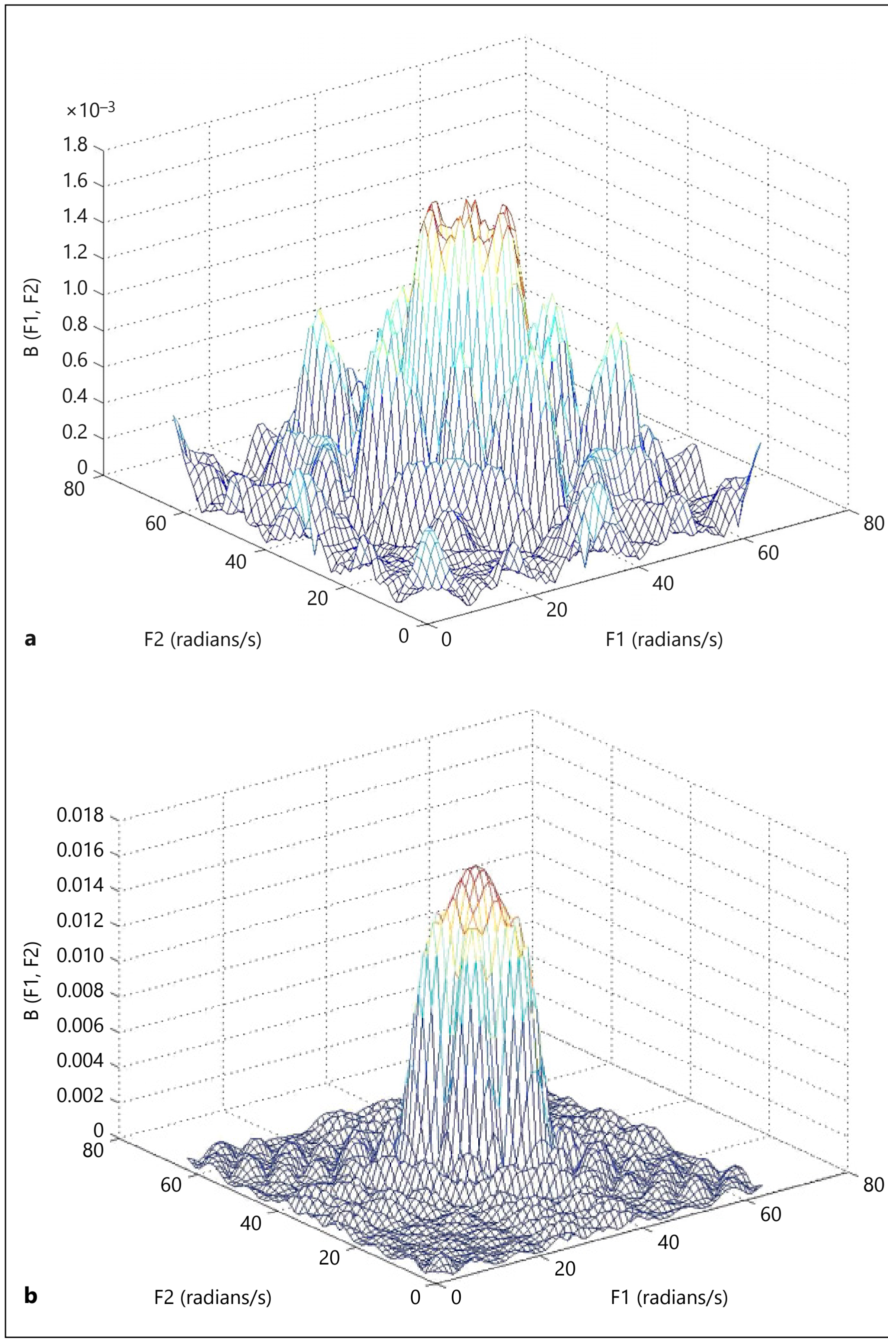


Fig. 2. Bispectrum plot of **a** Stage 0 (wake), **b** Stage 1 (drowsiness), where f1 and f2 are bi-frequencies.

drift of a random signal in the time domain. The x and y axes represent 2 different recurrence states i and j of a signal, respectively. Whenever a point on i-axis is close to a point on j-axis, a dot representing the point x (i, j) is created. Figure 4 shows the RP of different stages of sleep. The dotted pattern (patches of blue, green and red) becomes prominent as the sleep stage descends from Stage 0 to 4 illustrating reduction in the EEG signal variability and its frequency. The trivial patches in RP of REM sleep (fig. 4f) indicates an increase in EEG signal variability and presence of mixed frequencies in the EEG signal.

3.1.3 Analysis of Variance

Analysis of variance (ANOVA) is a statistical feature assessment tool applied to parametric (interval data) and non-parametric (ranking) data. It analyzes the overall

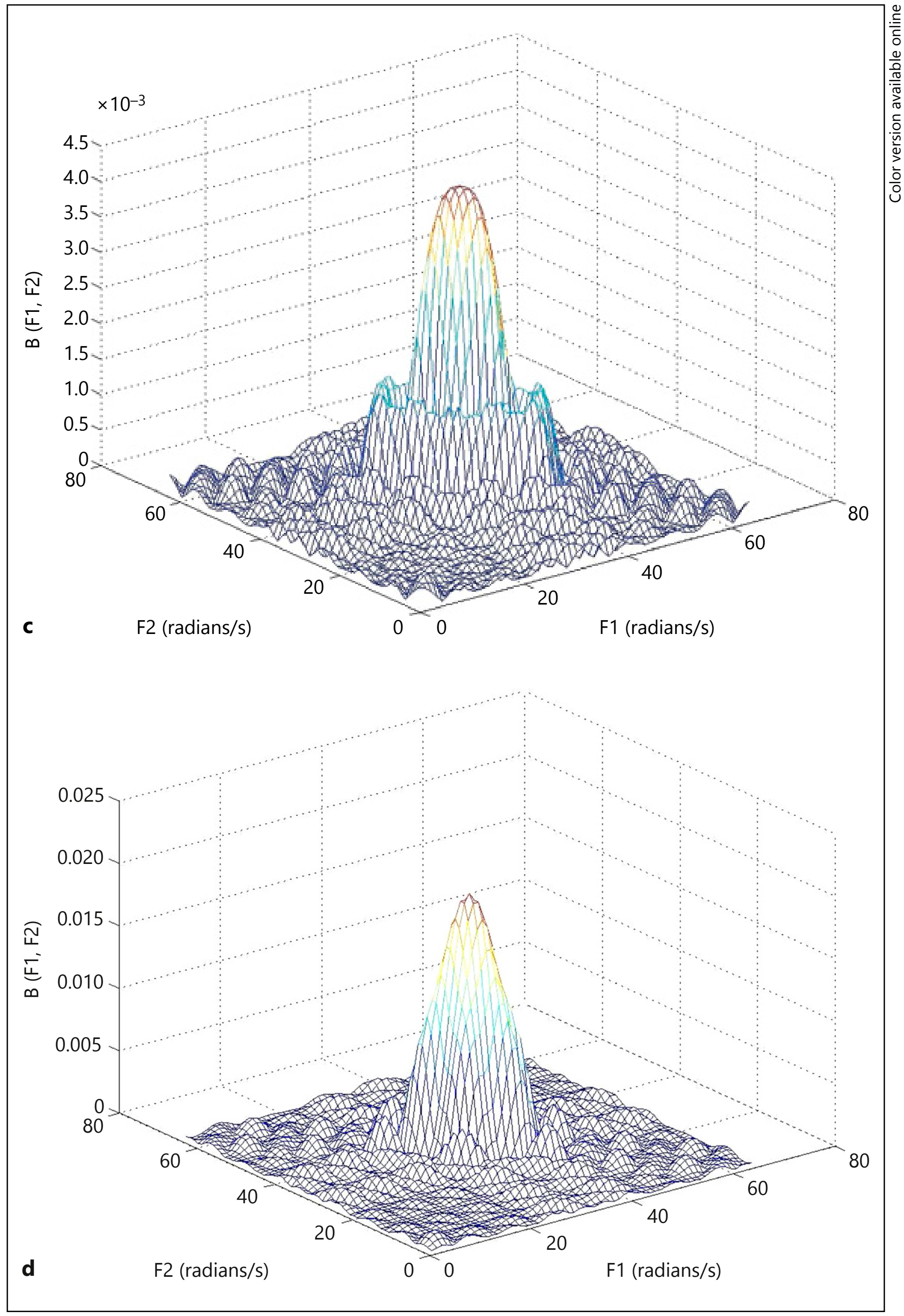


Fig. 2. Bispectrum plot of **c** Stage 2 (light sleep), **d** Stage 3 (deep sleep), where f1 and f2 are bi-frequencies.

data variability and divides it into 2 different components; random factors do not possess statistical influence on the given data set, and systematic factors do possess statistical influence on the given data set [82]. ANOVA test is used to compare the means of 2 or more test samples. It also helps to evaluate the linear relationship between an independent and a dependent variable. To compute this relationship, right skewed F-distribution (Fisher–Snedecor distribution) is used, which calculates the ratio of model mean square and residual mean square. The F-value is a measure of individual group deviation [83]. One-way ANOVA tests the null hypothesis that assumes the population means of 2 or more test samples are equal. Null hypothesis is rejected if the p value (probability value) is less than the threshold (0.0001) implying that test data sets are significantly different from each other [30].

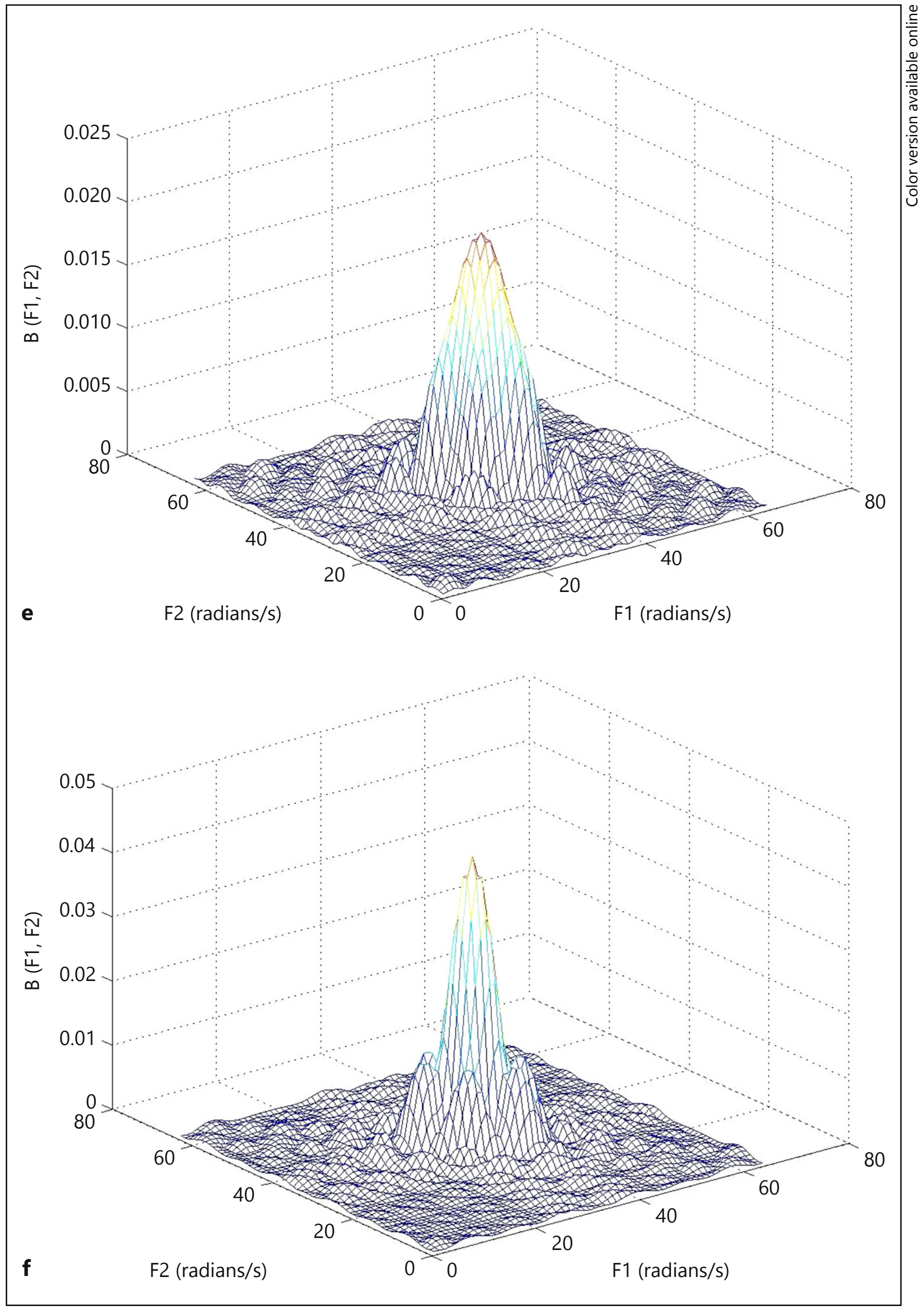


Fig. 2. Bispectrum plot of **e** Stage 4 (deep slow wave sleep), **f** Stage 5 (REM sleep), where f1 and f2 are bi-frequencies.

4. Results

Sleep is a dynamic process that alternates between NREM and REM sleep stages. The neuronal activity reduces as the sleep descends from Stage 1 to 4. A burst of neural activity is visible during REM sleep due to dreaming and random muscular twitches [84]. In the past, researchers assumed that EEG signals can be characterized by linear analysis but the underlying episodic behavior of EEG signals cannot be interpreted by time and frequency domain analysis due to its highly irregular nature [85, 86]. This work suggests that the dynamic activity of neurons during NREM and REM sleep can be differentiated and the subtle variations in the EEG signal can be characterized more effectively by nonlinear analysis.

Table 4 presents the ApEn, SampEn, CD and exponent values of sleep stages illustrated in figure 1. The ApEn

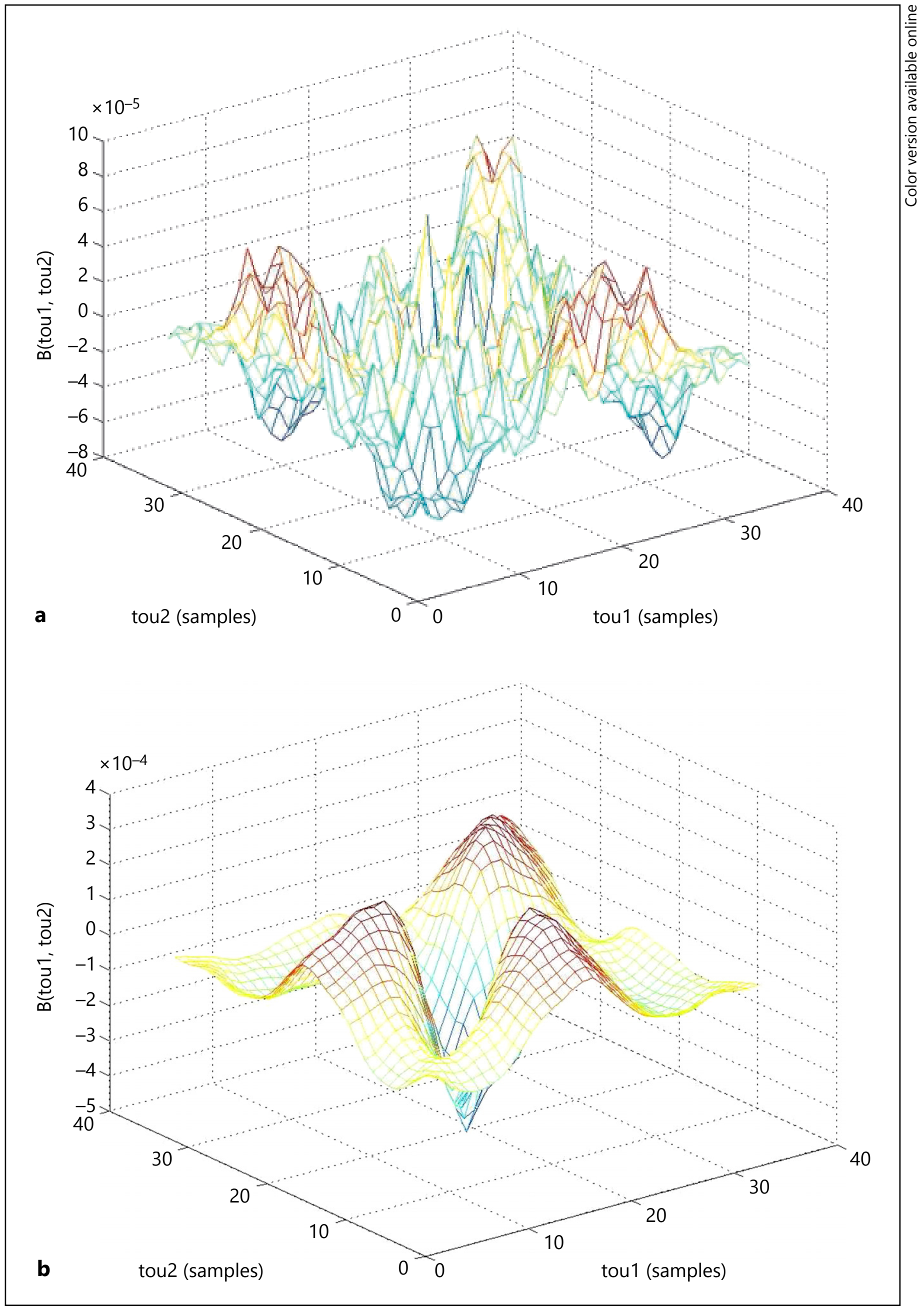


Fig. 3. Cumulant plot of **a** Stage 0 (wake), **b** Stage 1 (drowsiness), where tou1 and tou2 are time-lag parameters.

value of wake state is higher depicting random variability of EEG signals due to the dynamic cortex. It decreases gradually with increase in the depth of sleep (Stage 1–4) and simultaneously the cortex becomes inactive. The REM stage finds an increase in ApEn value as EEG irregularity increases due to REM and muscle twitches. SampEn value falls gradually exemplifying the reason for unconsciousness during deep sleep and EEG irregularity decreases from wake stage to Stage 4 but it increases during REM sleep as this stage marks the state of dreaming and active cortex.

The positive LLE value provides the rate of divergence and indicates that wake EEG signals are highly irregular and chaotic. CD value of REM sleep increases due to increased neural activity. It also indicates that complexity of sleep EEG signals reduces from Stage 0 to 4. The characteristics of sleep EEG signals can be determined by a scaling exponent (α) [87] that acts as an indicator of fluc-

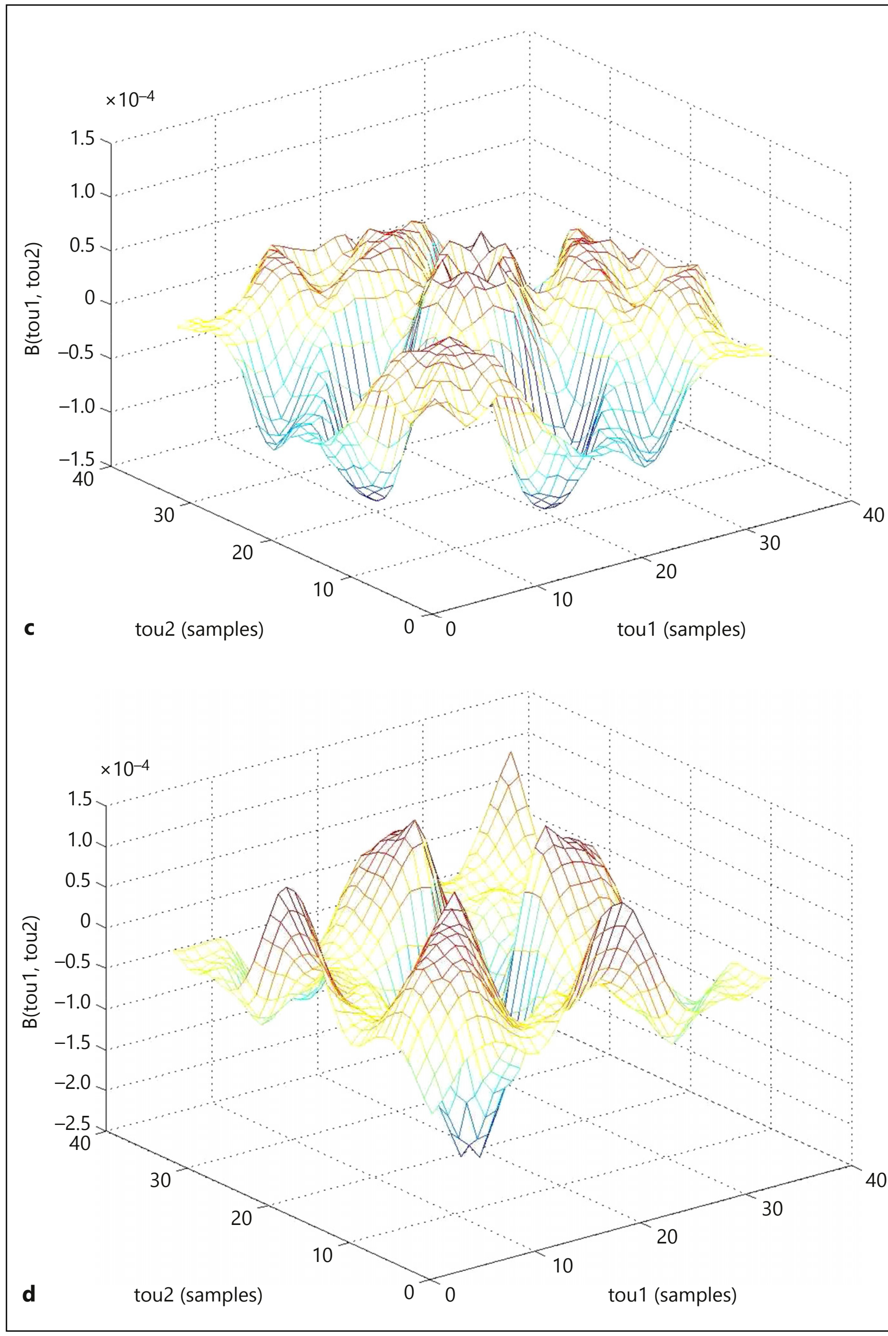


Fig. 3. Cumulant plot of **c** Stage 2 (light sleep), **d** Stage 3 (deep sleep), where tou1 and tou2 are time-lag parameters.

tuations and is considered as a nonlinear index of EEG signals' complexity. The α-value is different for each sleep stage as shown in table 4.

Both p- and F-values were used to examine the performance of features extracted using different nonlinear methods. A total of 29 clinically significant features are selected using p value (<0.0001) from the sleep EEG signals. The F-value acts as one of the best performance indicators for nonlinear parameters. Thus, the F-value is used to rank all the characteristic features as shown in figure 5. The F-value is linearly dependent on the feature performance. From figure 5, it is observed that the third moment of bispectrum and determinism (one of the RQA parameters) yield the highest F-value indicating that HOS and RQA parameters provide the best discriminant features.

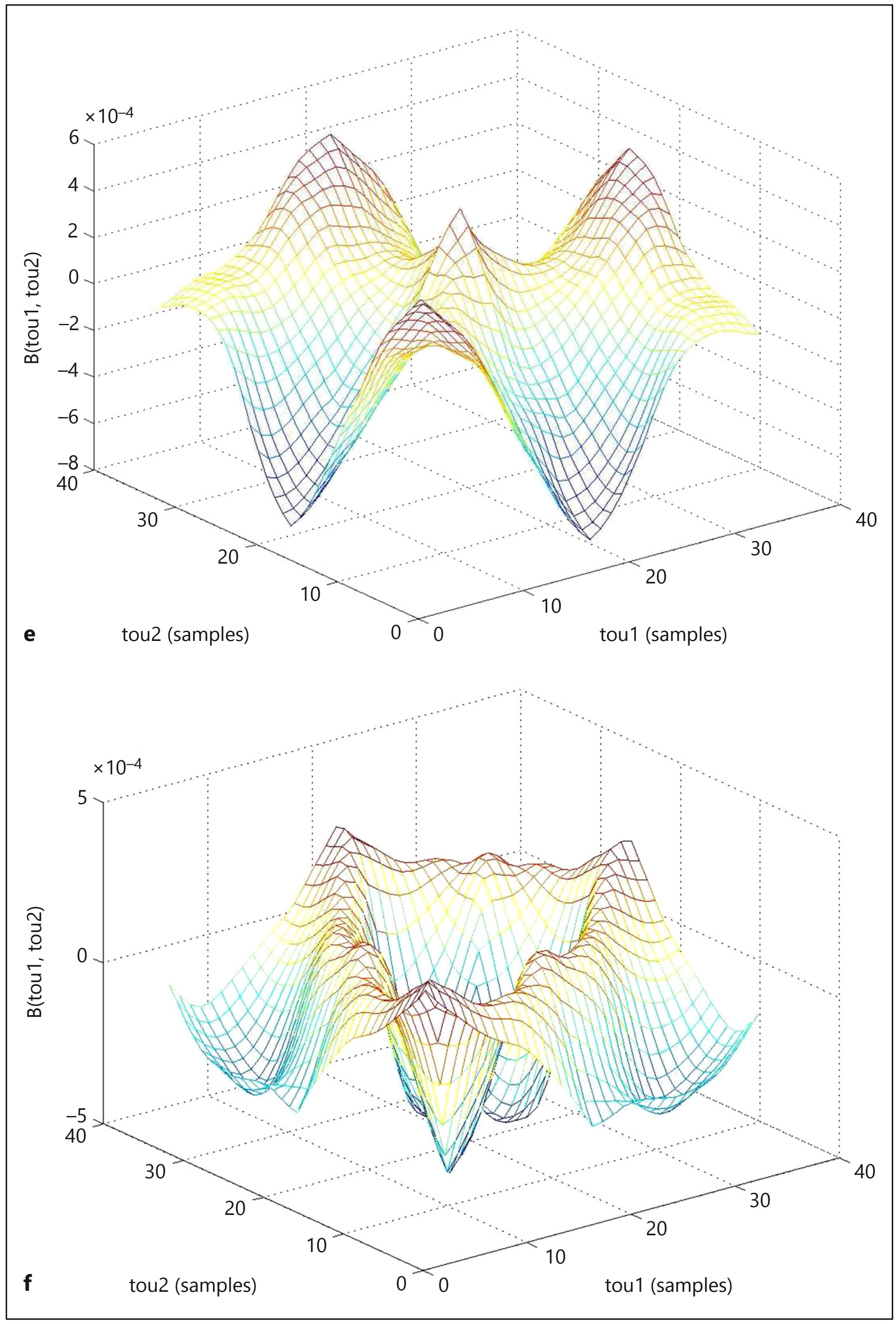


Fig. 3. Cumulant plot of **e** Stage 4 (deep slow wave sleep), **f** Stage 5 (REM sleep), where tou1 and tou2 are time-lag parameters.

5. Discussions

The sleep cycle characterized by the wake state, NREM and REM sleep repeats throughout 7–8 h of normal sleep. The complex interactions among neurons during sleep can be analyzed by EEG signals. Sleep stages can be distinguished by changes in the frequencies and EEG wave pattern. But, subtle variations in the sleep EEG signals cannot be detected through human observation. Nonlinear dynamics is an effective approach in the analysis of chaotic and highly irregular EEG signals.

Several studies have illustrated the significance of nonlinear analysis of sleep EEG signals. Acharya et al. [88] applied nonlinear methods in the analysis of sleep EEG signals to understand the cortical function at different sleep stages. Koley and Dey [89] presented an automatic

Table 2. HOS features for different sleep stages extracted for the entire database ($p < 0.0001$)

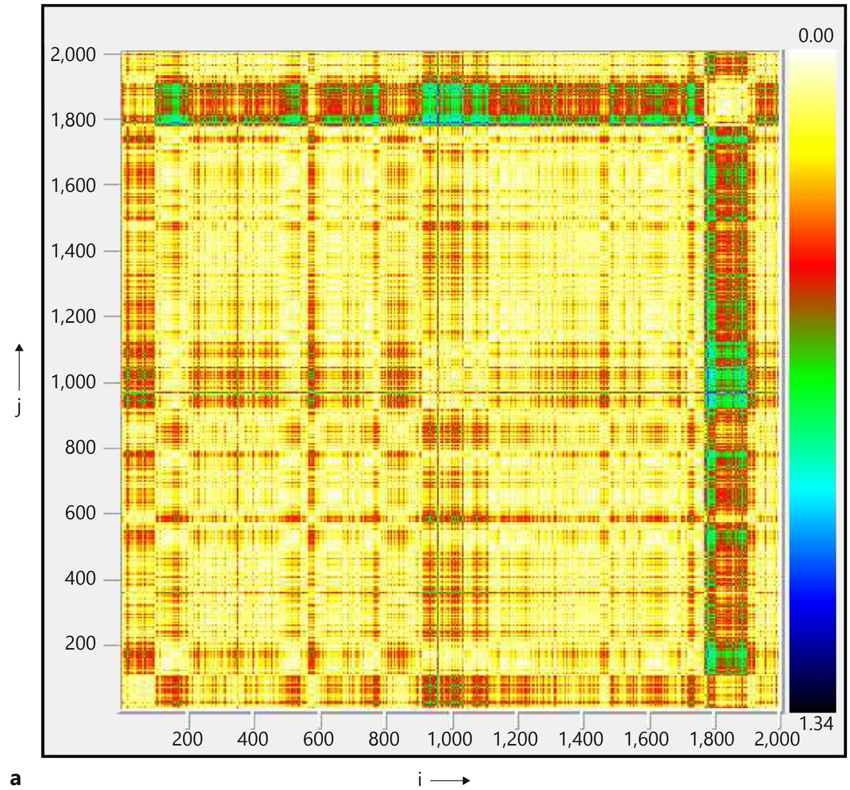
HOS features	Stage 0		Stage 1		Stage 2		Stage 3		Stage 4		REM	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
H1	0.6319	0.0933	0.5525	0.0685	0.5395	0.0595	0.5464	0.0549	0.5528	0.0511	0.5061	0.0724
H2	0.6496	0.0799	0.5870	0.0548	0.5811	0.0490	0.5856	0.0466	0.5886	0.04467	0.5513	0.0596
H3	0.6326	0.0910	0.5496	0.0672	0.5282	0.0583	0.5286	0.0547	0.5325	0.0525	0.5049	0.0687
H4	0.8077	0.0112	0.8030	0.0037	0.8025	0.0103	0.8027	0.0026	0.8029	0.0023	0.8000	0.0052
H5	0.0077	0.0310	0.0012	0.0048	0.0012	0.0038	0.0014	0.0021	0.0015	0.0021	0.0011	0.0048
Ent1	0.6817	0.2011	0.6700	0.1449	0.5507	0.1157	0.4862	0.0878	0.4499	0.0787	0.6409	0.1308
Ent2	0.2572	0.2055	0.2991	0.1793	0.2326	0.1206	0.1956	0.0892	0.1790	0.0775	0.2858	0.1652
Ent3	0.1409	0.1546	0.1787	0.1482	0.1528	0.1066	0.1312	0.0839	0.1223	0.0775	0.1705	0.1429

Table 3. RQA features for different sleep stages extracted for the entire database ($p < 0.0001$)

RQA features	Stage 0		Stage 1		Stage 2		Stage 3		Stage 4		REM	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
Det	0.7868	0.1484	0.8853	0.0735	0.9115	0.0498	0.9062	0.0541	0.9032	0.0625	0.9463	0.0340
Lam	0.8692	0.1188	0.9378	0.0476	0.9562	0.0281	0.9567	0.0294	0.9552	0.0358	0.9714	0.0180
Rr	0.2741	0.1647	0.2948	0.1094	0.2373	0.0847	0.1663	0.0598	0.1279	0.0501	0.3384	0.1070
t1	0.1821	0.1471	0.1412	0.0986	0.1727	0.0933	0.2429	0.1125	0.3001	0.1109	0.1164	0.0862
t2	0.0227	0.1367	0.0032	0.0019	0.0044	0.0123	0.0055	0.0023	0.0066	0.0021	0.0040	0.0031
Ent	0.1928	0.1231	0.2110	0.0355	0.2183	0.0281	0.2088	0.0243	0.2057	0.0273	0.2498	0.0264
Vmax	0.0490	0.1507	0.0169	0.0183	0.0164	0.0203	0.0133	0.0125	0.0117	0.0091	0.0223	0.0236
Lmax	0.0607	0.1533	0.0441	0.0379	0.0574	0.0533	0.0486	0.0333	0.0490	0.0341	0.0760	0.0567
Tt	0.0216	0.1371	0.0021	0.0006	0.0024	0.0128	0.0020	0.0008	0.0019	0.0004	0.0030	0.0027
Meanlen	0.0206	0.1370	0.0012	0.0004	0.0014	0.0125	0.0011	0.0004	0.0011	0.0002	0.0018	0.0019

sleep scoring process using different features extracted from time domain, frequency domain and nonlinear analysis. Significant features are selected using SVM-based recursive feature elimination technique followed by classification using binary SVMs. Doroshenkov et al. [90] used fast Fourier transforms to extract significant features from the sleep EEG signals. They applied the hidden Markov model for the classification and achieved an accuracy of 61.08%. Ebrahimi et al. [91] employed the wavelet packet decomposition [92, 93] on sleep EEG signals coupled with artificial neural networks for the classification of different sleep stages. They report a classification accuracy of 93%, sensitivity of 84.2% and a specificity of 94.4%. Acharya et al. [94] used HOS in the analysis and automatic identification of sleep stages using EEG signals. HOS features are extracted from the bispectrum and bicoherence plots of different sleep stages. Significant features are fed to a Gaussian mixture model classifier for the classification of sleep stages and a classification accuracy of 88.7% is obtained. Vural and Yildiz [95] used the principal component analysis [96] for the classification of hybrid features and reported an accuracy of 69.98%. Langkvist et al. [97] performed sleep stage classification using deep belief nets, an unsupervised feature learning approach.

This work provides a solid foundation for automated identification of sleep stages using EEG signals. Raw EEG signals, collected from the database, are pre-processed to remove unwanted ocular, muscular and electrical artifacts. Nonlinear methods such as entropies, fractality dimension [98], synchronization [99] HOS, CD, RQA and detrended fluctuation analysis are applied to the denoised EEG signals and characteristic features are extracted. The significant features extracted from sleep EEG signals can be classified using learning algorithms such as SVM [100, 101], clustering techniques [102, 103], classification methods [104, 105] and neural networks [106–108]. Table 5 summarizes some of the work on sleep stage classification based on R&K standard where classification accuracy was reported.



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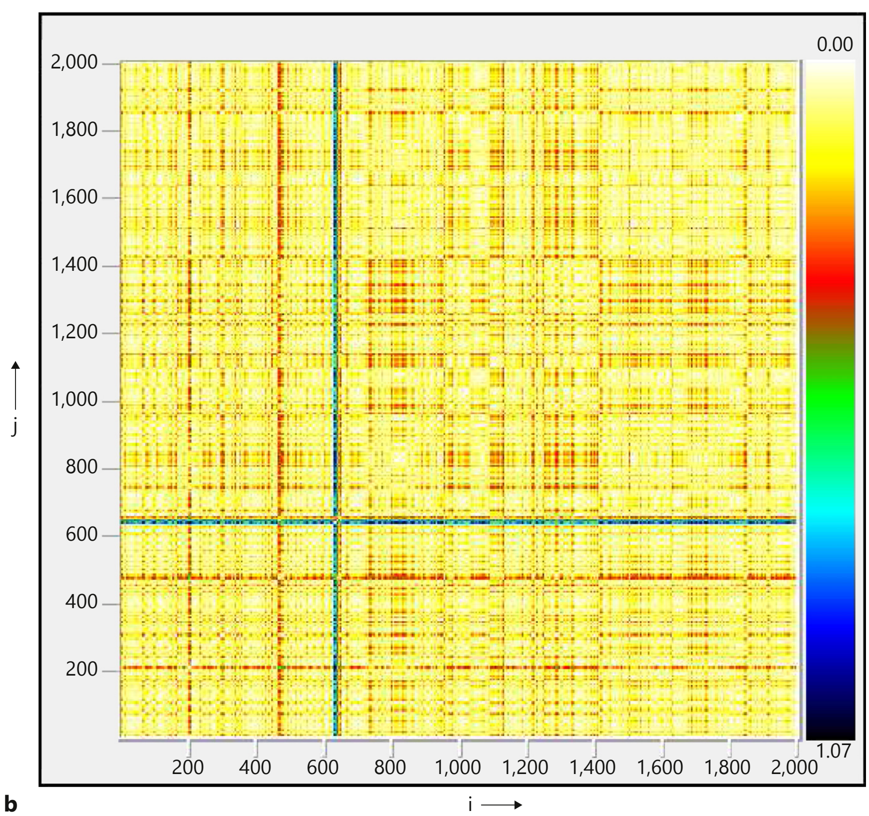

b

Fig. 4. Recurrence plot of **a** Stage 0 (wake), **b** Stage 1 (drowsiness).

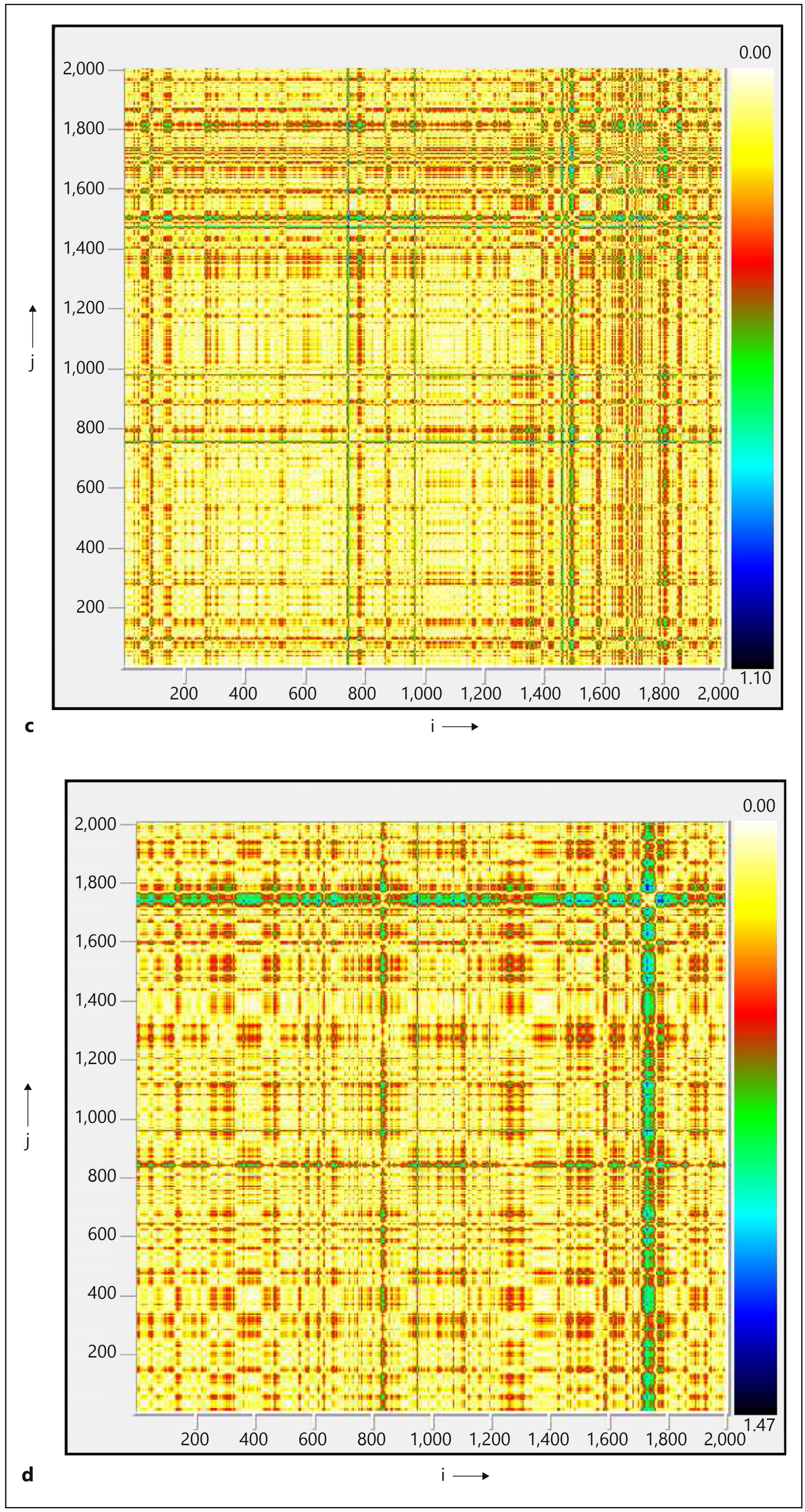

Fig. 4. Recurrence plot of **c** Stage 2 (light sleep), **d** Stage 3 (deep sleep).

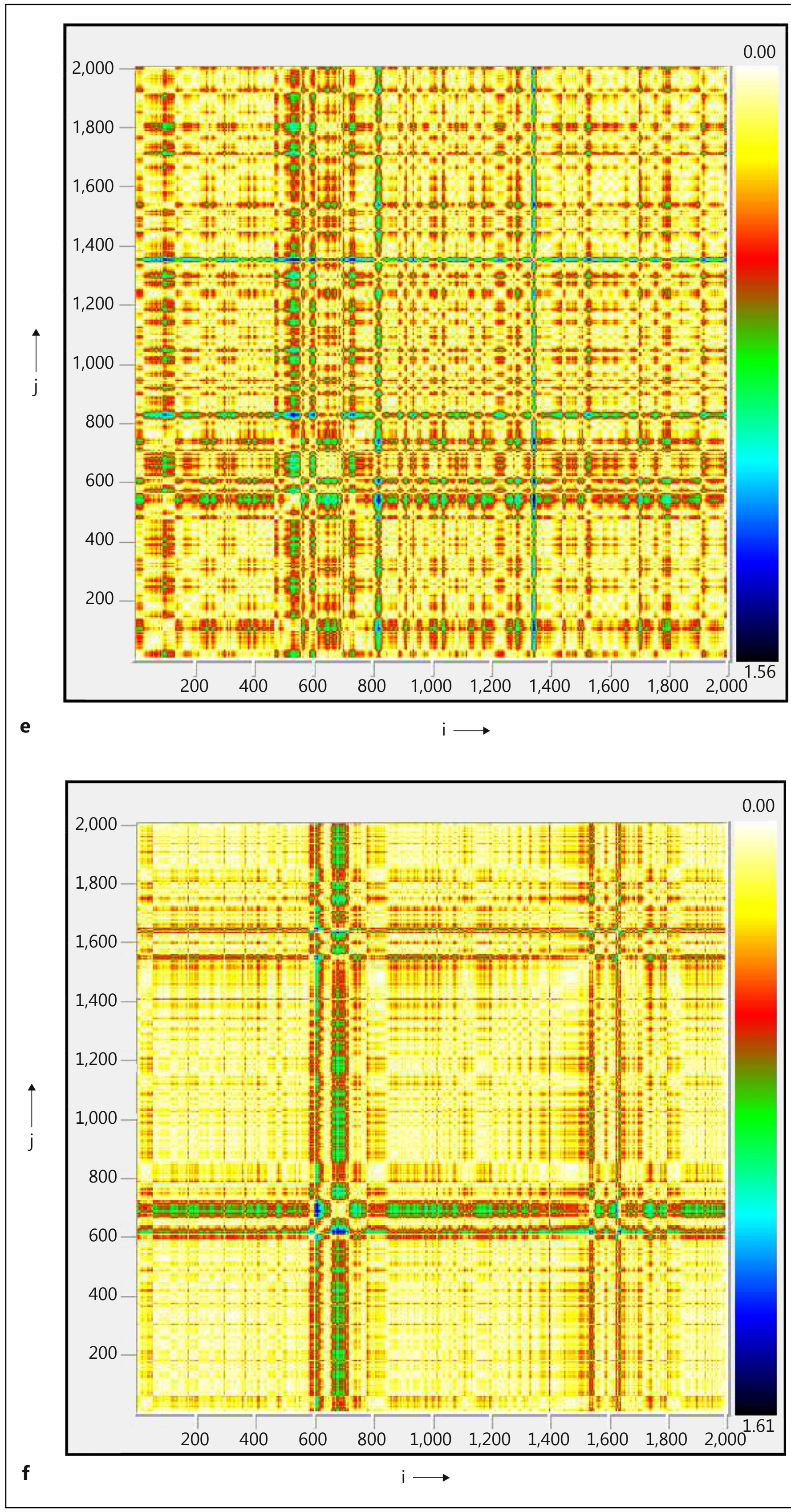

Fig. 4. Recurrence plot of **e** Stage 4 (deep slow wave sleep), **f** Stage 5 (REM sleep).

Table 4. Nonlinear features for different sleep stages extracted for the entire database ($p < 0.0001$)

	Stage 0		Stage 1		Stage 2		Stage 3		Stage 4		REM	
	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD	mean	SD
ApEn	0.7304	0.2471	0.7829	0.1615	0.8149	0.1445	0.7614	0.1240	0.7227	0.1123	0.6790	0.0927
SampEn	0.5592	0.2121	0.5222	0.1075	0.5681	0.1305	0.4798	0.0836	0.4418	0.0590	0.4215	0.0473
ReEn	−8.4428	1.6514	−7.9241	0.7661	8.2160	0.8136	−8.3954	0.7852	−7.8099	0.7814	−7.8909	0.8612
FuEn	0.1896	0.0867	0.1822	0.0554	0.1640	0.0417	0.1606	0.0400	0.1423	0.0394	0.1438	0.0437
PerEn	2.8114	0.4451	2.6936	0.2086	2.5478	0.1850	2.4513	0.1916	2.5075	0.1065	2.5631	0.1142
CD	0.9697	0.0187	0.9690	0.0068	0.9683	0.0071	0.9643	0.0076	0.9606	0.0070	0.9586	0.0055
DFA(α)	0.0303	0.0187	0.0310	0.0068	0.0317	0.0071	0.0357	0.0076	0.0394	0.0070	0.0414	0.0055
LLE	0.6358	0.1611	0.5380	0.1029	0.5756	0.0989	0.5768	0.0803	0.5811	0.0672	0.5830	0.0627
H	0.8168	0.1401	0.8111	0.0716	0.7861	0.0760	0.7713	0.0803	0.8159	0.0626	0.8273	0.0661
LZ	2.9573	1.7065	2.5640	1.1718	3.0291	1.6491	3.4474	1.9743	2.4309	1.0891	2.4869	1.2214
KC	6.3317	0.9916	6.3060	0.2452	6.4662	0.2937	6.5503	0.3078	6.1887	0.2850	6.2121	0.3039

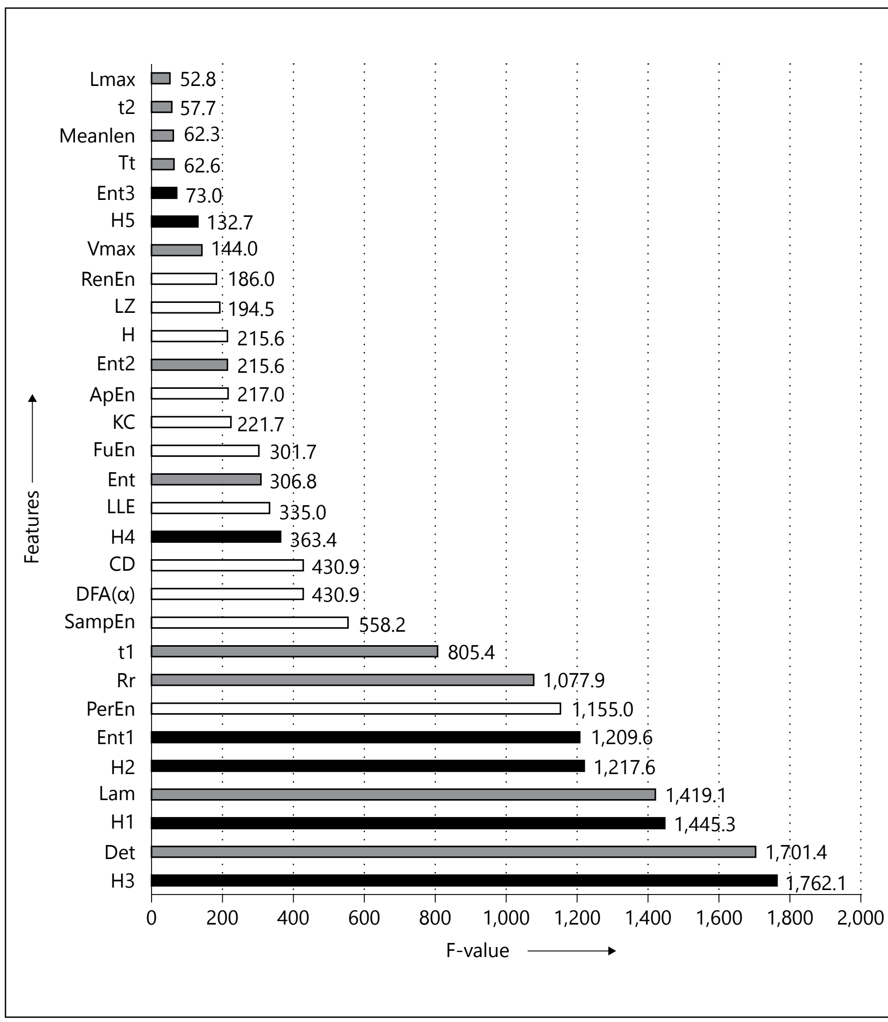

Fig. 5. Feature ranking. The length of each bar represents the F-value of a particular feature. The feature name is stated on the left side and the number on the right side indicates the corresponding F-value. Longer bars correspond to higher F-values and higher F-values indicate a more discriminative feature.

Table 5. Summary of research on the classification of sleep stages based on R&K standard

Authors	Methods	Classifiers	Performance
Doroshenkov et al. [90], 2007	Fast fourier transforms	Hidden Markov model	Accuracy: 61%
Ebrahimi et al. [91], 2008	Wavelet packet decomposition	Artificial neural networks	Accuracy: 93% Sensitivity: 84.2% Specificity: 94.4%
Acharya et al. [94], 2010	HOS	Gaussian mixture model	Accuracy: 88.7%
Vural and Yildiz [95], 2010	Hybrid features	Cluster-based classifier using PCA	Accuracy: 69.9%

6. Conclusion

This paper presented a comprehensive comparative review of 29 nonlinear methods/parameters for EEG-based sleep stage detection. Further, it illustrated the application of HOS and RQA in the characterization of diverse sleep stages. All nonlinear parameters produce clinically significant results, that is, the measures can discriminate the individual sleep stages. Feature ranking based on the statistical F-value, however, shows that the third order cumulant of HOS yields the most discriminative result. The distinct value ranges for each sleep stage and the discriminative power of the features can be used for sleep disorder diagnosis, treatment monitoring and drug efficacy assessment.

Disclosure Statement

None of the authors have any personal or financial conflict of interest that could unsuitably influence the writing or publication of this manuscript.

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