Finding the Most Sensitive Measures for Sleep Stages Detection

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Abstract

This study was concentrated on finding the most sensitive measures, which could discriminate between sleep stages. We have computed a variety of measures from classical spectral theory, as well as complexity measures and measures from information theory. Discriminant analysis done with Fisher quadratic classifier determined as the best measures relative powers in delta, theta, and sigma bands; coherence in theta and delta bands, fractal dimension, spectral exponent, average frequency, and entropy.

1. Introduction

Electroencephalogram (EEG) is one of the most important electrophysiological techniques used in human clinical and basic sleep research. By means of EEG it is possible to indicate various states of the brain as levels of vigilance or sleep stages. The evaluation of sleep stages is done after broadly appreciated Rechtschaffen-Kales manual [1], which involves parameters, techniques and wave patterns of three physiological signals: EEG, electrooculogram (EOG) and electromyogram (EMG) needed for definitive assignation of sleep stages. The main states of vigilance are wakefulness, REM sleep and non-REM sleep (NREM). NREM sleep is further divided into four stages from the lightest Stage 1 to the deepest Stage 4. Stages 3 and 4 are referred to as slow wave sleep (SWS). The convenience of developing a computerized system for automated analysis and classification of sleep states has been recognized by different authors. A few commercial systems are also available and they showed substantial differences from the visually scored polysomnographs in the distribution of the sleep stages. The objective of this study was to re-examine traditional characteristics of EEG and to check novel measures in providing broader basis for automatic sleep analysis.

2. Data

Data with all-night polysomnographic records were kindly provided by Prof. G. Dorffner, received by The Siesta Group Schlafanalyse GmbH. The records were obtained from 20 healthy subjects, 10 men and 10 women. Ages ranged from 23 to 82 years old with an average 50 $\pm$ 21.5 years. Analyzed signals were 6 EEG channels, derivations: Fp1-M2, C3-M2, O1-M2, Fp2-M1, C4-M1, O2-M1; 2 EOG channels, 2 EMG channels and also ECG. Amounts of particular sleep stages are in Table 1. All signals were sampled with 256 Hz. Sleep stages were scored by two independent judges, when there was an ambiguity, a third independent judge decided.

waking	Stage1	Stage2	Stage3	Stage4	REM sleep	Movement time	total
2069	1452	7860	1586	1865	3226	110	18107

Table 1: *Amounts of particular sleep stages*

3. Methods

- 57 different measures were computed in 30 s window for 11 channels. Computed measures included: *average frequency*, *average amplitude*, *data variance*, *data skewness*, *data kurtosis*, *normality test*, *spectral moments*, *spectral edge*, *spectral exponent*, *spectral entropy*, *fractal dimension*, *self-similarity exponent*, *entropy*, *mutual information*, *absolute spectral powers*, *relative spectral powers*, and *coherence* in following bands: *delta 1*: 0.5 - 2 Hz, *delta 2*: 2 - 4 Hz, *theta 1*: 4 - 6 Hz, *theta 2*: 6 - 8 Hz, *alpha 1*: 8 - 10 Hz, *alpha 2*: 10 - 12 Hz, *sigma 1*: 12 - 14 Hz, *sigma 2*: 14 - 16 Hz, *beta 1*: 16 - 25 Hz, *beta 2*: 25 - 35 Hz, *beta 3*: 35 - 45 Hz, *gamma 1*: 60 - 95 Hz, *gamma 2*: 95 - 128 Hz, and *total power*:0.5 Hz -128 Hz. Coherences and mutual information were computed for 29 combinations of EEG, EOG,EMG, and ECG channels.
- Discriminant analysis was done by Fisher quadratic classifier, which is appropriate for multinormal data and for classes with different covariance matrices [2]. Measures were tested on discriminating between following couples of sleep stages: **wake - sleep** (all sleep stages were taken together), **REM - NRem**, **Stage II - SWS** (slow wave sleep - Stages 3 and 4), **Stage II - REM**, **Stage I - wake**, **Stage I - REM**, **Stage I - Stage II** and on discriminating between four classes of sleep states - **Stage I, Stage II, SWS, REM**. Discriminant analysis was done for one-dimensional case (to find out the best single performing measures) and for combinations of 5 measures for couples of classes, and combinations of 15 measures in four classes respectively (in order to decrease the error rate). Training set was constructed as random choice of 90% of values of each class, testing was done on the rest of the data. This procedure was repeated 100 times for one - dimensional, and 10 times for multidimensional approaches. Error rate was computed as the ratio of all misclassified states to the size of the testing set.

4. Results

classes	measure	channel	error[%]	std [%]
W-S	r_delta2	C3	8.24	0.39
REM-NREM	r_delta2	C3	18.45	0.00
2-SWS	frac_dim	C4	11.29	0.57
2-REM	coh_delta1	Fp2-EOG2	16.53	0.58
1-W	r_delta2	C4	23.71	1.20
1-REM	r_gamma2	C3	21.00	1.06
1-2	r_delta1	C3	15.27	0.68
W-REM	r_delta2	C3	8.78	0.69
1-2-SWS-REM	frac_dim	C3	41.58	0.73

Table 2: *The best single performing measures in classification task with 2 classes (resp. 4 classes in the last row)*
Abbreviations: W - wake, S sleep, r -relative, frac - fractal, coh - coherence

classes	D	measures	channel	error	classes	D	measure	channel	error
W-S	1	zero_cross	EOG	9.44	1-W	1	norm. test	C4	27.39
	2	t_beta3	EOG2	7.15		2	r_sigma2	O1	22.02
	3	coh_theta1	Fp2-EOG2	6.11		3	r_sigma1	C3	19.22
	4	coh_delta2	O1-C3	5.92		4	zero_cross	EOG2	17.17
	5	coh_gamma1	Fp1-EOG	5.53		5	zero_cross	O2	15.87
REM-NREM	1	coh_delta2	Fp2-EOG2	14.16	1-REM	1	entropy	EKG	21.58
	2	r_theta2	EOG	12.34		2	r_theta1	EOG	17.27
	3	frac_dim	Fp1	11.14		3	coh_theta1	Fp2-EOG2	15.82
	4	entropy	EKG	9.53		4	t_beta3	Fp1	14.41
	5	coh_delta1	Fp2-EOG	8.68		5	coh_gamma1	Fp1-EOG	13.72
2-SWS	1	frac_dim	EKG	11.09	1-2	1	zero_cross	EOG	15.33
	2	s_exp	EKG	10.26		2	dfa	EMG	13.29
	3	entropy	EMG2	9.84		3	zero_cross	EKG	12.61
	4	s_kurtosis	O2	9.65		4	coh_delta2	O1-O2	12.01
	5	frac_dim	Fp1	9.48		5	r_sigma1	Fp2	11.69
2-REM	1	coh_delta1	Fp2-EOG2	16.65	W-REM	1	norm. test	C4	10.15
	2	s_exp	EMG	14.29		2	var	C4	7.15
	3	r_theta2	EOG	12.35		3	coh_gamma1	Fp1-EOG	6.11
	4	r_beta3	O2	9.79		4	amplitude	C3	5.13
	5	skewness	O1	9.14		5	r_sigma2	EMG	4.41

Table 3: *The best measures in 5 dimensional approach*
Abbreviations: W - wake, S - sleep, D - dimension, r - relative, t - absolute, s - spectral, frac - fractal, coh - coherence, dfa - self-similarity exponent

- The results for the one-dimensional approach are in Table 2. Error rates in classification into two classes varied from the value 8.24 % to the value 23.71 %, and error in classification into four classes was 41.58 %. Relative delta power appeared most frequently among one dimension discriminators. The most distinctive discrimination was achieved between wake and sleep classes, and similar error was obtained also for discrimination between wake and REM sleep. On the other hand, the least effective discrimination was between wake and Stage 1. Interestingly, the best measures were almost in all occasions located in central EEG derivation C3(C4).
- The results for 5 dimensional approach for two classes are in Table 3. Error rates were eliminated to 4.41 % in wake - REM classes; to 15.87 % in Stage 1 - REM sleep discrimination. Similarly as in one - dimensional approach, the best discriminating couples of stages were wake - REM and wake - sleep, and the largest error was in Stage 1 - wake discrimination.
- For classification into four classes, the percentage of error diminished in 5 dimensions from 44.20 % to 27.85 %, whereas also in 15 dimensions it was still 23.20 %. The most sensitive measures were average amplitude, relative power in theta band, entropy, self-similarity exponent, spectral decay, mutual information, and coherence in theta band.

5. Discussion and Conclusions

- The results can be influenced by two factors: normality of the data was not fulfilled (Jarque-Bera test), however this type of classifier is able to perform quite well even when some data are not normally distributed. Secondly, in multidimensional approach we did not check all the possible combinations of measures, but a semioptimal method of variable selection was chosen based on gradual adding of the most appropriate measure among previously selected group of measures.
- In conclusion, in this work a large amount of different measures was tested in sleep stages classification problem. The most appropriate measures sensitive to sleep stages were: relative powers in delta, theta, and sigma bands, coherence in theta and delta bands, fractal dimension, spectral exponent, average frequency, and entropy. Similarly to [3], our results suggest that the combination of spectral and nonlinear measures appears to be optimal for sleep stages discrimination.

References

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[3] Fell, J., Röschke, J., Mann, K., and Schäffner, C. Discrimination of sleep stages: a comparison between spectral and nonlinear EEG measures. Electroencephalography and clinical Neurophysiology 98, 1996, p. 401-410.

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