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Analysis of complexity of EEG during sleep

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Abstract. New multichannel descriptors of EEG activity: complexity (Ω), total power (Σ) and generalized frequency (Φ) were applied to whole night sleep analysis in 11 healthy subjects. The values of Ω and Φ decreased systematically from waking to slow wave sleep, and increased systematically in consecutive NREM-REM sleep cycles. The changes of Σ were opposite to Ω and Φ. These descriptors may be an alternative approach to the EEG sleep analysis.

Key words: sleep, EEG complexity

INTRODUCTION

It is generally accepted that sleep is a continuous process, and dividing it into discrete sleep stages is a compromise between simplicity and reliability. Borbély was one of adherents of a continuous power density analysis, which culminated in his two process model of sleep (Borbély and Achermann 1995). However, the evaluation of sleep on the basis of only one or two EEG channels, which is a standard method in polysomnography (Rechtschaffen and Kales 1968), is a similar compromise. A better strategy is the space oriented approach, which makes it possible to describe a whole potential field at a time (Lehmann 1987). Recently Wackermann proposed three global descriptors Ω, Σ and Φ, which could be used to describe the EEG activity from all channels at a given time interval.

Ω is a global measure of complexity, or synchronization, Σ is a measure of a total power, similar to the global field power of Lehmann (1987), and Φ is a descriptor of generalized frequency. Σ and Φ may be considered multichannel equivalents of Hjorth's activity and mobility (Hjorth 1973), Ω is a new, original descriptor, not related to other measures of complexity. The aim of our study was to test the applicability of multichannel descriptors in analysis of sleep.

METHODS

Investigation was performed in 11 healthy volunteers, 10 males and 1 female, in age 21-53. Polysomnograms were recorded in two consecutive nights, and only the data from the second night were analysed. EEG was recorded from 21 standard 10-20 derivations, referenced to the average electrode, the standard polysomnographic derivations were also used (Rechtschaffen and Kales 1968). Electrodes were applied with collodion, accepted maximal impedance was 10 kOhm. All data were stored on magnetooptical disks with the sampling frequency of 102.4 Hz, and 12 bit resolution. Sleep stages were scored visually on a computer screen in 20 s intervals (pages), from two EEG channels (C3, O1), two EOG and one EMG channel. On a separate run artifacts were marked visually in all channels in 2.5 s chunks (256 data points), so maximal artifact score for each page could be 8 when a whole page was contaminated. Sleep cycles were marked visually on the basis of polysomnogram and the value of Σ. The Ω, Σ and Φ were computed from 21 EEG

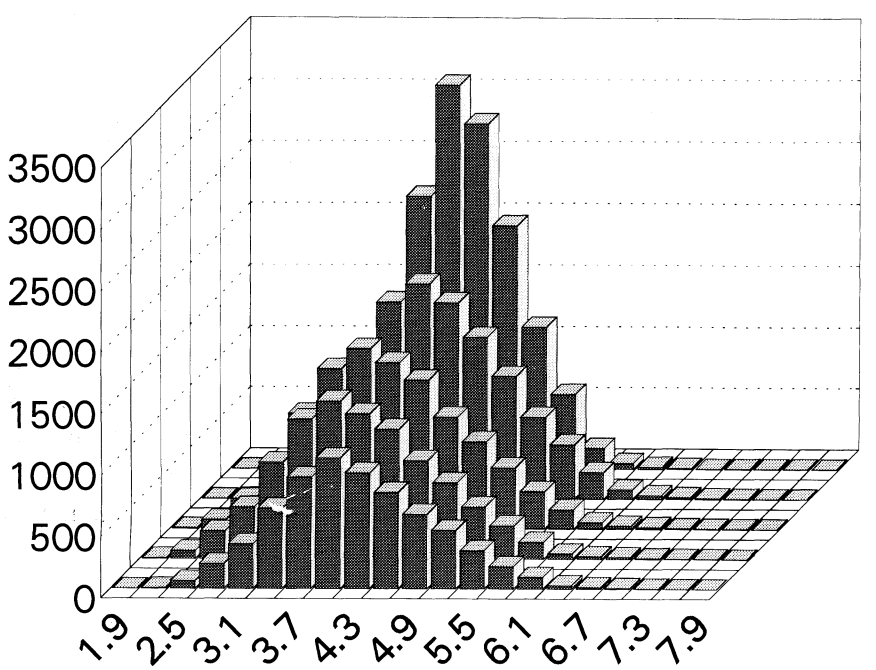

Fig. 1. The influence of artifacts on the distribution of Ω. X axis, value of Ω; Y axis , number of pages; Z axis, number of artifacts per page: from back to front: 8 artifacts, 6 artifacts, 4 artifacts, 2 artifacts, 0 artifacts.

channels for each 2.5 s data segment and then medians from 8 segments were selected to comply with the standard 20 s page, used in visual analysis. All pages with artifacts were rejected, which reduced the total number of pages from 14032 to 6720 (48%). SPSS package was used for the statistical analysis (Norusis 1990a,b)

RESULTS

The distribution of Ω in our data, and the influence of artifact rejection is presented in Fig. 1.

The distribution of Ω occurred normal with a slight right side skewness, independently on the number of artifacts.

In successive sleep cycles the value of Ω increased significantly, (Kruskal-Wallis, n=11, Chi^2=8.45, P=0.04, Fig. 2). Similar changes were observed in Φ (Kruskal-Wallis, n=11, Chi^2=14.09, P=0.03), and opposite in Σ (Kruskal-Wallis, n=11, Chi^2=9.37, P=0.02).

The median value of Ω was highest in waking, and lowest in slow wave sleep (fig. 3). The difference was significant (Kruskal-Wallis, n=6719, Chi^2=1932.6, P=0.0001).

Similar changes were observed in Φ (Kruskal-Wallis, n=6719, Chi^2=3878.9, P<0.0001), and opposite in Σ (Kruskal-Wallis, n=6719, Chi^2=3694.9, P<0.0001).

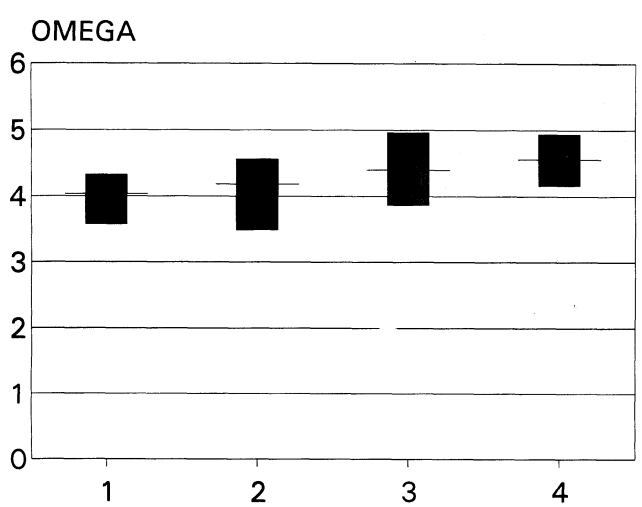

Fig. 2. Value of Ω in 4 sleep cycles, median and quartiles of 11 subjects. Kruskal-Wallis test, n=11, Chi^2=8.45, P=0.04.

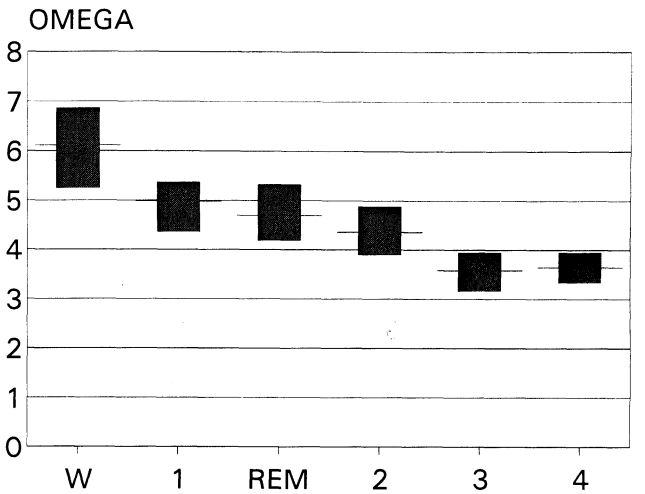

Fig. 3. Value of Ω in sleep stages, median and quartiles of all pages, Kruskal-Wallis, n=6719, Chi^2=1932.6, P=0.0001.

The configuration of Ω, Σ and Φ in three-dimensional space was similar in all subjects, however considerable interindividual differences were observed. Figure 4 presents individual scatterplots of Ω and Σ.

In all subjects stages 3 and 4 are characterized by low value of Ω and high Σ. Stages 1, REM and 2 are grouped together. The position of waking (W) was most differentiated in all individuals. The Table I presents differentiation of sleep stages by Ω, Σ and

TABLE I

Differentiation of sleep stages by Ω, Σ and Φ in all subjects. Results of Kruskal-Wallis test of variance. In all cases P<0.0001

Subject	Chi^2	Number of pages
102N	275.63	676
112N	24.30	514
122N	303.15	796
132N	140.31	542
142N	261.77	613
82N	253.33	639
92N	260.60	435
E04	168.05	513
E13	250.44	709
E16	239.50	392
E27	432.50	890

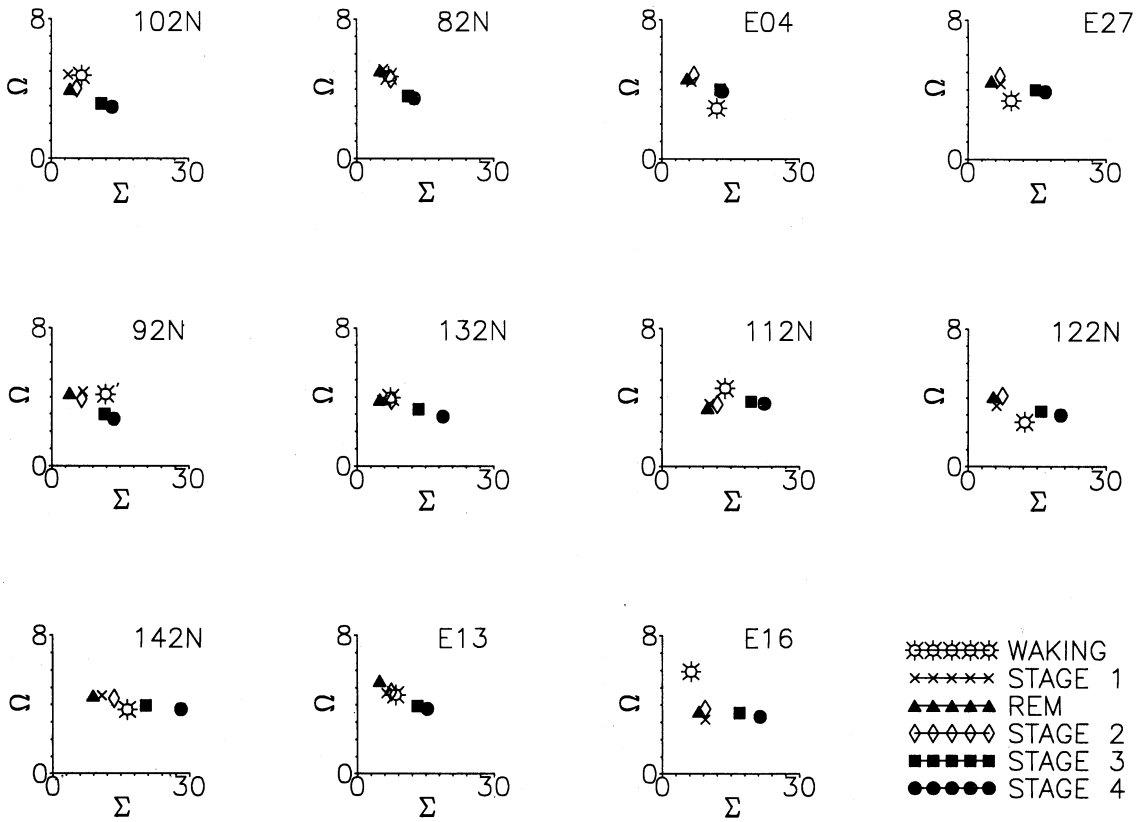

Fig. 4. Scatterplot of Ω and Σ in all subjects.

Φ in all subjects, as measured by Kruskal-Wallis test.

Discriminant analysis was applied to all data (Table II). Stages 3 and 4 were analysed jointly.

The total percent of correct classifications was 64.5%. The greatest number of correct classifications concerned stage 3+4 and W, 88.9% and 76.9% respectively. The worst classifications occurred in stages 1 and REM, 44.9 and 45% respectively, but even these results were much better than random (20%).

TABLE II

Classification of sleep stages. Percent of pages classified to sleep stages. Bold numbers on diagonal present correct classification

	W	S1	REM	S2	S3+4
W	76.9	3.8	15.4	3.8	0.0
S1	12.4	44.9	27.0	12.4	3.4
REM	13.3	31.1	45.0	10.6	0.0
S2	3.3	19.6	7.8	58.7	10.6
S3+4	0.0	0.1	0.1	10.9	88.9

DISCUSSION

Ziller et al. (1995) presented similar approach to sleep analysis. They applied Hjorth descriptors (Hjorth 1973) and correlation dimension (D_2), another measure of complexity. In spite of the fact that they analysed only one channel, and Ω is unrelated to D_2, the distribution of Ω and D_2 in sleep stages is strikingly similar. Ω has some advantages in comparison to D_2. Ω was designed for spatial analysis, therefore it is directly calculated from all channels, moreover, the calculation of Ω is less time-consuming.

D_2 during sleep was also calculated by Achermann et al. (1994). They observed parallel changes of D_2 and slow-wave activity, but in opposite phase. D_2 was low during slow wave sleep, and high in epi-

sodes of REM sleep. They did not observe progressive decline of D_2 in successive sleep cycles in contrast to the slow wave activity. Our results are similar, the value of Ω even increases in successive sleep cycles (Fig. 2).

Discriminant analysis showed that the classification of sleep stages on the basis of Ω, Σ and Φ was much better than random. In fact classification of slow wave sleep and waking was better than the average concordance of human scorers (Martin et al. 1972).

Ziller et al. (1995) concluded that Hjorth's descriptors occurred superior in classification of sleep stages in comparison to D_2. In our data changes of Ω in sleep cycles and stages were also less significant in comparison to Σ and Φ. However, in multichannel spatial analysis a descriptor of complexity is a necessary complementation of global frequency and power.

Moreover, it was not our aim to perform automatic sleep staging, without EOG and EMG it is always unreliable. This is a first application of Ω in sleep analysis, therefore finding a relationship to other data was necessary. The results of the discriminant analysis show that our global descriptors of EEG may be useful in future sleep studies. Figure 4 and Table I show that configuration of Ω, Σ and Φ is differentiated in individual subjects. Although some intuitive speculations are possible, the clinical meaning of these differences should be elucidated in future studies. Recently reactivation of interest in Hjorth's descriptors can be observed (Depoortere et al. 1995, Ziller et al. 1995). The advantage of global descriptors is that they were designed specially for multichannel analysis.

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