Does the Complexity of Sleep EEG Increase or Decrease with Age?

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Abstract. *The goal of this study is to contribute to discussions about age-related changes in electroencephalogram (EEG) complexity. Eight characteristics of complexity were evaluated for sleep EEG of 175 healthy subjects. The complexity of the sleep EEG significantly increased up to the age of about 60 years. Over 60 years, the complexity stagnated or slightly decreased. The same tendencies were manifested during all sleep stages and also during the episodes of wakefulness.*

Keywords: Sleep EEG, Complexity, Spectral measures, Fractal exponent

1. Introduction

Although there is no unique definition of complexity, a number of methods have been proposed that allow to measure the complexity of physiologic signals. Traditionally, the loss of complexity is characterized by relative reduction in the high-frequency components and increase in the low-frequency components. Furthermore, other measures of complexity, based on concepts from the modern field of nonlinear dynamics and chaos theory, can be used.

In 1992 Lipsitz and Goldberger [1] proposed that the aging process may be characterized by a loss of complexity in multiple physiologic processes including functioning of the brain. Since then, a number of studies hypothesized that aging or mental illness is accompanied by decline in the brain's adaptive capacity, demonstrated by changed patterns in brain signals.

An investigation of resting EEGs of 54 healthy children (new-borns to 14 years old) has shown that brain maturation is reflected in a highly significant increase in complexity with age [2]. The authors in [3] concluded that after a jump in the brain dynamics complexity during maturation (7–25 years) a linear increase, albeit more moderate, continues. Their oldest subject was 60 years old. In contrast, Takahashi claims that after reaching adulthood the complexity decreases with age [4].

In this study, to assess the complexity of young healthy subjects in comparison to the elderly, we have analysed EEG both by traditional spectral methods and by recently developed methods of complexity estimation.

The paper is organized as follows. Firstly, the data and the methods are described. Then eight characteristics of EEG complexity are introduced and estimated across the subjects and their individual sleep stages. Finally, the age-related changes of the measures are evaluated.

2. Subject and Methods

In total, 175 all-night sleep EEG recordings were analysed. They were taken from the SIESTA database of polysomnography recordings of healthy adults [5]. The average age of subjects was 51.2 year, the youngest subject was 20-year-old man, and the oldest was a 95-year-old woman. Subjects slept at their usual sleeping time, typically from 11 pm, the average recording time was about 8 hours. All subjects in the control group had a Pittsburgh Sleep Quality Index [6] of at most 5. Signals from electrodes C3-M2 and C4-M1 were used, where M1, M2 are the left and the right mastoids, following the 10-20 international electrode placement system. The data, originating from several departments, were resampled to 100 Hz.

We have used hypnograms (graphs that discriminate the sleep stages) based on the rules of Rechtschaffen and Kales (RKS) [7], obtained via the automatic RKS classifier Somnolyzer 24x7 [8]. Scoring consists in classifying all 30 s epochs of an all-night recording into one of the following five stages: wakefulness (W), rapid eye movement sleep (REM), the lightest sleep Stage 1 (S1), sleep Stage 2 (S2), and the deepest sleep stage referred to as slow wave sleep (SWS).

In the following, our eight characteristics of complexity are briefly introduced (more detailed descriptions can be found in [9]). All measures were computed for the EEG signals, step by step for the same 30 s long intervals, which were examined by the automatic sleep classifier.

The fractal dimension (*FD*), computed here by Higuchi algorithm [10], falls within an interval (1, 2) and reflects the property of a curve of filling more space than a line segment (*FD=1*) but less than an area (*FD=2*).

The fractal exponent (β), sometimes referred to as a spectral decay, or power-law exponent, is defined for signals with a power spectrum P(f), which is power-law dependent on the frequency f: $P(f) \sim f^{-\beta}$. This phenomenon is also known as 1/f-like behaviour. Power-law power spectra have also been validated in the case of EEG, especially when the slope of the spectral decay is calculated over the whole spectrum of EEG instead of considering narrow frequency ranges [11]. The power-law decay of the EEG spectrum is interpreted as an indication of non-trivial long-range correlations that are typical for scale-invariant or self-affine processes [12]. In our study, the fractal exponent was derived from the slope of the linear fit of spectral density in the double logarithmic graph over the frequency range of 0.5 - 40 Hz.

The Hurst exponent (*H*), defined and estimated as in [13], is another measure of long-term memory of time series. The closer the exponent value is to 0, the rougher are the traces. On the other end, as *H* approaches 1, the traces become more and more smooth. For traditional Brownian motion, *H=0.5*. Depending on whether *H* is larger than, or smaller than 0.5, the signal is persistent (with long-range correlations) or anti-persistent (anti-correlated).

The Hurst exponent estimated by a second method called *detrended fluctuation analysis* (H_{DFA}) is usually considered as more suitable for real data. Unlike some other methods designed for determining the statistical self-affinity DFA may also be applied to non-stationary signals [14].

With the Hurst exponent of EEG between 0 and 1 and fractal exponent β between 1 and 3, which are ranges characteristic for the fractional Brownian motion (fBm) of Mandelbrot and Van Ness [15], fBm begins to be considered as a suitable model for EEG. Recall that, for the fBm process, the following relationships between β, H and FD applies: $FD = \frac{5-\beta}{2} = 2 - H$.

The prediction error was evaluated for the evolution of an EEG trajectory reconstructed in a 3-dimensional space. Firstly, based on Takens' theorem [16], a state portrait was reconstructed from time delays of a one-dimensional observable: $\vec{x}_n = \left(X_{n-(m-1)\tau}, X_{n-(m-2)\tau}, \dots, X_n\right)$, where $\vec{x}_n$ is a vector in the reconstructed space, X is the one-dimensional variable, m is an embedding dimension and τ is the time delay. Next, from the trajectory, the nearest neighbours of the relevant point were found and the predicted value was assessed as their averaged image [17]. After search for optimal parameters for prediction, they were set as follows - embedding dimension 3, time delay 2, and number of nearest neighbours 20. As a prediction error, the root-mean-square error normalized by the standard deviation of the signal sample was taken.

The spectral entropy (spE) was calculated as $\mathrm{spE} = -\sum_{0.5\,Hz}^{40\,Hz} P(f) \ln P(f)$, where P(f) is a normalized power spectral density which can be treated as a probability density function.

The spectral mean is an example of a simple traditional estimate of the complexity using frequency properties of the signal.

The relative delta to relative beta power ratio (*delta/beta*) is the last of our measures of complexity, wherein relative power means an absolute spectral power in a specific band divided by the total spectral power. The power spectral density was estimated according to Welch's method of averaged modified periodograms. Spectral powers were computed in the frequency bands delta (0.5 - 4 Hz) and beta (16 - 30 Hz). The total power was computed from the frequency band 0.5 - 40 Hz.

The age-related trends in the computed characteristics were visualized with regression lines. How well the regression fits the data, is expressed as a correlation coefficient R^2. The closer R^2 to 1.00, the better the fit. Significance of parameters in the regression model was also tested, namely the relevant t-statistic and the p-values for the coefficients of the model were evaluated.

3. Results

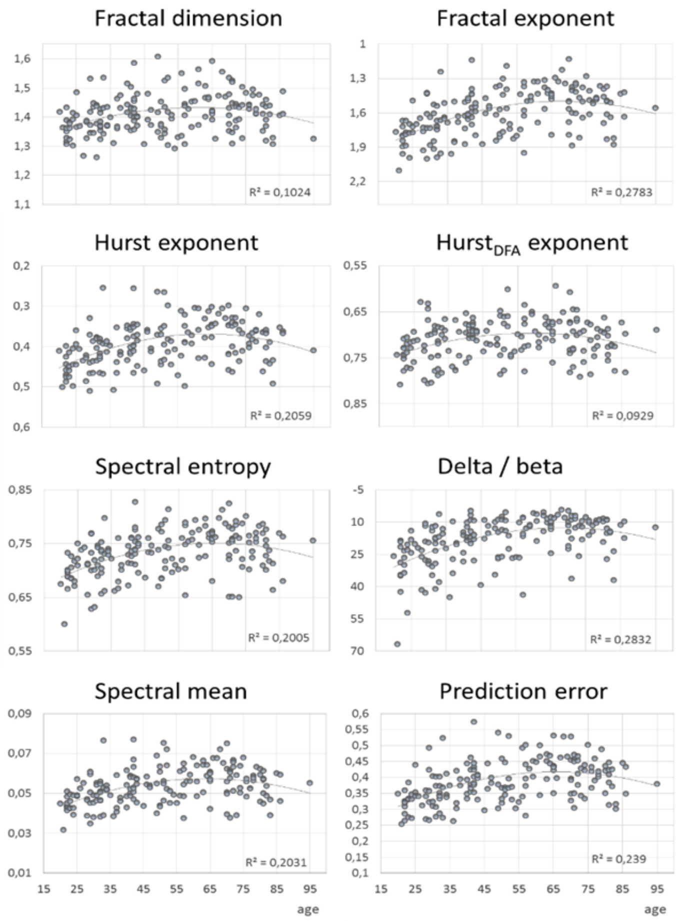

Fig. 1. Relation between the complexity measures and age presented through scatter plots and order 2 polynomial trend-lines. Each circle represents an all-night mean value of the respective measure for one of the subjects.

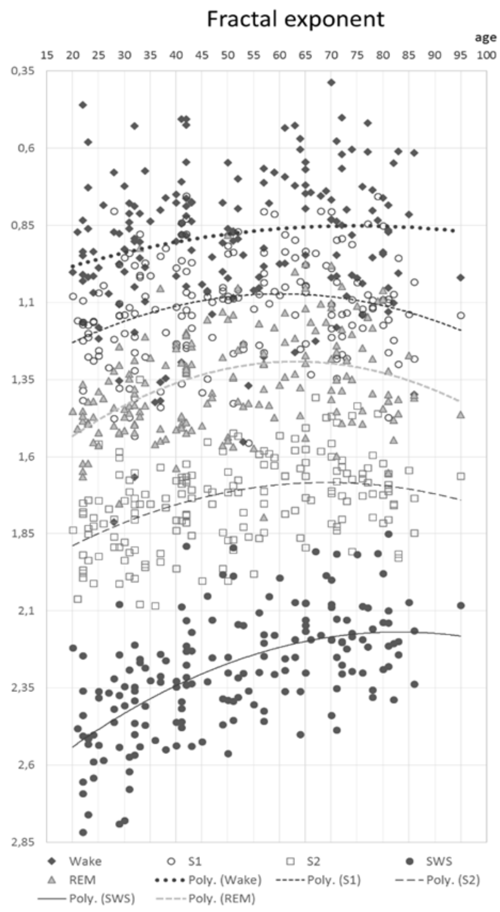

Fig. 2. Relationship between the fractal exponent and age presented through scatter plots and an order 2 polynomial. Mean values of the fractal exponent are presented for waking and the sleep stages separately.

The relative changes of the characteristics indicate that, in general, EEG complexity of healthy subjects increases with age. For interval 20-60 years, this was confirmed statistically (through the t-statistic and the p-values<0.05) if using simple linear regression for modelling the relationship between the individual complexity measures and age. In the scatter plots of Fig. 1, however, polynomial trend-lines of order 2 are shown, suggesting that over the age of 60 years, the EEG complexity could be stagnant or slightly declining.

We also evaluated the complexity for each sleep stage separately. The results for a selected measure (fractal exponent) are presented in Fig. 2. First of all, we see the highest EEG complexity during wakefulness and its decrease with the deepening of sleep. Secondly, looking at episodes of waking and each sleep stage separately does not reveal significant differences between the individual stages. In any case, the age-related complexity evolution shows the same course. The most pronounced increase of the complexity is observable in the SWS. In terms of spectral properties, considerably fewer delta waves and more faster beta waves were observed in elderly as compared to younger subjects.

4. Discussion and conclusions

Our results contradict the hypothesis of a loss of complexity of EEG in the healthy brain after reaching adulthood. In fact, we observed an increase in EEG complexity from age 20 to 60 years. After the age limit of about 60 years our findings do not exclude the possibility of a moderate age-related decrease of EEG complexity.

Recall that both the modern complexity measures (entropies, fractal exponent, fractal dimension, Hurst exponent, and prediction error) and the more traditional measures (spectral mean and the delta to beta ratio) led to the same conclusion. Higher complexity, simultaneously with considerably fewer delta waves and more faster beta waves were observed in elderly as compared to younger subjects.

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