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EEG Fractal Dimension Measurement before and after Human Auditory Stimulation

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Abstract: *The aim of this work is to investigate the change of fractal dimension D_f with the help of Higuchi Fractal Dimension measure (HFD) in Event-Related Potentials (ERP) of human EEG time series, obtained as a result of oddball paradigm usage and auditory stimulation with instruction for passive listening and counting tasks, depending on gender, personality type and task condition. In our study 77 healthy volunteers have been participated and 38 of them have been selected after a personality classification with Eysenck's personality questionnaire (EPQ).The achieved results showed specific functional meaning of ERP HFD change depending on the individual personality type and gender.*

Key words*: Fractal Dimension, Higuchi Fractal Dimension, EEG, ERP, Time series analysis, Personality and gender classification.*

Introduction

Physiological signals are usually characterized as complex dynamic non-stationary noise like structures resulting from living creatures' activities. This complex signal nature requires different approaches for analysis and possible understanding of real physiological processes and mechanisms. The natural self-similarity in different scales in such signals was found not long ago as a useful phenomenon (e.g. [3, 6, 8, 9]) and used as a basis for further investigations in the EEG time series analysis that show multifractality existence [14]. Generally, the fractal properties of EEG could be easily detected by double log plot of their power spectra and detrended fluctuation analysis [13]. In the present paper we use fractal dimension D_f in the analysis of series of ERP brain potentials. The change in D_f was investigated in a number of experimental conditions as sleep [17], cognitive tasks, different type of diseases and EEG biofeedback training. A model, which may explain the fractal changes in dimensional complexity as an ensemble of coupled oscillators, has been reported in [2]. The model explains the changes in the D_f as a result of coupling and decoupling of oscillators during cognitive task solving. On the other hand D_f can be interpreted simply as the degree meandering (roughness or irregularity) of a signal [16].

Patients with posttraumatic stress disorder were found to have lower D_f values than those of the healthy subjects; D_f was significantly reduced in each of the Alzheimer disease groups with respect to controls [10]. Demented patients had significantly lower D_f compared to controls. Non-linear analysis, based on the theory of deterministic chaos, revealed higher and more wide-spread EEG complexity in the patients with chronic pain disorder compared to the healthy controls during the recall of the personal pain scene.

There was found higher EEG dimensionality ("complexity") of imagery compared to actual perceptual processing [2]. Increased dimensional complexity of schizophrenic EEG was found in one of two examined brain regions. The higher dimensional complexity of functional brain mechanisms in schizophrenics vs normals is reminiscent of the loosened organization of thought and suggestions of certain superior abilities in the patients [11].

Results suggest that individual differences in the complexity of resting electrocortical dynamics are largely determined by genetic factors. Neuro-physiological mechanisms mediating genetic variation in EEG complexity may include the degree of structural connectivity and functional differentiation among cortical neuronal assemblies [1]. Using ERP oddball paradigm and applying the stepwise D_f in short data-segments there was estimated that D_f was reduced in the time interval of ERP appearance compared to time epochs before and after the ERP [18]. One of the problems of D_f approach, is the difficulty to record time series long enough to determine the "real" fractal dimension. Nevertheless it is possible to calculate fractal dimensions for very short data-segments. Using time series of different length it is possible to show, that there is a monotonous relation between fractal dimension and the number of data-points. This relation could be further interpreted with the help of an extrapolation scheme. In addition this effect is also seen with surrogate data, generated from that signal [15]. So it is feasible to use fractal dimension as a tool to characterize the complexity for short EEG time series, but it is not possible to decide whether the brain is a chaotic system or not.

In the scientific literature there are missing publications discussing the change of D_f depending on gender and personality characteristic neuroticism.

The aim of this work is to estimate the usefulness of Higuchi Fractal Dimension (HFD) approximation of D_f for analysis and comparison of the electroencephalographic D_f between males and females and neurotic and stable persons.

Materials and methods

EEG Recording

We recorded EEG from Fz, Cz, Pz, C3' and C4' records using Ag/AgCl "Nihon-Kohden" electrodes with reference to both processi mastoidei, according to the system 10-20 and sampling frequency f_s = 1000 Hz. The volunteers sitted within a soundproof, electrically shielded chamber (Faradey cage). We recorded EEG under two equal audio series in pseudorandomized order of 50 low (800 Hz) and 50 high (1000 Hz) tones with an intensity of 60 dB, duration 50 ms and randomized interstimulus interval between 2.5 – 3.5 s. The experiment consists of two experimental conditions. First the volunteers were instructed only to listen the high and low tones. The second instruction was to count only the low tones and to ignore the high tones.

After the EEG record each volunteer filled the self-report Eysenck's Personality Questionnaire (EPQ) adapted for Bulgarians [12]. The number of investigated persons was 77. According to the scores in the neuroticism scale the persons were divided in neurotic (NG) (from 14 to 20 points on EPQ) and stable (SG) (from 1 to 8 points on EPQ) groups.

After the personality classification for further analysis we used only 38 volunteers. The other 39 were excluded because of there intermediate neuroticism EPQ scores.

Measuring fractal dimension

For calculating the fractal dimension we used the Higuchi algorithm [7]. We chose to use this method because it is widespread in the EEG scientific literature and this will facilitate the comparison of our results. The Higuchi's algorithm shown in [7] performs approximated calculation of the fractal dimension D_f of time series directly in the time domain.

Let $X(1)$, $X(2)$, $X(N)$ is the analyzed N discrete EEG sequence. The Higuchi Fractal Dimension (HFD) principle is based on a measure of length $L(k)$, of the curve that represents the considered time series while using a segment of k samples as a unit. If $L(k)$ scales like:

$$L(k) \approx k^{-D_f} \tag{1}$$

Fractal dimension D_f measures the complexity and irregular characteristics of time series signals; $D_f = 1$ for a simple curve and $D_f = 2$ for a curve which nearly fills out the whole plane.

From a given time series: $X(1)$, $X(2)$, ..., $X(N)$ the algorithm constructs k new time series:

$$X_m^k: X(m), X(m+k), X(m+2k), \ldots, X(m + int((N - m)/k) * k),\ m = 1, 2, \ldots, k \tag{2}$$

where: N – total number of samples; m – initial time; k – interval time; $int(r)$ – integer part of a real number r.

The length, $L_m(k)$, of each curve X_m^k:

$$L_m(k) = \frac{1}{k}\left|\left(\sum_{i=1}^{M} \left|X(m + i * k) - X(m + (i-1) * k)\right|\right)\right|\left(\frac{N-1}{M * k}\right) \tag{3}$$

where:

$$M = int\left(\frac{N - m}{k}\right) \tag{4}$$

$L_m(k)$ is not a "length" in the Euclidean sense, it represents the normalized sum of absolute values of difference in ordinates of pair of points distant k (with initial point m). The length of curve for the time interval k, $L(k)$, is calculated as the mean of the k values $L_m(k)$, $m = 1, 2, \ldots, k$.

$$L(k) = \left(\frac{\sum_{m=1}^{k} L_m(k)}{k}\right) \tag{5}$$

The value of fractal dimension D_f is calculated by a least-squares linear best-fitting procedure as the slope coefficient of the linear regression of the log/log graph of (1). D_f of waveforms (e.g. EEG) can range between 1 and 2. D_f of highly spiky seizure discharges can range between 1.6 and 1.7, whereas D_f of a flat line (isoelectric) would be close to 1 [4].

Calibration

For the further calculations of the HFD of EEG record trials of ERPs we performed a calibration HFD measurement over a fractal curve with a priori known analytical representation and D_f = 1.5. In our case we have selected the Weierstrass fractal curve (see Fig. 1), defined as:

$$f(x) = \sum_{n=0}^{\infty} a^n \cos(b^n \pi x) \quad (6)$$

where 0 < a < 1, b is positive and: $ab > 1 + 3/2\pi$.

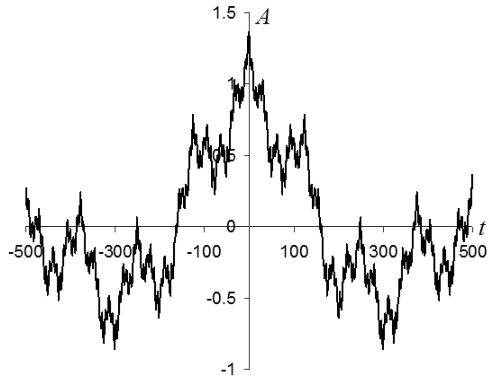

Fig. 1 A plot of the Weierstrass curve; time t is in [ms] and amplitude A is in relative units

The classical Weierstrass function is bounded above by (log a / log b) + 2, where a and b are the constants in (6) and is generally believed to be exactly that value, but that this has not been proven rigorously.

So, when a = 0.5 and b = 4, D_f = 1.5.

Using this curve we calculated the quality of approximation between real calculated HFDs and the preliminarily known one from the analytical representation (6). We computed the HFD of these curves using different lengths of the sliding windows: 50, 100, 50, 200 ms. We selected the 100 ms window for which HFD ≈ D_f and it is accurate enough for our further calculations. The results of this calibration technique are shown on Fig. 2:

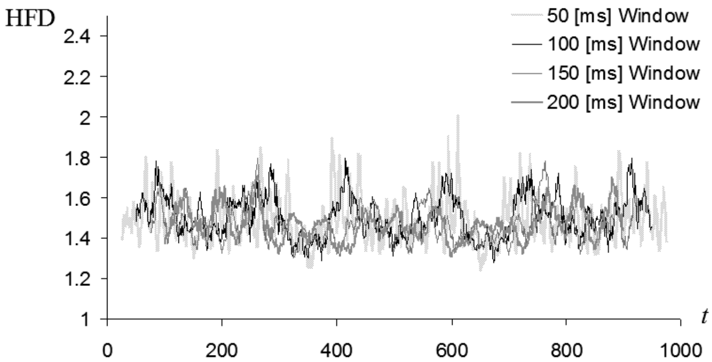

Fig. 2 Fractal dimension calculated with Higuchi algorithm using sliding windows with weight 50, 100, 150 and 200 ms shown in different colours from black to light grey

So, for each EEG trial we calculated a new HFD series using the selected sliding window of 100 points equal to 100 ms length. After this procedure we averaged the new HFD series for each tone, of the EEG records (Fz, Cz, Pz, C3' and C4') and for each experimental condition separately according to the instruction.

We compared the averaged HFD vectors of stable and neurotics, male and female, passive listening condition and counting condition using Kruskal-Wallis nonparametric test.

On Fig. 3 a general evidence for the fractal nature of our explored signals is shown by using the double log plot of their power spectra [13]. Additionally, we show the similarity of the Real Wavelet Transformation (that claims correctness in both time and frequency domains) of these signals (see Fig. 4) [5].

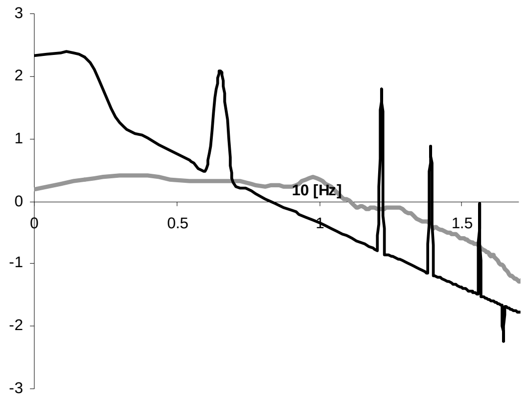

Fig. 3 log(Hz)/log(μV^2) plot of FFT Power Spectra of Weierstrass fractal curve with a priory calculated D_f = 1.5 (black line) and log(Hz)/log(μV^2) plot of averaged FFT power spectra of real EEG record trial (grey line)

It should be noted that D_f is not sensitive to the baseline adjustment in the time domain signals, while the utilization of the FFT power spectra is sensitive and so gives misleading results.

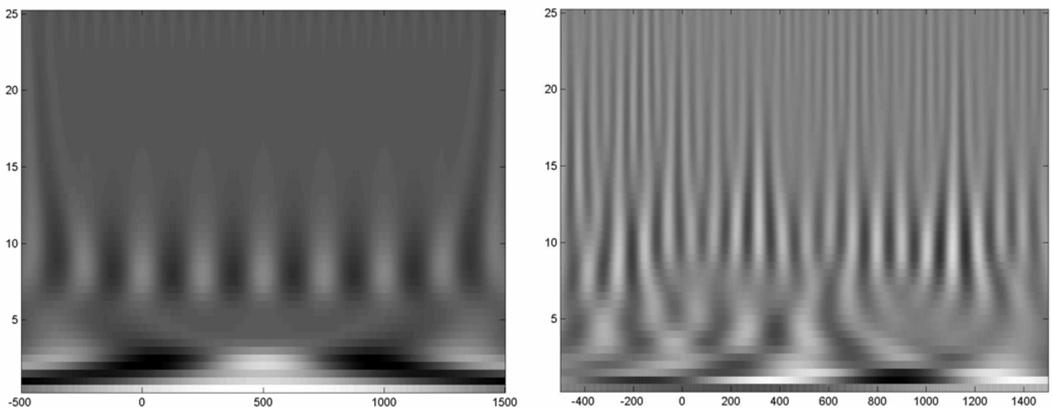

Fig. 4 A Real Wavelet Transformation of Weierstrass curve (left) and Real Wavelet Transformation of EEG single trial (right); the time (horizontal axis) is in [ms] and the frequency is in [Hz] (vertical axis)

Experimental results

Our results suggest that females are characterized with higher HFD compared to male subjects. The differences are significant in counting the low tone task condition for both high and low stimuli, but not in the passive listening task condition. The difference is prominent in the time period before auditory stimulation and 200 ms after the auditory stimulation. In the time interval from 0 to 200 ms after the presentation of auditory stimuli the gender difference is decreased. After the 200 ms the HFD trends returned to there previous baseline levels.

The mean HFD for male and female in time intervals: from 400 to 0 ms before the stimulus onset, time interval from 200 to 600 ms and time interval from 600 to 1000 ms are presented in Table 1:

Table 1. Comparison of the HFD for males, females, stable and neurotics for Cz

	Passive listening task					
	Neurotic group			**Stable group**		
	Female	*Male*	*P<*	*Female*	*Male*	*P<*
Cz High	1.25 ± 0.02	1.25 ± 0.02	0.40	1.28 ± 0.01	1.22 ± 0.01	0.00
	1.22 ± 0.02	1.23 ± 0.01	0.28	1.22 ± 0.01	1.20 ± 0.01	0.34
	1.24 ± 0.02	1.25 ± 0.02	0.44	1.28 ± 0.01	1.22 ± 0.01	0.01
	1.25 ± 0.02	1.26 ± 0.02	0.64	1.28 ± 0.01	1.22 ± 0.01	0.01
	Female	*Male*	*P<*	*Female*	*Male*	*P<*
Cz Low	1.25 ± 0.02	1.26 ± 0.02	0.54	1.28 ± 0.01	1.22 ± 0.01	0.01
	1.22 ± 0.01	1.24 ± 0.01	0.35	1.22 ± 0.01	1.20 ± 0.01	0.22
	1.24 ± 0.02	1.25 ± 0.02	0.44	1.27 ± 0.01	1.22 ± 0.01	0.01
	1.25 ± 0.02	1.26 ± 0.02	0.70	1.28 ± 0.01	1.22 ± 0.01	0.01
	Counting task					
	Neurotic group			**Stable group**		
	Female	*Male*	*P<*	*Female*	*Male*	*P<*
Cz High	1.24 ± 0.02	1.24 ± 0.01	0.87	1.28 ± 0.01	1.22 ± 0.01	0.01
	1.22 ± 0.02	1.22 ± 0.01	0.68	1.22 ± 0.01	1.20 ± 0.01	0.11
	1.24 ± 0.02	1.24 ± 0.01	0.93	1.26 ± 0.01	1.22 ± 0.01	0.04
	1.25 ± 0.02	1.24 ± 0.01	0.74	1.27 ± 0.01	1.22 ± 0.01	0.00
	Female	*Male*	*P<*	*Female*	*Male*	*P<*
Cz Low	1.25 ± 0.02	1.24 ± 0.01	0.87	1.28 ± 0.01	1.22 ± 0.01	0.01
	1.21 ± 0.01	1.22 ± 0.01	0.68	1.22 ± 0.01	1.20 ± 0.01	0.11
	1.25 ± 0.02	1.25 ± 0.01	0.62	1.27 ± 0.01	1.23 ± 0.01	0.02
	1.26 ± 0.02	1.25 ± 0.01	0.74	1.28 ± 0.01	1.23 ± 0.01	0.01

The mean values of HFD time series for male and female are presented in Fig. 5. Each point of this time series represent the mean value of HFD for time interval – 50 to 50 ms before and after the point. On figures below is presented only the data calculated from Cz record.

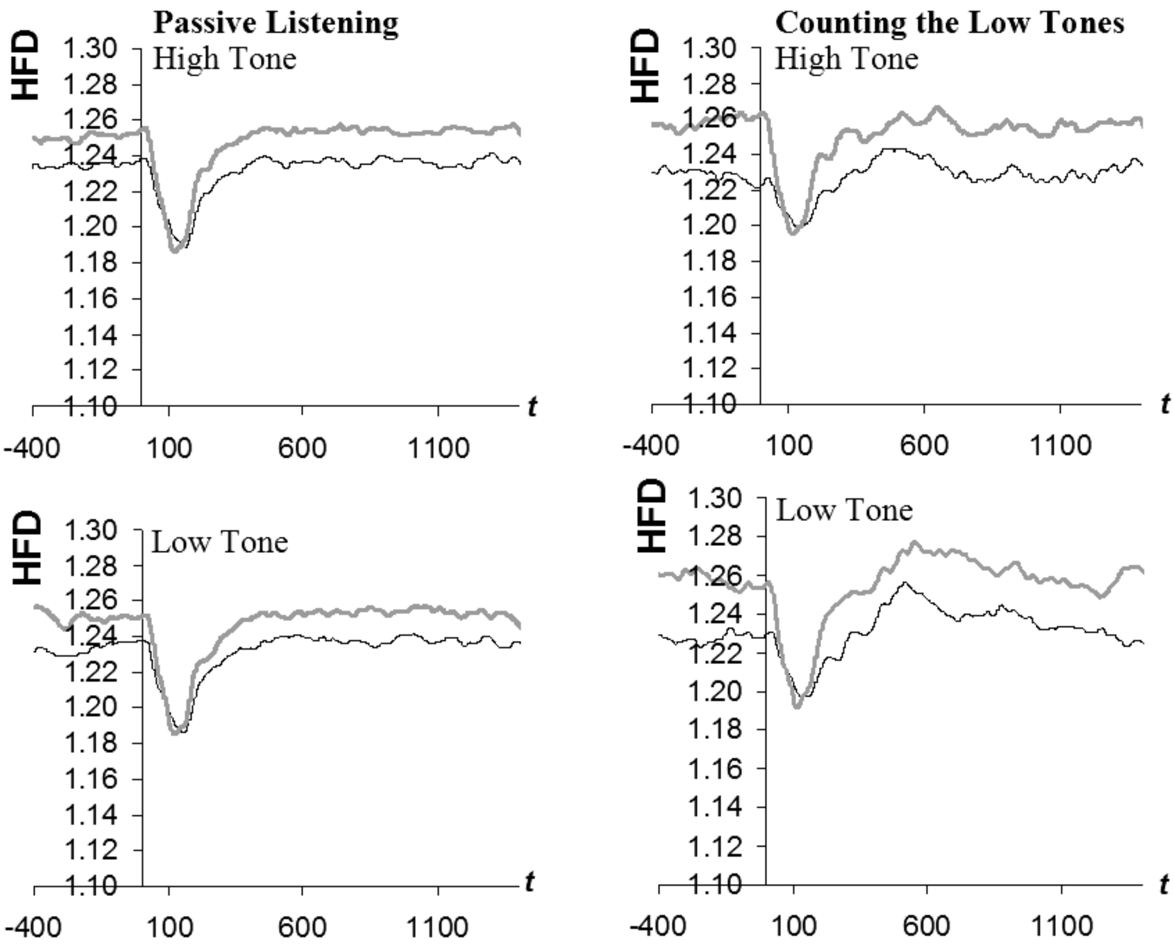

Fig. 5 Comparison between HFD time series of males (black) and females (grey); *t* is in [ms]

We have found HFD differences between stable (SG) and neurotics (NG) in the time interval form 0 to 100 ms after the stimuli presentation. The difference was significant only in the passive listening task condition. Nevertheless in both task conditions the SG is characterized with stronger decrease of HFD in time interval form 0 to 100 ms after the stimuli presentation compared to NG (see Fig. 6 and Fig. 7).

Further we decided to explore the dependence of gender differences from the personality trait neuroticism. We have found significant differences between male and female in stable group but not in the neurotic group. This result was found in both task conditions for both tones. The SG female was characterized with significantly higher HFD compared to SG male, but not when they were compared to NG female or NG male group. The results are shown in Fig. 7.

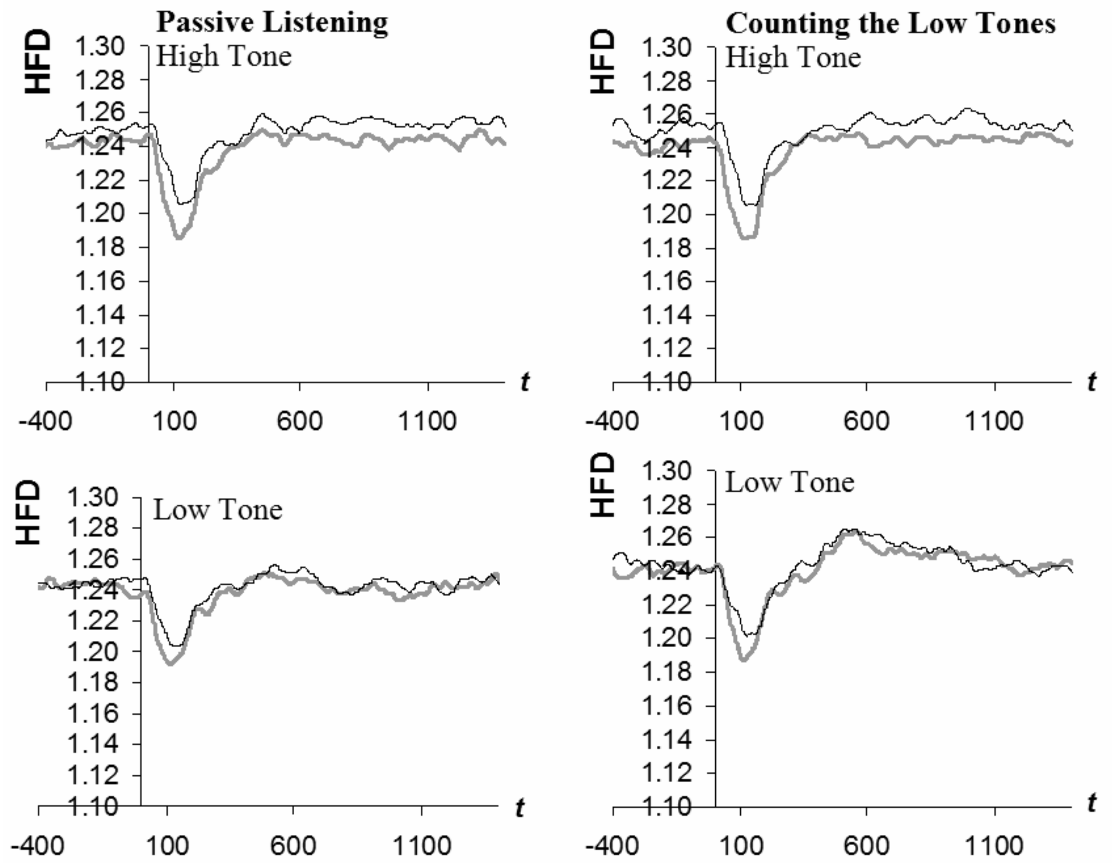

Fig. 6 Comparison between HFD time series of SG (blak) and NG (grey); *t* is in [ms]

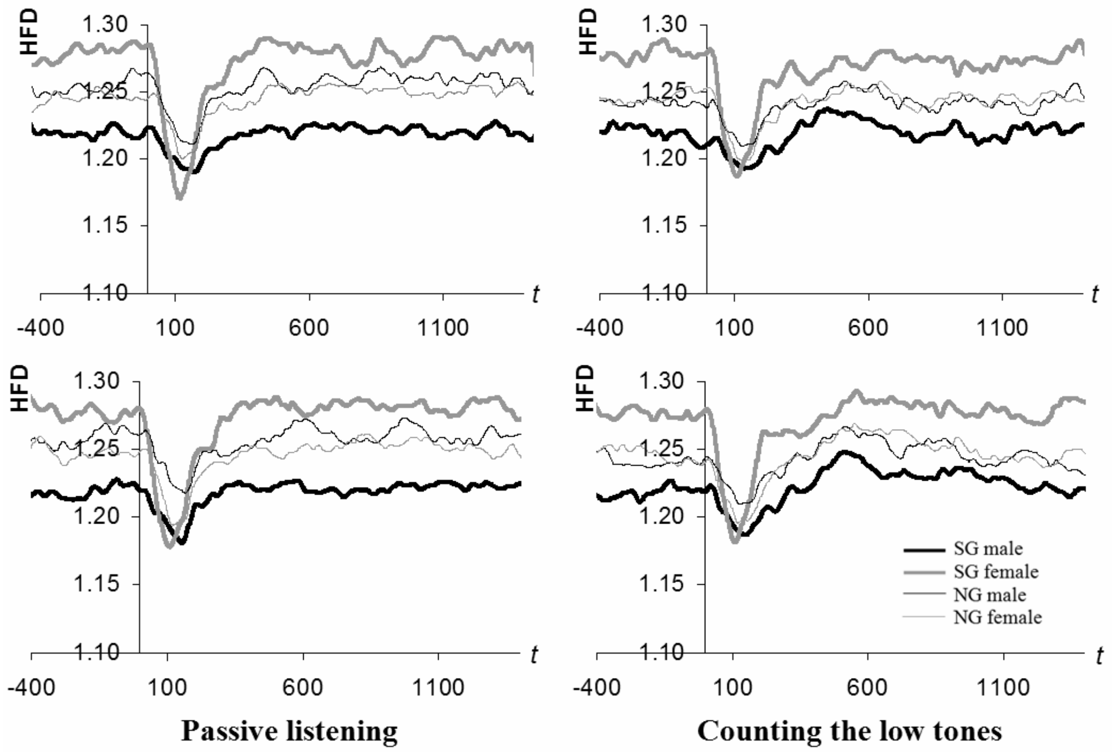

Fig. 7 Comparison between HFD time series of SG, NG, males and females; *t* is in [ms]

We have compared the HFD time series between passive listening condition and counting the low tone condition. There was no difference between both task conditions. Nevertheless there was tendency to increase HFD by target tone in counting the low tone task condition in time interval of late event-related oscillatory changes. This tendency was not significant, but attracts our attention for further investigations. The results are shown in Fig. 8:

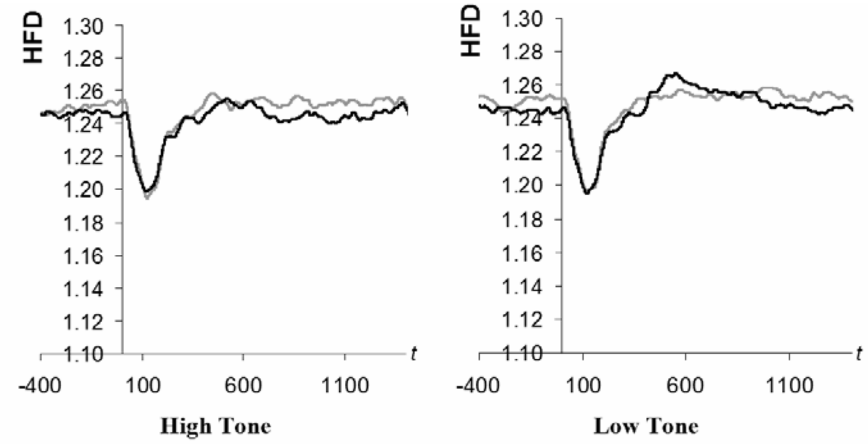

Fig. 8 Comparison of HFD time series between passive listening task condition (grey) and counting the low tone condition (black); *t* is in [ms]

Discussion

The obtained results, based on the Higuchi algorithm for calculating of the fractal dimension with sliding windows of ERP EEG time series showed a specific functional meaning of ERP fractal dimension change depending on the individual personality type and gender. The calculations of the values of EEG fractal dimension by HFD should be considered as an approximation of the real fractal dimension D_f, which shows the fractal nature of the explored signals rather then the exact value of D_f. However more important is that using the same algorithm and the same length of the sliding window we came to a useful comparison between the different groups: male, female, stable and neurotics.

Three main results of this study were achieved:

First: the female are characterized with increased HFD compared to male subjects. These differences are manifested in EEG time intervals without auditory stimulation. The gender difference was not available in time window between 0 and 200 ms after the stimuli presentation where the physical parameters of the stimuli have a greatest impact on the event-related oscillatory changes.

Second: The neuroticism as a personality trait has an influence on the HFD. There can be found a difference between stable and neurotic personalities in time interval between 0 and 100 ms after the stimuli presentation. The HFD of stable persons was lower in this time period compared to neurotic group.

Third: When we divided the stable and neurotic groups on male and female, the gender differences of HDF was evident only between stable males and stable females. The stable females have higher HFD compared to stable males in time interval before auditory stimuli and 200 ms after the stimuli presentation. So there is an interaction of gender factors and neuroticism concerning the HFD changes in EEG activity.

Drawing attention facts are the differences caused by the gender factor and neuroticism factor manifested in the different time intervals. Though that the number of the tested subjects is probably statistically insufficient and requires more tests, it can be speculatively concluded that these gender differences are mainly detected in the “basic” level of EEG fractal dimension, i.e. dependant from the number of coupled neuronal oscillators. So, the neuroticism as a factor is not related to this “basic” fractal dimension, but to the differences in the coupling of neuronal oscillators in the time moment of processing the physical parameters of the presented stimuli.

Finally, we have found no significant tendency for increased HFD in counting the low tone task condition for the low target tone compared to HFD for low tone in the task with passive listening instruction. This tendency is manifested in the time interval of stimuli cognitive information processing. The HFD seams to be a sensitive tool for investigating the differences in cognitive information processing between different type of tasks, mental and health conditions.

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