# Detrended Fluctuation Analysis of EEG in Depression

M. Bachmann[1], A. Suhhova[1], J. Lass[1], K. Aadamsoo[2], Ü. Võhma[2], and H. Hinrikus[1]

[1] Department of Biomedical Engineering, Technomedicum, Tallinn University of Technology, Tallinn, Estonia
[2] Clinic of Psychiatry, North Estonia Regional Hospital, Tallinn, Estonia

*Abstract*—**Diagnosis of depression is still based mainly on evaluation of the intensity of subjective and clinical symptoms by psychiatrists. This study is aimed to give additional objective information about depression analyzing the electroencephalographic (EEG) signal using the method of detrended fluctuation analysis (DFA). DFA is applied to evaluate the presence and persistence of long range correlations in time in EEG signals. EEG recordings were carried out on the groups of depressive and healthy subjects of 18 female volunteers each. The DFA was calculated on EEG signals from P3-Pz channel at a length of 5 minutes. The DFA method revealed statistically significant difference between healthy and depressive subjects. Resting EEG of healthy subjects exhibited persistent long-range correlation in time. In depression the long-range correlation was less persistent and for about half of the depressed subjects (44%) the EEG revealed long-range anti-correlation in time.**

*Keywords*—**EEG, DFA, depression, mental disorder.**

## I. INTRODUCTION

According to World Health Organization depression is expected to rank second by 2020 and current predictions indicate that by 2030 depression will be the leading cause of disease burden globally calculated for all ages, both sexes [1]. However, the methods of diagnosis of depression and also other mental disorders have been traditionally based mainly on evaluation of the intensity of subjective and clinical symptoms by psychiatrists. Currently no objective indicator in clinical practice exists.

As electroencephalography (EEG) is easily available, cost effective method and reflects the ongoing bioelectric activity. EEG is a valuable method for getting objective information about changes in brain physiology specific in depression.

We have previously successfully differentiated the healthy controls and depressive subjects using spectral asymmetry index (SASI) [2, 3]. However, the coherence analysis performed on the data did not reveal statistically significant difference between groups.

Since EEG exhibits complex behavior [4, 5], nonlinear measures can be a good alternative to more frequently applied linear methods. For instance, a nonlinear method, detrended fluctuation analysis (DFA), a modified root mean square analysis of a random walk allows to detect long-range correlations in a seemingly nonstationary time series [6]. DFA has been previously successfully applied on various physiological data [6, 7, 8, 9, 10]. There exist also EEG studies of depression using DFA [11, 12]. However, the EEG signal amplitude is rarely used as an input to DFA, with the exception of the study by Hosseinifard et al [12]. The main emphasis of the study is classification accuracy of healthy and depressive subjects, which reaches more than 75%. However, there is no information about the values of different parameters needed to calculate DFA nor the outcome of DFA calculations. Therefore, no conclusion can be drawn about the differences in EEG characteristics of healthy and depressed subjects.

The aim of this work is to gain additional objective information about depression by clarifying whether resting EEG exhibits long-range correlation. For this purpose, the character of the EEG long range correlations in depression and health will be evaluated.

## II. METHODS AND EQUIPMENT

### A. Subjects

The experiments were carried out on a group of 18 female patients with major depressive disorder, mean age 35 years, standard deviation 11 years.

Subjects with depressive disorder without antidepressant treatment were selected from a hospital inpatient unit. Subjects with nonpsychotic depressive disorder as defined by ICD-10 criteria and determined by 17-item Hamilton Depression Rating Scale (HAM-D) score higher than 14 were eligible. The average score for the group was 22.8 (standard deviation 3.3).

The study was conducted in accordance with the Declaration of Helsinki and was formally approved by the local Medical Research Ethics Committee.

### B. Experimental Procedure and EEG Recording Equipment

The experimental procedure for a subject included continuous EEG recording during 30 minutes between time interval 9 a.m. to noon.

The experimenter and a subject were in the same laboratory room during the experiments. The room was dark but

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no other special conditions were provided. The subjects were lying in a relaxed position, eyes closed and ears blocked during the experiments.

Cadwell Easy II EEG measurement equipment was used for the EEG recordings. The EEG was recorded using 19 electrodes, which were placed on the subject's head according to the international 10 20-electrode position classification system. Bipolar parietal channel P3-Pz was chosen for analysis. Raw EEG signals were recorded using the Cadwell Easy EEG data acquisition system within a frequency band of 0.3-70 Hz. The impedance of recording electrodes was monitored for each subject prior to data acquisition and it was always below 5 kΩ. The sampling frequency was 400 Hz. Due to computational load, only the first 5 minutes of each recording was used for further analysis.

*EEG Analysis*

DFA is calculated directly in the time domain [6, 7]. First the 5 minutes EEG signal was divided into 20 s segments, giving 15 segments for further processing. Next, the DFA was calculated for each segment. After that the median value of the DFA algorithm over all segments was calculated for each subject and the statistical analysis was performed.

The DFA was calculated for all the segments as follows [6]. First, the EEG signal segment x(i), where i is the length of the segment ranging from 1 to N (N=8000), is integrated to generate a new time series y(k).

$$y(k) = \sum_{i=1}^{k} \left[ x(i) - \bar{x} \right] \quad k = 1,\ldots, N \tag{1}$$

where $\bar{x}$ is the average of the EEG signal x(i). After that the new time series y(k) is divided into n equal windows. Window length started from 4 samples up to 812 samples varying equidistantly on logarithmic scale (0.01 s up to 2.03 s). The maximum window length was selected as about 1/10 of the signal segment length [13].

In each window n, the least squares line, $y_n(k)$, is fit to the data y(k). The fitting range was chosen from 0.1 s, excluding the prominent alpha frequency [14], to 1.1 s, as brain often suppresses large fluctuations on longer timescales [15]. Next, the local trend $y_n(k)$ is subtracted from the data y(k). The root mean square fluctuation of the demeaned, integrated and detrended signal segment is calculated as:

$$F(n) = \sqrt{\frac{1}{N} \sum_{k=1}^{N} \left[ y(k) - y_n(k) \right]^2} \tag{2}$$

Those final steps are repeated for all window sizes giving the average fluctuations as a function of window length. Those fluctuations are expected to increase with the window length. The scaling is present in case on a log-log graph of F(n) vs. n appears a linear correlation. The slope of the line, that is the scaling exponent α, relating logF(n) to logn describes the type of scaling. For white noise, no correlation between consecutive values, the integrated value (y(k)), corresponds to a random walk and α = 0.5 [16]. A scaling exponent between 0.5 and 1 indicates correlation. Large fluctuations are likely to be followed by large fluctuations and small fluctuations are likely to be followed by small. In case a scaling exponent is between 0 and 0.5, the data is anti-correlated. Therefore, large fluctuations are likely to be followed by small fluctuations and vice versa. While scaling exponent 0.5 corresponded to white noise, the scaling exponent 1 corresponds to 1/f noise and scaling exponent 1.5 represent Brownian noise.

Student's t-test was performed to evaluate the differences between the scaling exponents of depressive and control group. The difference was considered statistically significant for p values lower than 0.05.

## III. RESULTS

Figure 1 illustrates the DFA results for a control subject. The root mean square fluctuations F(n) are plotted against window length n in a log-log plot marked with 'x'. The solid line represents the linear least squares fit in the predefined region from 0.1-1 seconds. The scaling exponent α is calculated as the slope of the linear fit. For this subject, the scaling exponent is 0.819.

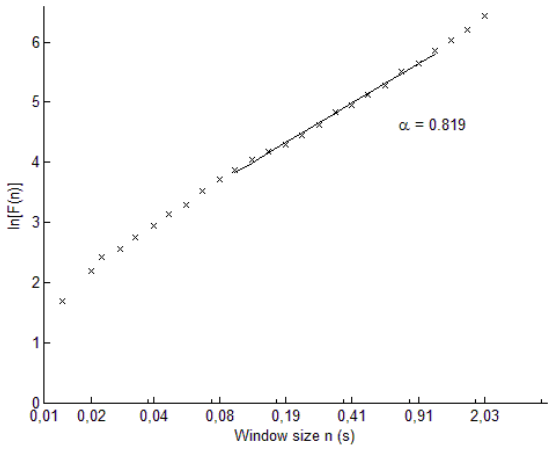


Fig. 1 F(n) versus n (in seconds) in a log-log plot for one control subject. The scaling exponent α was obtained over the fitting range 0.1s-1.1s.

Figure 2 illustrates the DFA algorithm calculation results for a depressive subject. In this case the scaling exponent has a lower value, α = 0.617. In addition, the crossover emerges on larger window length.

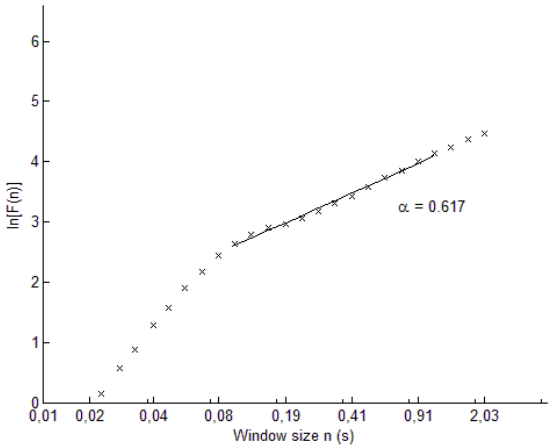


Fig. 2 F(n) versus n (in seconds) in a log-log plot for one depressive subject. The scaling exponent α was obtained over the fitting range 0.1s-1.1s.

Scaling exponents for control group and for depressive group averaged across all subjects and the corresponding standard deviations are presented in Figure 3. While control group has an average scaling exponent with a value of 0.735, the scaling exponent of the depressive group is much lower 0.571. According to the student's t-test, the difference in average scaling exponent between control group and depressive group is statistically significant ($p < 0.05$).

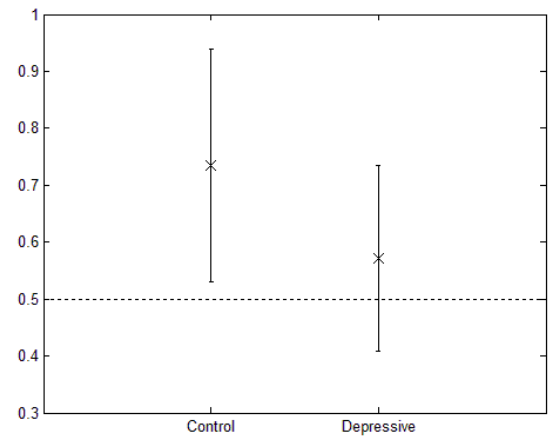


Fig. 3 Scaling exponents for control group and for depressive group averaged across all subjects. Vertical lines represent standard deviation.

The horizontal dotted line in Figure 3 represents the scaling exponent level for uncorrelated white noise (α=0.5). Considering the vertical lines representing the standard deviation of average scaling exponent, we can see that a part of depressive subjects are characterized also by a scaling exponent smaller than 0.5 indicating anti-correlation. To be more precise, about half of the depressive subjects (44.4%) show anti-correlation while only one subject (5.6%) in control group indicate anti-correlation phenomena.

## IV. Discussion

The average scaling exponent (α = 0.735) of the control group indicate that for majority of healthy subjects the EEG signal exhibits long-range correlation in time. Consequently, fluctuations are larger for larger time-scales. On the other hand for 44.4 % of depressive subjects the signals are temporally anti-correlated. Thus, for larger time-scales the fluctuations are smaller than in case of white noise. The rest of the depressive group exhibits also long-range correlations in time, but those are not as persistent as for controls.

The linear least squares fit was performed on a log-log plot at window lengths 0.1-1.1 seconds. However, Figure 1 and 2 indicate that at least for control subjects even longer window lengths can be used. Therefore, in future it would be interesting to analyze whether the length of the linear scaling region can characterize the EEG signal difference for control and depressive group. Will the brain in depression suppress the large fluctuations on shorter time-scales compared to controls?

The results of this study cannot be directly compared to other studies due to different window lengths starting from 5 seconds up to 50 seconds [17, 18]. In addition, different studies apply DFA to different EEG parameters - signal amplitude [12], amplitude envelope of different EEG rhythms [18], synchronization likelihood [11] etc. In a recent study, Hosseinifard et al [12] differentiated depression patients from controls by calculating various linear and nonlinear features – DFA of the EEG signal amplitude as one of them – and applying different machine learning techniques for classification. However, only the classification results are explicitly presented leaving out the values of different parameters in use while calculating the DFA. From all the parameters used as an input for classifiers, only the results of a linear method, the highest accuracy power band, were presented. The mean alpha power band was significantly higher in left hemisphere of depressed subjects compared to the left hemisphere of controls. The bipolar channel P3-Pz, used in this study, belongs to the same region. However, for better localization of significant brain areas characterizing depression, all EEG channels need to be analyzed.

Hosseinifard et al [12] used linear and non-linear methods for classification of depression. The classification accuracy was up to 90 % combining only nonlinear measures, as opposed to about 77% with linear power features in use. Our previous study using linear method, the coherence

analysis, to differentiate between depressive and control subjects did not reveal statistically significant difference between groups. However, in this study, the nonlinear DFA indicated that healthy EEG exhibits more persistent long-range correlation than EEG in depression. Even more, for about half of the depressive subjects' long-range anti-correlation was revealed.

In future, the length of scaling region for depressive and control subjects will be analyzed as during the current analysis, the scaling region for control group seemed to be even larger than was used in this study and also larger than the scaling region of the depressive group. Also different channels will be of interest.

## V. CONCLUSIONS

The results indicate that resting EEG of healthy subjects exhibits persistent long-range correlation in time. In depression the long-range correlation was less persistent than for healthy subjects. In contrast, for about half of the depressed subjects (44%) the EEG revealed long-range anti-correlation.

More specific analysis is needed to consider the extended lengths of scaling region and different brain areas.

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Author: Maie Bachmann
Institute: Tallinn University of Technology
Street: Ehitajate Rd 5
City: Tallinn
Country: Estonia
Email: maie@cb.ttu.ee