Detrended Fluctuation Analysis (DFA) in biomedical signal processing: selected examples

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Abstract. Detrended Fluctuation Analysis (DFA) quantifies fractal-like auto-correlation properties of the signals. It is useful for analyzing biomedical signals which are mostly complex and non-stationary. In this paper we review selected examples of application of the DFA method in cardiology, neurology and other studies. We also present our findings – some of our original work. We conclude that using the DFA method we can determine which signal is more regular and less complex (in practice to distinguish healthy from unhealthy subjects).

Introduction

Biomedical systems exhibit complexity and nonlinear structure and this complexity is present in measured signals, such as ECG or EEG [4]. It is generally accepted that the remarkable complexity of biological signals is a result of two factors [6]: high complexity of systems (many degrees of freedom) and their susceptibility to environmental factors. Chaotic systems exhibit characteristics of stochastic systems, but can be described using only a few variables (in some cases only one). Also biological signals are difficult to analyze because they are mostly non-stationary [4, 9].

Classical methods of signal analysis work well mostly on stationary signals, so we need a new solution – new methods. Nonlinear dynamics (more precisely in this case – chaos theory) provides many new ways of analyzing signals, such as fractal methods. Some of these methods determine the scaling exponent of the signal which indicates the presence or absence of fractal properties (self-similarity) [9]. DFA is a scaling analysis method that provides a simple quantitative parameter to represent the autocorrelation properties of a signal [4]. It is also known for its robustness against non-stationarity [9].

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Detrended Fluctuation Analysis (DFA)

Detrended Fluctuation Analysis is an interesting method for scaling the long-term autocorrelation of non-stationary signals. It quantifies the complexity of signals using the fractal property [12, 14]. DFA was first proposed by Peng et al. in 1995 [12]. This method is a modified root mean square method for the random walk. Mean square distance of the signal from the local trend line is analyzed as a function of scale parameter. There is usually power-law dependence and interesting parameter is the exponent. In many cases the DFA scaling exponent can be used to discriminate healthy and pathological data [15].

DFA algorithm

We will illustrate the DFA algorithm on 1-dimensional signal $B(i)$, $i = 1, \ldots, N$ [11–12]. First, we compute the integrated signal according to the formula

$$y(k) = \sum_{i=1}^{k} (B(i) - B_{\mathrm{avg}}) \tag{1}$$

where B_{avg} is the mean value of the signal. Next we divide the data into segments of length n and find the linear approximation y_n using least squares fit in each segment separately (representing the trend in a given section).

The average fluctuation $F(n)$ of the signal around the trend is given by this formula:

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

The calculations are repeated for all considered n. We are interested in the relation between $F(n)$ and size of segment n. In general $F(n)$ will increase with the size of segment n.

Next, we create a plot – double logarithmic graph ($\log F(n)$ vs $\log n$). The linear dependence indicates the presence of self fluctuations and the slope of the line $F(n)$ determines the scaling exponent α [1, 9, 12, 15–16]:

$$F(n) \sim n^{\alpha} \tag{3}$$

For example, recent studies have shown that DFA functions of different R-R series (from ECG) are approximated by power-law [1, 12, 15] as well as synchronization signals EEG [9, 16].

Scaling exponent α

The parameter α (scaling exponent, autocorrelation exponent, self-similarity parameter) represents the autocorrelation properties of the signal [2, 4, 9, 13, 15–16]:
1. $\alpha < 0.5$ anti-correlated signal
2. $\alpha = 0.5$ uncorrelated signal (white noise)
3. $\alpha > 0.5$ positive autocorrelation in the signal
4. $\alpha = 1$ 1/f noise
5. $\alpha = 1.5$ Brownian noise or random walk

Gifani et al. [4] claim, that using scaling exponent α one should be able to completely describe the significant autocorrelation properties of the biomedical signals. Often computed separately exponent for low and high n can describe short-range scaling exponent (or fast parameter) α_1 and long-range scaling exponent (or slow parameter) α_2 for time scales [3].

Example of the DFA method

In [Fig. 1] and [Fig. 2] we present an example of application of the DFA method. We selected R-R intervals signal (from ECG). Original signal was integrated and detrended – presented in [Fig. 1]. Next, double logarithmic plot was created and scaling exponents were calculated.
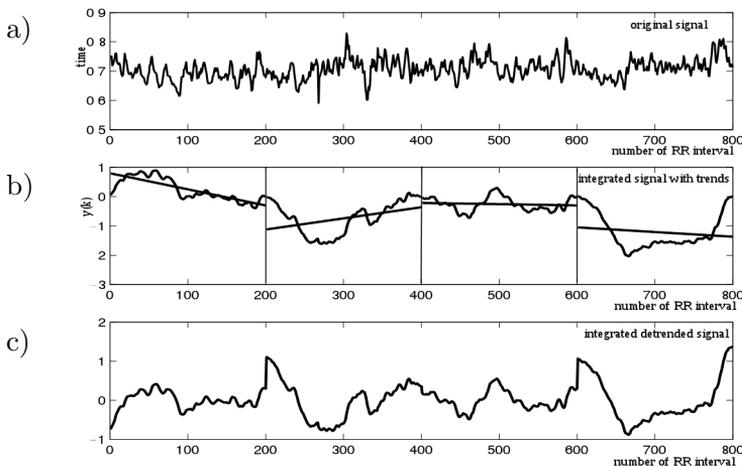

Fig. 1. DFA method: a) selected original signal (R-R intervals from ECG), b) integrated signal with local trends estimated in each section, c) detrended integrated signal

In [Fig. 2] double logarithmic graph $\log F(n)$ vs $\log n$ is shown. The slope of the line determines the scaling exponent (short-range scaling exponent α_1 and long-range scaling exponent α_2).
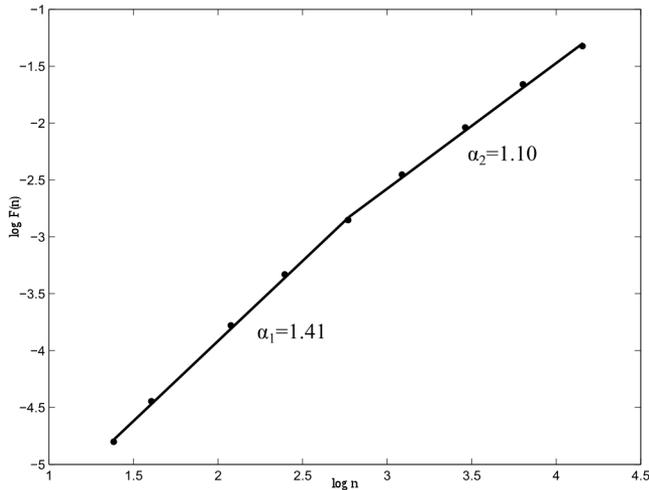

Fig. 2. Scaling exponent (short-range scaling exponent α_1 and long-range scaling exponent α_2) for an example RR intervals signal

Application in biomedical processing

Selected examples in cardiology, neurology and other studies

In biomedical signals analysis DFA is mostly used in ECG studies [1–3, 14–15] and EEG studies [4, 9–10, 16].

Acharya et al. [2] classified certain disease using DFA in ECG studies. DFA was also used in the analysis of atrial signal during adrengenic activation in atrial fibrillation [3]. Pikkujamsa et al. [14] studied cardiac inter-beat interval dynamics from childhood to senescence. They claim that the loss of complexity and alterations of fractal organization related with aging (also apparent in many diseases) may be associated with the reduced ability to adapt to physiological stress. The DFA method can also help to diagnose heart failure [1]. In this paper DFA was applied to R-R intervals studies and differences are observed between scaling exponent α of healthy and unhealthy subjects. Rodriguez et al. [15] showed that significant differences in scaling of intra-beat dynamics can be observed with time series of about 5–30 min. This could make intra-beat scaling analysis potentially applicable to real

clinical data. Also intra-beat dynamics displays differences in the scaling behavior of healthy and unhealthy subjects.

Gifani et al. [4] claim, that using DFA, they can describe the dynamics of brain during anesthesia. They found the optimum fractal-scaling exponent by selecting the best domain of box sizes, which have meaningful changes with different depth of anesthesia. Lee et al. [9–10] analyzed the EEG in sleep apnea and long-range autocorrelations by calculating its scaling exponents. The scaling exponents of the apnea were lower than those of the healthy subject. Stam et al. [16] examined the hypothesis that cognitive dysfunction in Alzheimer's disease is associated with abnormal spontaneous fluctuation of EEG synchronization levels during an eye-closed resting state.

Phinyomark et al. [13] claim that DFA's scaling exponent is an efficient parameter in practical surface EMG controlled prostheses. The studies show that scaling exponent in various hand motions have the significant difference value and small experimental variation. The authors think that DFA could be considered as an element of multifunction myoelectric control system.

Selected examples from our studies

In our work [7–8] we applied the DFA method to heart rate variability studies (RR intervals). We have analyzed two groups of children: children with diabetes type 1 with microalbuminuria and healthy children. For each child 24 hours ECG (R-R intervals) was recorded. Then we divided these records into two segments: day (6.00–22.00) and night (22.00–6.00) respectively.

The DFA method showed statistically important differences between studied groups of children and also differences between night and day [7–8]. We obtained scaling exponent for healthy and unhealthy children near 1.0, which is consistent with studies performed by Yeh et al. [17] and Pikkujamsa et al. [14]. Also values of scaling exponents were higher for unhealthy subjects than for healthy, which suggest more regular, less complex signals for unhealthy children. This could indicate too regular heartbeat. In these cases heart could not rest, works like in an athlete, which is very dangerous.

We concluded that using nonlinear dynamics methods (DFA) we could quantitatively and qualitatively study the heart rate variability and distinguish healthy from unhealthy subjects.

Here we present our recent findings – analysis of EMG signals. These signals were obtained from Physionet [5]. We concentrated on short EMG recordings from three subjects: healthy, one with myopathy and one with

neuropathy (presented in [Fig. 3]). EMG records were obtained using 25 mm concentric needle electrode placed in tibialis anterior muscle. Subjects dorsiflexed the foot gently against resistance and then relaxed.
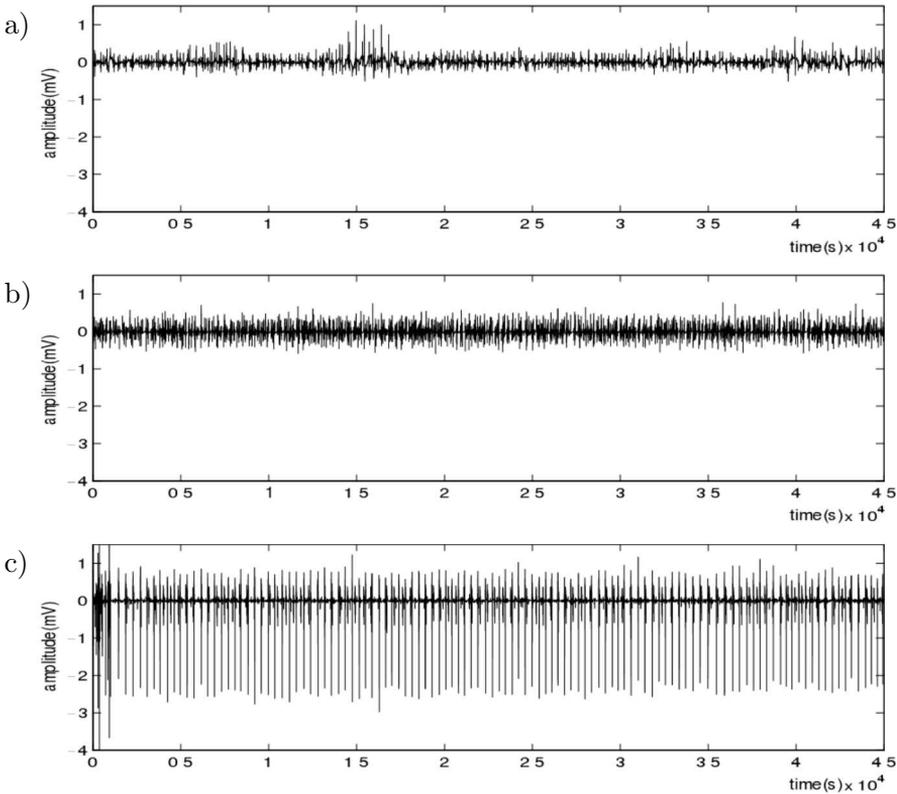

Fig. 3. Selected EMG signals from: a) healthy subject, b) subject with myopathy, c) subject with neuropathy

In [Fig. 4] we present values of scaling exponents and the slope of the line $F(n)$ on double logarithmic plot obtained by using the DFA method for studied signals. All results are between 0.52 and 1.41, which suggest self-similarity properties of these signals. We can also observe differences between values of short-range scaling exponent α_1 and long-range scaling exponent α_2. For unhealthy subjects values are lower than for the healthy one, especially values of α_2. So signals from unhealthy subjects are less regular and more complex than from the healthy one. Differences in values of α_2 are consistent with work by Pikkujamsa et al. [14] – alterations of long-range (fractal, self-similarity) organization related with disease.

a)

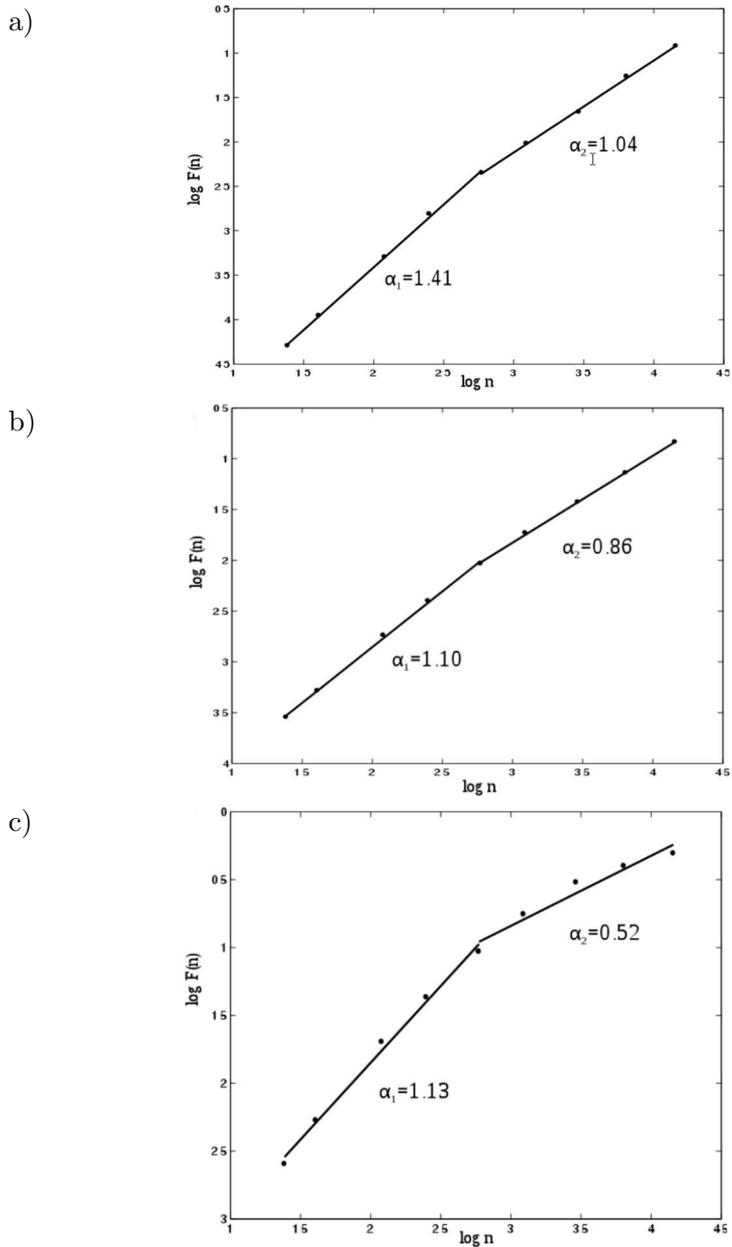
b)

c)

**Fig. 4. Scaling exponents for: a) healthy subject, b) subject with myopathy,
c) subject with neuropathy**

Conclusions

Using the DFA method we can distinguish healthy from unhealthy subjects. Also we can determine which signal is more regular and less complex – useful for analyzing biomedical signals. We concluded that using nonlinear dynamics methods, like the DFA method we could quantitatively and qualitatively study physiological signals.

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