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Multifractal characteristics of external anal sphincter based on sEMG signals

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ABSTRACT

Up to 40% of patients treated for rectal cancer suffer from therapy-related symptoms. Innervation injury is one of the suggested pathomechanisms of those symptoms hence the development of a valid, non-invasive tool for the assessment of neural systems is crucial. The aim of this work is to study the fractal properties of the surface electromyography signals obtained from patients suffering from rectal cancer. The anal sphincter activity was investigated for the group of 15 patients who underwent surgical treatment. Multifractal detrended fluctuation analysis was implemented to analyze the data, obtained at four different stages: one before treatment and three times after the surgery. The results from the standard detrended fluctuation analysis and empirical mode decomposition methods are presented and compared. The statistically significant differences between the stages of treatment were identified for the selected spectral parameters: width and maximum of the spectrum.

1. Introduction

Over last few decades, surface electromyography (sEMG), due to its non-invasive characteristics, has gained a wide range of applications for neuromuscular systems. This work is focused on an application of the sEMG concerning the diagnosis of the anal sphincter of the patients suffering from rectal cancer [1,2]. Rectal cancer remains to be one of the most frequent cancers in humans [3]. It requires complex multimodal treatment composed of surgery, irradiation and chemotherapy. All of those methods can cause significant stool continence-related problems hence proper assessment of anorectal innervation before and after the treatment can be crucial for the prevention and treatment of complications. The diagnostics of innervation of the anal sphincter is undeniably a central issue for the evaluation of treatment progress but there is still no practical diagnostic test whose usefulness is scientifically proven. sEMG enables non-invasive monitoring of the anal sphincter function [4–6] and is a very promising method of testing of innervation of muscles.

Regardless of the application, sEMG always represents highly complex signals with a low signal to noise ratio [7]. The nonlinearity of sEMG data has been investigated in recent years [8] and great effort has been devoted to the application of variety of non-linear methods. Traditional analysis, mainly based on the conventional statistical tests of mean, median or frequency components brings only limited knowledge on the actual process hidden behind the acquired data [9].

In recent years there has been a growing interest in the fractal properties of physiological data and also in the context of sEMG signals [10–12]. This work proposes the application of modified Multifractal Detrended Fluctuation Analysis (MFDFA) based on Empirical Mode Decomposition (EMD) to the sEMG signals. The EMD and MFDFA techniques can be used to trace out the features of non-linear and non-stationary signals. Moreover, both methods have a broad spectrum of applications individually. MFDFA, introduced by Halsey et al. [13] and developed later by Kantelhardt et al. [14] has been used in many disciplines and still attracts considerable attention in the field of physiology, economics, climatology, to name but a few. In relation to electrophysiological signals, MFDFA brought a significant contribution to the analysis of heart rate variability [15,16]. For Empirical Mode Decomposition (EMD) an equally wide range of applications can be found such as the removal of artifacts and noise reduction from the signals [17]. EMD also exhibits better results in the process of detrending in comparison, for example, with the typically used least square method [18]. This aspect has been used in the modified detrending algorithm which is presented in this paper. The use of the EMD method in the context of detrending operations results in a more accurate

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trend which is not predetermined and therefore is closely related to the nature of real data [19]. Moreover, it is documented in the literature that this approach outperforms standard MFDFA for large fluctuations [20].

2. Method

2.1. Detrended Fluctuation Analysis (DFA)

The DFA method was first proposed by Peng in 1994 for investigating the correlation in DNA structure [21]. Recent years have seen a renewed importance in the application of this method to biological data and also for distinguishing healthy and pathological states [22]. The basic idea of this technique relies on the assumption that the signal is influenced by the short-term and long-term features. For the proper interpretation of effects hidden behind internal dynamics the signal is analyzed at multiple scales [23]. The brief description of the original DFA algorithm is presented below.

The procedure starts with the calculation of the profile y_i as the cumulative sum of the data x_i with the subtracted mean $\langle x\rangle$:

$$y_i = \sum_{k=1}^{i}[x_k - \langle x\rangle] \tag{1}$$

Next, the cumulative signal y_i is split into N_s equal non-overlapping segments of size s. Here for the length s of the segments we use powers of two, $s = 2^r, r = 4\ldots 11$. For all segments $\nu = 1,\ldots,N_s$ the local trend $y^m_{\nu,i}$ is calculated. In a standard DFA method, the trend is calculated by means of the least-square fit of order m. In this work $m = 2$ was used. The variance F^2 as a function of the segment length s is calculated for each segment v separately.

$$F^2(s,\nu) \equiv \frac{1}{s}\sum_{i=1}^{s}\left(y^m_{\nu,i} - y_{\nu,i}\right)^2. \tag{2}$$

For the last step, the Hurst scaling exponent H is calculated as the slope of the regression line of double-logarithmic dependence, $\log F \sim H \log s$.

2.2. Empirical Mode Decomposition (EMD)

The EMD is an iterative technique which decomposes the signal x(t) into a finite number of Intrinsic Mode Functions (IMFs) $c_i(t)$ and final residual signal $r_n(t)$

$$x(t) = \sum_{i=1}^{n} c_i(t) + r_n(t). \tag{3}$$

The latter can be interpreted as an actual trend. The calculated signal must satisfy two conditions in order to be an IMF: (i) the number of extrema and the number of zero crossings must be equal to or differ at most by one; and (ii) the mean value of the upper and lower envelope defined by local maxima and minima must be zero. The standard EMD method often faces some difficulties, which are recurrently the consequence of signal intermittency referred to as the Mode-Mixing problem. Ensemble Empirical Mode Decomposition (EEMD) [24] and more recent Complete Ensemble Empirical Mode Decomposition (CEEMD) [25] have been proposed in order to overcome this complication. Both methods are based on the averaging over several realizations of Gaussian white noise artificially added to the original signal. For this work however, we use only standard EMD due to the fact that only residual r_n, i.e. the data trend, is needed for further calculations and none of the individual IMFs is considered here explicitly.

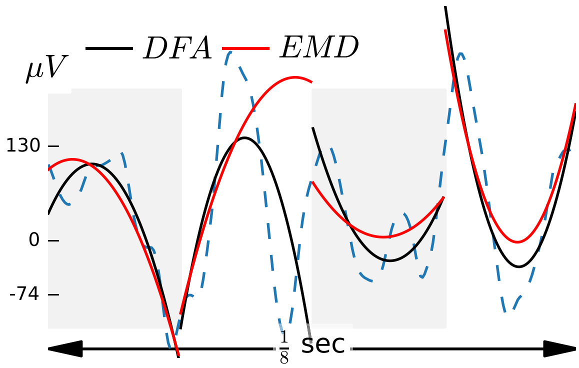

Figure 1. Two detrending methods: DFA (solid black) and EMD (solid red) are presented for the profile y_i of the sEMG example data (dashed blue). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.3. EMD based DFA

The analysis is now branched into a standard DFA algorithm and non-standard based on EMD techniques. The former method uses the least-square estimation of the order m. The latter utilizes the fact that the residual r_n (3) represents the local trend, thus the standard polynomial fit (DFA) can be replaced by a residuum for each segment [26]. An example of local trends calculated with both methods is presented in Figure 1 for the segment size $s = 64$. The slight differences between solid black and red lines, which represent DFA and EMD methods respectively, influence the further results.

2.4. MFDFA

MFDFA is based on the scaling properties of the fluctuations. The brief description of the method is presented below, however, for detailed specification we suggest works by Kantelhardt et al. [14,27], Ihlen [28] or Salat et al. [29]. In order to extend the monofractal DFA (2.1) to the multifractal DFA it is necessary to indicate the qth statistical moment of the calculated variance (2).

$$F_q(s) = \begin{cases} \left(\dfrac{1}{2N_s}\displaystyle\sum_{\nu=1}^{2N_s}[F^2(s,\nu)]^{\frac{q}{2}}\right)^{\frac{1}{q}}, & q \neq 0, \\ \exp\left\{\dfrac{1}{4N_s}\displaystyle\sum_{\nu=1}^{2N_s}\ln\left[F^2(s,\nu)\right]\right\}, & q = 0. \end{cases} \tag{4}$$

Next, the determination of the scaling law $F_q(s) \sim s^{h(q)}$ of the fluctuation function (4) is performed with the use of the log–log dependencies of $F_q(s)$ versus segment sizes s for all values of q separately. The q-order Hurst exponent $h(q)$ is required in order to calculate further dependencies. The mass exponent is obtained via the formula

$$\tau(q) = qh(q) - 1. \tag{5}$$

It is then used to calculate a q-order singularity Hölder exponent $\alpha = \tau'(q)$ where the prime means differentiation with respect to the argument. In turn, the q-order singularity dimension can be constructed

$$f(\alpha) = q\alpha - \tau(q) = q[\alpha - h(q)] + 1. \tag{6}$$

The singularity dimension $f(\alpha)$ is related to the mass exponent $\tau(q)$ by a Legendre transform. The multifractal spectrum, i.e. the dependence $f(\alpha)$ vs α is the final result of MFDFA method.

The mf-spectrum describes how often the irregularities of certain degrees occur in the signal. $f(\alpha)$ represent q-order singularity