MULTISCALE PEAK DETECTION IN EMG SIGNAL ANALYSIS

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Abstract

Electromyography (EMG) represents a method used for the acquisition of electrical activity produced by skeletal muscles. The following analysis based upon the digital signal processing methods can be used to find relation between their neurological activation and separate motor units firing with the typical frequency of 7-20 Hz. Signals obtained can be used for analysis of biomechanics of the human and for the detection of medical abnormalities including those of muscles (myopathy) and neurons (neuropathy). The paper presents the use of wavelet transform for data analysis for the selected decomposition level and the threshold value. Results include (i) the description of the proposed graphical user interface and (ii) comparison of results for healthy and neuropathic patients.

1 Introduction to Electromyography

Electromyography (EMG) is a wide medical area based upon the analysis of muscle activity detecting the relationship between muscle behaviour and neurons. Data acquisition according to Fig. 1 provides signals with their typical samples in Fig. 2 allowing extraction of desired information. Descriptions of these topics started by the paper published by Francesco Redi in 1666 and this area is still widely studied.

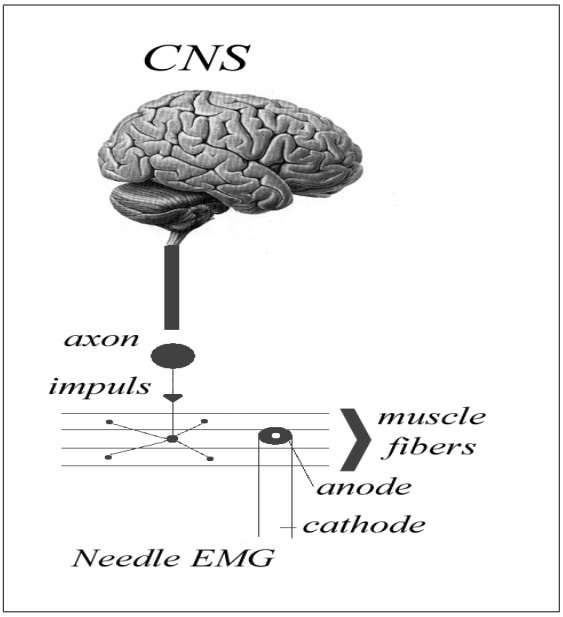

Figure 1: The EMG signal acquisition

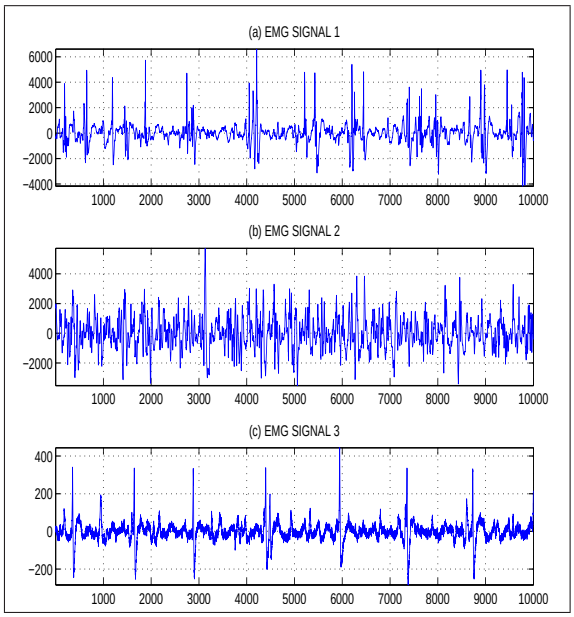

Figure 2: Selected EMG signals

Every human muscle is controlled by Central Nervous System (CNS). The information or impuls is sent from the brain and spinal cord to the individual executive units called axons. The axon then sends an electric impuls through synaptic knobs to bundle of muscles. This transport of information determine whether the muscle should react or not. Its action is followed by the change in balance between ions Na^+, K^+ and Cl^-. EMG signal provides the record of these balances in time in one bundle of muscle fibres, typical is complicated signal, full of the sharp positive/negative vibrations (see Fig. 2).

There are many problems related to peak detection. The main characteristics of EMG signals include duration, amplitudes, firing rates of Motor Units Action Potentials (MUAPs). At a low force of contraction, individual MUAPs can be identified and the extraction of various MUAP parameters can provide valuable data for differential diagnosis [3]. As the force od contraction increases, more MUs become active and the firing rates of MUs already activated increases. The combined effect od these processes at higher forces of contraction produces so many MUAPs that they cannot be distinguished individually in the signal, which is then called the interference pattern (IP) [1].

2 EMG Signal Description

EMG signal is usually taken at increasing level of voluntary muscle contraction. As the level grows, more MUAPs appear, so there is higher frequency and bigger amplitude of combined signal.

2.1 Data Acquisition

To obtain the EMG signal the needle electrode is used. Patient is instructed to control examined muscle from weak effort to maximum effort. This procedure is quite painful, but no other method is known.

2.2 Principles of EMG Analysis

There are many different approaches to EMG data processing and analysis described in many papers and dissertations [8]. Nandekar et al. [10, 2] chose the utilization the spike components of the EMG signal to identify the MUAP discharges and to classify them. Stalberg et al. [4, 9] used a parameter called "the rise time" which measures the time of the main "rising edge" of the MUAPs. The likelihood of the superposition of two MUAP rising edges is low, due to their short time duration, enabling MUAPs to be identified even at high forces of contraction. McGill et al. [5, 6, 7] used a low-pass filter to cut high-frequency noise followed by a differentiating filter to accentuate changes associated with the rapidly rising spike components [1].

3 Mathematical Methods of Signal Preprocessing

A common problem in signal and image processing is in the rejection of signal noise components and the increase of the signal-to-noise ratio. This process involves the correct selection of signal sampling frequency, frequency regions of desired signal components and cut-off frequencies for their extraction.

In most cases the low-pass filter is applied at first to reject signal noise and to reduce the auto-aliasing effect followed by the high-pass filter to remove signal trend components. The EMG signal is nonstationary as its statistical properties change over time. In most cases its sampling rate is greater then 1 kHz affecting possibilities of noise reduction. The MUAPa are transients that exist for a short period of time, which is not identical in all cases. For that reason, time-frequency methods are now being used to characterize the localized frequency content of each MUAP [1]. Most often and even in our case, wavelet transform is used.

4 Principle of Haar Wavelet Decomposition

One of the transforming function, that is suitable for wavelet transform, is the Haar function. We can express its use by relations:

$$d_s(\frac{j+1}{2}) = \frac{1}{\sqrt{2}}(x(j) + x(j+1)) \quad (1)$$

$$d_w(\frac{j+1}{2}) = \frac{1}{\sqrt{2}}(x(j) - x(j+1)) \quad (2)$$

It's obvious that these two vectors will have half length unlike the original one. One signal is downsampled, second one upsampled. These function was used in GUIemg to decomposition into two levels.

5 Proposed Method for Multiscale Signal Peak Detection

This method is inspired from method Interscale Wavelet Maximum - A Fine to Coarse Algorithm of the EMG Pattern [1], but is slightly modified. We use to detect individually peaks a simple thresholding, but in first and second level of discrete wavelet transform of given signal. Then the real count of peaks is reduced, because this method sometimes detect one peak in signal as several neighbouring maxims. The main idea is based on knowledge of changes due to neuropathy disease. Neuropathy causes eliminations of some axons, so their neighbouring axons will adapt themselves. They have to take control over more muscle fibers, that leads to change in their necessary effort. This change can be detected in EMG signal with higher amplitudes and lower frequencies of MUAPs firings.

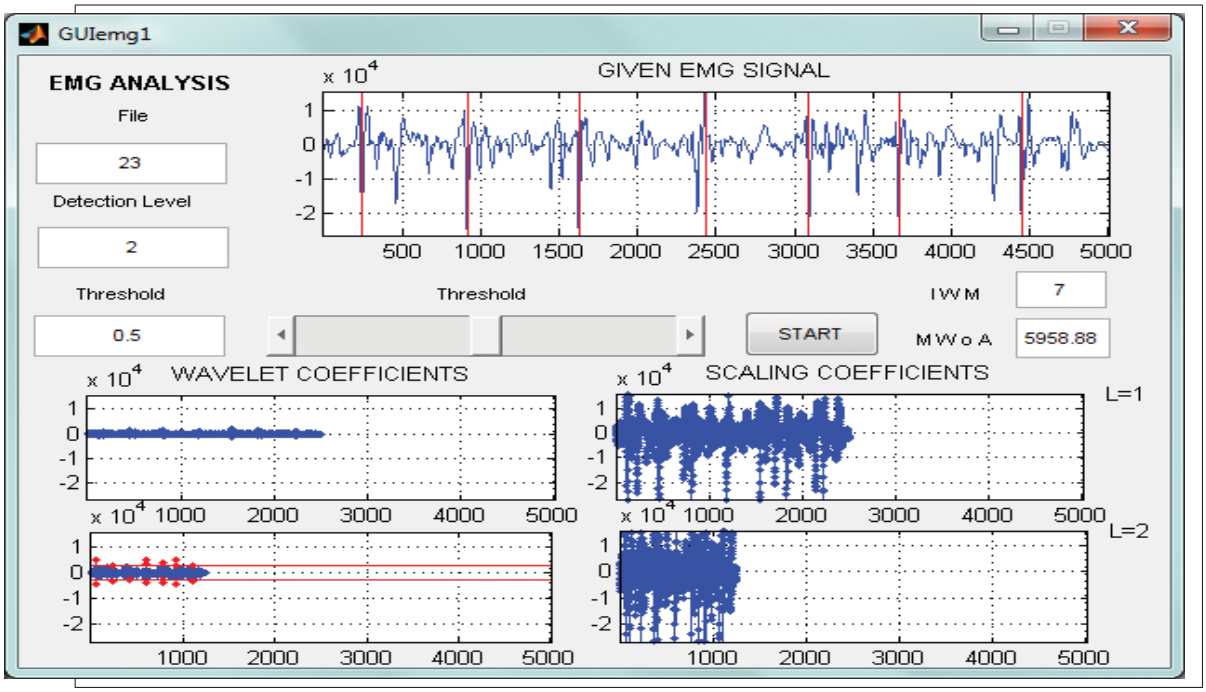

Figure 3: Graphical user interface for EMG data wavelet decomposition and their analysis using selected detection level and the threshold value

6 Results

EMG data from concentric needle electrode were collected on EMG ALIEN Machine with the sampling frequency of 10000 Hz with adjustment $1mV/bit$ for time less than a minute (which is not important as we use the part of the signal only). The data base file is composed of two groups: 40 healthy patients and 30 patients with neuropathic disease.

Figs 4-11 present results obtained for sets of healthy and neuropathic patients. Both Haar and Daubechies wavelet transform was used with different wavelet decomposition levels and threshold values. Each couple of results presents the number of peaks detected and their mean absolute value obtained for the selected part of data observed after their de-nosing.

Comparison of results obtained is presented in Fig. 12. Number of peaks and their mean value is plotted for different threshold values comparing these characteristics for healthy and neuropathic patients.

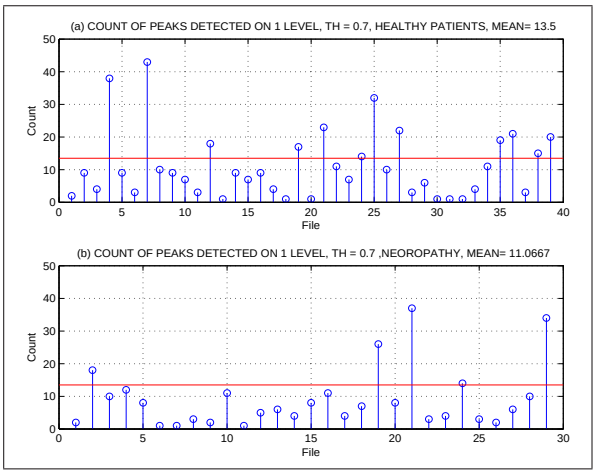

Figure 4: The number of peaks detected on level 1 using the threshold th=0.7 for (a) healthy and (b) neuropathic patients

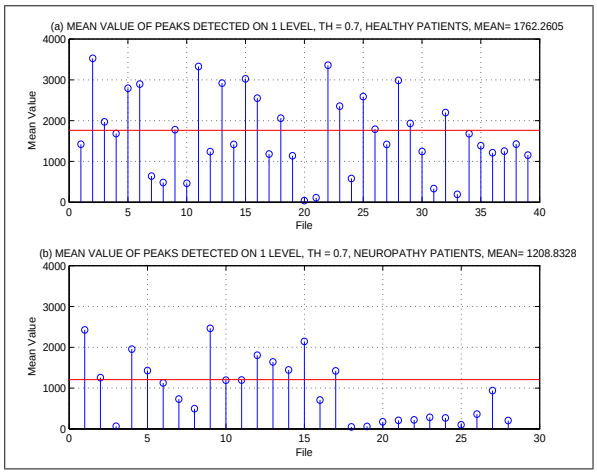

Figure 5: The mean value of peaks detected on level 1 using the threshold th=0.7 for (a) healthy and (b) neuropathic patients

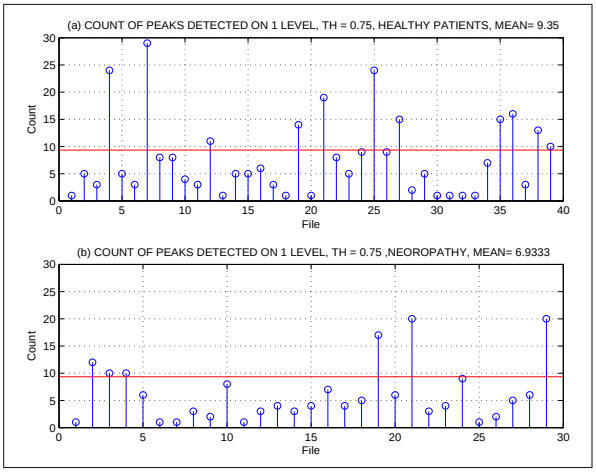

Figure 6: The number of of peaks detected on level 1 using the threshold th=0.75 for (a) healthy and (b) neuropathic patients

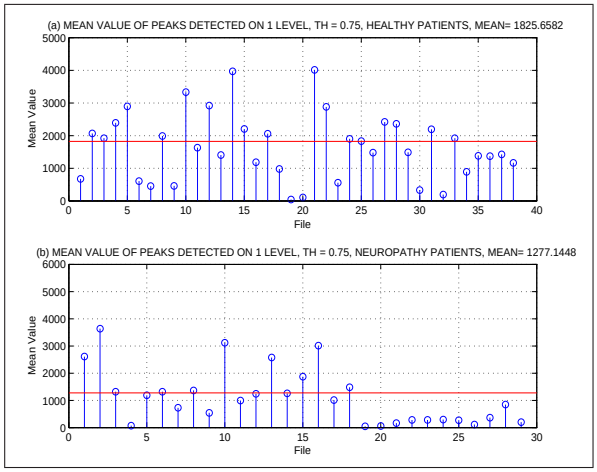

Figure 7: The mean value of peaks detected on level 1 using the threshold th=0.75 for (a) healthy and (b) neuropathic patients

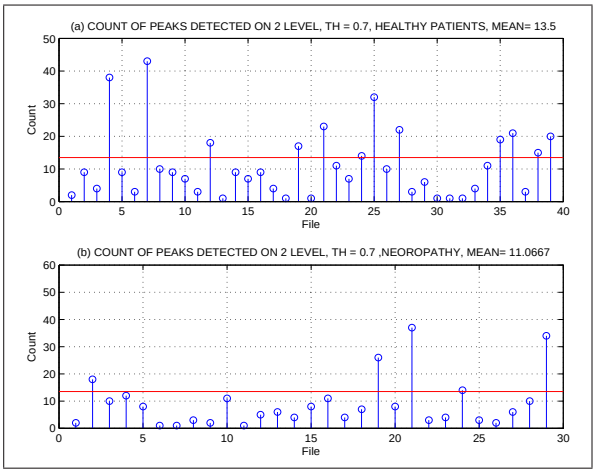

Figure 8: The number of of peaks detected on level 2 using the threshold th=0.7 for (a) healthy and (b) neuropathic patients

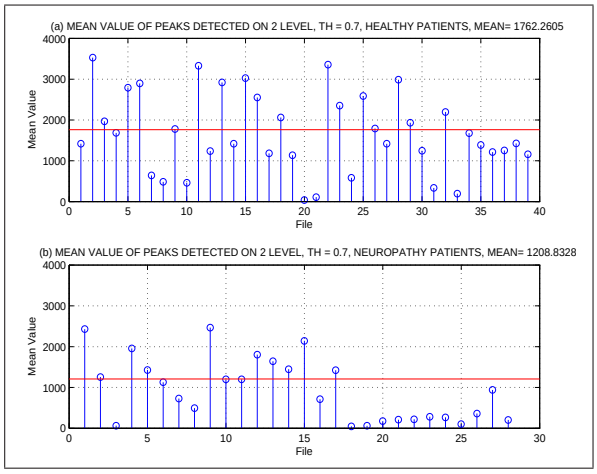

Figure 9: The mean value of peaks detected on level 2 using the threshold th=0.7 for (a) healthy and (b) neuropathic patients

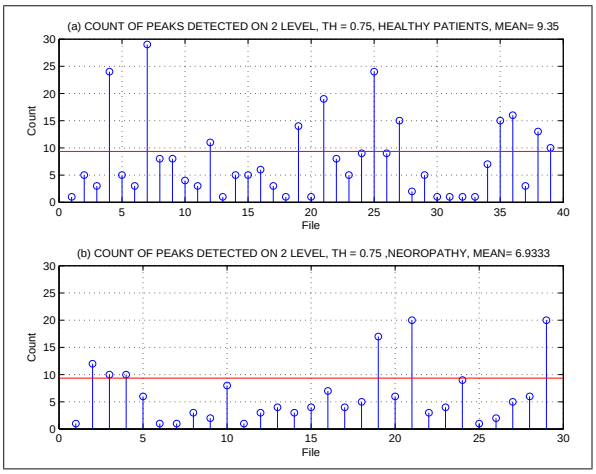

Figure 10: The number of of peaks detected on level 2 using the threshold th=0.75 for (a) healthy and (b) neuropathic patients

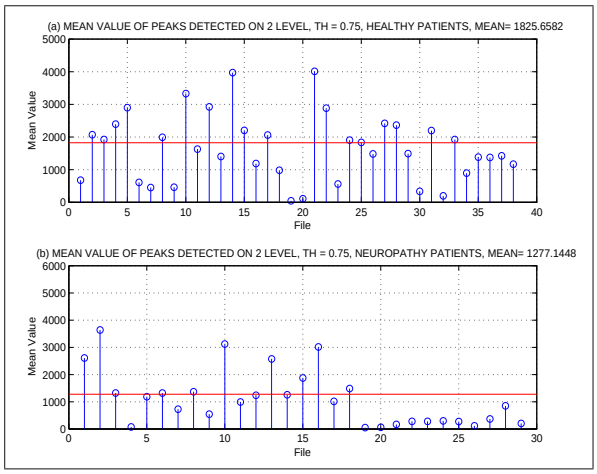

Figure 11: The mean value of peaks detected on level 2 using the threshold th=0.75 for (a) healthy and (b) neuropathic patients

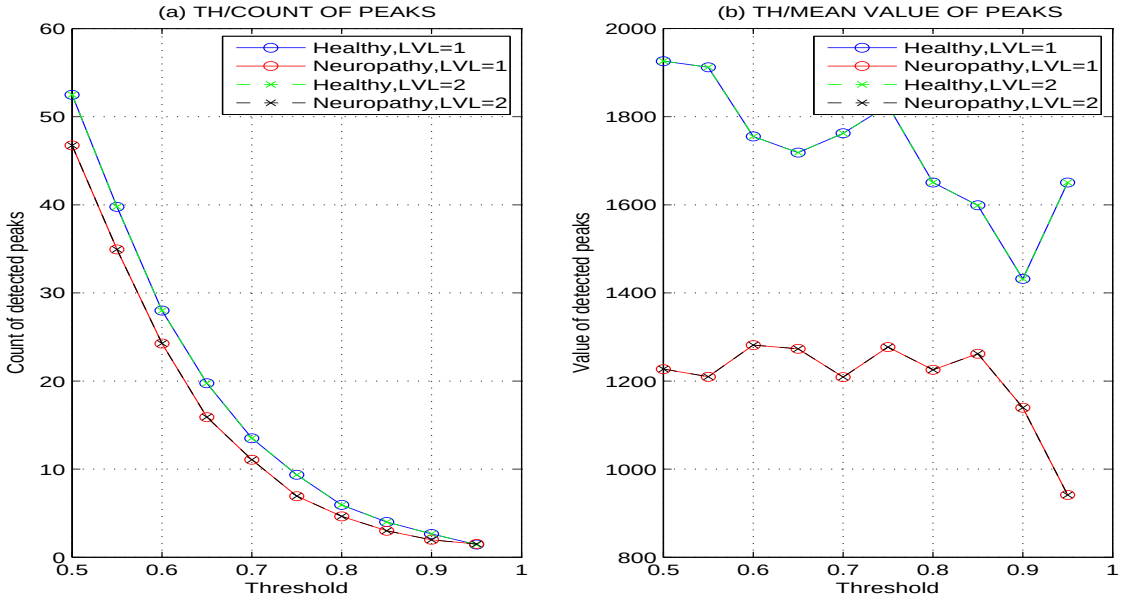

Figure 12: The evolution of (a) the number of peaks and (b) the mean values of peaks for levels 1 and 2 in relation to the threshold value comparing results for healthy and neuropathic patients

7 Conclusion

Fig. 12 presents the average frequency of peaks and their average value for different detection methods after the removal of incorrect observations. It is possible to find the significant difference of these average values between the set of 40 healthy people and the set of 30 patients with neuropathy for all threshold values allowing signal classification using signal wavelet decomposition.

Further interest will be devoted to analysis of the Receiver Operating Characteristic (ROC) curve to reveal optimal threshold. This method will be also devoted to the detection and analysis of data sets of healthy patients and patients with neuropathy. Further methods will be used for detection of further diseases (myopathy, multiple sclerosis) that can be observed using EMG records as well.

Aknowledgement

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