Arm EMG Wavelet-Based Denoising System

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Abstract. These paper presents research results of muscle EMG signal denoising. In the same time two muscles were examined – an adductor muscle (*biceps brachii*) and an abductor muscle (*tricpeps brachii*). The EMG signal was filtered using the wavelet transform technique, having selected the crucial parameters as: wavelet basis function (*Daubechies 4*), 10^{th} decomposition level, threshold selection algorithm (*Heurestic*) and a sln rescaling function (based on scaled white noise). After denoising the signal, a short analysis of the outcome signal is performed. Such developed system has a wide application possibility, mainly in Mechatronic systems where it can be used for example in teleoperation of a robot arm, control signals for a prosthetic arm, biomedical signal filtering or in rehabilitation aiding robots.

Keywords: signal denoising, wavelet transforms, muscle EMG.

1 Introduction – EMG

Electromyography (EMG) is one of the most frequently used diagnostic techniques of peripheral nervous system – both in conventional and sports medicine. Muscle contraction is an effect of the nervous system functioning, therefore EMG is useful in diagnostics of various diseases associated with muscle reaction (contraction and relaxation) [1], and even in speech synthesizer development [2]. As a test method, EMG has been completely recognized and mastered, that makes the purchase of devices equipped with appropriate sensors and data acquisition modules achievable. The examination of electrical potential generated by muscle cells during contraction and relaxation is the essence of the EMG [3]. The value of the potential varies in relation to the signal from the central nervous system and at rest is determined at the level of about 70 mV (it may vary depending on the muscle size [4]). The electrical signal transmitted from the synapses to the muscle alters the value of the cells membrane potential in the range of 50 μV to 30 mV. Hence, by the usage of appropriate sensors, the detection of these changes results in a continuous signal. In turn, the muscle condition may be estimated based on the potential change in the received signal. Then all collected information may also be used to determine the values of all the exoskeleton parameters, e.g. the force of a moved limb or the angle of the bended limb. Currently, EMG may be performed non-invasively via the sensors placed directly on the skin.

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Many companies offer various models of electrodes of high sensitivity and accuracy, e.g. Delsys co., which offers sensors of 1.2 μV accuracy. A sensor generates continuous voltage signal depending on the potential level of an examined muscle. However, the recorded signal is exposed to many disturbances of external and internal origin. Electromagnetic interference, drift of reference electrode or high frequency noises occurring during the measurement are the main cause of this disturbances. Frequency spectrum of this noises overlap the spectrum of the signal, therefore the problem with filtration of EMG signal is a complex one.

During the EMG examinations, each time the sensors is placed by the user in a slightly different location. Therefore, it is appropriate and well-founded to conduct the research on the influence of sensor placement on the final result of the measurement. It is crucial to determine whether the sensors displacement of millimetres leads to the significant errors, and whether to allow the user's latitude in placing the sensor. In the case of EMG, the sensor displacement leads only to shift in the time of the signal graph, no significant differences in the levels or nature of results obtained have been noted [5].

2 Wavelet Denoising in EMG

Wavelet analysis provides a powerful tool for signal analysis and in comparison with Fourier analysis, it allows to distinguish precisely both, the time and the frequency contents, and therefore enable to read many diagnostically useful information not only for the EMG signal but also for other biomedical signals [6]. Studies that used muscle bioelectric signals wavelet filtration provided significant and interesting findings.

In the study [7] wavelet analysis was used to decompose the EMG signal of people affected by Parkinson's disease, significantly expanding knowledge of the nature of involuntary contractions in relation to that used by treatment of Parkinson's. In the study [8] the authors use a new, original method – interscale wavelet maximum to support the diagnostic methods of neuromuscular diseases. Application of wavelet analysis allowed for separation of the unwanted measurement noise, allowing for searching of pathological signs of myopathy and neuropathy in the given test result. Studies [9] assumed applying wavelet analysis to assess the muscle fatigue, while the studies [10] and [11] wavelet filtration was used to support the analysis and classification process of EMG signals in an active hand prosthesis.

3 Upper Arm EMG Filterning

Literature studies showed a lack of information regarding wavelet filtering of the *biceps brachii* and *triceps brachii* EMG signals. In order to cover that gap, research studies were carried out in the area of muscle tension during a simple pulling procedure.

The experiment procedure involved pulling a stationary newton meter, applying up to 20 N pulling force. The position of the arm during the experiment was planned in a way to extort the arm from a rest position into full extension and then back to a rest position. That way, it would be expected, the triceps muscle would have to overtake most of the force needed for the move. The role of the biceps muscle in that move was to be seen. Moreover, certain exact values correlated with the pulling force (from 0 N to 20 N and then back to 0 N) were possible do estimate.

In the experiment a NeuroTrack MyoPlus 2 electromyography device was used. Five signal electrodes were placed – two measurement electrodes and one reference electrode were placed on the *biceps brachii*, two other measurement electrodes were placed on the *triceps brachii*.

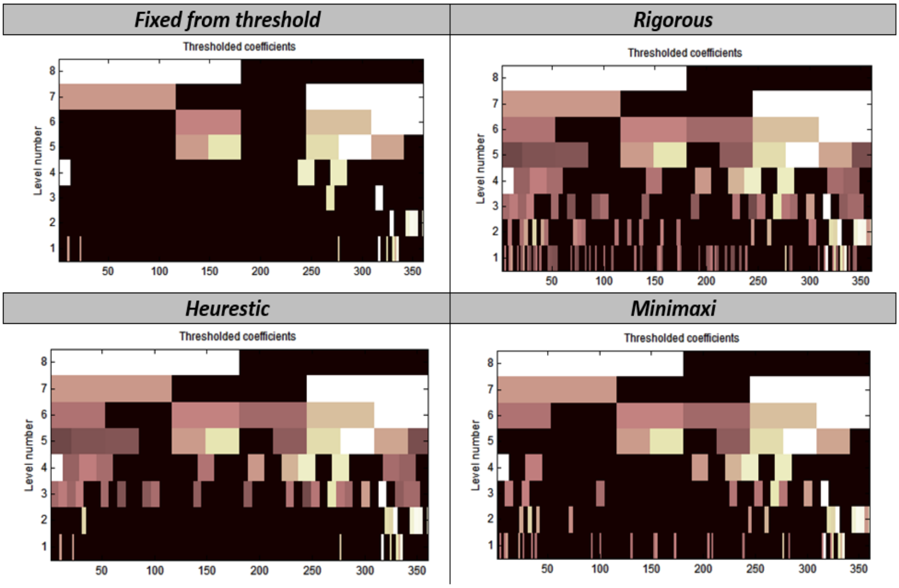

Fig. 1. Comparison of wavelet details involved in signal filtering

To properly reject the noise content from the signal a number of parameters should be considered. Firstly during the signal's decomposition an appropriate decomposition level and subsequently, the wavelet basis function should be selected thoughtfully. To prevent data losses only orthogonal wavelet basis should be taken into account. Previous studies have shown that the *Daubechies 4* (*db4*) basis is the most effective for analysing EMG signals [12]. Therefore, it can be assumed that the wavelet will also be best in filtering of the signal, and therefore, it was selected.

Wavelet filtering exploits the fact that some of the signal details relate to the average value of the signal, while other to an average noise value. Therefore, if less important details related to noise are removed, the signal can be reconstructed on the basis of other details, without loss of significant information contained in the signal. On that basis, the next very important step is a selection of the appropriate threshold. To do this, it is essential to choose an appropriate threshold algorithm (Table 1) and the corresponding threshold scaling function.

Table 1. Threshold selection rules [13]

Name	Description
Rigrsure	Adaptive threshold selection using principle of Stein's Unbiased Risk Estimate
Sqtwolog	Threshold is equal to sqrt(2·log(length(X)))
Heursure	Heuristic variant of above options
Minimaxi	Minimax thresholding principle

The comparison of wavelet coefficients for different threshold selection algorithms is presented in the Fig. 1. Thoughtful analysis of obtained results leads to the conclusion, that during the reconstruction of the signal with the *Sqtwolog* threshold selection algorithm, fewer coefficients are involved in the reconstruction. Therefore, the reconstructed signal can be considered as losing too much information. On the other hand, the *rigrsure* threshold method uses the biggest number of coefficients in the reconstruction process and may be considered as leaving too much noise.

The *minimaxi* threshold selection algorithm removes more coefficients from 1–6 levels than the *heuristic* method, which removes more coefficients from 7–10 levels. Therefore, the *heuristic* algorithm may be found as the best removing noise from the EMG signal. However the lower details are correlated with lower frequencies and are related to the noise. Taking all that into consideration, it can be stared, that the *Heurestic* method is the best among all the other mentioned above and delivers the best filtered signal.

The next step is to choose a threshold rescaling function. In MATLAB toolbox, three algorithms are available: a method based on basic white noise (*one*), scaled white noise (*sln*) and noise model with non-white noise algorithm (*mln*). The comparison of rescaling methods is presented in the Fig. 2 where the details (d_1–d_{10}) of decomposed EMG signal are also presented. The values of the details that are not within determined threshold range are removed from the signal. Using the algorithm based on the white noise model, most of the details are deleted and the important information contain in the signal is lost, so therefore this method is unusable in this situation. One must note, that most of the noise acquired with the signal is white noise. The *mln* rescaling method basis on (black in the Fig. 2) does not effectively remove the noise. In this case, the determined thresholds are too low and almost the whole signal is classified as the original signal, and consequently none of its details are removed. Hence, threw comparison, the best method that can be used is the scaled white noise method (*sln*).

What is more, it can be observed, that the 10th decomposition level is the most suitable one, because the details from each of levels actively participate in the signal denoising process.

Moreover, the soft tresholding method was used during the whole procedure of finding the best rescaling threshold function. This is due the fact, that the method provides high reliability in a lack of discontinuity of the filtered signal [13, 14].

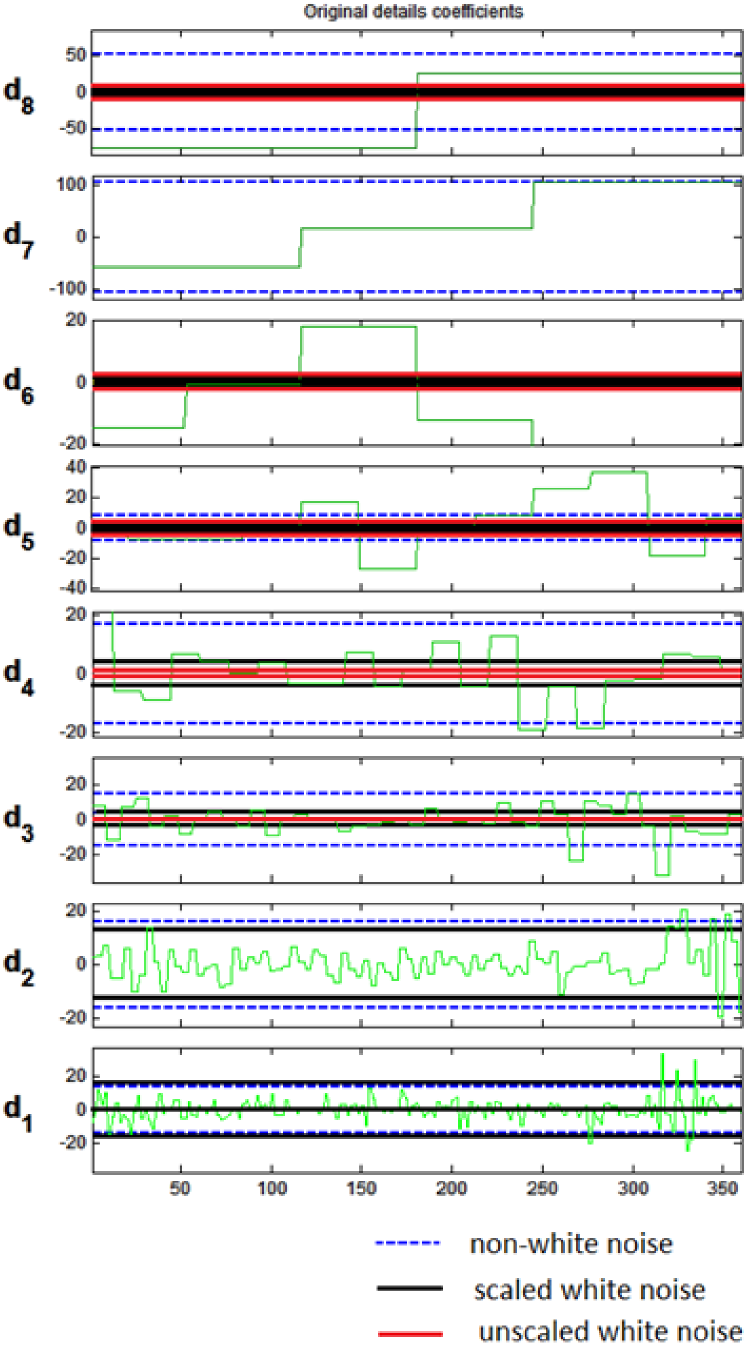

Fig. 2. Threshold rescaling function comparison

4 Data Analysis

The EMG data obtained during the experiment was filtered using the parameters described in paragraph 3. The results are shown on Fig. 3 and Fig. 4. As it can be observed, thanks to the applied wavelet denoising procedure, a clear EMG signal was obtained.

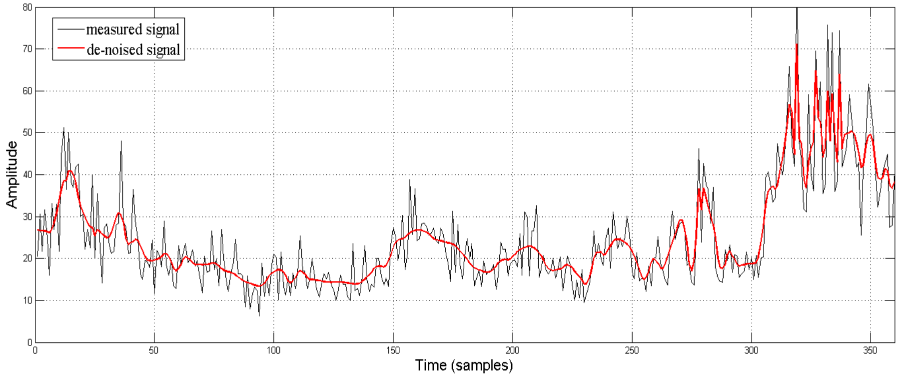

Fig. 3. Filtered biceps muscle EMG signal during contraction

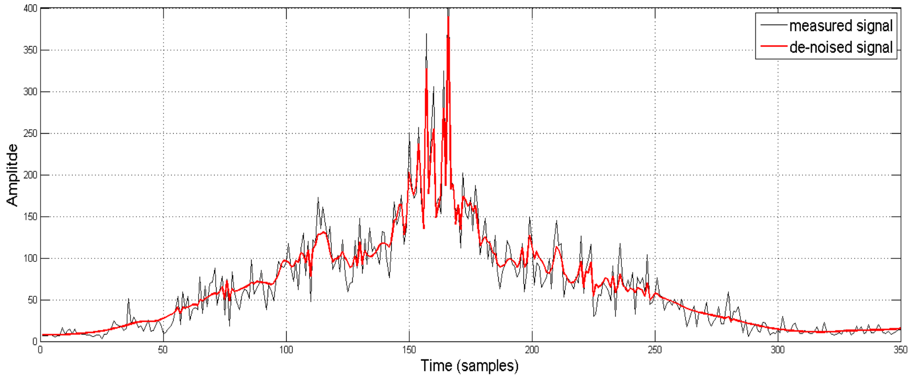

Fig. 4. Filtered triceps muscle EMG signal during contraction

The results shown of Fig. 3 matched the expectations adopted at the beginning of the experiment. During the arm's move the triceps muscle contracted gradually. When the pulling force was 20 N (at the extreme value) the registered muscle EMG signal was 400 mV. The triceps muscle should be maximally contracted at that point. The EMG signal confirms that theory. At this point, it can be observed that the *biceps muscle*, did not contract much. On the contrary, Fig. 4 shows that since the beginning of the move, its contraction weekend to the extreme value point (around 180 s). What can be surprising is that during the second part of the arm's movement (pulling force from 20 N to 10 N), the biceps muscle should behave as in the first part of the movement. Yet, the Fig. 4. clearly shows muscle contractions at the end of the movement. Their values and frequency indicate fast and strong contractions. This can be a sign of muscle vibration. During the arm's movement the *biceps muscle* acted more like a stabilizing mechanism and it is likely that at the end of the movement the muscle's fatigue factor occurred.

5 Conclusion

Wavelet filtration of the muscle's EMG signal provides sensible and reliable effects, when all of the wavelet denoising parameters are selected properly. In this paper the best wavelet denoising parameters of arm EMG signal filtration are found, that is: wavelet (Daubechies 4), 10th decomposition level, threshold selection algorithm (Heurestic) and a sln rescaling function (based on scaled white noise). Moreover, the EMG signal analysis clearly showed that both muscles, the *biceps* as well as the triceps, were involved in the arms movement, one muscle acting as the main mover, the second more as the arm's stabilizer.

This system has wide application possibility, mainly in pre-processing in many Mechatronic systems. The denoised EMG signals, such as we can see in the Fig. 3. and Fig. 4 can be used in a practical matter, as for example, control signals for a prosthetic arm, in teleoperation of a robot arm, biomedical signal filtering [15] or in rehabilitation aiding robots.

Further research should be focused on the development of suitable arm recognition system, which e.g. could base on LPC feature extraction algorithm [16, 17], combined with neural network or swarm classifier [18].

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