WAVELET DENOISING EMG SIGNAL USING LABVIEW

Bonilla Vladimir
post graduate
Litvin Anatoly
Candidate of Science, assistant professor
Deplov Dmitriy
Master student
Shapovalova Yulia
Ph.D., assistant professor

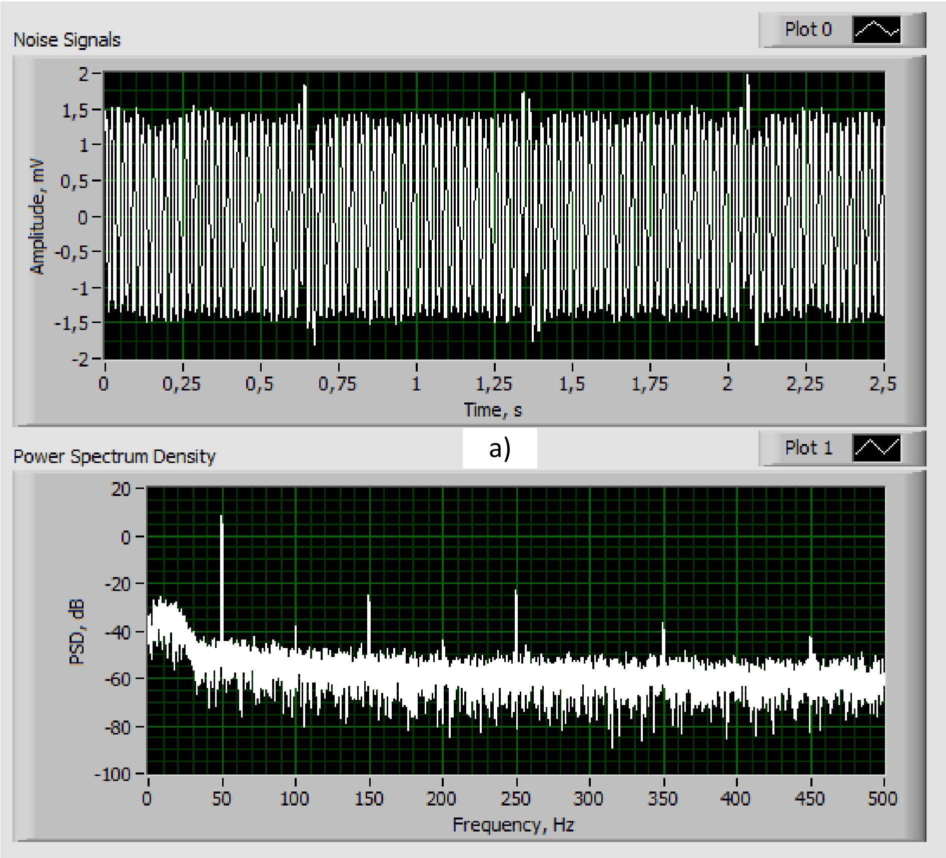
Introduction. Over recent times electromyography (EMG) have attracted a great deal of attention in medical rehabilitation engineering. Surface electromyography (sEMG) has numerous advantages in practical use. sEMG is a complex biological signal generated during the skeleton muscle contractions and not alone being consistent with the muscles contraction but also with the neuromuscular control system [1]. sEMG contains information about physiological action of a patient. For this reason, sEMG is widely applied in motion recognition, and bioelectrical control of mechatronic devices [2]-[3].

An unfiltered and unprocessed surface electromyography signal is called a raw sEMG signal. The raw sEMG signal is a complex signal having different noises and interfering components therefore its analysis is rather difficult and it can’t be used for mechatronic control.

Interference and noise sources can be divided into internal and external. The internal noises are a physiological noise and the noise of the electrodes, for example: EMG other muscles; noise associated with the functioning of other organs such as the heart or stomach. External sources affect the processes of registration that can be the effect of lightning discharges, interference from operating industrial equipment, etc., To remove noise from the raw sEMG signals band-pass and lattice filters are usually used however, such denoising change the signal removing useful information [4].

The aim of the study is to analyze the interference and noise nature of sEMG signal and to compare of the methods of wavelet and digital filtering denoising of raw sEMG.

Experimental study. The study was made in two stages. In the first stage the noises signals were recorded by using the Ag/AgCl bipolar surface electrodes with 5 mm in diameter, located 20mm apart, and the sampling rate to be 1 kHz (Fig.3). The subject' skin was shaved and cleaned with an alcohol in order to have a good skin contact with the electrodes. The sampling data were amplified by 2300 times and pre-processed with band pass filter having cut frequencies 10 and 250 Hz then were passed through NI ELVIS into LabVIEW [5]. During the recording of the noise and interference the subject's right hand was motionless, i.e., the biceps was not reduced.



b)

Figure 1. Noises induced on the electrodes installed on the right M. Biceps Brachii: a) - the total interference; b) - the spectral power density of the total noise.

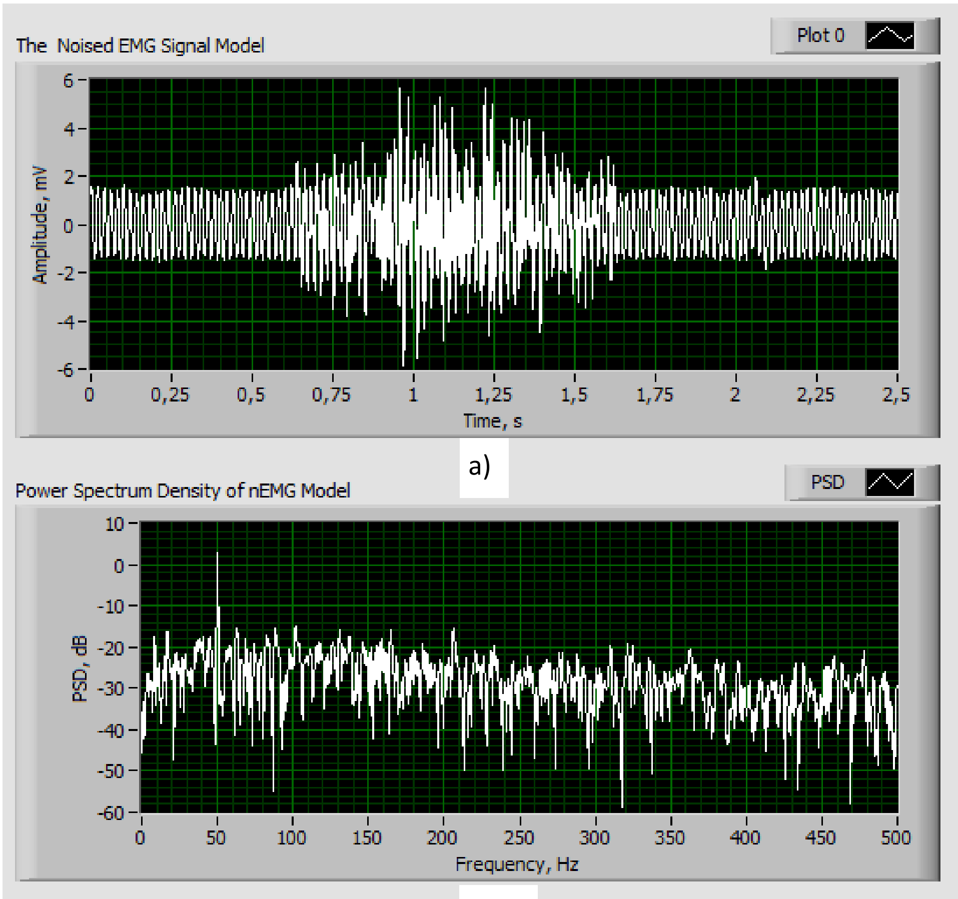
We investigated the noises and interferences caused by the operation of industrial equipment, electric lines, EMG signals of skeletal muscles and heartbeat.

Figure 1 shows the total noise and interference induced by the 0.55 kW three-phase asynchronous electromotor at a distance of 0.5 - 1 m, the 50 Hz electric lines, EMG of skeletal muscles due to rotations of the trunk and the ECG signal.

The study showed that the high power spectrum densities were observed in the 50 Hz electric lines interference and its odd harmonics.

In the second stage of study of EMG signals without interference and with interference was simulated using as raw EMG the signal from the LabVIEW biomedical signals data base.

Figure 3 shows the simulated EMG signal and the power spectrum density of the signal. The odd harmonics of noise and interference is not evident in the spectrum of the EMG signal due to high biopotentials at these frequencies.



б)

Figure. 2. The simulated EMG signal with noise (a) and the power spectrum density (b).

To denoise the EMG signal discrete wavelet transform (DWT) was used. It is known that the DWT of a signal x is calculated by passing it through a series of filters. According to Mallat's and the common notation [6] the samples first are passed through a low pass filter with impulse response h resulting in a convolution of the two. The signal x is also decomposed simultaneously using a high-pass filter g

However, since half the frequencies of the signal have now been removed, half the samples can be discarded according to Nyquist's rule. The filter outputs are then subsampled by 2:

$$y_l[n] = \sum_{k=-\infty}^{\infty} x[k]h[2n-k] \tag{1}$$

$$y_h[n] = \sum_{k=-\infty}^{\infty} x[k]g[2n-k] \tag{2}$$

This decomposition has halved the time resolution since only half of each filter output characterizes the signal. However, each output has half the frequency band of the input so the frequency resolution has been doubled.

The denoising based on DWT is fulfilled in three steps:

Step 1. The DWT transforms of the EMG signal;

Step 2. Defying thresholds of wavelet coefficients;

Step 3. Reconstruction of the EMG signal by using inverse wavelet transforms with thresholded wavelet coefficients.

The four classical thresholds are generally used: universal, SURE, minimax and hybrid.

The noise from the simulated EMG signal was removed using the LabVIEW VI “wavelet denoise”, its setup window is shown at figure 3. The following mother wavelets were analyzed to denoise the simulated EMG signal: Daubechies, Haar, coiflets, simlets; biorthogonal wavelets The choice of the wavelet is determined by the shape of the sEMG signals. The results of denoising the noised EMG signal is shown in the table. The smallest error was observed in the case when the mother wavelet coif5 of level 6 with thresholding rule “Minimax”was used (Table).

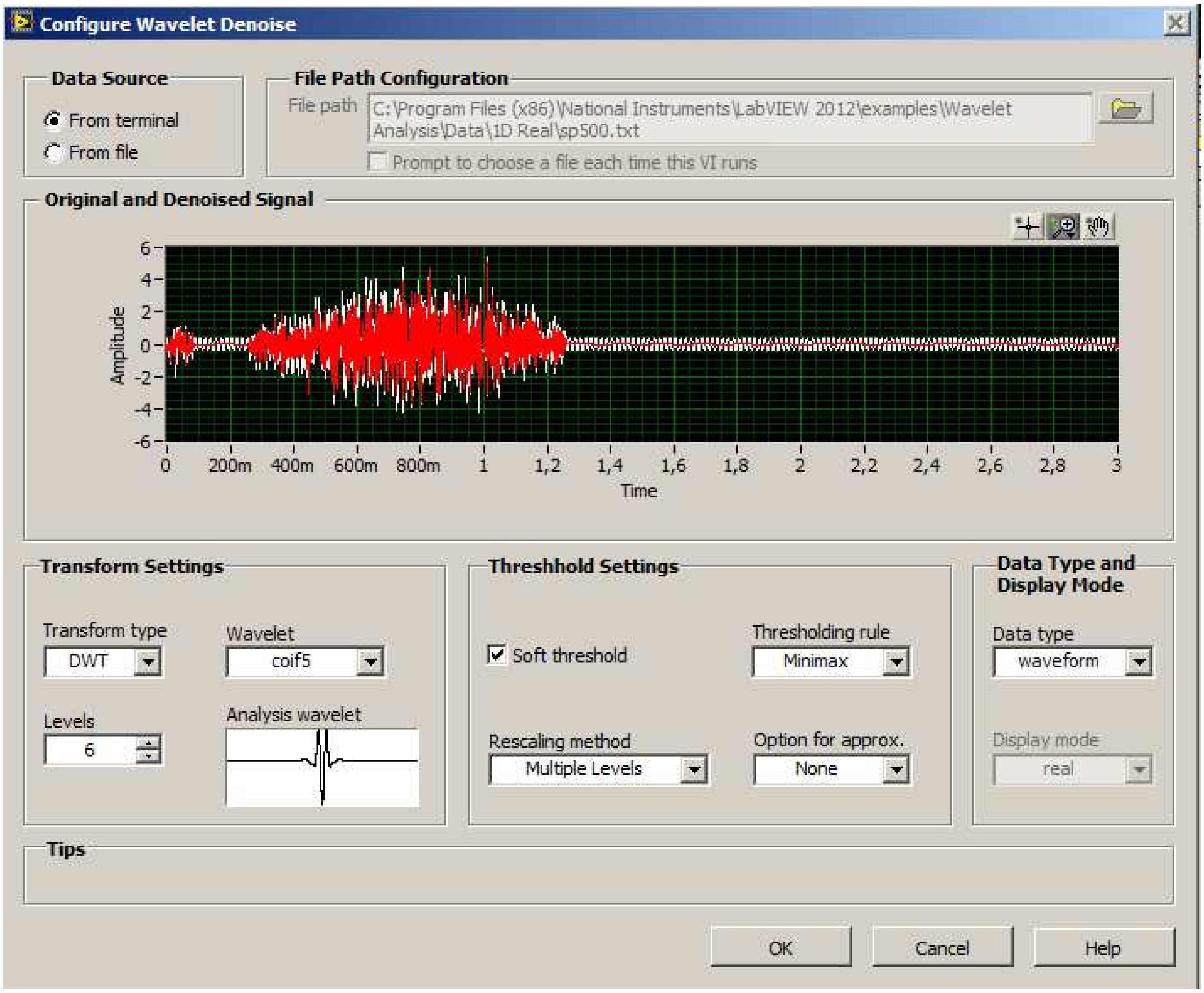


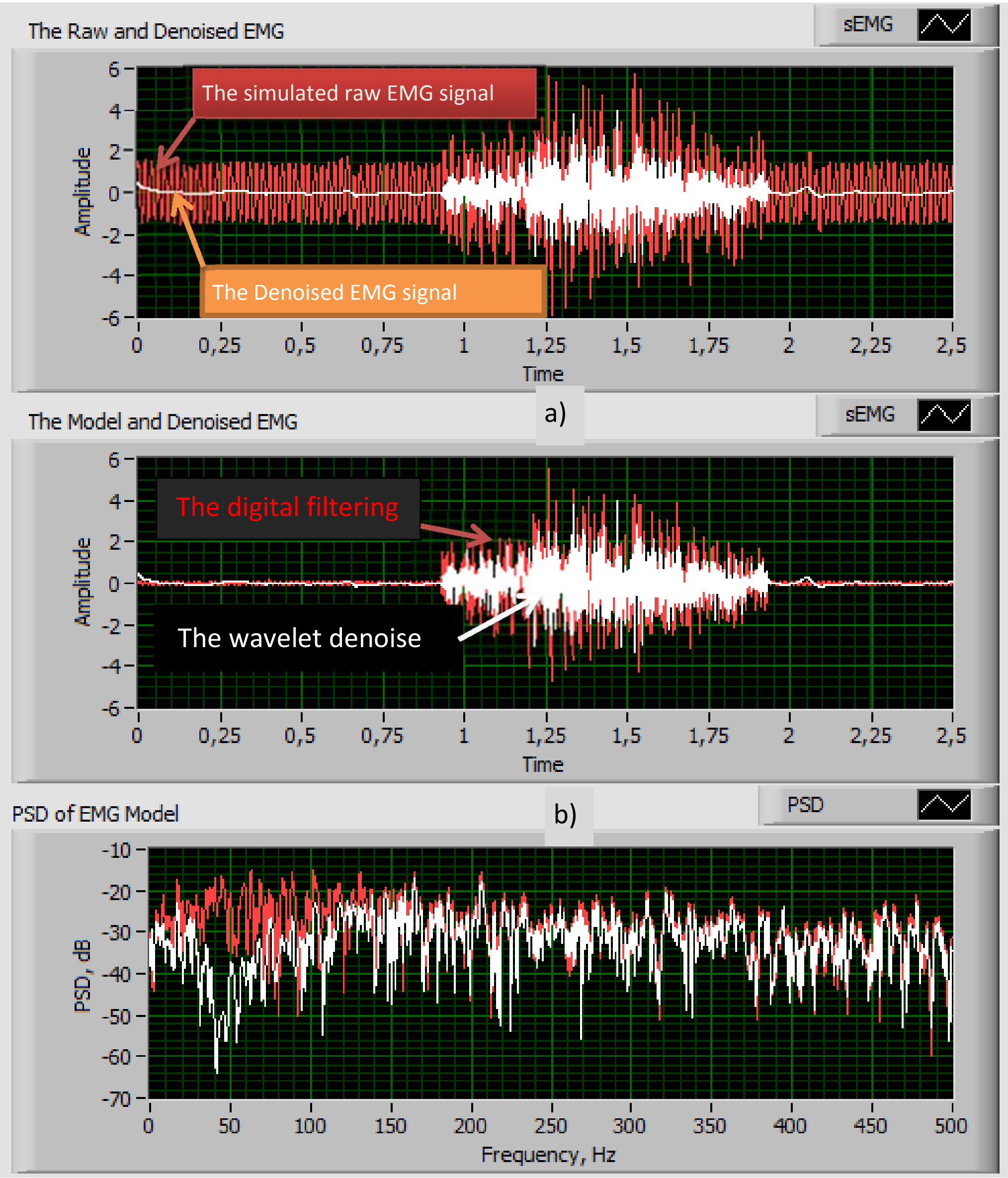
Figure 3. Setup window of wavelet denoise

Table. Standard deviation of EMG signal after denoisin

Mother wavelets									
DF	db4	db6	haar	coif3	**coif5**	sym3	sym6	bior 3.7	bior 3.9
Standard deviation, мV									
0.997	0.561	0.538	0.719	0.524	***0.506***	0.586	0.525	0.561	0.566

In the above table: DF - digital filtering: the Butterworth 4th order band-pass filters with cutoff frequencies of 10 and 250 Hz and notch filters -50 and 150 Hz.

Figure 4 shows the results of the simulated EMG signal denoising using coif5 wavelet at different threshold values compared with digital filtering.



c)

Figure 4. The simulated EMG signal and the power spectrum density: a) – the noised EMG signal and after wavelet denoising; b - the digital and wavelet denoising of EMG signal; power spectrum density of the digital filtered (red) and wavelet denoise (white) EMG signals.

Conclusion. The carried out researches have allowed to define the main components of the noise and interference present in the real-life sEMG signal, and to estimate their amplitude, frequency and spectral characteristics. To construct the wavelet filter were selected generating function of the coiflet class that provides the minimum standard deviation when denoising the EMG signals. It is shown that the wavelet transform coif5 6 level with threshold rule "minimax" provides quality filtration of the noise and interference from EMG signals, which improves the reliability of bioelectrical control of mechatronic devices.

REFERENCES

1. Stroeve, S. A non-linear, combined feedback and feedforward, learning control model for multiple degrees of freedom musculoskeletal systems, applied to the control of a human arm model / Stroeve S// Proceedings of the First Conference of the ISG A non-linear control model –Режим доступа: http://internationalshouldergroup.org/files/proceedings1997/stroeve.pdf/ (Дата обращения 25.02.2015)

2. 2. Shenoy , Pradeep Online Electromyographic Control of a Robotic Prosthesis / Shenoy Pradeep . [et al] // –Режим доступа: http://homes.cs.washington.edu/~rao/emg-08.pdf. (Дата обращения 25.02.2015)

3. Pradeep Shenoy Online Electromyographic Control of a Robotic Prosthesis/ Pradeep Shenoy , Kai J. Miller, Beau Crawford, and Rajesh P. N. Rao IEEE Transactions on biomedical engineering, VOL. 55, NO. 3, MARCH 2008.

4. Konrad, P. The ABC of EMG A Practical Introduction to Kinesiological Electromyography.- Version 1.4, March 2006.- Noraxon INC / P. Konrad. - Режим доступа: http://www.noraxon.com/docs/education/abc-of-emg.pdf.

5. Бонилья, В. Ф. Анализ сигнала ЭМГ двуглавой мышцы плеча в среде LabVIEW/ Бонилья, В. Ф. , А. В. Литвин, Е. А. Лукьянов, А. Н. Чернышов// Инновации, экология и ресурсосберегающие технологии (инэрт-2014).- Труды XI международного научно-технического форума.- Ростов-на-Дону 2014, с. 1394-1401.

6. Mallat, S. G. A Theory for Multiresolution Signal Decomposition: The Wavelet Representation / http://www.cmap.polytechnique.fr /~mallat/papiers/ MallatTheory89.pdf