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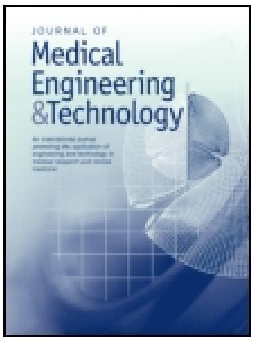

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INNOVATION

Comparative study of wavelet denoising in myoelectric control applications

Tanu Sharma[a] and Karan Veer[b]

[a]Global College of Engineering and Technology, Ropar, India; [b]Department of Electrical & Instrumentation Engineering, THAPAR University, Patiala, India

ABSTRACT
Here, the wavelet analysis has been investigated to improve the quality of myoelectric signal before use in prosthetic design. Effective Surface Electromyogram (SEMG) signals were estimated by first decomposing the obtained signal using wavelet transform and then analysing the decomposed coefficients by threshold methods. With the appropriate choice of wavelet, it is possible to reduce interference noise effectively in the SEMG signal. However, the most effective wavelet for SEMG denoising is chosen by calculating the root mean square value and signal power values. The combined results of root mean square value and signal power shows that wavelet db4 performs the best denoising among the wavelets. Furthermore, time domain and frequency domain methods were applied for SEMG signal analysis to investigate the effect of muscle-force contraction on the signal. It was found that, during sustained contractions, the mean frequency (MNF) and median frequency (MDF) increase as muscle force levels increase.

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Electromyography; muscle contraction; wavelet; denoising; mean frequency

1. Introduction

The surface electromyography signal collected from the skin surface using non-invasive bipolar electrodes has been widely used in many clinical and biomedical applications. At present, there are three common applications of the EMG signal—first, determining the activation timing of the muscle, i.e. when the excitation to the muscle begins and ends; second, estimating the force produced by the muscle; and third, obtaining an index of the rate at which a muscle fatigues. Recently, the scope of SEMG has widened, with the development of advanced signal processing methods.[1]

Once appropriate algorithms and methods for EMG signal analysis are readily available, the nature and characteristics of the signal can be properly understood [2] and hardware implementations can be done for various EMG signal-related applications. So far, research and extensive efforts have been made to acquire and process EMG signals using better algorithms, upgrading existing methodologies, improving detection techniques to reduce noise, etc. Varieties of noise originating from measuring instruments are major problems in the analysis of SEMG signals.

During the last two decades, many extraction techniques like time domain, frequency domain and the time-frequency domain have made it practical to develop advanced EMG detection and analysis procedures. However, frequency domain features like mean frequency (MNF) and median frequency (MDF) show better performance than other-domain features in the case of assessing muscle fatigue.[3–5] These parameters have been shown to be affected by firing statistics of the motor units and conduction velocity of the muscle fibres (directly related to the diameters of the muscle fibres). Research studies [6] have reported the relationship between the median frequency of SEMG and muscle conduction velocity (MCV) at various level of contractions. The choice of right wavelet function becomes important to achieve the optimal performance.[7]

Wavelet denoising algorithms proposed by Donoho [8] are often used for SEMG signals. The objective of this present investigation was to develop a system to assess the effect of different voluntary contractions on muscle activities for the design of an above-elbow prosthetic arm.

The result shows that the wavelet-based noise removal technique using wavelet function Db4 works best to remove interference noise from the SEMG signals. After removing the noise, time frequency domain analysis was introduced for analysing the effect of voluntary contraction on sEMG signals. The analysis also determines the effectiveness of the wavelet-based denoising method. The study presents the usefulness of mean frequency (MNF) and median frequency (MDF) in electromyography analysis, especially during voluntary contraction. In order to analyse the EMG signals, the effects of muscular force contraction and electrode placement were given more attention.

CONTACT Karen Veer karan.una@gmail.com Department of Electrical & Instrumentation Engineering, THAPAR University, Patiala, India

1.1. Previous work

The main issues to be noticed while comparing the results against previous studies are: electrode placement sites; acquisition set ups; subject protocols and the ways of presenting recoded data; and there is always non-uniformity in these parameters, hence it is hard to compare results with previous studies.

The paper is organized as follows: section 2 presents signal acquisition and wavelet analysis sub-divided into wavelet denoising and feature extraction. In section 3, experimental results are presented and, finally, discussions and conclusions are given in sections 4 and 5.

2. Materials and methods

2.1. Computer synthesized sEMG signal acquisition and processing

The myoelectric signals (MES) were detected by using two silver–silver chloride surface bipolar electrodes placed on the muscle under investigation with an electrolyte gel applied to the skin with a distance of 1 cm between the electrodes, i.e. biceps brachii muscle, which generally has a larger diameter. A reference electrode was attached near the forearm at a distance of 5 cm from the muscle of interest. The myoelectric signals recorded from the biceps brachii muscle were differentially amplified at two different stages with a gain of 5000 at a sampling frequency of 1 kHz for 3 s. Then signals were band pass filtered with a pass band frequency of 10–500 Hz.[9,10] In order to understand the signal's characteristics, the signals were recorded from the biceps brachii and triceps brachii muscles at low, medium and high voluntary contractions under isometric conditions. The whole process of the recording and analysis of the signal is shown in the block diagram (Figure 1).

2.2. Denoising using wavelet analysis

The principle of wavelet denoising [11–13] consists of decomposing the signal by performing a wavelet transform, followed by applying suitable thresholds to the detail coefficients, zeroing all coefficients below their associated thresholds, and finally reconstructing the denoised signal based on the modified detail coefficients. The underlying model for the sEMG signal, u(n), is the superposition of the signal, f(n), and noise, e(n),

$$u(n) = f(n) + e(n) \tag{1}$$

Once the signal is through wavelet decomposition, a threshold needs to be selected for estimation of the signal of interest, f(n), from u(n) by discarding the corrupting noise e(n).

Wavelet de-noising can be divided into the following steps:

- Make multi-scale decomposition of the raw EMG signals to observe the signal wavelet coefficients.
- Estimate the noise, choose the threshold and apply the threshold analysis to wavelet coefficients to get new coefficients.
- Reconstruct the EMG signals by the revised wavelet coefficients.

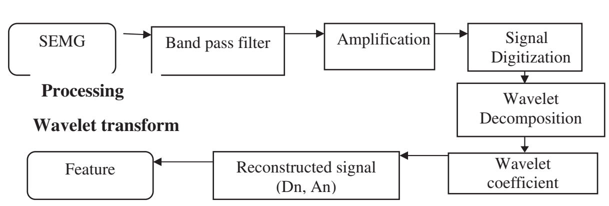

Figure 1. Block diagram for wavelet analysis of the sEMG signal.

2.3. Feature extraction

As the SEMG signal is a time- and force-dependent signal whose amplitude varies at random above and below the zero values, so signal analysis becomes important in a way to define characteristic properties of thesignal. A wide variety of features have been considered individually and in a group,[14,15] representing both EMG amplitude and spectral content. The calculation of some of the extracted parameters is as follows:

(1) *Root mean square* (*RMS*): The root mean square is a statistical measure of the magnitude of a varying quantity. It is especially useful when variants are both positive and negative. RMS value is used to quantify ac variables. Signals with higher energy have higher RMS values. It is defined as:

$$\mathrm{Vrms} = \sqrt{\frac{(x_1^2 + x_2^2 + x_3^2 + \ldots\ldots\ldots\ldots\ldots\ldots.. + x_n^2)}{n}} \tag{2}$$

(2) *Median Frequency* (*MDF*): Median frequency (MDF) is described as the frequency which divides the power contained in the signal into two equal halves. The unit of measurement is Hz.

(3) *Standard Deviation* (*SD*): This is the measure of variability or diversity used in statistics and probability theory. It shows variation or dispersion of the data from the average (mean or expected value). A low standard deviation indicates that the data points tend to be very close to the mean value, whereas a high standard deviation indicates that the data are spread out over a large range of values. It is given by the equation:

$$SD = \sqrt{\frac{\sum (x_i - \bar{x})^2}{n-1}} \quad (3)$$

where $\bar{x}$ is the arithmetic mean of sample values

(4) *Energy* (*E*): This is also defined as simple square integral (SSI). It is the summation of square values of the amplitude of sEMG signal samples and is given by the equation:

$$\mathrm{E} = \sum_{n=1}^{\mathrm{N}} |x(n)|^2 \quad (4)$$

(5) *Power Spectrum* (*PS*): For a given signal, the power spectrum gives a plot of the portion of a signal's power (energy per unit time) falling within given frequency limits. Power spectrum of a signal gives peaks at the fundamental harmonics. Quasi periodic signals give peaks at linear combinations of two or more irrationally related frequencies (often giving the appearance of a main sequence and sidebands) and chaotic dynamics gives broad band components to the spectrum.

(6) *Integrated EMG* (*IEMG*): This is defined as a summation of absolute values of the EMG signal amplitude. Integrated EMG is normally used as an onset detection index in EMG non-pattern recognition and in clinical applications:

$$\mathrm{IEMG} = \sum_{n=1}^{\mathrm{N}} |x(n)| \quad (5)$$

(7) *Mean frequency* (*MNF*): This is an average frequency which is calculated as the sum of product of the EMG power spectrum and the frequency divided by the total sum of the power spectrum. The definition of MNF is given by

$$\mathrm{MNF} = \frac{\sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{fiPi}}{\sum_{\mathrm{i}=1}^{\mathrm{M}} \mathrm{Pi}} \quad (6)$$

where fi is the frequency value of the EMG power spectrum at the frequency bin i, Pi is the EMG power spectrum at the frequency bin i and M is the length of frequency bin.

However, according to research studies,[2,16] mathematical analysis has been done to investigate the various parameters of the power spectral density and the median and mean frequencies (MNF, MDF) were found to be most reliable. During the past decade, time–frequency analyses techniques have evolved effectively in the field of electromyography and during the past decade these techniques have proved useful in investigating the muscle force relationship.

3. Results

3.1. Computer synthesised analysis

In this study, the wavelet denoised based signal analysis was performed by dividing the signal into three different types: low, medium and high SEMG signal. The time and frequency domain analyses were done to analyse the relationship between myoelectric signals vs different force levels on human arm muscles. For this, this study was initiated to investigate the surface myoelectric signal force relationship and to know whether it is dependent on rate of force production. In the first part, the raw SEMG signal for different muscle voluntary contractions was acquired, with processing done using classical filters and the wavelet transform approach. The processing of signal includes the following steps:

(1) Filtering the signal with a band-pass filter (10 Hz and 500 Hz) updating the waveform graph cursors to represent the current values of the upper and lower cut-off frequency.
(2) Dual channel spectral measurement on the pre-filtered and the filtered signal to determine the frequency response of the filter.
(3) Determination of different features like root mean square, standard deviation, energy of signal, integrated EMG and spectrogram. The front panel of the system is presented in Figure 2.

In the second part, band pass filtering and Discrete Wavelet transform (DWT) denoising of the sEMG signal was done, as shown in Figure 3. Here, different Daubechies (Db1 to Db14) wavelet functions were utilised for the extraction of different decomposition coefficients and for reconstruction of the signal. A comparative data of raw signals for three subjects with extracted features for different muscular contraction force is presented in Table 1. To describe the results of these wavelet features, various representatives for denoised RMS, signal power and variance are discussed in Tables 2–4.

The raw SEMG signals were used to calculate the RMS value, denoised power and standard deviation values for all the wavelet functions suitable for biomedical signal processing with four levels of decomposition. Table 2 gives the results of the average RMS value, Table 3 gives the average power and Table 4 gives the average standard deviation values of all the chosen wavelet functions for the three subjects at various muscle contraction (force) levels.

According to the results in Table 2, the wavelet functions from the Daubechies (Db) family show better performance; however, the wavelet function Db4 shows

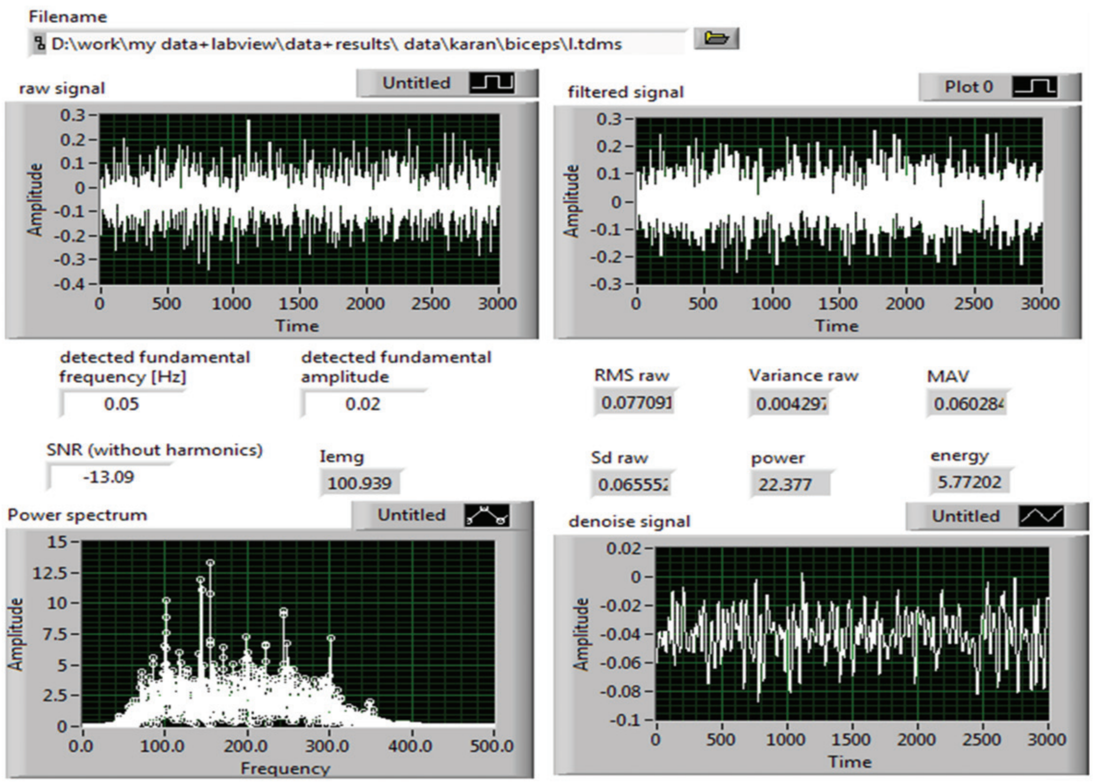

Figure 2. Front panels showing extracted features.

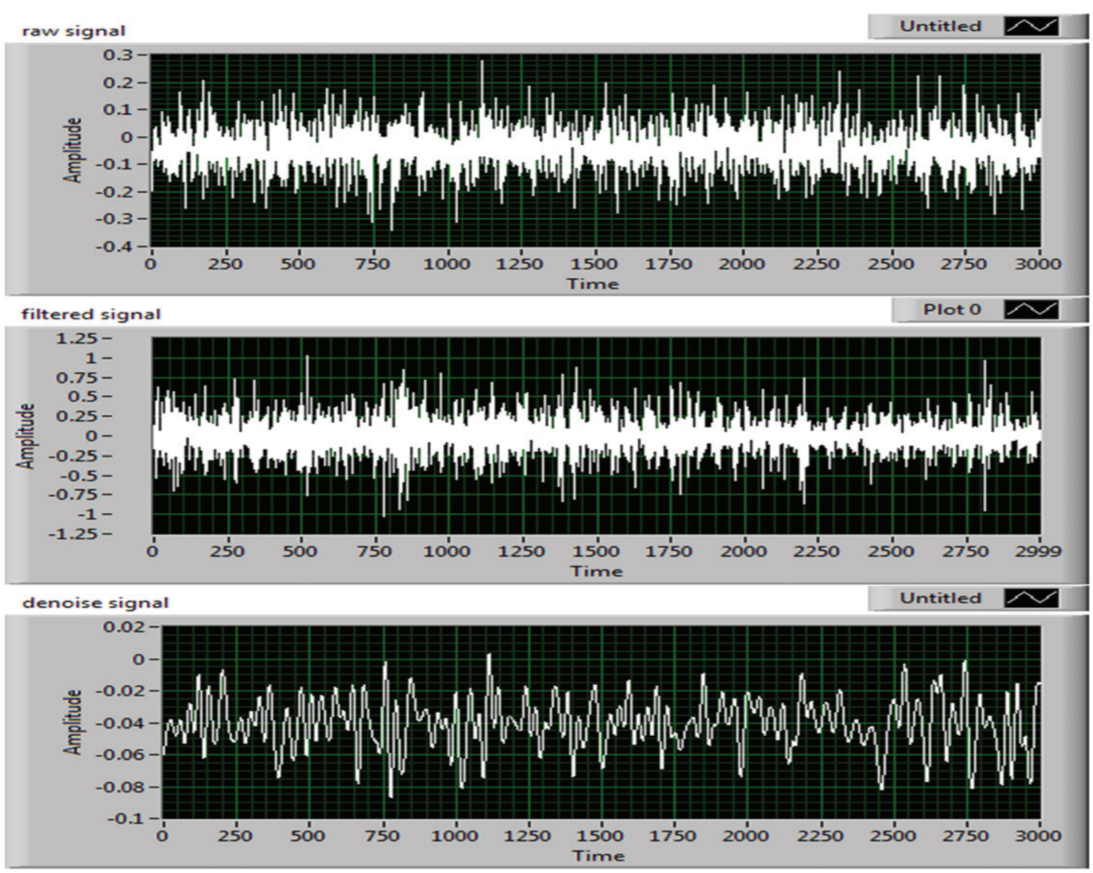

Figure 3. sEMG signals before and after band pass filter and DWT denoising.

Table 1. Feature sets for different movement from biceps position.

	Voluntary contraction (Force)								
	Low			Medium			High		
Feature name	S1	S2	S3	S1	S2	S3	S1	S2	S3
RMS	0.08	0.10	0.14	0.32	0.28	0.31	0.59	0.54	0.47
MAV	0.06	0.07	0.10	0.23	0.20	0.23	0.41	0.36	0.31
VAR	0.004	0.007	0.018	0.09	0.07	0.09	0.34	0.27	0.21
SD	0.06	0.08	0.13	0.31	0.27	0.30	0.58	0.52	0.46
PSUM	0.008	0.014	0.013	0.147	0.116	0.141	0.607	0.426	0.257

Table 2. Average RMS of Db family (three subjects).

	RMS			
Feature name	Low	Medium	High	Average
Db2	0.036226	0.067439	0.099853	0.067839
Db3	0.049237	0.065988	0.101665	0.072296
Db4	0.050267	0.066477	0.10081	0.072518
Db5	0.049168	0.066450	0.100005	0.041873
Db6	0.049149	0.066569	0.098088	0.071538
Db7	0.0491	0.066028	0.098711	0.071279
Db8	0.049122	0.006569	0.099983	0.071601
Db9	0.049862	0.066122	0.099703	0.071895
Db10	0.049223	0.066603	0.098567	0.071464
Db11	0.049153	0.066335	0.098281	0.071256
Db12	0.049077	0.065797	0.099114	0.071329
Db13	0.049174	0.065878	0.099600	0.071550
Db14	0.049241	0.066366	0.099127	0.071578

Table 3. Average power of Db family (three subjects).

	Power			
Feature name	Low	Medium	High	Average
Db2	26.436	23.278	19.946	23.22
Db3	26.405	23.480	19.698	23.194
Db4	26.380	23.455	19.470	23.101
Db5	26.412	23.307	19.729	23.149
Db6	26.445	23.336	20.033	23.271
Db7	26.446	23.505	19.898	23.283
Db8	26.426	23.530	19.463	23.200
Db9	26.408	23.383	19.714	23.168
Db10	26.416	23.312	19.951	23.226
Db11	26.443	23.422	19.985	23.283
Db12	26.451	23.509	19.803	23.254
Db13	26.423	23.548	19.727	23.232
Db14	26.393	23.349	19.725	23.197

Table 4. Average standard deviation of Db family (three subjects).

	SD			
Feature name	Low	Medium	High	Average
Db2	0.01920	0.04560	0.08415	0.04965
Db3	0.01924	0.04429	0.08517	0.04957
Db4	0.019219	0.043553	0.086276	0.049682
Db5	0.018981	0.043917	0.084193	0.049030
Db6	0.018835	0.044204	0.081612	0.048217
Db7	0.018752	0.043411	0.082347	0.04817
Db8	0.018878	0.043152	0.084134	0.048721
Db9	0.01904	0.043426	0.083865	0.048777
Db10	0.019006	0.044212	0.082311	0.048509
Db11	0.018834	0.043851	0.081819	0.048168
Db12	0.018729	0.043048	0.082969	0.048248
Db13	0.018996	0.043101	0.083737	0.048611
Db14	0.019111	0.043794	0.083102	0.048669

better performance value than the other wavelet functions. This means that wavelet function Db4 (from the average column in Table 2) is capable of denoising SEMG signals better than the other wavelet functions of the same family. According to Tables 3 and 4, wavelet power and standard deviation values show similar results where the wavelet function Db4 shows better performance than the other wavelet functions of a similar family (Figure 4).

The mean square error of SEMG signals has been calculated to evaluate the quality of robustness function:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{n} (s - s_e)^2}{N} \tag{7}$$

where N denotes the length of the signal, s represents the wavelet coefficients of the original signal and s_e are the wavelet coefficients of the denoising signal. The performance of algorithms is the best when mean square error has the smallest value. The average smallest mean square error after denoising is 0.0033, 0.033 and 0.0866, respectively, in contrast to the conventional filter technique where the mean square error (MSE) value is 0.0166, 0.1433 and 0.4533 for low, medium and high signals, respectively, which means that the useful information in the SEMG signal is retained and undesirable parts of the signals are removed.

3.2. Surface myoelectric signals

Root mean square [17] has been termed as the 'gold' standard for analysing the SEMG signal, since it reflects the physiological correlates of the motor unit action potential behaviour during a sustained muscle contraction, so was computed for each signal and force data file.

Since wavelet function Db4 shows better performance from the results, it was considered for the SEMG signal denoising process and further feature extractions. In order to make a reliable signal and muscle force determination, the two time-varying factors (MNF, MDF), muscular force and muscle geometry, are the major factors involved in dynamic muscle contractions. The average values of mean and median frequencies of the myoelectric (ME) signal-force data from the three different subjects with different muscle force contraction levels are displayed in Tables 5 and 6. These data are an aggregate of all of the contractions performed by all subjects during the experiment.

It is well known now that, during a sustained constant-force contraction, the amplitude of the detected myoelectric signal increases as a function of time. In fact, this phenomenon may be clearly seen from Table 6, where for each separate motion the curves of the three force rates are arranged in a similar orderly sequence, which means that the myoelectric (ME) signal–force relationship approaches towards linearity with considerable confidence for the biceps brachii, i.e. increasing level in terms of mean and median frequency.

Table 5. Average median (MDF) value with force level (three subjects).

Feature Name	MDF Low	MDF Medium	MDF High	MDF Average
Median frequency (Raw)	328.3	346.9	358.2	344.46
Median frequency (Denoised)	142	226.4	288.4	218.93

Table 6. Average mean (MNF) value with force level (three subjects).

Feature name	MNF Low	MNF Medium	MNF High	MNF Average
Mean frequency (Raw)	337.8	355.4	364.4	352.53
Mean frequency (Denoised)	151.4	231.8	296.4	226.53

4. Discussion

The objective of this study was to present effectiveness of algorithms to extract features of the signal during static contractions after eliminating noise. Noise contaminating the SEMG signals has its frequency components falling in the energy band of the SEMG signal and this creates major problems. Band pass filter of range has been used to remove noise. However, some other types of noise still affect feature extraction of the SEMG signal. To remove the wideband noise and for full-fledged reconstruction of the original signal, one used wavelet transform approach utilising multi-resolution analysis using classical features; RMS, IEMG, MAV, standard deviation, power, etc. as time domain and mean and median frequency as frequency domain parameters using a wavelet denoising technique. In order to define the decomposition level,[18] each level was related to its analysed frequency range. One selected wavelet functions to decompose the original SEMG signals to the 4th level and, then, achieved a soft threshold de-noising arithmetic based on the universal thresholding rule.

Our results suggest that the wavelet method has a slightly lower mean square error than the classical method. However, the behaviour of MNF and MDF is similar; the mean frequency is slightly higher than the

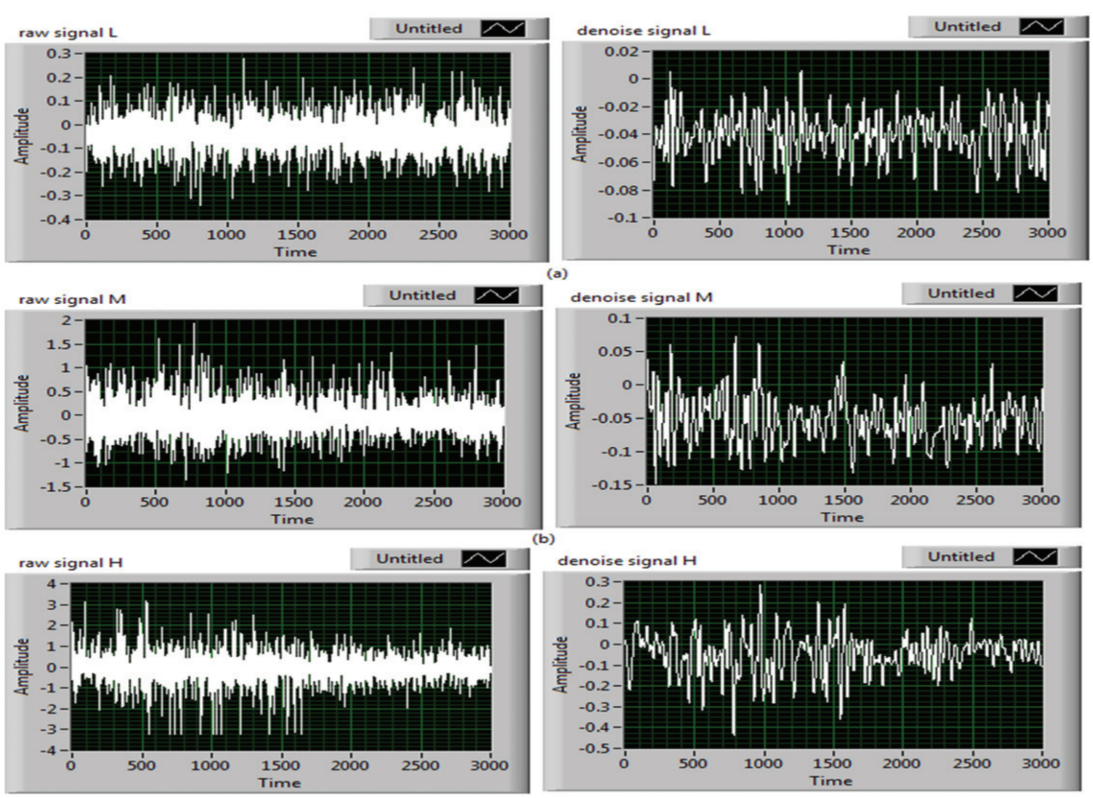

Figure 4. Raw SEMG signal and denoised SEMG signal at different contraction levels for subject 1 using wavelet function db4 at four levels of decomposition: (a) low contraction; (b) medium contraction; (c) high contraction.

median frequency because of the skewed shape of the SEMG power spectrum. Further, these features can be made universal indices to identify factors including muscle geometry, muscular force and voluntary contraction level. These findings have been supported [2] by researchers who explained that the EMG signal amplitude should increase linearly in concert with the contraction level in the muscle.

5. Conclusion

To summarize, (i) the surface myoelectric signal force relationship is primarily determined by different muscle geometries including electrode configuration, fibre diameter and subcutaneous tissue thickness, etc., (ii) the electrode locations over the muscle are different during the experiment and (iii) MNF and MDF increase as contraction level increases. They are linear for the biceps brachii muscle, with the amplitude of the myoelectric signal increasing linearly with the force exhibited. Based on the results of this study, few values of SEMG signal and wavelet denoising parameters are as follows:

- Ag-AgCl bipolar electrode: time–force relationship of sEMG signal (1 cm inter-electrode distance and 5 cm for reference electrode, small size (< 10 mm diameter));
- Electrode location: halfway between the centre of the innervations zone and the further tendon;
- Amplifier characteristics: CMRR-110 db, gain 5000 (two stage);
- Firing angle: 30–45° for different contractions;
- Wavelet function: db4;
- Decomposition level: 4;
- Threshold selection rule: Universal;
- Threshold re-scaling methods: LD defines σj as the estimated standard deviation for every possible decomposition level and Nj as the length of the wavelet coefficients at decomposition level j;
- Data type: waveform; and
- Linear relationship for MNF/MDF muscle signal with voluntary contractions.

Disclosure statement

The authors report no conflicts of interest. The authors alone are responsible for the content and writing of the paper.

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