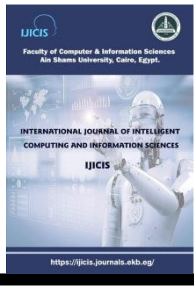
IJICIS, Vol.23, No.2, 145-156
DOI: 10.21608/ijicis.2023.190345.1253

International Journal of Intelligent Computing and Information Sciences

https://ijicis.journals.ekb.eg/



LOWER LIMB SEMG DENOISING USING DAUBECHIES

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Received 2023-01-29; Revised 2023-03-16; Accepted 2023-03-17

Abstract: *This paper represents a different way of denoising lower limb Surface electromyography sEMG signals using Daubechies wavelets Much noise will be needed to remove as we can from this signal for it to function properly. The previous works couldn't accurately determine the most suitable method to be used for lower limbs. This paper uses different thresholding approaches to calculate the highest value of SNR to identify the best denoising method. And a complete detailed survey of denoising techniques for reducing noise from surface electromyography signals is provided. This research has important implications for the practical application of lower limb EMG. This paper aimed to ascertain what are the most optimal parameters to be applied while using wavelet transform (Daubechies wavelets) to achieve the highest possible SNR in sEMG of the lower limb. The sample that was used came from 11 healthy subjects doing 3 different movements, using 4 electrodes to extract the signal. To identify the best denoising is calculated using different thresholding types, Daubechies levels, and noise structures. The result from this experiment indicates that the hard-rigorous SURE threshold and scaled white noise provide the highest SNR in every signal tested but the Daubechies level differs from one signal to another.*

Keywords: *Surface electromyography sEMG, Signal Processing, Lower Limb, Daubechies wavelets, Denoising.*

1. Introduction

A biomedical signal is defined as any electrical signal exhibited by and acquired from any organ. Said signal adheres to the time domain. Where parameters such as amplitude, frequency and phase can be observed, calculated, and acquired. The EMG signal is a biomedical signal that is a quantification of the electrical activity sparked due to muscle activity. Thus, EMG is quite a convoluted signal [1]. Electromyography (EMG) is a predominantly used technique for the diagnosis of peripheral nervous system-associated problems. Muscles are controlled by the nervous system. Hence, EMG is quite useful in the diagnosis of diseases and disabilities relevant to muscles and their reactions [2]. As a diagnosis

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method, EMG is a tried-and-true technique. Thus, the required equipment, sensors and devices are readily available in the market. The examination of the electrical activity sparked to life due to the muscles contracting and relaxing is the heart and soul of EMG [3]. electrical variations are relative to the signal from the central nervous system [4]. Action potential (AP) is actualized due to a brain signal and triggers as the membrane potential of a certain axon location quickly ascends and descends [5]. This is sent towards the ―endplate‖ of a muscle fiber. The AP spreads from the endplate towards both endings of the tendons. Two methods are available to quantify the electrical signal of the AP: (1) promptly, through interpolating electrodes in the muscle tissue, or (2) superficially, through orienting the surface electrodes (EMG) on the skin [6][7][8][9][10]. A multitude of noises is sparked from the measurement devices themselves. Said noises are an extremely problematic existence when examining surface electromyography (sEMG) signals. Hence, ways to dispose of or minimize the consequence A biomedical signal is defined as any electrical signal exhibited by and acquired from any organ. Said signal adheres to the time domain. Where parameters such as amplitude, frequency and phase can be observed, calculated, and acquired. Noise caused by the electrodes or the electrode orientation and power line. interference can be disposed of using classical filters, but the intrusion of white Gaussian noise (WGN) is challenging to remove using the previously used classical filters. Wavelet denoising algorithms on the other hand have achieved great results in removing white Gaussian noise [11][12][13]. Wavelet transform is a relatively freshly developed signal processing tool, that aids in the analysis of a multitude of timescales of aspects of a complex signal. The goal of [14] was to scrutinize the usage of wavelet denoising to reduce noise for the multifunction myoelectric control system. Two electrode channels were used per the following six upper limb motions: hand open, hand close, wrist extension, wrist flexion, pronation, and supination. A comparative study of four classical de-noising algorithms as well as universal thresholding, SURE thresholding, hybrid thresholding, and minimax thresholding are applied in order to dispose of white gaussian noise at numerous signal-to-noise ratio ratios (SNRs) from electromyogram signals. Applications of soft and hard thresholding moreover threshold rescaling techniques were regarded and therefore the whole procedures of noise reduction were applied with totally different wavelet functions and different decomposition levels. Evaluations of the performance of noise reduction are determined via mean squared error (MSE). The results show that Daubechies wavelet with second orders (db2) provides marginally superior performance than other prospects. An appropriate range of decomposition levels is four. Universal and soft thresholding is the finest of wavelet denoising algorithms from eight potential denoising processes under investigation. Additionally, the threshold employing a level-dependent estimation of level noise showed superior to others. This paper[15] presents analysis results of muscle electromyogram signal denoising. within the same time, two muscles were examined – an adductor muscle (biceps brtoachii) and an abductor muscle (triceps brachii). The electromyogram signal was filtered via the wavelet transform technique, having chosen the crucial parameters as wavelet basis function (Daubechies 4), tenth decomposition level, and threshold setting method (Heuristic). Following denoising the signal, a brief analysis of the end result signal is performed, which has shown that the chosen parameters give the best results. Such a developed system features a wide application option, primarily in Mechatronic systems where it may be used for instance in teleoperation of a robot arm, command signals for a prosthetic arm, biomedical signal filtering, or in rehabilitation aiding robots. The purpose of [16] is to research surface electromyography (SEMG) signal analysis from the right rectus femoris muscle as it is performed throughout a walking movement. To dispose of the noise from the surface electromyography, wavelet transform has been applied. Gaussianity tests are conducted to grasp changes in muscular contraction and to quantify the effectiveness of the noise removal method. Results show that the projected technique will effectively dispose of noise from the unprocessed SEMG signals for additional analysis. The goal of [1] is to study how Wavelet analysis is usually highly effective due to the fact that it provides a straightforward approach for coping with native aspects of a signal. Electromyography (EMG) signals may be used for EHW) development, and contemporary human computer interaction. Electromyography signals obtained from muscles demand advanced techniques for detection, decomposition, processing, The target of [17] to look into how Myoelectric Signals (MES) have an extended tradition with regards to prostheses manipulation. Thanks to the signals' nature, Myoelectric Signals are vulnerable to interference and noise. Numerous techniques exist for preprocessing these signals before classification algorithms to derive control data are applied. whereas these ways facilitate enhancing the source signals, parameters must be meticulously chosen and incorporated on a case-to-case basis. Following presenting many noise removal techniques and downsides, they introduce a unique approach by applying wavelet detrending to the signal. The approach brought forward yields a wonderful signal-to-noise ratio and provides in some cases an almost perfect removal of noise interference. Weak signals and muscle fatigue don't impact the results. Besides serving as input for a multitude of classification techniques, the detrended signal is possible to even be directly used for implementing strong command techniques like Cookie crusher or threshold algorithms. A basic Cookie crusher management model was chosen to verify the approach as compared to conventional amplitude level schemes. Results show that detrended signal information may be utilized for reliable prosthesis manipulation even for users exhibiting low amplitude Myoelectric Signals. The aim of [18] was to provide a completely unique approach to mono channel power line interference (PLI) and baseline wander (BW) removal from surface electromyograms (EMG). It is derived from non-negative matrix factorization (NMF) employing a priori information concerning the interferences. It performs a linear decomposition of the input signal spectrogram into non-negative elements, that represent the power line interference, baseline wander and electromyogram spectrogram estimates. all of them exhibit terribly divergent time-frequency patterns: power line interference and baseline wander are both sparse whereas electromyogram is noise-like. Booting of the classical non-negative matrix factorization algorithm with accurately designed power line interference, baseline wander and electromyogram structures and a meticulously adjusted matrix decomposition rank will increase the separation performance. The results of the study suggest that the projected technique outperforms other progressive strategies. This paper, Daubechies wavelets are used to realize the optimum wavelet reconstruction which provides the most effective result for EMG feature extraction. Diverse levels and orders of Daubechies wavelets are evaluated. This paper provides a complete detailed survey of denoising algorithms via Daubechies wavelets for removing noise from surface electromyography signals. The objectives of this paper are to determine.

1) The appropriate wavelet functions and their scale level
2) The most effective threshold estimator method
3) Forms of noise to dispose of

2. Methodology

The Dataset used was downloaded from [1] and is as follows, eleven male subjects. They execute three movements to research the behavior related to the knee muscle, gait, leg extension from a sitting position, and flexion of the leg up. The configuration of the data set is shown in Table 1. The data was acquired through four electrodes (Vastus Medialis, semitendinosus, biceps femoris, and rectus femoris). The Datalog device used was MWX8 by biometrics of eight digital channels and four analog channels, of which four for sampling were used SEMG. This information were sent on to the computer MWX8 internal storage with a microSD card and transmitted in real-time Datalog software through Bluetooth adapter, 14-bit resolution and sampling frequency of 1000Hz.The total number of electrodes is four, corresponding to the time series one for each channel (1 to 4). Each series contains ~ 5 shares or motion repetitions for each subject.

- ♣ RF: Recto Femoral.
- ♣ BF: Femoral Biceps.
- ♣ VM: Vastus Medialis.
- ♣ ST: Semitendinosus
- ♣ FX: Flexion at the knee

Table 1 configuration of the data set [19]

Segment	Lower Limb			
Channel	Ch1	Ch2	Ch3	Ch4
Muscle	RF	BF	VM	ST
Column	0	1	2	3

These SEMG signals were denoised using discrete wavelet transform and a variety of threshold methods. The discrete wavelet transform and threshold based denoising was implemented using the MATLAB Wavelet toolbox

2.1. Block Diagram

The fundamental stage is pre-processing EMG data for successful feature extraction and high-accuracy classification. sensed EMG data are amplified to increase the amplitude of the signal, where an amplification factor of approximately 1000 is done before sampling.
De-noising. EMG Signals are subject to noise caused by different sources. Therefore, signal denoising is a fundamental step for further signal processing. Figure 1 shows the wavelet denoising block.

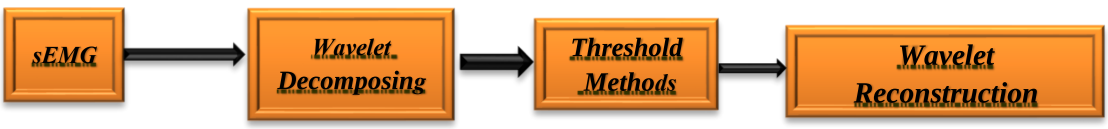

Figure .1. The wavelet denoising block diagram

2.2 WAVELET DECOMPOSITION

The wavelet transform's 1st step in denoising is to decompose the unprocessed (noisy) signal using DWT (Daubechies), into a variation of multiresolution components by decomposing the signal into approximations am[n] and details dm[n] coefficients. The previous decomposition into different frequency bands is simply achieved using a collection of lowpass and high-pass filters. For this paper wavelet functions Daubechies (db1: db10) are used at level 5 of decomposition

2.3 THRESHOLD METHOD

The Resultant discrete wavelet transforms (DWT) coefficients are thresholded using either of the two types of thresholding (soft) or (hard) thresholding. Suppose that the equation below represents a simple model of EMG signal

$$f(t)= s(t) + n(t) \quad (1)$$

where: f(t): Is the unprocessed EMG signal. s(t): Is the untainted EMG signal Signal-to-noise-ratio (SNR) The equation below is how the signal-to-noise ratio after the previous process was calculated in order to evaluate our work and determine which method got better results.

$$SNR=10*\log (S / N) \quad (2)$$

Where: SNR: Is signal-to-noise ratio in dB (decibels),
10 is the factor used if signal strength figures are in units of voltage,
S: Is the measured n(t): Is the noise part of the unprocessed signal.

The original signal f(t) intensity is recorded, mostly by coefficients whose values are higher than a threshold, $Ts > 0$.

The noise signal's coefficients values are mostly lower than a noise threshold Tn satisfy $Tn < Ts$. Then the noise in the unprocessed signal f(t) can be disposed of by thresholding it's transform. All quantifications of its transform that is lower than Tn are set to 0 [1].

2.4 SIGNAL RECONSTRUCTION

Inverse transform is applied, resulting in a close approximation of f(t). As it implies, the reconstruction is basically walking back the process of decomposition. The approximations am[n] and details dm[n] coefficients at every level of our 5 levels are up sampled by two, passing through the low and high pass filters then added. After the 5 levels we obtain a close approximation of the original signal f(t) [21].

3. RESULTS AND DISCUSSION

Any of the wavelet functions (db2, db6 and db8) are effective in disposing of noise pertaining to sEMG based on [22][23]. In this paper we didn't want simply effective levels of Daubechies wavelets, we wanted the most effective level of Daubechies wavelets tailored for lower limb sEMG. Thus, we tested every possible combination of Daubechies wavelets, thresholding types, methods, and types of noise at decomposition level 5 as shown in the samples from denoising the four channels while in the standing movement in figure (2), (3), (4) and (5), the samples from denoising the four channels while in the sitting movement in Figures (6),(7),(8), and(9), and the samples from denoising the four channels while in the gait movement in figure(10),(11),(12) and (13).

3.1 Movement

3.1.1 standing

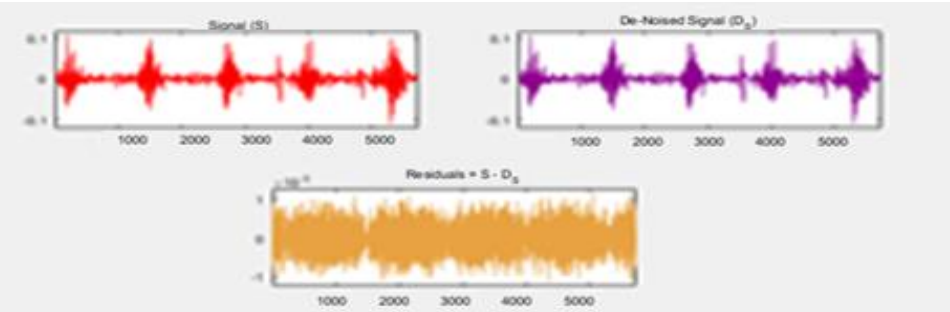

Figure .2: Top left is channel 1 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db3, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied,The Recto Femoral (Ch1) had a SNR = 33.1079451172642 db

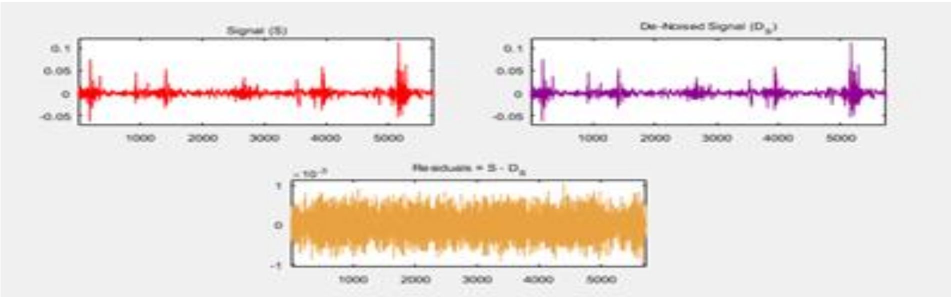

Figure. 3: Top left is channel 1 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db3, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied The Femoral Biceps (Ch2) had a SNR = 29.1783065773 dB

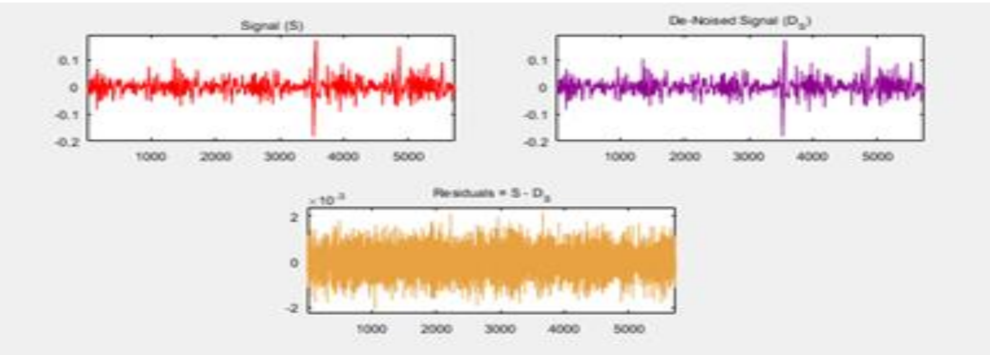

Figure .4: Top left is channel 3 unprocessed signal f(t), top right is denoised signal s(t) and the middle bottom is the removed noise n(t). Where db8, hard rigorous SURE thresholding, scaled white noise structure. The Vastus Medialis (Ch3) had a SNR = 32.8205025149732 dB

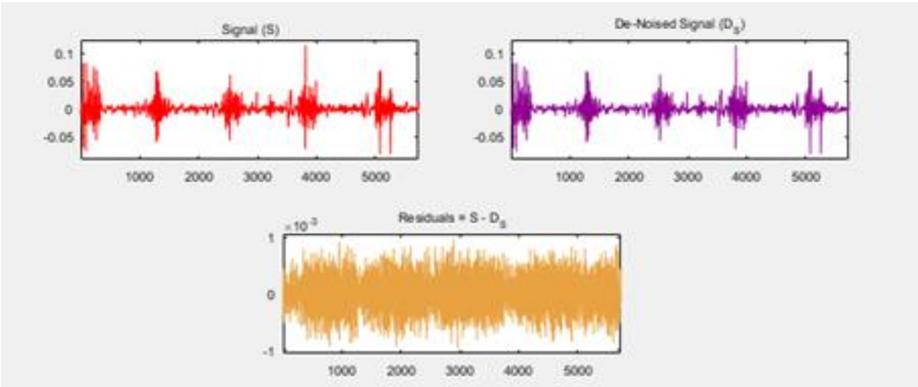

Figure .5: Top left is channel 4 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db2, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied. The Semitendinosus (Ch4) had a a SNR = 31.7330606314 dB

3.1.2 Sitting

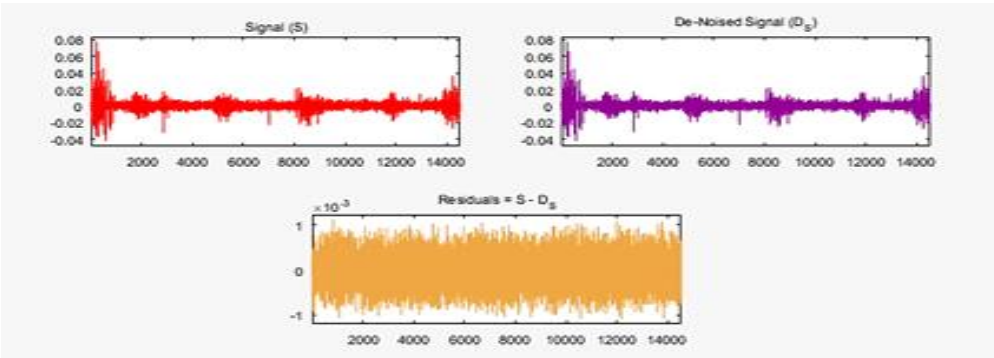

Figure . 6: Top left is channel 1 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db4, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied. The Recto Femoral (Ch1) had a SNR = 23.52773525933 dB

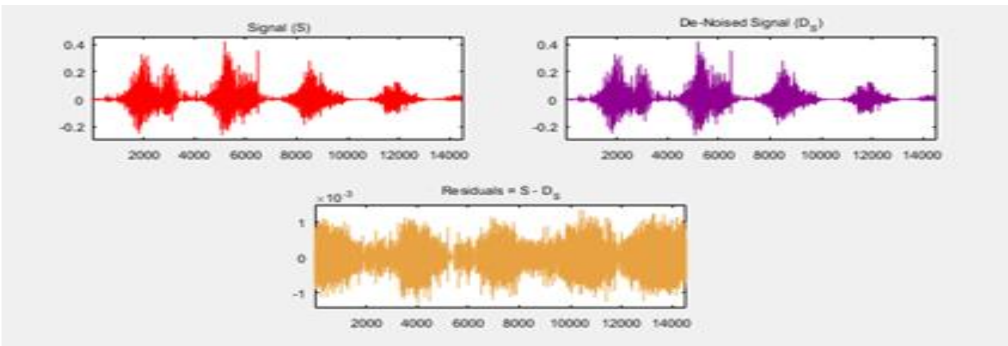

Figure.7: Top left is channel 2 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db8, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied The Femoral Biceps (Ch2) had a SNR =42.0562935026 dB

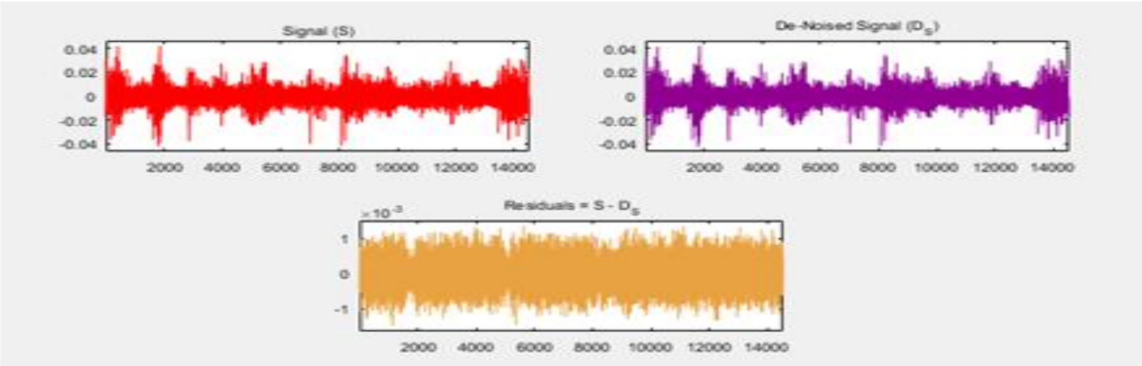

Figure. 8: Top left is channel 3 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db10 hard rigorous SURE thresholding, scaled white. The Vastus Medialis (Ch3) had a SNR = 24.6108433016158 dB

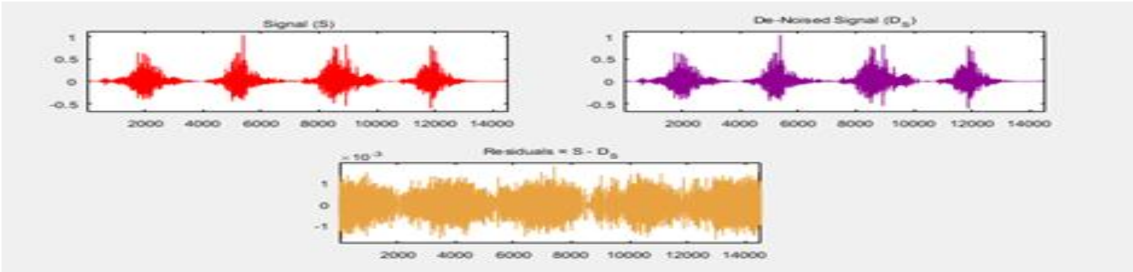

Figure. 9: Top left is channel 4 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db6, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied. The Semitendinosus (Ch4) had a SNR = 47.2673288003 dB

3.1.3 Gait

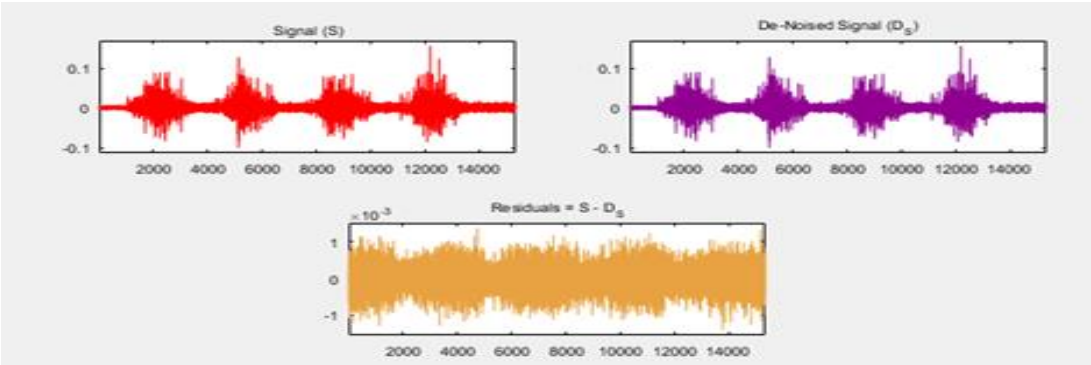

Figure.10: Top left is channel 1 unprocessed signal f(t), top right is denoised signal s(t) and the middle bottom is the removed noise n(t). Where db10, hard rigorous SURE thresholding, scaled white noise, and decomposition level 5 is applied. The Recto Femoral (Ch1) had a SNR = 34.0962698307663dB

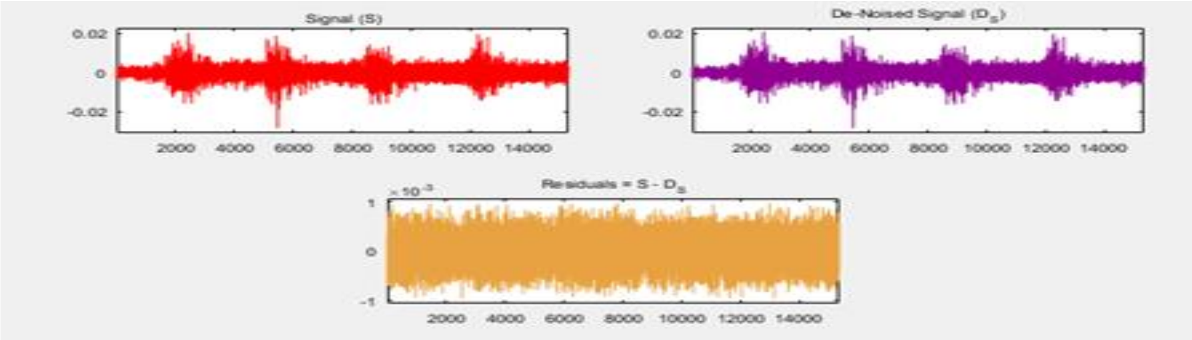

Figure .11: Top left is channel 1 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db3, hard rigorous SURE thresholding, scaled white noise and decomposition level 5 is applied The Femoral Biceps (Ch2) had a SNR = he Femoral Biceps (Ch2) had a SNR = 20.336416574814 dB

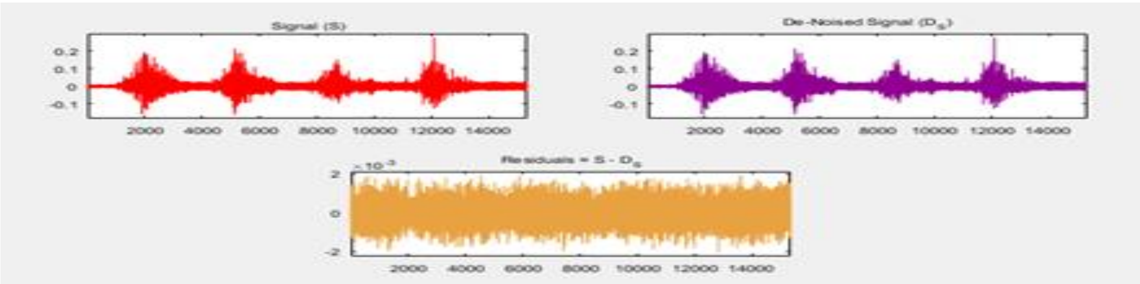

Figure. 12: Top left is channel 3 unprocessed signal f(t), top right is denoised signal s(t) and middle bottom is the removed noise n(t). Where db9, hard rigorous SURE thresholding, scaled white. The Vastus Medialis (Ch3) had a SNR = 34.0246477691133 dB

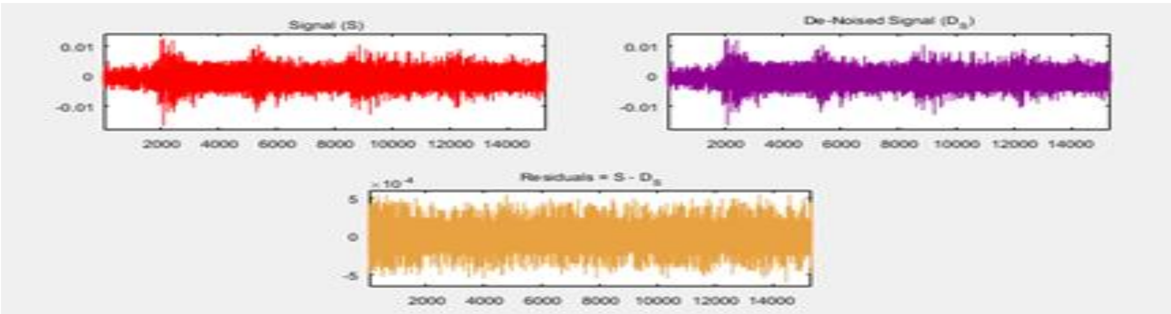

Figure.13: The top left is channel 4 unprocessed signal f(t), the top right is denoised signal s(t) and the middle bottom is the removed noise n(t). Where db1, hard rigorous SURE thresholding, scaled white noise, and decomposition level 5 is applied. The Semitendinosus (Ch4) had a SNR =5.490762230542 dB

Results obtained by this research determined the following: By processing three movements with four channels each using ten Daubechies levels, level five decomposition, seven different thresholding methods, two threshold types, and three noise structures a total of 5040 SNR values are compared and determined the best denoising method for each signal, it was found that using hard rigorous SURE thresholding and scaled white noise will yield the best SNR and the results varied between the different Daubechies levels as shown in table 2.

Table 2. Optimal Daubechies level

Movement	Standing				Sitting				Gait			
Channel	1	2	3	4	1	2	3	4	1	2	3	4
db level	3	3	8	2	4	8	10	6	10	3	9	1

4. Conclusion

The aim of this study was to ascertain what are the most optimal parameters to be applied while using wavelet transform (Daubechies wavelets) to achieve the highest possible SNR in sEMG of the lower limb. As we tried all ten different Daubechies levels alongside the seven different thresholding methods then being: fixed form, heuristic SURE, rigorous SURE, penalize low, penalize medium, penalize high and minimax. All of which were applied both soft and hard We learned that, though the decomposition level, thresholding method and types of noise best results were the same for all the signals, the Daubechies levels varied based on what kind of movements and which muscle is observed at the time as proven in the results previously. Wavelets are powerful tools which are meant to be employed in signal processing and data compression. wavelet transforms are a wonderful stand-in to Fourier transforms in several applications. In Fourier analysis, a signal is broken down into periodic components; in wavelet analysis, a signal is broken down into coefficients localized in both time and frequency domains. Thus, wavelet transforms are ideal once signals don't seem to be periodic. Wavelets are taking the signal processing field by a storm, it’s excelling in denoising, and better results are achieved with each passing day. What method will rein supreme will be left for the future to decide.

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