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Myopathic Disease Detection Using Wavelet Packet Based Denoising Technique

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Abstract- The technology of EMG recording is relatively new. There are still limitations in detection and characterization of existing nonlinearities in the surface electromyography (SEMG). Wavelet packets are advance and effective method for analysing signal processing work. EMG signal represents the neuromuscular activities and analysis of EMG signals can lead to diagnose myopathy and neuropathy related muscular diseases. Here we have analyzed the filtering performance by using Balance Sparsity-norm & fixed form thesholding (soft &hard) methods where the mean, standard deviation & mean abs deviation is calculated at different global threshold for Healthy & Myopathic EMG signals. The residuals of both Healthy and Myopathic EMG signals are providing significant results which help in symptoms detection of myopathic disease conditions.

Keywords-EMG, Myopathy, Neuropthy, Wavelet packet, Balance Sparsity-norm, fixed form thresholding

I. INTRODUCTION

The Electromyogram (EMG) signal is a biomedical signal that measures electrical currents generated in muscles during its contraction representing neuromuscular activities. A muscle is composed of Many Motor Units (MUs). EMG signals detected directly from the muscle or from the skin by using surface electrodes, respectfully, show a train of Motor Unit Action Potentials (MUAP) plus noise [1]. EMG signal acquires noise while travelling through different tissues. Moreover, the EMG detector, particularly if it is at the surface of the skin, collects signals from different motor units at a time which may generate interaction of different signals. Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering. The capability of detecting Electromyographic signals improved steadily from the 1930s through the 1950s and researchers began to use improved electrodes more widely for the study of muscles [3][14]. It is not until the middle of the 1980s that integration techniques in electrodes had sufficiently advanced to allow batch production of the required small and lightweight instrumentation and amplifiers. At present a number of suitable amplifiers are commercially available.

With increasing muscle force, the raw EMG signal shows an increase in the number of MUAP recruited at increasing firing rates, resulting in the Interference Pattern (IP). The firing pulses are normally considered a random function of time, which is non-Gaussian in nature [3][6] The main reason for the interest in EMG signal analysis is in clinical diagnosis and biomedical applications. The shapes and firing rates of Motor Unit Action Potentials (MUAPs) in EMG signals provide an important source of information for the diagnosis of neuromuscular disorders. Once appropriate algorithms and methods for EMG signal analysis are readily available, the nature and characteristics of the signal can be properly understood and hardware implementations can be made for various EMG signal related applications. So far, research and extensive efforts have been made in the area, developing better algorithms, upgrading existing methodologies, improving detection techniques to reduce noise, and to acquire accurate EMG signals. SEMG becomes less Gaussian with increase of MVC.

Quantitative analysis of the IP is useful in the diagnosis of neuromuscular disorders. In the past years, several computer-aided techniques for IP analysis have been proposed such as turns amplitude analysis, decomposition methods and power spectrum analysis. It is difficult to obtain high-quality electrical signals from EMG sources because the signals typically have low amplitude (in range of mV) and are easily corrupted by noise. The simplest way method of removing narrow bandwidth interference from recorded signal is to use a linear, recursive digital notch filter. But the disadvantage of the notch filter is that, it distorts the signal [5]. Wavelet-based noise removal is performed in this research for the EMG signal analysis. Wavelet denoising (noise removal) has already been used in denoising a number of physiological signals and other kind of signals [2][7][10]. This method is preferred over signal frequency domain filtering because it can maintain signal characteristics even while reducing noise.

The wavelet based noise removal technique is also able to remove noise effectively from raw SEMG signals. The use of Fourier analysis to study biological signals such as EMG recordings is not the most efficient method for transient data analysis. However, the time frequency analysis based on the wavelet transform is better suited to handle the non-stationary characteristics of the EMG signals. Our Proposed analysis involves the wavelet packet based different thresholding methods for filtering noise from the EMG signals.

II. ELECTROMYOGRAM (EMG)

An Electromyogram (EMG) measures the electrical activity of muscles at rest and during contraction. Nerve conduction studies measure how well and how fast the nerves can send electrical signals. Nerves control the muscles in the body with electrical signals called impulses. These impulses make the muscles react in specific ways. Nerve and muscle problems cause the muscles to react in abnormal ways.If you have leg pain or numbness, you may have these tests to find out how much your nerves are being affected. These tests check how well your spinal cord, nerve roots, and nerves and muscles that control your legs are working. An EMG is done to find diseases that damage muscle tissue, nerves, or the junctions between nerve and muscle. These problems may include a herniated disc, amyotrophic lateral sclerosis (ALS), or myasthenia gravis (MG) and also find the cause of weakness, paralysis, or muscle twitching. Problems in a muscle, the nerves supplying a muscle, the spinal cord, or the area of the brain that controls a muscle can cause these symptoms. The EMG does not show brain or spinal cord diseases.

A ***nerve conduction study*** is done to find damage to the peripheral nervous system, which includes all the nerves that lead away from the brain and spinal cord and the smaller nerves that branch out from those nerves. This test is often used to help find nerve problems such as carpal tunnel syndrome or Guillain-Barré syndrome.

To acquire surface EMG (sEMG) signal, electrodes are placed on the skin overlying the muscle. Alternatively, wire or needle electrodes are used and these can be placed directly in the muscle. When EMG is acquired from electrodes mounted directly on the skin, the signal is a composite of all the muscle fiber action potentials occurring in the muscle or muscles underlying the skin. Hence, the EMG signal is a complicated signal, which is controlled by the nervous system and is dependent on the anatomical and physiological properties of muscles. The EMG signal may be either positive or negative voltage as shown in Fig. 1.

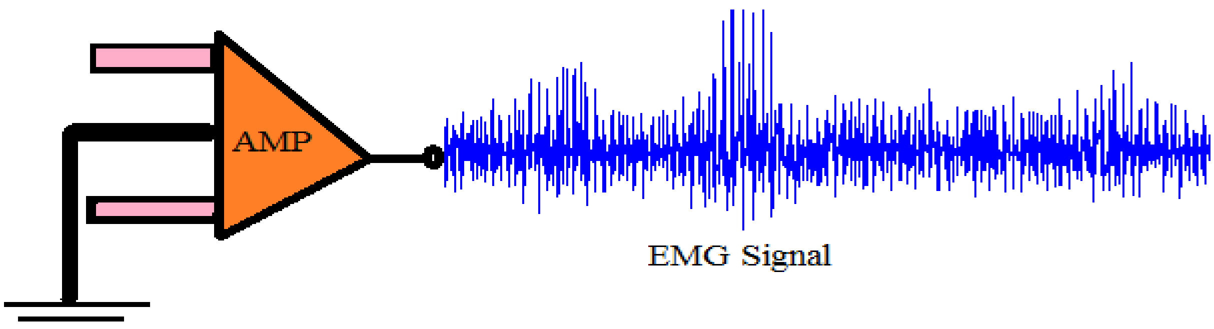


Figure.1. Surface raw EMG signal

III. NOISE IN EMG SIGNAL

Before we can develop strategies to eliminate unwanted noise we must understand what the sources of noise are. The two types of noise are ambient noise and transducer noise.

Ambient noise is generated by electromagnetic devices such as computers, force plates, power lines etc. Essentially any device that is plugged into the wall A/C (Alternating Current) outlet emits ambient noise. This noise has a wide range of frequency components, however, the dominant frequency component is 50Hz or 60Hz, corresponding to the frequency of the A/C power supply (i.e. wall outlet).

Transducer noise is generated at the electrode – skin junction. Electrodes serve to convert the ionic currents generated in muscles into an electronic current that can be manipulated with electronic circuits and stored in either analog or digital form as a voltage potential. There are two types of noise sources that result from this transduction from an ionic to an electronic form: D/C (Direct Current) Voltage Potential & A/C (Alternating Current) Voltage Potential

The goal with EMG measurements is to maximize the signal to noise ratio. Technological developments have decreased the level of noise in the EMG signal. The most important development was the introduction of the bipolar recording technique. Bipolar electrode arrangements are used with a differential amplifier, which functions to suppress signals common to both electrodes. Essentially, differential amplification subtracts the potential at one electrode from that at the other electrode and then amplifies the difference. Correlated signals common to both sites, such as from power sources and electromagnetic devices, but also EMG signals from more distant muscles are suppressed. Moreover, the D/C components such as the over-potential generated at the electrode skin junction will be detected with similar amplitude (see below) and will therefore be suppressed. In contrast, signals from muscle tissue close to the electrodes will not be correlated and will be amplified. The advent of bipolar recordings with differential pre-amplification has enabled the recording of the full EMG bandwidth while increasing the spatial resolution .This also has the effect of increasing the signal to noise ratio.

IV. WAVELET PACKET (1-D) BASED DE-NOISING

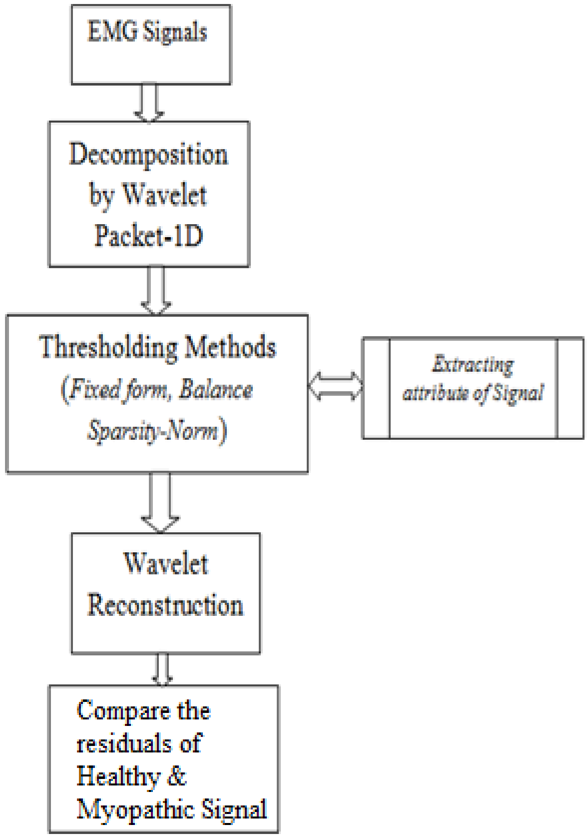


Fig.2.Block Diagram of our propose model.

The EMG is collected from PhysioBank ATM having 4000 samples of a healthy subject and the length of the recorded signals was 10 seconds. The simulation part is carried out in Matlab platform.

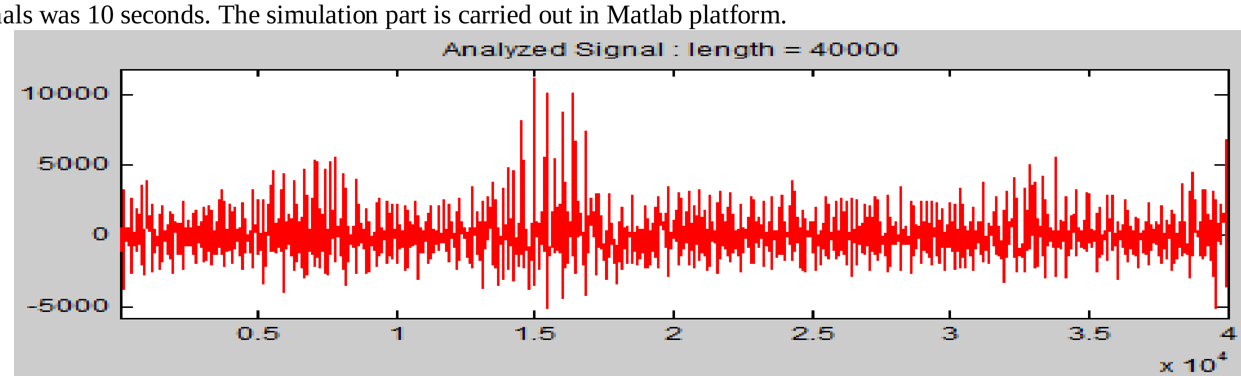


Fig.3.Input Healthy EMG Signal having length 40000 samples.

We have analyzed the input signal by applying wavelet ‘haar’ with level-3 & the selected entropy is Shannon. The decomposed tree showed in length type Node level.

A. **Wavelet Packet Decomposition**

Originally known as Optimal Subband Tree Structuring (SB-TS) also called Wavelet Packet Decomposition (WPD) (sometimes known as just Wavelet Packets or Subband Tree) is a wavelet transform where the discrete-time (sampled) signal is passed through more filters than the discrete wavelet transform (DWT).In the DWT, each level is calculated by passing only the previous wavelet approximation coefficients (cA_j) through discrete-time low and high pass quadrature mirror filters. However in the WPD, both the detail (cD_j (in the 1-D case), cH_j, cV_j, cD_j (in the 2-D case) and approximation coefficients are decomposed to create the full binary tree.

For n levels of decomposition the WPD produces 2^n different sets of coefficients (or nodes) as opposed to (3n + 1) sets for the DWT. However, due to the down sampling process the overall number of coefficients is still the same and there is no redundancy.

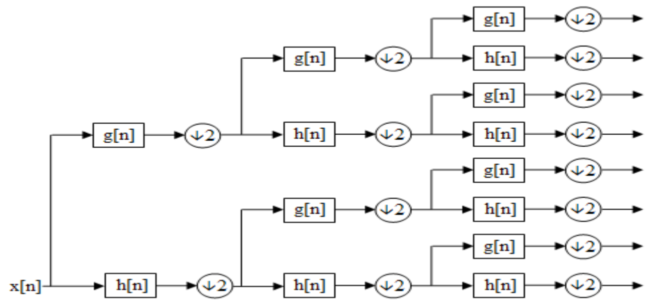
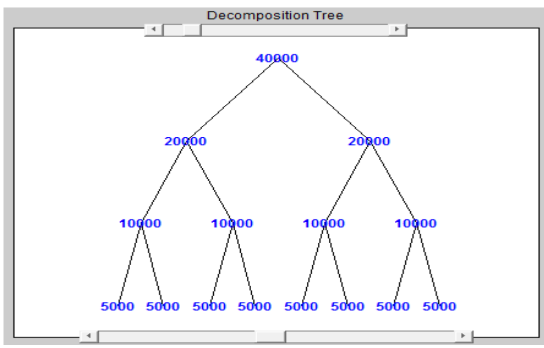


Fig4: Wavelet Packet decomposition over 3 levels. g[n] is the low-pass approximation coefficients, h[n] is the high-pass detail coefficients



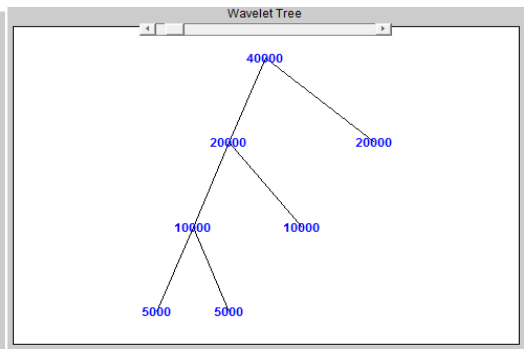


Fig.5.Wavelet Decomposition of length 4000 samples Fig.6. Wavelet tree

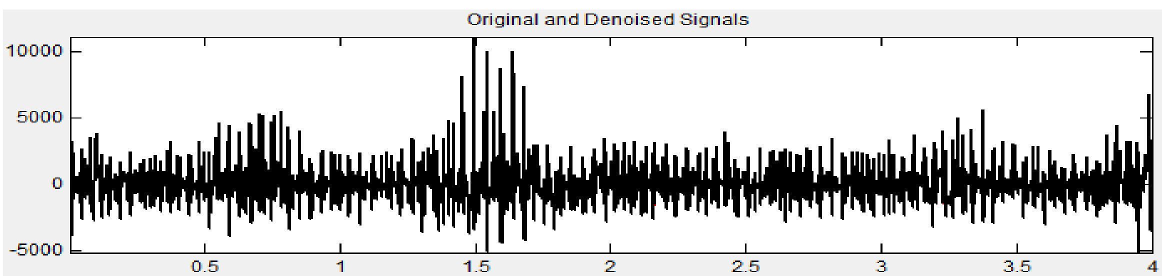


Fig.7.fixed form thr (soft) at global thr ‘0’ of Healthy EMG Signal

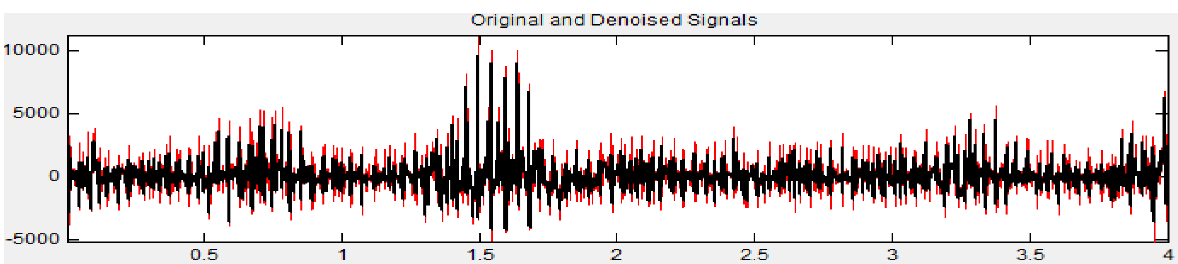


Fig.8. fixed form thr (hard) at global thr ‘5000’ of Healthy EMG Signal

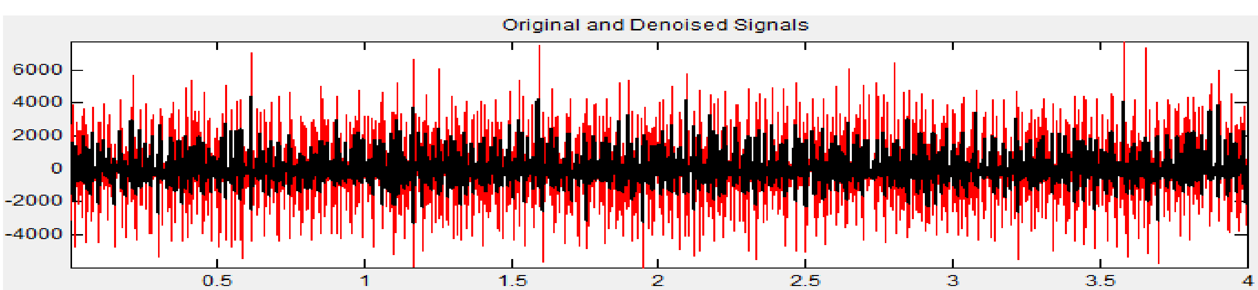


Fig9. Fixed form thr (soft) at global thr ‘5000’ of Myopathic EMG Signal

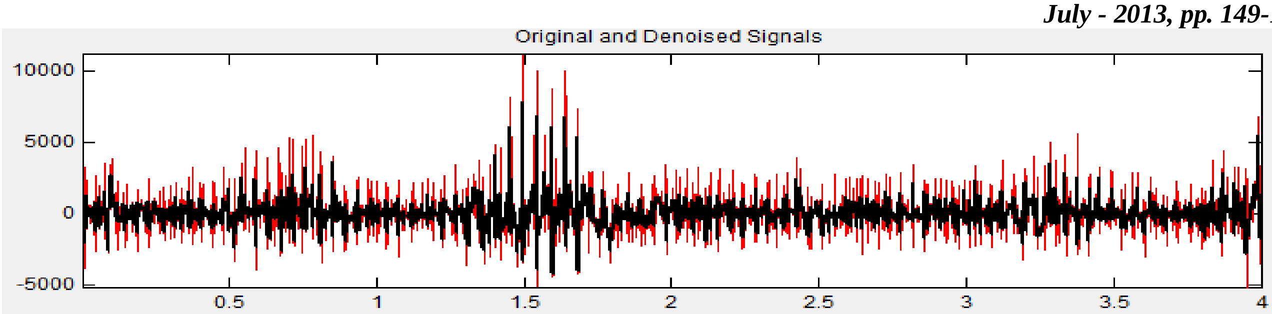
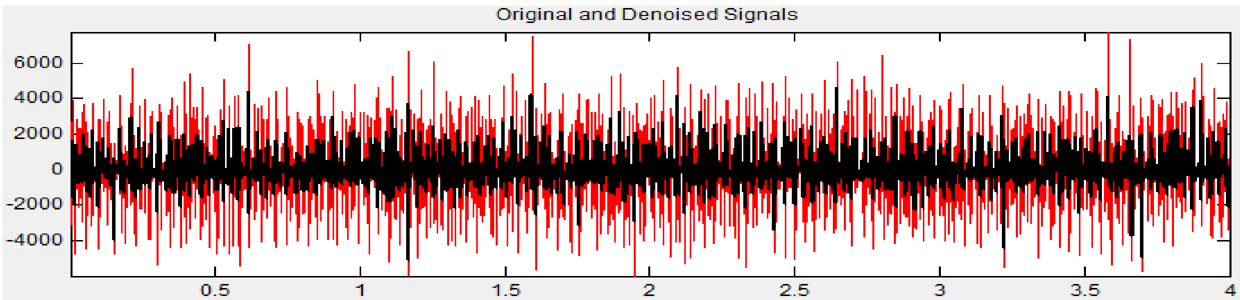


Fig.9. Fixed form thr (soft) at global thr '6000' of Healthy EMG signal



Fixed form thr (hard) at global thr '6000' of Myopathic EMG signal

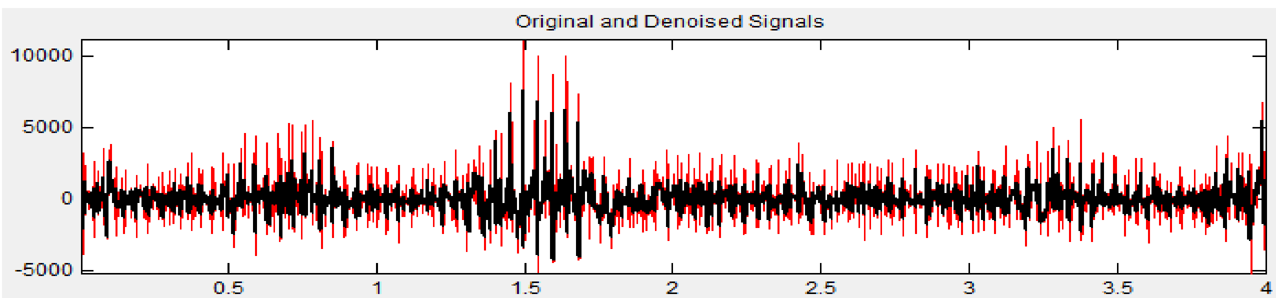


Fig.10. fixed form thr (soft) at global thr '8000/9000/1e+004'

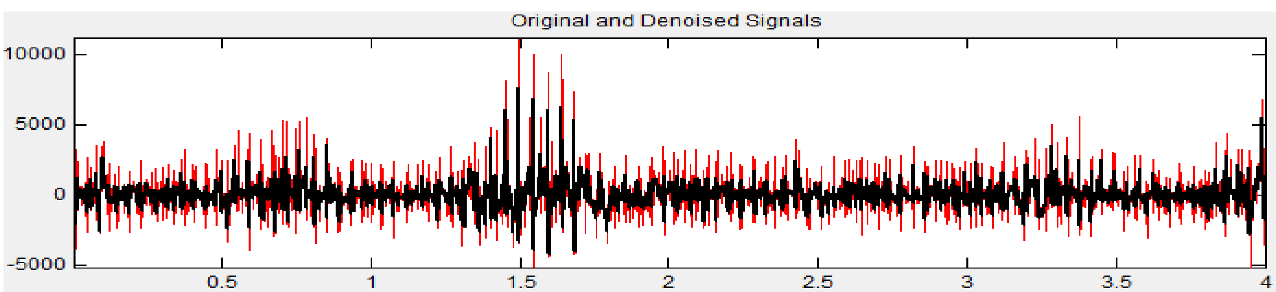
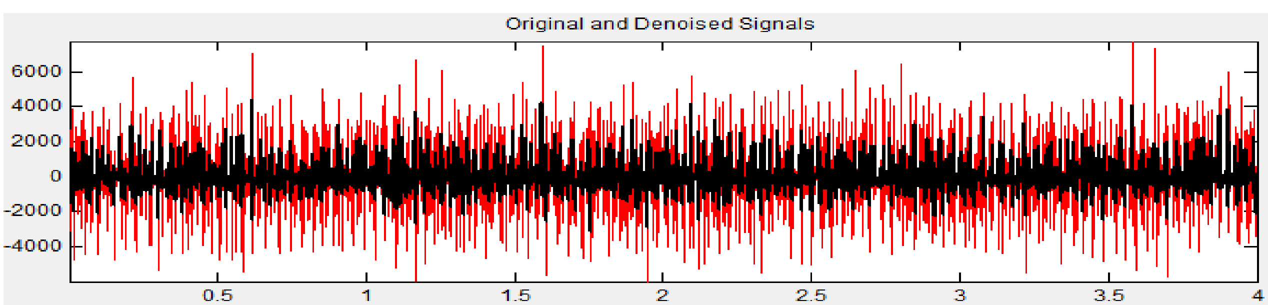


Fig.11. Balance Sparsity-norm (hard) at global thr '8000/9000/1e+004'



Fixed form thr (hard) at global thr '9000' of Myopathic EMG signal

Table.1. Mean, Standard Dev. & Mean abs Dev. Of Fixed from thersholding for Healthy EMG signal

Fixed from thld	**Soft**			**Hard**		
Global thld limit	**Mean**	**Standard Dev.**	**Mean abs Dev.**	**Mean**	**Standard Dev.**	**Mean abs Dev.**
0	-2.302e-015	3.6e-01	0	-2.302e-015	3.6e-01	0
100	-2.612e-015	58.19	43.5	-1.466e-015	29.34	21.54
1000	-8.782e-o15	254	136.6	-8.129e-016	186.8	109.1
2000	-8.2e-016	329.1	161.4	-5.016e-016	280.2	145.4
3000	-7.063e-016	360	169.7	-5.471e-016	328.3	160.5
4000	-9.109e-016	372.7	172.5	-7.063e-016	358.5	168.9
5000	-1.025e-015	377.8	173.5	-9.337e-016	366.9	171.1
6000	-1.047e-015	380.8	174.1	-1.184e-015	379	173
7000	-1.275e-015	382.2	174.3	-1.184e-015	379	173.7
8000	**-1.002e-015**	**382.9**	**174.4**	-1.002e-015	380.8	174.1
9000	-1.002e-015	382.9	174.4	**-1.002e-015**	**382.9**	**174.4**
10000	-1.002e-015	382.9	174.4	-1.002e-015	382.9	174.4

For Fixed from soft thresholding the denosing process continues upto 8000 (global threshold limit)where the mean is **-1.002e-015, the standard deviation is 382.9and the mean abs deviation is 174.4 where as for the same hard thesholding case the threshold limit comes at 9000 and the** mean is **-1.002e-015, the standard deviation is 382.9and the mean abs deviation is 174.4.**

Table.2. Mean, Standard Dev. & Mean abs Dev. Balance Sparsity-norm thersholding of Healthy EMG signal

Balance Sparsity-norm	**Soft**			**Hard**		
Global thld limit	**Mean**	**Standard Dev.**	**Mean abs Dev.**	**Mean**	**Standard Dev.**	**Mean abs Dev.**
0	-2.302e-015	3.6e-01	0	-2.302e-015	3.6e-01	0
100	-1.466e-015	29.34	21.54	-1.466e-015	29.34	21.54
1000	-8.129e-016	186.8	109.1	-8.129e-016	186.8	109.1
2000	-5.016e-016	280.2	145.4	-5.016e-016	280.2	145.4
3000	-5.471e-016	328.3	160.5	-5.471e-016	328.3	160.5
4000	-7.063e-016	358.5	168.9	-7.063e-016	358.5	168.9
5000	-9.337e-016	366.9	171.1	-9.337e-016	366.9	171.1
6000	-9.564e-016	373.6	172.5	-9.564e-016	373.6	172.5
7000	-1.184e-015	379	173.7	-1.184e-015	379	173.7
8000	-1.002e-015	380.8	174.1	**-1.002e-015**	**382.9**	**174.4**
9000	**-1.002e-015**	**382.9**	**174.4**	-1.002e-015	382.9	174.4
10000	-1.002e-015	382.9	174.4	-1.002e-015	382.9	174.4

For Balance Sparsity-norm soft thresholding the denosing process continues upto 9000 (global threshold limit) where the mean is **-1.002e-015, the standard deviation is 382.9and the mean abs deviation is 174.4 where as for the same hard thesholding case the threshold limit comes at 8000 and the** mean is **-1.002e-015, the standard deviation is 382.9and the mean abs deviation is 174.4.**

Table.3. Mean, Standard Dev. & Mean abs Dev. Of **Fixed from Thersholding** for Myopathic EMG signal

Fixed from thld	**Soft**			**Hard**		
Global thld limit	**Mean**	**Standard Dev.**	**Mean abs Dev.**	**Mean**	**Standard Dev.**	**Mean abs Dev.**
0	-4.5717e-015	4.293e-013	0	-4.5717e-015	4.293e-013	0
100	-4.3e-015	72.06	54.79	-3.792e-015	26.77	18.65
1000	-4.25e-015	416.7	266.4	-4.233e-015	273	180.7
2000	-4.006e-015	516.9	344.6	-4.801e-015	460.6	288.6
3000	-4006e-015	649.6	375.6	-4.71e-015	573.6	341.6
4000	-4.142e-015	684.2	388.9	-4.642e-015	636.7	369.3
5000	-3.96e-015	698.1	394.1	-4.46e-015	676.7	385.2
6000	-4.233e-015	703.2	395.9	-4.688e-015	697.4	393.6
7000	-4.369e-015	704.4	396.3	-4.597e-015	701.8	395.3
8000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**
9000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**
10000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**

For Fixed from soft thresholding the denosing process continues upto 8000 (global threshold limit)where the mean is **-4.278e-015, the standard deviation is 704.6 and the mean abs deviation is 396.3 where as for the same hard thesholding case the threshold limit comes at 8000 and the** mean is **-4.278e-015, the standard deviation is 704.6 and the mean abs deviation is 396.3 which is quite higher as compared to Healthy EMG signal.**

Table.4. Mean, Standard Dev. & Mean abs Dev. Of **Balance Sparsity-norm** for Myopathic EMG signal

Balance Sparsity-norm	**Soft**			**Hard**		
Global thld limit	**Mean**	**Standard Dev.**	**Mean abs Dev.**	**Mean**	**Standard Dev.**	**Mean abs Dev.**
0	-4.5717e-015	4.293e-013	0	-4.5717e-015	4.293e-013	0
100	-4.3e-015	72.06	54.79	-3.792e-015	26.77	18.65
1000	-4.25e-015	416.7	266.4	-4.233e-015	273	180.7
2000	-4.006e-015	516.9	344.6	-4.801e-015	460.6	288.6
3000	-4006e-015	649.6	375.6	-4.71e-015	573.6	341.6
4000	-4.142e-015	684.2	388.9	-4.642e-015	636.7	369.3
5000	-3.96e-015	698.1	394.1	-4.46e-015	676.7	385.2
6000	-4.233e-015	703.2	395.9	-4.688e-015	697.4	393.6
7000	-4.369e-015	704.4	396.3	-4.597e-015	701.8	395.3
8000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**
9000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**
10000	**-4.278e-015**	**704.6**	**396.3**	**-4.278e-015**	**704.6**	**396.3**

Mean, Standard Dev. & Mean abs Dev. Of **Balance Sparsity-norm** for Myopathic EMG signal for both soft & hard thresholding are same with Fixed from soft thresholding

V. CONCLUSION

Two threshoding methods for denoising one-dimentional signals using wavelet packets are described in this paper. The algorithm performs quite well in term of both numerical and visual distortion. The tabulation shows the signals residuals values of the filtering performance at different level of thresholding. Our proposed method is efficient enough to filter out unwanted signals from the desired signal without degrading the quality of the original signal. T**he** mean of Healthy EMG signal was found to be **-1.002e-015, the standard deviation is 382.9 and the mean abs deviation is 174.4 at threshold limit 8000 for** fixed form (soft) and Balance Sparsity-norm (hard) thresholding technique whereas for Myopathic EMG signal the mean is **-4.278e-015, the standard deviation is 704.6 and the mean abs deviation is 396.3 in both the thesholding techniques.** We have also analysed filtering performance by plotting the original and de-noised signal in the same plot. Our future research involves with the compression of muscular signals and the characteristic change during compression process using wavelet packet.

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