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Effect of Different Thresholding Techniques for Denoising of EMG Signals by using Different Wavelets

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***Abstract*—The Electromyogram (EMG) was at first produced for diagnosing the neuro-muscular disorders and abnormalities. Clinical applications before long wound up obvious, most eminently in epilepsy, lastly it ended up well known because of the introduction of prosthetics, explicitly body-powered prosthesis. The EMG recorded amid different movements to know the electrical action and functional state of the muscles which recognizes the medicinal variations from the normal conditions. The aim of this paper is to remove noise using the thresholding values at each and every level of the decomposition using wavelet can be a better technique, if the thresholding values are appropriate so that the loss of the EMG signal chances will be less.**

Keywords—EMG, Discrete Wavelet transform, Denoising, Thresholding.

I. INTRODUCTION

The aphorism of new period in therapeutic sciences is ***"Repair it if you can. Replace it if you can't"***.

Whenever the muscle fibers are contract, it generates an electrical signal that can be measured by placing the electrodes on the surface of skin at top of the muscle group. During the electrical activity, the signal is recorded in the form of spikes which is called as electromyogram signal or "raw" EMG signal. The sEMG signal recorded utilizing extensive electrodes (for example diameter 0.5 cm) that observes the action of various muscle fibres can be very much demonstrated as a zero-mean time-varying indeterminate procedure. The smallest and functional group of muscles is the motor unit. The number of activated motor units and the rate of its activation is observed monotonous related to the standard deviation of the raw EMG signal. The standard deviation estimates the magnitude of the electrical activity of the muscles which is referred to as EMG amplitude [1]. EMG amplitude has an assortment of uses, such as for myoelectrical prostheses purpose, a control signal is provided by EMG amplitude, for evaluating ergonomic assessments, and also helps to find the approximation of torque around a joint [2-5]. EMG signal processing is of huge importance and can't be emphasized enough, as electromyography is such a powerful, electrodiagnostic and physiologically easily available tool, therefore as expressed by De Luca, the misuse of this tool can lead to very harmful consequences [2]. The EMG signal require more attention on the configuration of the electrodes so that the signal processing techniques becomes advanced.[6]

The SNR ratio is computed as a ratio of the power of the signal to the power of noise and is represented in terms of decibels. It is also defined as a function of complicated interactions between the conductive ions (i.e. electrolytes) in the skin and the metal of the spot out surfaces of the electrode terminal. This is a complicate subject that is very far away from the scope of this small treatise. There are various approaches for decreasing the noise, such as by using large surface areas for the detection surfaces, employing conductive electrolytes to make better contact with the skin, and altering dead (rarely conductive) dermis from skin surface. For detection of the surfaces that is made up of unadulterated (>99.5%) silver in the form of bars 10 mm in length and 0.1 cm in width provide a sufficiently better medium for the detection of the surfaces.

The separation between the detection surfaces fluctuates straightly concerning the EMG signal amplitude is straightforwardly corresponding. Thus, this separation ought to be maximized. Be that as it may, when this separation was expanded it presented an unwanted characteristic in the design of the electrode. As the size of electrode expanded, it ends up cumbersome and can't be utilized to identify EMG signals from similar smaller size of muscles (in width just as long muscles), for example, such type of muscles spotted in the hand, lower arm and the leg muscles. In addition of that, as the distance increases, there is a decrement in the bandwidth of the filtering characteristics of the differential amplification (Description of this esoteric point may be got in Chapter 2 of Muscles Alive (1985) by Basmajian and De Luca). From Literature review, it is clarified that an acceptable compromise is provided if the distance of 1 cm is applied between the inter detection surfaces.

II. DATA ACQUISION

EMG signal in differential mode was recorded using two channels of MP 100A Biopac systems Inc. The subject aged between 23-30 years was used for this purpose. The recording session was around two hours for the subject. Recording was accomplished for six unique movements

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specifically supination, pronation, flexion, different types of grasping (Power Grasp and Precision Grasp) and extension.

The subject was clarified about the hand motions that should have been recorded. Two active surface electrodes were put on the surface of skin covering the ‘Flexor Digitorum Superficialis’ muscle in the forearm in differential mode with one centimetre separated and the other two active surface electrodes were put on the surface of skin covering the ‘Brachioradilis’. The single surface electrode was set upon the unconcerned muscle for the reference purpose.

III. EMG SIGNALS AFTER ADDING NOISE

EMG signal is not difficult to be distorted by the noises that is generated randomly as well as not correlated with the EMG signal which can be approximating by the help of a source of white Gaussian noise**.** [7,8]. In this paper, results of the Denoising algorithms for different methods (Universal Thresholding & Bayes Thresholding) are discussed.

The denoising is done after adding the Gaussian Noise of different SNR (10 db, 15 db and 50 db) with the 5 level of discrete wavelet transform in the original EMG signal. The PSNR and MSE are calculated and compared for both the methods. The results are obtained after using different wavelet families.

A. Signal after adding noise

The original EMG signal taken is shown below:

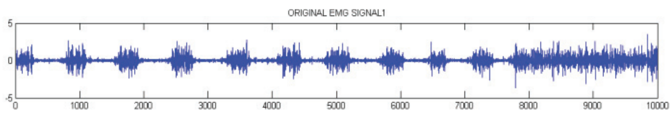


Fig. 1 Original EMG signal

The signal after notch filter is shown below:

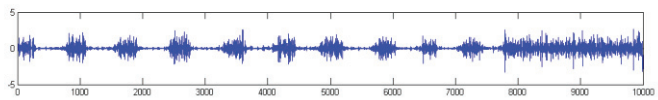
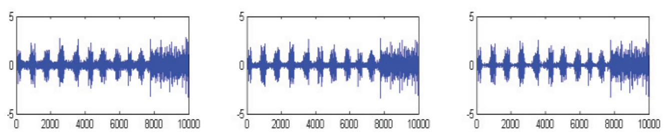


Fig. 2 EMG signal after notch filter

Then the Gaussian noise of 10 SNR, 15 SNR, and 50 SNR are added in the output of the notch filter. The resulted EMG signal is shown below:



(a) SNR 10 (b) SNR 15 (c) SNR 50

Fig. 3 Signal after adding Gaussian noise of different SNR

IV. METHODOLOGY USED

From so many years, the engineers and the applied scientists have faced a problem related to the recording of the EMG signals i.e. the noise and the distortion of signal. The Denoising is done to reduce the noise and make the signal noise free. Denoising is always done before the pre-processing of the signal. A quite variation is found in the problem of denoising due to a large number of variety of noises and signals. Reduction of noise is always trying after some sort of signal transformation. The projection of a signal can be done by an appropriate transform to a domain where the energy of signal is concentrated in small number of coefficients. On the other side, if this domain has noise which is evenly distributed then, denoising will be done very nicely in this domain. The SNR ratio is greatly rise up in few important coefficients, or the noise is not highlighted in this domain only the signal is highlighted. However, in such aspect, the denoising should be done in frequency domain for those signals that consists of a larger number of sinusoids

Similarly, it is always beneficial for piece wise constant signals as well as for piece wise polynomial signals to reduce the noise in a domain where these signals presence is very thin and scattered representation. So, the wavelet transforms domain and the time scale domain are the domains that is used for the reduction of noise. Since a broad span of signals can be classified into piece-wise polynomial. Now in signal processing, the wavelet transform become an important and essential tool for the processing of various types of signals.

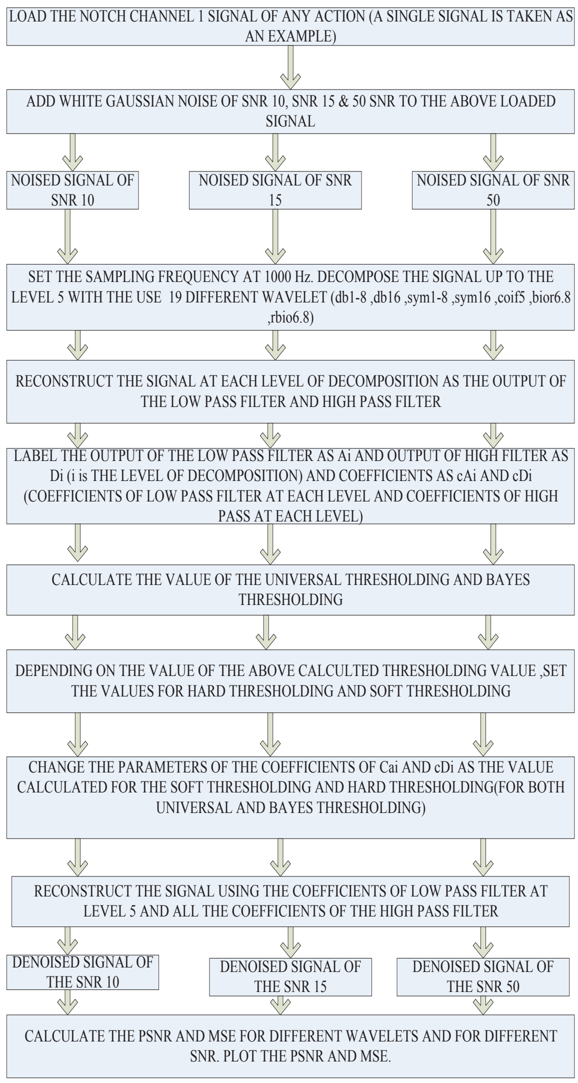


Fig.4 General Flowchart for Denoising the EMG signals

V. RESULT ANALYSIS

A. Universal Thresholding Method& Bayes Thresholding Method

Initially at the first stage, the EMG signal is decomposed to the level 5 by using discrete wavelet transform. In this study, Level dependent thresholding is used.

Median parameter (sigma) is computed for each decomposition level. On account of that, the different values of threshold are found for each individual level as the values of universal threshold are different in each level. Also, the threshold values are different as Bayes theorem depends on the sigma value calculated for each individual level as the values of threshold are calculated. Using different wavelets, hard and soft transformation can be done by applying the thresholding.

The denoising is done by taking one notch signal as an example of channel 1.

B. Changes in the Value of PSNR and MSE for Different Wavelets

The PSNR and MSE are calculated and compared for both the methods. The results are obtained with the Bayes & Universal Thresholding methods.

PSNR is referred as peak signal / noise ratio across two signals. This term is related to the engineering field that is used to compute the ratio across the peak possible signal power to the power of the signal which is corrupt due to noise that changes the accuracy of the representation.

PSNR is generally represented in respect of (log db) scale because most of the signals fall in wide range of dynamic. It is a parameter that is used to check the quality of a signal after its reconstruction in image-processing, denoising etc. The following way is used to compute the PSNR:

$$MSE = \frac{1}{N}\sum_{i=1}^{N} (x(i) - x_1(i))^2 \ldots\ldots\ldots\ldots \quad (1)$$

$$PSNR = 10\log \sum_{i=1}^{N} (x(i)^2 / MSE) \ldots\ldots\ldots\ldots \quad (2)$$

The PSNR value is generally as nearer to infinity as the MSE value tends to zero. This indicates that the signal quality is higher if the PSNR value is high [3].

The following graphs indicate the variation in the value of PSNR and MSE by varying thresholding methods and different wavelets for decomposing of signals.

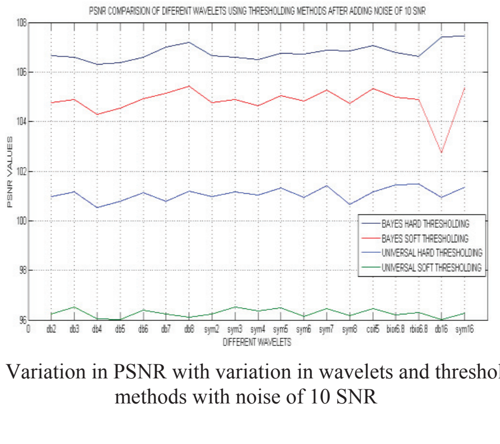


Fig. 5 Variation in PSNR with variation in wavelets and thresholding methods with noise of 10 SNR

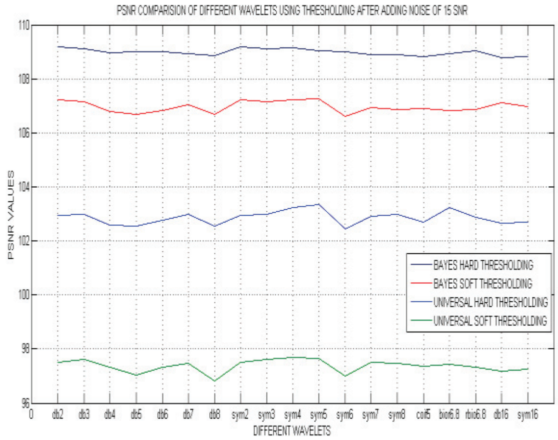


Fig.6 Variation in PSNR with variation in wavelets and thresholding methods with noise of 15 SNR

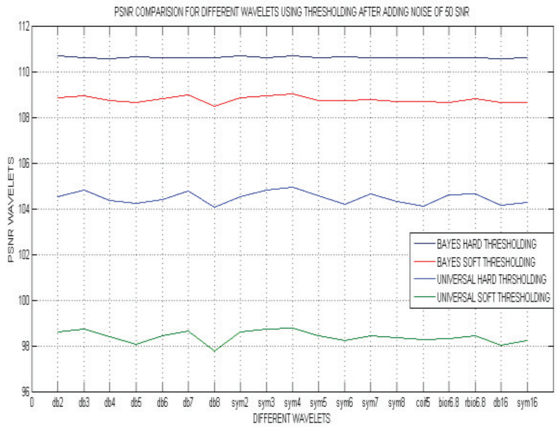


Fig.7 Variation in PSNR with variation in wavelets and thresholding methods with noise of 50 SNR

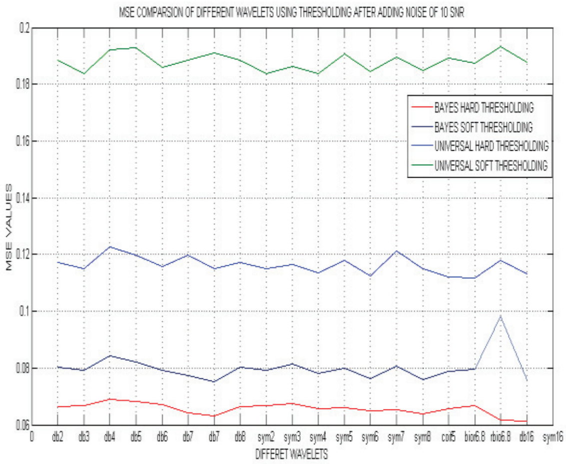


Fig.8 Variation in MSE with variation in wavelets and thresholding methods with noise of 10 SNR

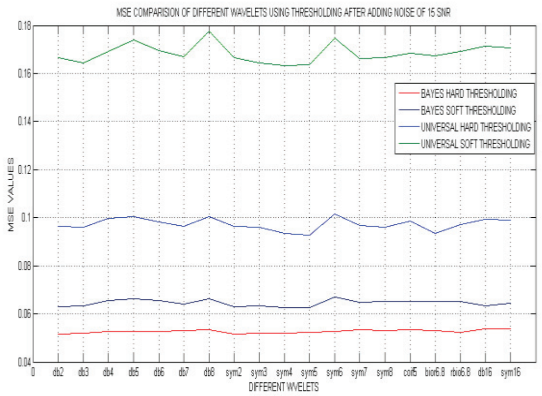


Fig.9 Variation in MSE with variation in wavelets and thresholding methods with noise of 15 SNR

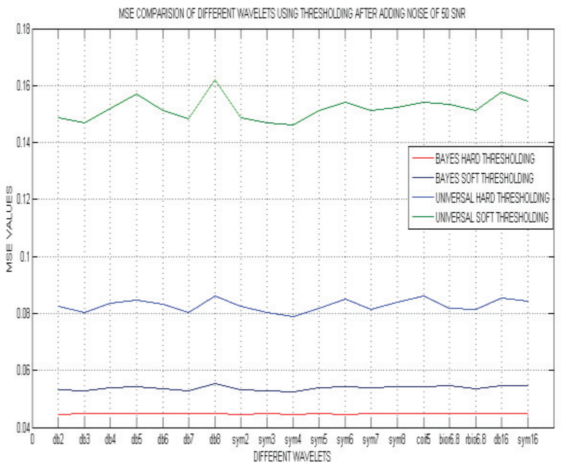


Fig.10 Variation in MSE with variation in wavelets and thresholding methods with noise of 50 SNR

VI. CONCLUSION & FUTURE SCOPE

From the results it is evident, that the highest value of PSNR was obtained by Bayes Hard Thresholding. But in case of Hard Thresholding changes of signal loss are higher and hence Bayes Soft Thresholding is found to be better than other selected methods.

By applying this method, the satisfying results are achieved in both numerically & visually aspects. In addition, this technique is easy to implement as well as considered as fast & effective for thresholding of EMG signals. However, there is also a possibility to find some other thresholding functions which is much coherent and effectively related to the adjacent coefficients. Neigh Shrink & Bayes can be further enhanced to denoise the signals. This technique is a complementary add on to the previously existing denoising techniques which is used for the denoising of the EMG signals. This technique is added up as a complement to the previously existing methods of denoising which is applied for the denoising of the EMG signals**.**

Moreover, for future work, this algorithm can be trained by using different artificial intelligence methods like fuzzy logic process or neural network process**,** so as to achieve the optimum solution without doing more computations for every individual combination. By using of these AI techniques, the optimal solution will be found directly, with more efficiency and less monotonous work.

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