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EMG Signal Enhancement Using Subband Soft-thresholding

Sabina Yasmin[1], MSU Zaman[2], Md. Ali Hossain[2]
[1]*(Department Computer Science and Engineering, Varendra University, Rajshahi, Bangladesh)*
[2]*(Department Computer Science and Engineering, Rajshahi University of Engineering and Technology Rajshahi, Bangladesh)*

Abstract:
Background*: The electromyogram (EMG) signal indicates electrical activity of muscles, which is the summation of all motor unit action potentials within the detection area of the electrode. However, when the surface EMG signal is recorded, it inevitably contaminated with various artifacts originated from different sources like inherent noise in the electronic components of detection and recording equipment, ambient noise, motion artifacts, inherent instability of signal and other physiological signals. Although different methods have been proposed to denoising EMG signals the problem of accurate and effective de-noising technique of EMG still remains a challenge.*
Materials and Methods*: In our study, a hybrid algorithm based on subband approach is implemented for EMG signal enhancement. Subband energy based enhancement using discrete wavelet transform (DWT) is first employed to separate high energy EMG component. Then the residual signal contains EMG and noise component. The EMG from the residual signal is extracted by using soft-thresholding. It is observed that wavelet thresholding works better for the signal with lower signal-to-noise-ratio (SNR), whereas, discrete cosine transform (DCT) based soft-thresholding performs well for higher SNR. A noise ratio factor (NRF) is introduced to select proper soft-thresholding method depending on the level of noise in the analyzing signal.*
Results*: The proposed hybrid algorithm maximizes the performance. The EMG signals of healthy and myopathy patient are collected from publicly available dataset to evaluate the performance of different enhancement methods. The experimental results show that the proposed method performs better than the traditional soft-thresholding approaches for a wide range of noise levels.*
Conclusion: *In this study, it is observed that DWT and DCT based soft-thresholding methods work better for low and relatively high SNR signals respectively. One decision factor is introduced to select the appropriate soft-thresholding algorithm between DWT and DCT. It improves the performance and hence the proposed method produces high SNR improvements of the EMG signal.*
Key Word*: Bandpass filtering; discrete cosine transform; electromyography; noise suppression; wavelet transform.*

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I. Introduction

Acquisition of electromyography (EMG) signal is most complicated and corrupted by various factors during acquisition or transmission, which result as noise effect. 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, hence, when detecting and recording the EMG signal, there is a main issue of concern that influence the fidelity of the signal that is the signal-to-noise ratio. The EMG signal should be processed to suppress the noise before being displayed or stored [1].These noisy effects decrease the performance of visual and computerized analysis. It is usually affected by noise, which may be generated by different sources, such as the hardware employed for signal amplification and digitization, the movement of cables during data collection and the activity of motor units distant from the detection point. The traditional way of reducing the noise from a signal is to use a low pass or band pass filter with cut off frequencies. However, the traditional filtering techniques are only able to remove a relevant portion of the noise but they are incapable if the noise is in the band of the signal is to be analyzed. Therefore, many denoising techniques are proposed to overcome this problem. As a multiband signal analysis technique, the wavelet transform offers the possibility of selective noise filtering and reliable parameter estimation, and therefore, can contribute efficiently to morphological analysis. For this reason wavelets have been extensively used in biomedical signal processing, mainly due to the versatility of the wavelet transform tools. As a multiband signal analysis technique wavelet based methods are recently more successful than filter based methods. Detection of EMG signals with powerful and advance methodologies is becoming a very important requirement in biomedical engineering.

A novel noise suppression method for electromyography (EMG) signals based on statistical modeling of wavelet coefficients is introduced in [2]. Then, they use GARCH model for wavelet coefficients after demonstrating effect of wavelet in EMG signal. In consequence, they introduce a maximum *a-posteriori* (MAP) estimator, based on GARCH modeling, for estimating the clean wavelet coefficients. And finally they compare their proposed method with other wavelet based denoising methods and then verify the performance improvement in utilizing the new strategy.

The discrete Wavelet Transform (DWT) has been applied for removing noise from the surface EMG [3]. Gaussianity tests are conducted to understand changes in muscle contraction and to quantify the effectiveness of the noise removal process. Wavelets are functions that satisfy certain mathematical requirements and are used in representing data or other functions. In this paper we analyze the performance of different level DW T for EMG signal denoising and compare the results considering mean square error (MSE).The Denoising analysis concludes using bior multilevel wavelet and the mean was optimal in nature for different global threshold.

In [4], three different denoising methods of sEMG signals, empirical mode decomposition, discrete wavelet transform (DWT), and median filter, are examined. These methods are applied to 5 different levels of noise-added synthetic sEMG signals. For the DWT-based denoising technique, 40 different wavelet functions, 4 different threshold-selection-rules, and 2 threshold-methods are tested iteratively. Three different window-sized median filters are applied as well. The SNR values of denoised synthetic signals are calculated and the results areused to select DWT and median filter method parameters. Finally, 3 methods with the optimum parameters are applied to the real sEMG signal acquired from the flexor carpi radial is muscle and the visual results are presented.

The effects of mechanical perturbations and noise are typically encountered during sEMG recordings in clinical and related applications [5].

The analysis established the relationship between the attenuation rates of the movement artifact and the sEMG signal as a function of the filter band pass. When this relationship is combined with other considerations related to the informational content of the signal, the signal distortion of filters, and the kinds of artifacts evaluated in this study, a Butterworth filter with a corner frequency of 20 Hz and a slope of 12 dB/oct is recommended for general use. The results of this study are relevant to biomechanical and clinical applications where the measurements of body dynamics and kinematics may include artifact sources. One of challenges in the area of muscle diseases is the requirement of clean EMG signals. Therefore, extensive work is required to be performed to increase the quality and information content of the EMG signal.

II. Material And Methods

A data adaptive temporal domain filtering of spatiotemporal EMG signal is implemented by multi-signal wavelet transform. In recent studies, it is employed in multivariate signal decomposition especially for multichannel signal denoising [6], [7]. The strength of wavelet transform (WT) based signal decomposition lies in using short high frequency basis functions and long low frequency ones to isolate different characteristics of the signal. The decomposition consists of observing the signal at different resolution levels and different translations in time by bandpass filtering [6]. By observing the significant spatial correlation between wavelet coefficients of different channels at each decomposition level, an array wavelet transform is implemented in [7].

Wavelet thresholding

After The EMG signal suffers with a major problem of distortions created by noise. A noise is an unwanted signal which deteriorates the characteristics of original signal. There are various types of noises present in environment such as colored noise, burst noise, White noise etc. Therefore, noise signal may occupy either some specific frequency band or entire frequency band. When noise also share the frequency band of signal, then it becomes very difficult to remove this noise without losing some signal information. Therefore, noise removal without losing original features of signal is a challenging task and has become an active area of research.

Traditionally Fourier Transform based frequency selective filters is the simplest choice to remove the noise but such filters may fail when noise shares the same frequency band with signal. Over Fourier transform, wavelet transform became the first choice in the area of signal denoising due to its various advantages such as time frequency localization & multi resolution analysis in recent years.

Thresholding is one of the most often used processing tools in wavelet signal processing. It is widely used in noise reduction, in signal and image compression, and sometimes in signal recognition. Wavelet based nonlinear thresholding is effective and efficient method for noise reduction only to the extent to which the wavelet representation of the noise-free signal is sparse [8]. In this method, the process of each coefficient from the detail sub bands with thresholding function is applied to obtain the output. .

Hard thresholding is the simplest method to implement whereas the soft thresholding has complicated mathematical derivations**.** Hard thresholding is a process in which all the coefficients below a fixed threshold τ that depends on noise variance are discarded. It can be represented by the following equation:

$$\tilde{w}_n = \begin{cases} w_n, \; for \quad w_n \geq \tau \\ 0, \; for \quad w_n < \tau \end{cases} \tag{1}$$

where, w_n is the wavelet coefficient and $\tilde{w}_n$ is the value of the coefficients after hard thresholding.

Soft thresholding is a process in which not only all the coefficients below threshold are discarded but all the coefficients above a fixed threshold τ are shrunk. It is defined as:

$$\tilde{w}_n = \begin{cases} f(w_n - \tau), \; for \quad w_n \geq \tau \\ 0, \qquad\quad for \quad w_n < \tau \end{cases} \tag{2}$$

where, w_n is the wavelet coefficient and $\tilde{w}_n$ is the value of the coefficients after soft-thresholding. This shows that soft thresholding is an extension of hard thresholding: first, setting the elements to zero whose absolute values are lower than the threshold, and then shrinking the nonzero coefficients towards zero**.** Usually hard thresholding is used for data compression purpose. In wavelet analysis low frequency coefficients mainly represent signal & high frequency coefficients with randomness represent noise. Wavelet Thresholding is applied for denoising purpose. Choice of a suitable wavelet function, thresholding methods and the thresholding rule play a vital role in signal denoising [9]. Thresholding methods used with discrete wavelet transform based filtering are to modify the obtained coefficients. By using wavelet thresholding, the noise in the signals can be removed. The wavelet coefficients at different scales could be obtained by taking WT of the noisy signal. Normally, those wavelet coefficients with smaller magnitudes than the preset threshold are caused by the noise and are replaced by zero, and the others with larger magnitudes than the preset threshold are caused by original signal mainly and kept (hard-thresholding case) or shrunk (the soft-thresholding case). Then the denoised signal could be reconstructed from the resulting wavelet coefficients. The general model of wavelet thresholding based signal enhancement approach is illustrated in Fig. 1.

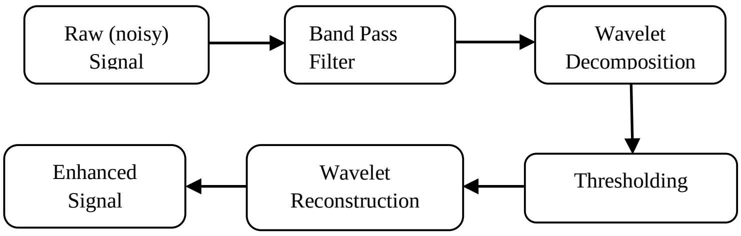

Fig. 1: The general model of wavelet thresholding based signal enhancement

Wavelet thresholding de-noising methods deals with wavelet coefficients using a suitable chosen threshold value in advance [10]. There are several methods to choose the best analyzing function, the type of thresholding and the threshold values. Denoising is achieved by selecting a threshold for such high frequency coefficients.

Rigrsure thresholding method is implemented in this study. It is a soft threshold evaluator of unbiased risk. Suppose $W = [w_1, w_2, ... w_N]$ is a vector consists of the square of wavelet coefficients from small to large. Select the minimum value r_b from risk vector, which is given as,

$$R = \{r_i\}_{i=1,2,,...,N} = \frac{\left\lfloor N - 2i + (N-i)w_i + \sum_{k=1}^{l} w_k \right\rfloor}{N} \tag{3}$$

as the risk value, where N is the length of wavelet coefficient vector. The selected threshold is $\tau = \sigma\sqrt{w_b}$ where, w_b is the bth squared wavelet coefficient (coefficient at minimum risk) chosen from the vector W and σ^2 is the variance of the noisy signal.

Threshold determination is an important problem. A small threshold may yield a result which may be noisy and large threshold can cut significant part of signal thus losing the important details of the signal.

DCT Soft thresholding

In this study, the enhancement method in the discrete cosine transform (DCT) domain using soft thresholding strategy is also employed. Exploiting the behavior of the amplitude distribution of the DCT coefficients, a linear function is introduced for amplitude thresholding, unlike conventional constant noise-level subtraction rule. Transform domain signal enhancement method commonly uses amplitude subtraction based soft thresholding defined by,

$$\hat{X}_k = \begin{cases} sign(X_k)(|X_k| - \tau) & if\ |X_k| > \tau \\ 0 & otherwise \end{cases} \quad (4)$$

where τ denotes the noise level, X_k is the kth coefficient of the noisy signal obtained by the analyzing transformation and $\hat{X}_k$ represents the corresponding thresholded coefficient. Since all the coefficients are thresholded by τ, the speech components are also degraded during this process. This degradation results in a loss in speech quality. Unlike the conventional constant noise-level subtraction rule in equation Eq. (4), a frame based soft thresholding strategy was proposed in [11]. The strategy depends on segmenting the signal into short time intervals and applying DCT on each frame. The DCT coefficients of each frame are divided into frequency bins which are categorized as either signal or noise dominant depending on its speech and noise energy distribution. There are some problems of the conventional constant noise level subtraction rules given in Eq. (4). For instance, subtraction of a constant value from the noisy speech coefficients in order to obtain the clean signal coefficients as is inadequate. Furthermore, due to the second part of thresholding a significant amount of speech information may be lost, resulting as a source of another noise. Therefore a linear thresholding is followed in noise dominant frames. On the other hand, soft thresholding is very inaccurate for signal dominant frequency bins and will most probably degrade the signal components, therefore giving more damage than its contribution to the enhanced signal. Therefore, the signal dominant frames should better be kept as they are in order not to degrade the high energy signal components. This enables even signal with high SNRs to be processed effectively.

The noisy signal is first segmented into 32 ms frames and a 512 point DCT is applied on each frame. The DCT coefficients of the frames are further divided into 8 frequency bins, each containing 64 DCT coefficients. As discussed before, for adaptive thresholding, each bin is categorized as either signal or noise-dominant. The classification pertains to the average noise power associated with that particular bin. If the ith bin satisfies the following inequality,

$$\frac{1}{N}\sum_{k=1}^{N}\left|X_k^i\right|^2 \geq \sigma_n^2 \quad (5)$$

where σ_n^2 denotes the variance of the noise, X_k^i is the kth DCT coefficient of the ith frequency bin and N (=64) is the number DCT coefficients of the bin, then the bin is characterized as signal dominant, otherwise as noise dominant. The signal dominant bins are not thresholded, since it is highly possible to degrade the signal, especially for high SNRs [12]. In the case of a noise dominant frequency bin, the absolute values of the DCT coefficients are sorted in ascending order and a linear thresholding is applied:

$$\hat{X}_k = sign(X_k)[\max\{0, (|X_k| - \gamma_j)\}] \quad (6)$$

where γ_j is the linear threshold function obtained as,

$$\gamma_j = j\,\frac{\rho\sigma_n N}{\sum_{k=1}^{N} k^2} \quad (7)$$

where j is the index of sorted $|X_k|$. It is evident from Eq. (5) that for the noise-dominant frequency bins, the average noise power added would be less than the average noise power estimated over the entire speech signal. Here, the added average noise power over any of these frequency bins is denoted as $\rho\sigma_n$. To find a reasonable value for ρ, three EMG signals contaminated with white noise at 10dB SNR are used. Using the categorization in Eq. (5) at each frequency bin, the noise dominants are identified and value of ρ is calculated by simply dividing the variance of that frequency bin with the overall noise variance. It can be observed that the value of ρ vary between 0.2 and 0.8 for different EMG signals. In this study, the value of ρ is set to 0.4 and it gives better results for the EMG signals of healthy and non-healthy subjects.

Proposed hybrid thresholding method

In this section we introduce a novel signal enhancement algorithm as a combination of subband energy based enhancement (SEE) approach [6], wavelet soft-thresholding and DCT soft-thresholding. It is noted that the SNR improvement of SEE method is not satisfactory. The suppressed noise component contains the EMG signal, whereas, the separated relatively higher energy signal only contain the EMG component. Hence, it is required to further process the noise part to extract the EMG components. Then the purified EMG signal $\tilde{z}_m$ (of mth channel) can be represented as –

$$\tilde{z}_m = \widehat{z}_m + \hat{z}_m \quad (8)$$

where, $\tilde{z}_m \approx z_m$, $\widehat{z}_m$ represents the EMG component separated from the noisy signal x_m using SEE method and $\hat{z}_m$ is the EMG component extracted from the noise $\widehat{\eta}_m$. The noise term $\widehat{\eta}_m$ is obtained as the output of SEE approach. The actual noise is removed from $\widehat{\eta}_m$ by applying soft-thresholding technique yielding the residual EMG component $\hat{z}_m$. In other word, the noise component $\widehat{\eta}_m$ is then represented as –

$$\widehat{\eta}_m = \hat{z}_m + \widetilde{\eta}_m \tag{9}$$

where, $\widetilde{\eta}_m \approx \eta_m$ and *m* is the channel index in case of multichannel EMG. The main objective is to separate $\hat{z}_m$ from $\widehat{\eta}_m$ using effective denoising algorithm.

It is observed that the wavelet and DCT soft-thresholding is suitable for low and high SNR signal respectively. For a typical EMG enhancement, the output SNR of both soft-thresholding approaches as a function of input SNR is illustrated in Fig. 2.

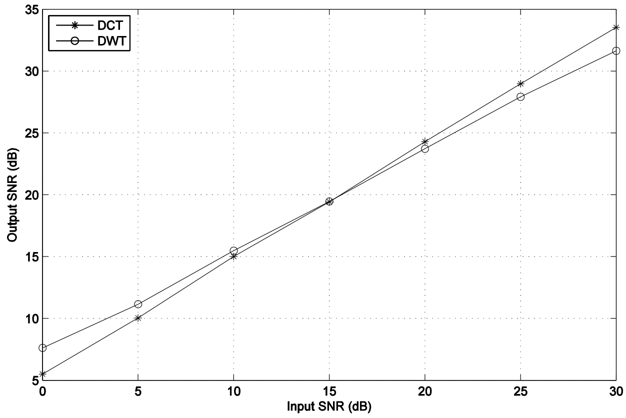

Fig. 2: Comparative performance of wavelet and DCT soft-thresholding for EMG enhancement in different input SNR.

It is possible to obtain best performance if the wavelet soft-thresholding is employed for lower SNR signal and DCT soft-thresholding technique is used for higher SNR signal. The main challenge here is to detect the noise level of the analyzing noisy signal. After applying SEE method, the noisy signal xm is decomposed into pure EMG component $\widehat{z}_m$ and very noisy EMG component $\widehat{\eta}_m$. An effective technique is introduced here to detect the noise level of analyzing signal using these two components. A noise scale factor (NSF) is defined as:

$$\beta = \sigma_{\widehat{z}}^2 / \sigma_{\widehat{\eta}}^2 \tag{10}$$

where, $\sigma_{\widehat{z}}^2$ and $\sigma_{\widehat{\eta}}^2$ are the variances of $\widehat{z}_m$ and $\widehat{\eta}_m$ respectively. If $\beta > 2$, i.e. the variance of pure EMG is twice of that of the noisy one, the signal is treated as higher SNR signal and DCT soft-thresholding the applied for enhancement. When $\beta \le 2$, it is considered as lower SNR signal and then wavelet soft-thresholding method is used to achieve the denoising of the analyzing signal. It is noted that the NSF plays an important role to improve the performance of soft-thresholding based EMG enhancement. The proposed hybrid enhancement algorithm (HEA) is illustrated below:

i) The noisy EMG signal is decomposed into pure EMG $\widehat{z}_m$ and noise component $\widehat{\eta}_m$ containing EMG signal using subband energy based enhancement (SEE).
ii) The noise level of the signal is detected using these two components $\widehat{z}_m$ and $\widehat{\eta}_m$.
iii) Based on the detected noise level using Eq. (10), wavelet or DCT based soft-thresholding technique is employed to separate EMG component $\hat{z}_m$ from $\widehat{\eta}_m$.
iv) Finally, the complete EMG signal is obtained by summing up $\widehat{z}_m$ and $\hat{z}_m$.

III. Experimental Results and Discussion

The proposed hybrid algorithm for EMG signal enhancement is evaluated using real EMG signals collected from publicly available dataset. It is found that the proposed algorithm performs better than that of the traditional signal enhancement approaches.

Data description

An electromyogram (EMG) is a common clinical test used to assess function of muscles and the nerves that control them. EMG studies are used to help in the diagnosis and management of disorders such as the muscular dystrophies and neuropathies. Nerve conduction studies that measure how well and how fast the nerves conduct impulses are often performed in conjunction with EMG studies. The experimental data are obtained from PhysioNet with the courtesy of Seward Rutkove, MD, Department of Neurology, Beth Israel Deaconess Medical Center/Harvard Medical School. The data collection experiment was conducted with a Medelec Synergy N2 EMG Monitoring System (Oxford Instruments Medical, Old Woking, United Kingdom). A 25mm concentric needle electrode was placed into the tibialis anterior muscle of each subject. The patient was then asked to dorsiflex the foot gently against resistance. The needle electrode was repositioned until motor unit potentials with a rapid rise time were identified. Data were then collected for several seconds, at which point the patient was asked to relax and the needle removed. Two types of data are analyzed: 1) a 44 year old man without history of neuromuscular disease; and 2) a 57 year old man with myopathy due to longstanding history of polymyositis, treated effectively with steroids and low-dose methotrexate. The data were recorded at 50 KHz and then down-sampled to 4 KHz. During the recording process two analog filters were used: a 20 Hz high-pass filter and a 5K Hz low-pass filter.

Result analysis
The EMG data of a healthy and a subject with myopathy are shown in Fig. 3. It is difficult to differentiate the two types of EMG signals by visual inspection, whereas, they are absolutely different signals in nature.

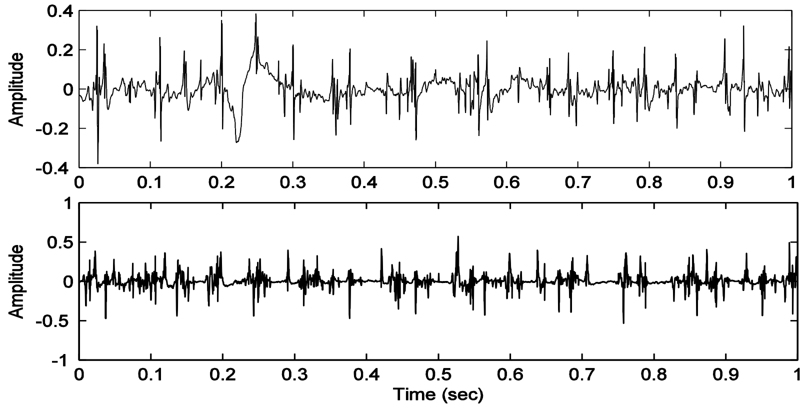

Fig. 3: The EMG signal of healthy subject (top) and a subject with myopathy problem (bottom)

To implement the subband energy based enhancement (SEE), each of the EMG vector is decomposed into 10 subbands using discrete wavelet transform (DWT). A ‘db4’ wavelet is used for decomposition. The subband signals of the EMGs as well as the fractional Gaussian noise (fGn) are illustrated in Fig. 4. The fGn is generated with the same sampling frequency as for EMG. It is noted that the EMG and the fGn are normalized before decomposition. The scaling factors of normalization are preserved for next stage processing.

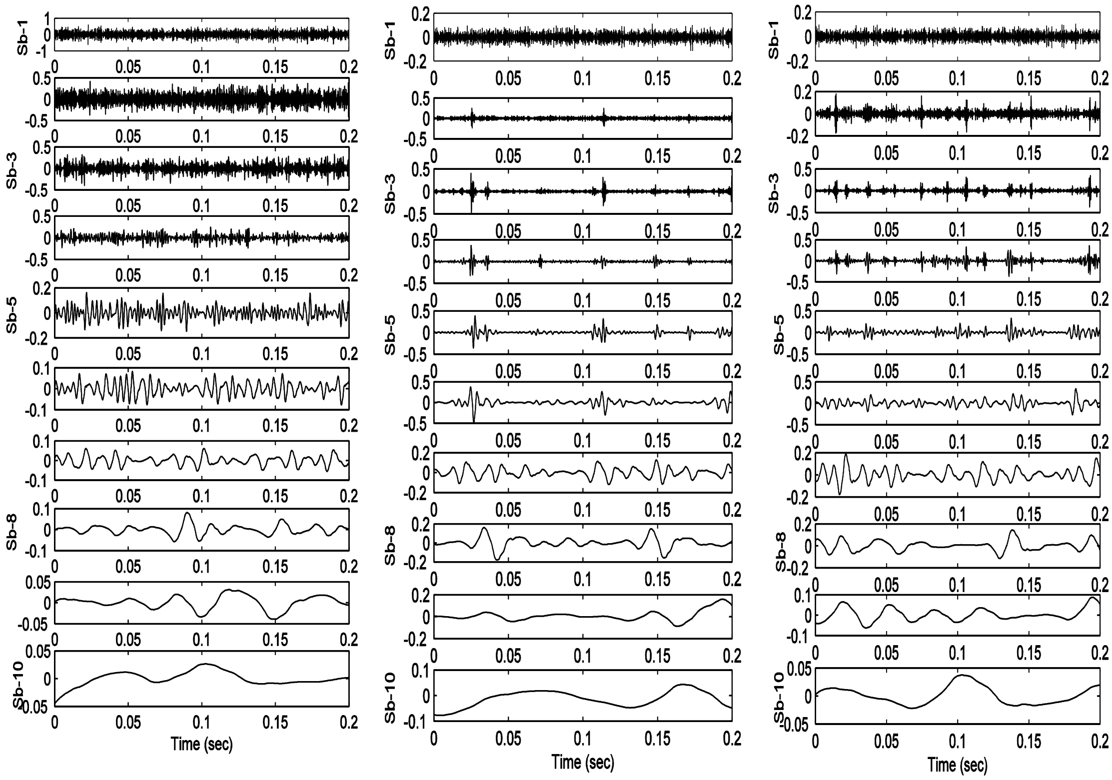

Fig. 4: The subband signals of fGn (left), normal EMG (middle) and myopathy EMG (right) obtained by using DWT of 9 levels.

The subband energy in logarithmic scale of fGn as well as its 95% confidence limits (upper and lower) are calculated to be used as the reference for threshold detection. The subband energy of the noisy (10dB SNR) EMG signal of normal subject is compared with the upper confidence limit of that of the fGn. The energy of the 7th subband exceeds the upper limit as illustrated in Fig. 5. Then the subbands 7-10th are summed up to reconstruct the pure EMG component. The noisy EMG, reconstructed pure EMG and the separated noise components are shown in Fig. 6.

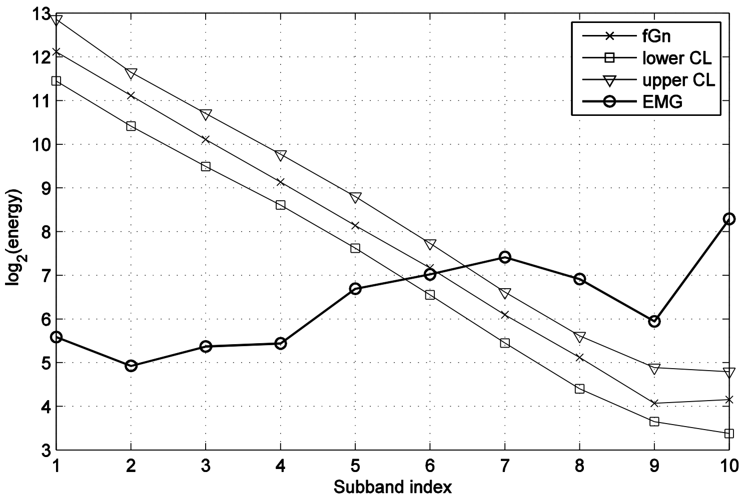

Fig. 5: The subband energy of noisy healthy EMG of 10dB SNR, fGn and its confidence limits with 95% confidence interval.

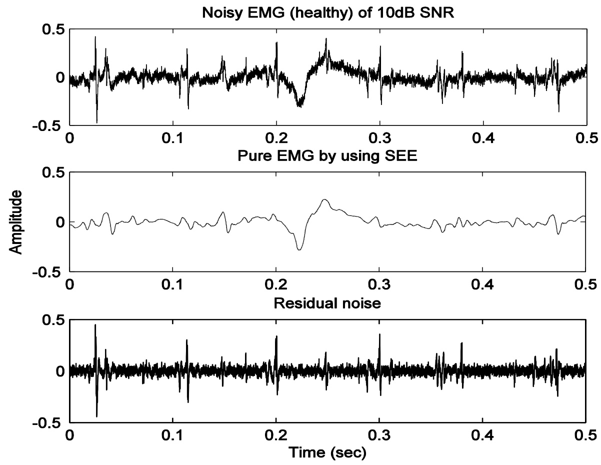

Fig. 6: The noisy EMG of 10dB SNR (top), reconstructed pure EMG (middle) and noise component (bottom).

It is observed that the noise component also contains the EMG signal which is required to be separated. The noise suppression is performed using wavelet based soft-thresholding. The outcome of the thresholding technique is presented in Fig. 7 which illustrates that the actual noise and the residual EMG are perfectly separated. Thus obtained residual EMG and the EMG component separated by SEE method are added to yield the purified EMG signal as shown in Fig. 8. The purified EMG signal is to be used in classification or other applications.

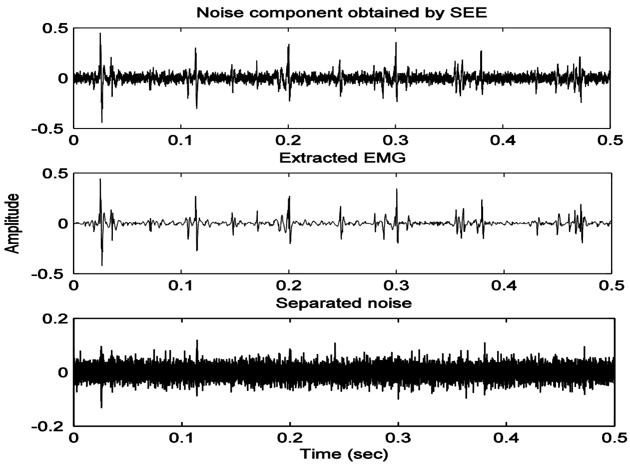

Fig. 7: Noise component (top), extracted residual EMG (middle) and separated noise (bottom).

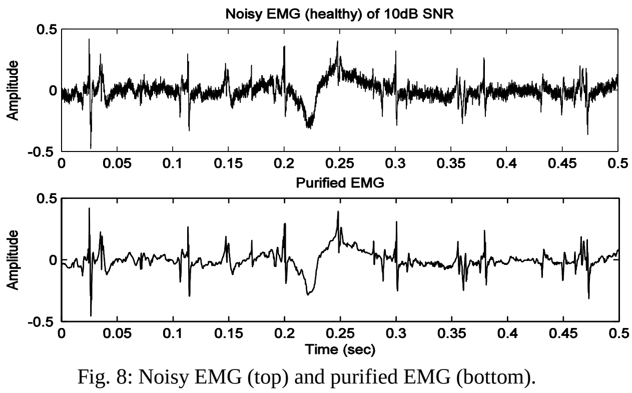

Fig. 8: Noisy EMG (top) and purified EMG (bottom).

The quantitative evaluation of performance of the enhancement algorithms are measured by signal-to-noise-ratio (SNR). The input SNR_I and output SNR_O are defined as:

$$SNR_I = 10\log\left(\frac{\sum_t s^2(t)}{\sum_t [s_m(t)-s(t)]^2}\right) \tag{4.1}$$

where, $s(t)$ is the original signal and $s_m(t)$ is the noisy signal. If $s_e(t)$ is the enhanced signal, the output SNR_O is defined by:

$$SNR_O = 10\log\left(\frac{\sum_t s^2(t)}{\sum_t \left[s(t) - s_e(t)\right]^2}\right) \tag{4.2}$$

The performance of the proposed hybrid algorithm is compared with wavelet and DCT based soft-thresholding to separate the residual EMG from the noise component obtained by SEE method. The performance is studied for a wide range of input SNR. It is observed that the wavelet based soft-thresholding works better for lower input SNR, whereas, DCT based soft-thresholding performs better for higher input SNR. The proposed hybrid algorithm maximizes the performance for whole range of input SNR. Total duration of data collected from PhysioNet dataset are used to evaluate the performance. The comparative performance in term of output SNR as a function of input SNR is illustrated in Fig. 9. It is observed that the performance of the proposed hybrid algorithm is always met the maximum SNR improvement.

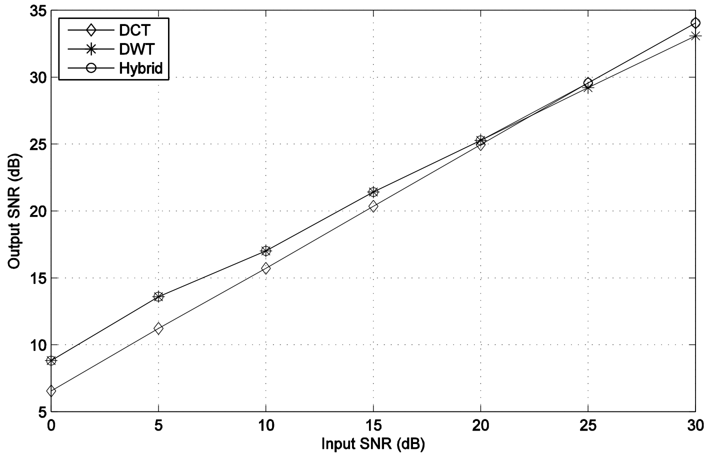

Fig. 9: The output SNR of different enhancement algorithms as a function of input SNR for healthy EMG

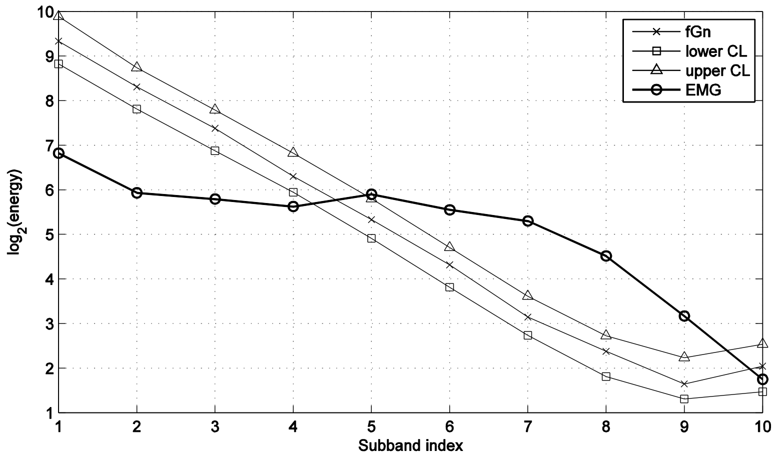

Fig. 10: The subband energy of noisy myopathy EMG of 10dB SNR, fGn and its confidence limits with 95% confidence interval.

The subband energy of noisy myopathy EMG of 10dB SNR in addition to that of fGn and its confidence limits are shown in Fig. 10. It is observed that the energy of 5th subband exceeds the upper confidence limit of fGn's subband energy. Hence, the 5-10th subbands of myopathy EMG are summed up to reconstruct the pure EMG components. The rest of the subbands are used to find the residual noise which contains EMG component in addition to noise.

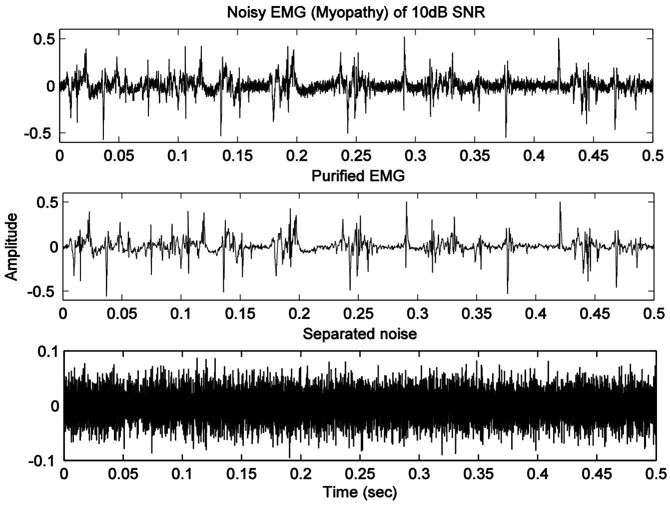

Fig. 11: Noisy myopathy EMG of 10dB SNR (top), extracted purified EMG (middle) and separated noise component (bottom).

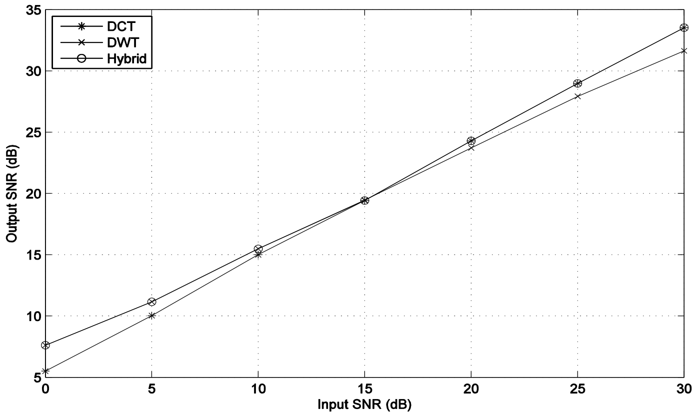

Fig. 12: The performance of different enhancement algorithms for myopathy EMG in term of SNR_O as a function of SNR_I

The purified myopathy EMG is separated using the similar method as employed for healthy EMG is presented in Fig. 11. The noise is well separated from the noisy myopathy EMG signal. Total duration of data collected from PhysioNet dataset are used to evaluate the performance for myopathy EMG. The comparative performance of different enhancement algorithms in terms of output SNR as a function of input SNR is illustrated in Fig. 12. It is observed that the performance of the proposed hybrid algorithm is always met the maximum SNR improvement.

IV. Conclusion

Due to extensive applications of surface EMG signals in clinical diagnosis, motion analysis, prosthetic device, and etc., it is required to remove the interference components from the EMG signals. Although there are several methods for denoising EMG signal, an effective noise suppression method is still demanding. A novel subband approach of EMG denoising is introduced in this study. A subband energy based pre-filtering method is employed first. It is observed that DWT and DCT based soft-thresholding methods work better for low and relatively high SNR signals respectively. A decision factor is introduced based of the results of pre-filtering to select the appropriate soft-thresholding algorithm between DWT and DCT. It maximizes the performance and hence the proposed method produces high SNR improvements for a wide range of input SNR of the EMG signal. The experimental results of these methods are analyzed for two types of EMG signals – healthy and myopathy subjects. Based on the results it is illustrated that the proposed approach achieved the high SNR value for all data set. This method can successfully remove artifacts from different EMG signals. The perceptual quality of the enhanced signal is high. It can be used for prediction and controlling hand motion as well as in clinical applications. The importance of the proposed method lies on the removal of noise without distorting the EMG signal and that is proved by input and output SNR analysis for a wide range. The evaluation of performance of the proposed method with high volume of dataset with adverse types of EMG signals and the study on the effects of denoising algorithm in further application (EMG classification, diagnosis etc.) are considered as the future extension of this study.

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