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Abstract. Denoising of the Electromyography (EMG) signal is critical in the diagnosis of muscle illnesses and several EMG-based mechatronics applications. This paper presents an improved EMG denoising method based on the Discrete Wavelet Transform (DWT) and the Non-Local Means (NLM) estimates. The DWT-based denoising method is quite effective in reducing the noise present in high-frequency regions. Unfortunately, this method demands large decomposition levels to mitigate the noise in low-frequency regions. The NLM method is efficient in mitigating noise from low-frequency regions but its performance is limited by the rare patch effect that results in signal distortion. Henceforth, these techniques are unable to meet the growing demand of the new generation applications. Subsequently, an improved denoising technique that effectively integrates the capabilities of both NLM and DWT is proposed in this paper. The performance of the proposed method is evaluated and compared to the proposed work on the signal taken from the EMGLAB database.

Keywords: Electromyography (EMG), Discrete Wavelet Transform (DWT), Denoising, Wavelet Thresholding, NeighShrinkSURE (NSS), Non-Local Means (NLM).

1 Introduction

Electromyography (EMG) is a myoelectric signal that specifies the information on the electrical activities of the human neuromuscular system. These signals have a vital role in several applications including psychomotor and neuromuscular research, neurological diagnostics, and robot limb control [1]. However, these signals often get contaminated with artifacts during their acquisition, recording, and transmission process. The noises that affect these biopotential signals generally come from electrodes, cables, data collection equipment, and amplifiers. Moreover, even the body itself influences the signal acquisition from the body surface such as motion artifacts.

Several mathematical frameworks for EMG denoising in the literature are based on filtering, Empirical Mode Decomposition (EMD) [2], DWT [3], NLM [4], Variational Mode Decomposition (VMD) [5], and Generalized Variational Mode Decomposition (GVMD) [6]. The EMD-based denoising [2] approaches tend to enhance the signal-to-noise ratio (SNR) but are less efficient in preserving the morphological structure of EMG signals [7]. Furthermore, these methods are computationally expensive when it comes to extracting intrinsic mode functions (IMFs) [8]. The VMD is used to decompose the signal into a set of modes generated using a non-recursive process such that the spectrum of each mode is concentrated around center frequencies. However, its centre frequencies cannot be flexibly adjusted [6]. The DWT-based denoising approach is effective in removing only the high-frequency noise which results in signal distortion and information loss. Moreover, accessing the very low-frequency components requires substantial decomposition levels that lead to computational overhead [3]. Inversely, the NLM-based methods effectively remove the low–frequency noise but suffers from the rare-patch effect due to its incompetence in high-frequency regions [4]. In this paper introduces a competitive method utilizing the efficacy of both DWT- and NLM-based techniques for EMG signal denoising.

This paper is structured as: Section 2 explains the materials and methods while Section 3 describes the proposed EMG denoising approach and performance metrics. Next, section 4 discusses the qualitative analysis of the results. Finally, the conclusion is presented in Section 5.

2 Materials and Methods

Let's say that the real EMG signal *x(i),* the noise *n(i),* and the noisy version of the EMG signal *S(i),* are all related as follows:

$$S(i) = x(i) + n(i); \qquad i = 1,2,\ldots\ldots,N \tag{1}$$

The number of samples in the signal *S(i)* is *N*. The purpose of this research is to remove noise from a corrupted EMG signal, *S(i)* without impacting the EMG's morphological components. This section briefly explains the DWT- and NLM-based EMG denoising techniques.

2.1 Discrete Wavelet Transform (DWT)-Based Denoising

The wavelet-based denoising techniques are widely preferred for denoising the EMG signals due to their inherent time-frequency resolution [9]. It has become a powerful tool for nonstationary signal analysis due to the availability of multiple wavelet functions. The DWT-based denoising methods are implemented in three steps where the signal is decomposed into detail and approximation coefficients in stage 1. In stage 2, the signal is denoised by implementing thresholding on the obtained detailed coefficient. Finally, the signal is reconstructed from the modified coefficients.

In DWT, a signal can be disintegrated and recreated using low- and high-pass filters with impulse responses *L(i)* and *H(i)*, respectively. The approximation coefficient from the particular decomposition level is fed into these filters to get higher-level approximation and detailed coefficients. These filters are related as follows:

$$H(i) = (-1)^{1-i} L(1-i) \tag{2}$$

After decomposition, the detailed coefficients are exposed to the thresholding techniques for denoising the signal. These techniques are broadly classified into two categories namely Hard and Soft Thresholds. The Hard Threshold is a keep or kills rule and it is more suited only when the detail coefficient is either a signal or a noise coefficient which is generally not the case. On the contrary, the Soft Threshold (Cf. Eq. (3)) is preferred when the detail coefficient contains both signal and noise [10].

$$\widehat{D}_{j,k} = \begin{cases} sign(D_{j,k})\left(\left|D_{j,k}\right| - \lambda\right), & \left|D_{j,k}\right| \geq \lambda \\ 0, & \left|D_{j,k}\right| < \lambda \end{cases} \tag{3}$$

where λ is the threshold value, $D_{j,k}$ and $\widehat{D}_{j,k}$ denotes the detail and estimated coefficients, respectively. This method denoises the high-frequency noise well but demands large decomposition levels to diminish the noise from low-frequency regions. A higher decomposition level means more filter banks, which increases computing time and complexity. The last approximation coefficient will still contain residues of very low-frequency noise components even after a larger number of decompositions. The elimination of crucial diagnostic information from the EMG signal is also a result of the thresholding of larger detail coefficients. The quality of the denoised EMG signal is affected as a result of this. Moreover, the efficacy of these methods depends on the noise characteristics' estimation that helps to compute its optimum threshold value at any decomposition level. An inappropriate threshold setting results in the loss of important signal information, resulting in a poorly denoised EMG signal.

2.2 Non-Local-Means (NLM)-Based Denoising

The NLM algorithms were originally developed for image denoising. However, the algorithms have evolved and have been applied to EMG signal denoising due to their repetitive characteristics similar to that of the EMG [11]. The NLM method calculates an estimate for each sample in the noisy EMG signal. The estimated m^{th}sample value $\hat{S}(m)$ can be expressed as the weighted sum of *n* samples in the search neighborhood. The centers of the local patches that occur inside a search neighborhood of *R(m)* correspond to *m* and *n* for a given signal. Each patch will have B_δ samples ranging from *–P : P*. Subsequently $B_\delta = (2P + 1)$ samples where δ represents the patch number. The following is a representation of the estimated signal:

$$\hat{S}(m) = \frac{1}{s(m)} \sum_{n \epsilon R(m)} w(m,n) S(n) \tag{4}$$

here, $s(m) = \sum_n w(m,n)$ is the total of the weight values over a search neighborhood ($n\epsilon[-Q{:}\,Q]$) and $w(m,n)$ is the weight value specified as:

$$w(m,n) = exp\left(-\frac{\sum_{\Delta \epsilon \delta}(S(m+\Delta)-S(n+\Delta))^2}{2B_\delta \tau^2}\right) \quad (5)$$

Where δ is the patch width ($-P : P$) in Eq. (5) and Δ is a variable that ranges over B_δ. The bandwidth parameter, τ determines how much smoothing will be applied to the signal. The discrepancy between the data points of the patches centered at m and n, accordingly, is represented by d. The weight value is calculated by summing the difference value over δ and normalizing it. There have been other weighting approaches presented, but the most accepted is squared patches with a central reference point. A patch correction technique is used to achieve better results in the instance of image de-noising as follows:

$$w(m,m) = \max_{n \epsilon S(m), n \neq m} w(m,n) \quad (6)$$

The under averaging of high-frequency areas due to the infrequent patch effects [12] results in signal distortion. It a computationally demanding as each sample is estimated over the entire search neighborhood.

3 Proposed W-NLM EMG Denoising Method

The DWT and NLM algorithms are two powerful denoising approaches with a complementary set of advantages and limitations. Subsequently, combining these approaches can result in an effective EMG denoising technique. However, a direct cascading of these approaches will result in an ineffective and computationally expensive denoising system. Henceforth, this research work presents an effective method of combining these approaches to get the desired results.

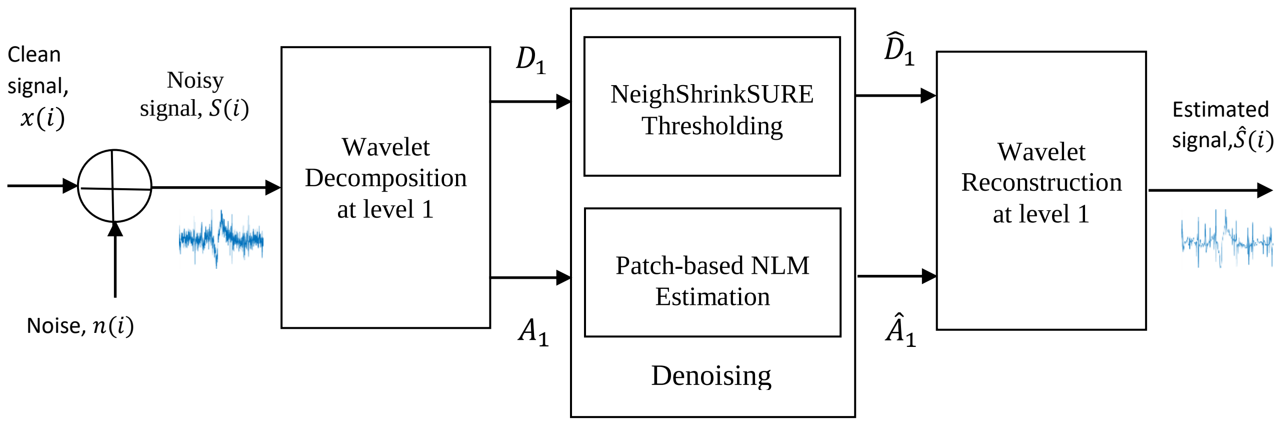

Fig.3. Block diagram of the W-NLM EMG de-noising approach

The proposed W-NLM method is implemented in the following three steps: 1) Signal Decomposition using DWT 2) denoising using NLM and thresholding 3) signal reconstruction. A block diagram representation of the proposed work is illustrated in Fig. 3.

Wavelet Decomposition: Initially, the acquired signal (given in Eq.(1)) is decomposed using DWT to get detailed (D_1)-and approximation (A_1)-coefficients. The signal is decomposed to a level such that it maintains the signal's morphological structure and keeps computations low. A single-level decomposition is selected after several experimental analysis, in this paper. Furthermore, a wide range of mother wavelet function's performance was compared in terms of *SNR* output *(SNR_{out})*, root mean square error *(RMSE)*, and percent root distortion *(PRD)* as performance measures. On basis of preliminary experimental analysis, *Symlet* wavelet function of order 9 *('sym9')* was chosen for decomposition of the signal [8].

Denoising the Signal: In this stage, the decomposed signal is denoised using NLM estimation and thresholding. The DWT's detailed coefficients are exposed to soft thresholding techniques for denoising the signal. The various strategies for thresholding are available in the literature such as VisuShrink [10], SURE-Shrink [12][13], NeighShrink [14], and NeighShrinkSURE [15]. The NeighShrinkSURE is an upgraded version of NeighShrink thresholding approach [16]. A performance comparison of various threshold selection techniques was conducted at different SNR_{in}. On basis of preliminary results, NeighShrinkSURE is selected for Soft Thresholding of detail coefficients.

The approximation coefficients A_1 being low-frequency coefficients are denoised by applying the NLM method. The selection of the following NLM parameters is crucial for the proposed work: patch half-width *(P)*, the search neighborhood half-width *(Q)*, and the bandwidth parameter *(τ)*. The patch half-width *P* chooses the scale to compare the patches. Moreover, raising the neighborhood half-width *M* (which results in a "less local" search) should improve performance, in principle. Although a wider search neighborhood *(2Q+1)* provides better estimation, it increases the computational load. The smoothness degree provided to the given signal is determined by the parameter τ. Over-smoothing and patch similarity problems will occur if τ is too large or too small. The value of τ is chosen in the majority of the previous research [4] so that it is proportionate to noise standard deviation. SNR_{out} for various combinations of *P* and *Q* values averaged across the developmental set at a given *SNR* level of 5 dB. The ideal *P* and *Q* values were determined to be 6 and 900 samples, respectively. Similarly, on comparing the SNR_{out} for various values of τ, its value is taken as 0.65σ.

Wavelet Reconstruction: Following noise removal, the enhanced EMG signal is subjected to a reverse decomposition (Inverse DWT). The signal is reconstructed using the modified detail and approximation coefficients.

Performance Measures: We have used the SNR_{in}, SNR_{out}, *RMSE*, and *PRD* as the performance measures [17]. SNR_{in} and SNR_{out} measure the signal-to-noise ratio before and after denoising. In contrast, *RMSE* is a measure of error between the original and denoised signal, and the *PRD* identifies the distortion present in the denoised output. Eq. (7-10) represents the performance measures used.

$$SNR_{in}(dB) = 10log_{10}\left[\frac{\sum_{i=1}^{N} x^2(i)}{\sum_{i=1}^{N} n^2(i)}\right] \tag{7}$$

$$SNR_{out}(dB) = 10log_{10}\left[\frac{\sum_{i=1}^{N} \hat{S}^2(i)}{\sum_{i=1}^{N}(\hat{S}(i)-x^2(i))^2}\right] \tag{8}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{S}(i) - S(i))^2} \tag{9}$$

$$PRD(\%) = 100\sqrt{\frac{\sum_{i=1}^{N}(\hat{S}(i)-S(i))^2}{\sum_{i=1}^{N} S^2(i)}} \tag{10}$$

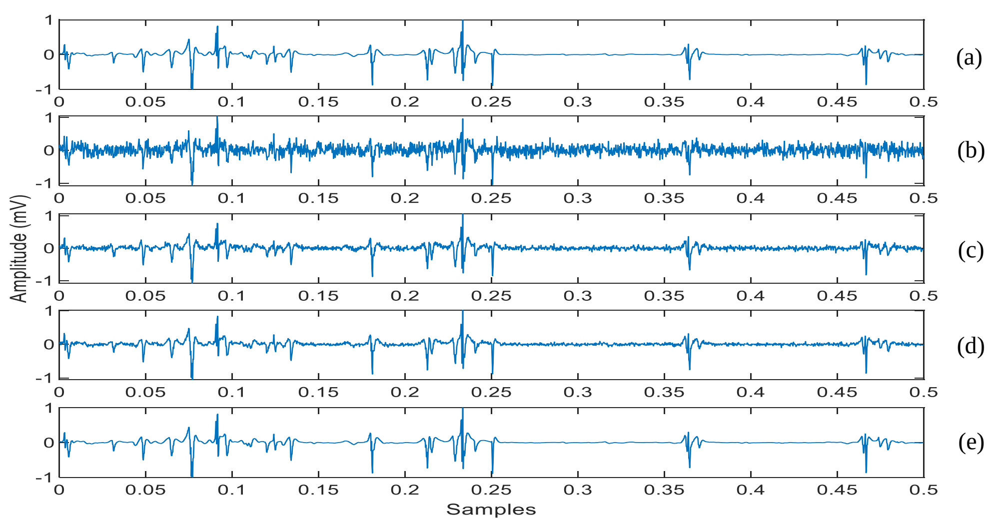

Fig. 4. Denoising of the EMG signal with W-NLM and reference methods (a) Clean EMG signal, (b) Noisy signal at 0 dB input SNR, (c) DWT, (d) NLM, and (e) W-NLM.

4 Experimental Results

The performance of the proposed work is evaluated on synthetic EMG signals available on the EMGLAB database [18]. It provides synthetic EMG signals generated using a model closely resembling the physiology of skeletal muscles and a line source model for needle positioning consistent with clinical studies. Three signals S00101, S00111, and S00121 were taken from the database, and each signal consists of 50000 samples.

This section presents the performance validation of the proposed work while exporting a comparative study of reference methods [4, 18] in different scenarios. The AWGN is added to synthetic EMG signals to generate different *SNR* levels. The comparison of W-NLM with DWT and NLM in denoising an EMG signal is demonstrated in Fig. 4. The noisy EMG signal (Fig 4(b)) is created by adding AWGN noise to the healthy EMG signal (Fig. 4(a)). The input SNR of the signal is set at 0 dB for this experiment. As it is observable from the results, the W-NLM has effectively denoised the signal and retained the signal's morphological structure. Furthermore, the two references have distorted the information present in the EMG signal.

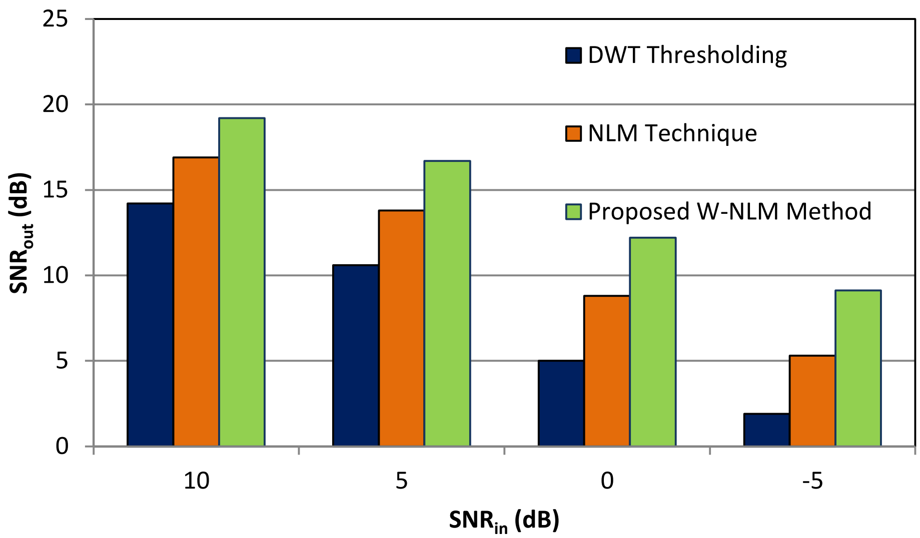

Fig. 5. Performance Comparison in terms of SNR_{out} of the proposed with existing work for various input *SNR.*

Whereas, the reference methods show a sharp decay in SNR_{out} for the drop-in input *SNR*. The *PRD* metric is employed to determine the amount of distortion present. Distortion should be kept to a bare minimum. For all input *SNR* levels, the W-NLM method has the least *RMSE* and *PRD* values. The improvements in SNR_{out} for a given EMG report are plotted in Fig. 5. Here, the performance is evaluated at SNR_{in} of -5dB, 0dB, 5dB, and 10dB. As shown by the results, the SNR_{out} of the proposed W-NLM technique is much greater than that of other existing methods.

Table 1. Performance comparison of the proposed work with exiting methods at different SNR_{in}.

EMG Records	SNR_{in}	DWT-based denoising			NLM-based denoising			Proposed W-NLM Method		
		SNR_{out}	RMSE	PRD	SNR_{out}	RMSE	PRD	SNR_{out}	RMSE	PRD
S00101	**-5**	1.92	0.073	27.6	5.32	0.063	20.5	9.12	0.053	14.4
	0	5.01	0.061	22.9	8.81	0.051	16.5	12.2	0.042	11.5
	5	10.6	0.045	14.8	13.8	0.036	10.7	16.7	0.028	7.53
	10	14.2	0.027	9.21	16.2	0.022	7.13	19.2	0.016	5.23
S00111	**-5**	2.01	0.070	27.4	5.51	0.061	20.3	9.32	0.051	14.2
	0	5.23	0.058	22.6	9.01	0.049	16.3	12.4	0.039	11.3
	5	10.8	0.043	14.6	14.01	0.034	10.5	16.9	0.025	7.34
	10	14.4	0.025	8.99	17.2	0.021	6.88	19.4	0.015	4.98
S00121	**-5**	1.73	0.075	27.7	5.12	0.065	20.7	8.89	0.055	14.6
	0	4.82	0.063	22.9	8.61	0.053	16.8	11.9	0.044	11.7
	5	10.4	0.048	14.9	13.6	0.038	10.9	16.5	0.030	7.72
	10	13.9	0.029	9.42	16.7	0.024	7.37	18.9	0.018	5.45

Table 1 shows the quantitative analysis in terms of SNR_{out}, $RMSE$, and PRD values concerning three test EMG signals at different SNR_{in}. The SNR levels of the input are fixed at -5dB, 0dB, 5dB, and 10dB. The results show that SNR_{in} drops, and the SNR_{out} degrades gradually for the proposed method.

5 Conclusion

The efficiency of DWT- and NLM-based denoising techniques are exploited to propose an EMG denoising method in this paper. In other words, the proposed method retains the efficacy of NLM in low-frequency zone and DWT methodology in reducing high-frequency noises. The DWT decomposes into the detailed and approximation coefficients. Subsequently, the detail coefficient is Soft Thresholded to diminish the high-frequency noise. Further, the signal is exposed to the NLM technique to remove the low-frequency noise. The W-NLM significantly reduces the computing time to that of NLM and DWT methods. The performance of the proposed method has been validated on various EMG signals in different noisy conditions.

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