An ECG Signal Denoising Method Based on Enhancement Algorithms in EMD and Wavelet Domains

Md. Ashfanoor Kabir, Grad. student member, IEEE and Celia Shahnaz, Member, IEEE
Department of Electrical and Electronic Engineering
Bangladesh University of Engineering and Technology
Dhaka, Bangladesh
E-mail: ashfanoor@eee.buet.ac.bd; celia@eee.buet.ac.bd

***Abstract*—This paper presents a new method based on enhancement algorithms in Empirical Mode Decomposition (EMD) and Discrete Wavelet Transform (DWT) domains for ECG signal denoising. Unlike the conventional EMD based ECG denoising methods that neglect a number of initial IMFs containing the QRS complex as well as noise, we propose a windowing method in EMD domain to filter out the noise from the initial IMFs without discarding them completely thus preserving the QRS complex. The comparatively cleaner ECG signal thus obtained from the EMD domain is employed to perform an adaptive soft thresholding in the DWT domain considering the advantageous properties of the DWT compared to EMD in preserving the energy and reconstructing the original ECG signal with a better time resolution. The performance of the proposed method is evaluated in terms of standard metrics by performing extensive simulations using the MIT-BIH arrhythmia database. The simulation results show that the proposed method is able to enhance the noisy ECG signals of different levels of SNR more accurately and consistently in comparison to some of the state-of-the-art methods.**

***Index Terms*—ECG, EMD, Wavelet, SNR improvement, MSE, PRD.**

I. Introduction

ECG is an important biological signal to diagnose cardiac arrhythmia. Usually ECG signals are subjected to contamination by various noises [1]. Numerous methods have been reported to denoise ECG signals based on filter banks, principal component analysis (PCA), independent component analysis (ICA), neural networks (NNs), adaptive filtering, EMD, and wavelet transform [2]-[5]. The filter bank based denoising process smoothes the P and R amplitude of the ECG signal and it is less robust to different levels of noise [2]. By exploiting PCA or ICA or NNs, a statistical model of the ECG signal and noise is first extracted and then, the in-band noise is removed by discarding the dimensions corresponding to noise [3],[4]. Although PCA, ICA and NNs based schemes are powerful for in-band noise filtering, the statistical model derived therein is not only fairly arbitrary but also extremely sensitive to small changes in either the signal or the noise unless the basis functions are trained on a global set of ECG beat types.

Comparatively, the EMD and wavelet based denoising methods are found more effective in denoising ECG signals. Since ECG signals are relatively weak and may have strong background noises, the thresholding performed on EMD or wavelet alone will result in an inadequate denoising as far as reliable clinical applications are concerned [5]. In an EMD-wavelet based method presented in [5], since the QRS complex of the ECG signal embedded in the first few IMFs consisting of high frequency noise is subject to wavelet thresholding, the thresholding technique cannot distinguish between high frequency noise and the QRS information. This leaves a scope for performing the ECG denoising up to a more accurate level.

In this paper, an ECG denoising method capable of overcoming the limitations of the existing methods is presented. In order to preserve the QRS information, the noisy ECG signal is first enhanced in the EMD domain. Then, the relatively enhanced ECG signal is transformed in the wavelet domain. Finally, an adaptive thresholding scheme is employed to the wavelet coefficients prior to reconstructing a more cleaner ECG signal. It has been shown by the simulation results that the proposed method provides a more accurate donoising performance for the ECG signals at different levels of SNR in comparison to some of the state-of-the-art methods.

II. Proposed Denoising Method

A. Windowing in the EMD domain

In this subsection, unlike the EMD based conventional ECG denoising approach that discards completely the initial IMFs containing the QRS complex as well as noise, we intend to preserve the QRS complex information in the first three high frequency IMFs by discarding noise from them. The key task here is to identify the intrinsic oscillatory modes by their characteristic time scales in the signal empirically, and accordingly, decompose the signal into intrinsic mode functions (IMFs). As a result, EMD is especially applicable for nonlinear and non-stationary signals, such as ECG. For example, for an L level decomposition, the original signal $x[n]$ can be represented in terms of the sum of the decomposed IMFs and the resulting residue $r_L[n]$ as given by,

$$x[n] = \sum_{i=1}^{L-1} c_i[n] + r_L[n]. \quad (1)$$

Generally, the first IMF $c_1[n]$ contains mostly high frequency noise. The second and third IMFs ($c_2[n]$ and $c_3[n]$) contain not only the high frequency noise but also the components of the QRS complex. The rest of the IMFs mainly carry useful information about the ECG signal. With a view to remove noise, discarding the first IMF as done in literature may retain considerable noise and removing the first two IMFs may result in a heavy distortion in the R waves of the denoised signal. Therefore, in the EMD domain the technique of thresholding the initial IMFs as performed via removing them is not accurate enough for ECG denoising.

The rate of information change in the QRS complex is very high compared to that of the other parts of an ECG signal. An analysis of the EMD on clean and noisy ECG indicates that the QRS information is mainly embedded in the first three high frequency IMFs [6]. As a consequence, in a noisy case, a desirable approach to denoise the corrupted ECG signal $y[n]$ would be to filter out the noisy parts of the first three IMFS without discarding them completely thus preserving the QRS complex. This can be achieved by temporal processing in the EMD domain. With this motivation in mind, we analyze the characteristics of the ECG signal along with that of the sum of the first three IMFs: $d[n] = c_1[n]+c_2[n]+c_3[n]$ obtained from the corresponding ECG signal. Fig. 1 presents the original clean and noisy ECG signals, and the respective plots of $d[n]$ in each case. It is revealed from this figure that the oscillatory pattern of the QRS complex, and that of the $d[n]$ in the QRS complex region are highly similar to each other. Also, the QRS complex is bounded by the two zero-crossing points of $d[n]$, where one zero-crossing point is on the left hand side, and the other is on the right hand side of the local minimum near the fiducial point (peak of the R-wave) as vivid from Fig. 1(a). This feature remains valid in the noisy case as depicted in Fig. 1(b). Moreover, it is evident from Fig. 1(b) that $d[n]$ from the noisy ECG follows the QRS complex pattern of the clean ECG in the QRS complex region, whereas, it follows the pattern of the noisy ECG outside that region. This analysis attests that it is reasonable to exploit $d[n]$ for detecting the QRS complex from the noisy ECG signal since the information of the QRS complex remains unaffected by the noise inside $d[n]$[6]. Therefore, we detect the QRS complex first and then, preserve the QRS complex by proper windowing and finally, synthesize a cleaner ECG by a partial reconstruction scheme.

1) Detection of the QRS complex: With a view to detect and specify the QRS complex from $d[n]$, we proceed as follows,

a. The peak of the R wave (fiducial point) along with its location are determined from the maximum of the noisy ECG beat.
b. EMD is applied to the noisy ECG beat to compute $d[n]$.
c. From $d[n]$ its two nearest local minima, located on both sides of the fiducial point that is already identified from the noisy ECG, are found.
d. One zero-crossing point on the left hand side of the left minimum and the other on the right hand side of the right minimum are detected. These two points are assumed as the boundaries of the QRS complex.

2) Preservation of the QRS complex: With a pre-idea of the span of the QRS complex thus obtained, we apply a time domain window ψ[n] to $d[n]$ centered at the fiducial point such that the window length covers the QRS complex. The choice of the window ψ[n] should be sch that it offers a flat gain at the R wave and decays gradually to zero for ensuring a smooth transition with minimal distortion. The window size is adjusted according to the QRS duration that varies among different ECG signals. The effect of such a windowing operation on $d[n]$ computed from the noisy ECG is presented in Fig. 2.

3) Synthesis of cleaner ECG: By preserving the QRS complex based on the windowing in the EMD domain, the windowed $d[n]$, the remaining IMFs, and the residue, $r_L[n]$ of the EMD operation are employed to synthesize a cleaner ECG as below,

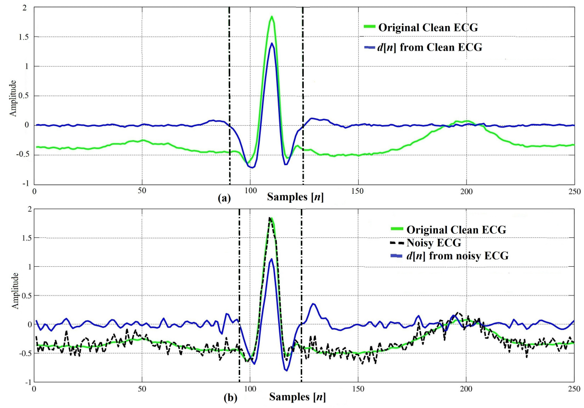

Fig. 1. (a) Original clean ECG and summation $d[n]$ of first three IMFs from clean ECG (b) Clean and Noisy ECG and summation d(n) of first three IMFs from noisy ECG

$$\widetilde{x}[n] = \begin{cases} \psi[n]\left(\sum_{i=1}^{3} c_i[n]\right) + \left(\sum_{i=4}^{L-1} c_i[n] + r_L[n]\right) \\ \psi[n]d[n] + \left(\sum_{i=4}^{L-1} c_i[n] + r_L[n]\right). \end{cases} \tag{2}$$

It is clear from the above approach that analyzing an ECG signal in the EMD (time) domain has the advantage of simplicity in calculation and physical interpretation. It is known that ECG signals are more consistently and easily analyzed in the DFT and DWT domains than in the EMD domain.

B. Thresholding in the wavelet domain

In this subsection we will transform the signal at hand in the wavelet domain for further reduction of noise, even after achieving a cleaner ECG signal via windowing in the EMD domain as described in the previous subsection. Although, DFT provides a signal representation in terms of amplitude and phase as a function of frequency, the DWT replaces the fixed bandwidth of DFT with one proportional to frequency, which allows better time resolution at high frequencies than the DFT. The resulting loss of frequency resolution as frequency increases is acceptable in applications involving biological signals. In discrete wavelet transform (DWT), a signal is analyzed and expressed as a linear combination of the sum of the product of the wavelet coefficients and mother wavelet. A family of mother wavelet is available [7] that has the energy spectrum is concentrated around the low frequencies like the ECG signal as well as better resembles the QRS complex of the ECG signal. Therefore, in practice, discrete wavelet transform (DWT) is in use for the analysis of an original signal $x[n]$, such as ECG at different scales.

ECG signal denoising using the DWT consists of the three successive procedures, such as, decomposition of the EMD-enhanced ECG signal $\widetilde{x}$[n] (EMDECG) into DWT coefficients, thresholding of the DWT coefficients, and the ECG signal reconstruction.

1) Decomposition in wavelet domain: The EMDECG signal $\widetilde{x}[n]$ can be expressed as

$$\widetilde{x}[n] = x[n] + \widetilde{v}[n], \tag{3}$$

where, x[n] is the original clean ECG signal and $\widetilde{v}[n]$ is the additive noise remaining after the EMD operation. We carry out wavelet transform on $\widetilde{x}[n]$ up to a chosen level. If W denotes a wavelet transform matrix, (3) can be written in the wavelet domain as

$$\widetilde{X} = X + \widetilde{V}, \tag{4}$$

where, $\widetilde{X}$ = $W\widetilde{x}[n]$, $\widetilde{V}$ = $W\widetilde{v}[n]$ and X = $Wx[n]$.

2) Adaptive soft thresholding: By performing a thresholding operation on $\widetilde{X}$, we can estimate the denoised ECG signal as,

$$\widehat{X} = THR(\widetilde{X}, \delta), \tag{5}$$

where, the *THR*(.) denotes a thresholding function and δ denotes a threshold value. The performance of ECG denoising in wavelet domain depends on the estimation of δ. Several methods have been proposed for estimating δ values [reference needed]. In particular, for denoising a normally distributed Gaussian noise, Donoho and Johnstone [8] proposed the universal threshold δ with orthonormal basis as given by,

$$\delta = \sigma\sqrt{2logM}, \tag{6}$$

In our case, σ is the standard deviation of the detailed DWT coefficients of a wavelet level and M is the length of the vector of the DWT coefficients. We determine δ according to (6), where σ values change depending on the detailed DWT coefficients of the level. Since, the approximate DWT coefficients contain the low frequency of the original ECG signal, where most energy exists, we proposed to exclude the approximate coefficients in the intended thresholding operation [9]. Since, ECG signals are non-stationary in nature, application of hard or soft thresholding technique based on a fixed threshold value δ, which is non-adaptable to signal intensities, may not improve the ECG signal degradation in noise. Therefore, we perform soft thresholding in the wavelet domain based on a threshold value δ adapted to the detailed DWT coefficients of each level. The adaptive soft thresholding is defined as,

$$\widehat{X}_d(l) = THR(\widetilde{X}_d(l), \delta_l), \qquad l = 1, 2, \tag{7}$$

where, $\widehat{X}_d$ signifies the array of thresholded detailed DWT coefficients, l represents a wavelet level, and δ_l is the determined threshold value for that level. In general, at a wavelet level l, the thresholding operation performed on a particular detailed DWT coefficient d_i can be expressed as,

$$\widehat{X}_{di}(l) = \begin{cases} |\widetilde{X}_{di}(l)| - \delta_l, & |\widetilde{X}_{di}(l)| \geq \delta_l \\ 0, & |\widetilde{X}_{di}(l)| < \delta_l, \end{cases} \tag{8}$$

where, i stands for the index of the detailed DWT coefficients at a level l. To this end, for a two level wavelet decomposition the array of the thresholded DWT coefficients can be expressed as,

$$\widehat{X} = \begin{bmatrix} \widehat{X}_d(1) & \widehat{X}_d(2) & \widehat{X}_a(2) \end{bmatrix}. \tag{9}$$

3) Reconstruction of the ECG signal: Finally, we obtain an estimate of the original ECG signal $\hat{x}[n]$ by using inverse wavelet transform on $\widehat{X}$ as given by,

$$\widehat{x}[n] = IDWT[\hat{X}], \tag{10}$$

where, IDWT represents an inverse DWT operation.

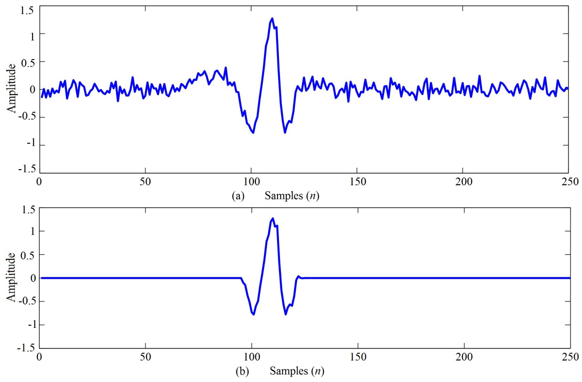

Fig. 2. First three IMFs *d*[*n*] computed from noisy ECG (a) Before windowing operation (b) After windowing operation

III. Simulation and Results

In this Section, we perform a number of simulations to evaluate our proposed method. The performance of the proposed method is compared with some of the state-of-the art methods in terms of several conventionally used metrics.

A. Database and other simulation details

In our simulation, we employ Physionet MIT-BIH arrhythmia database [10] for ECG signals. For our simulation, we consider the ECG signals numbered as 100, 103, 104, 105, 106, 115 and 215.

For windowing in EMD domain, we have employed the Tukey window centered at the fiducial point (peak of the R-wave) with a span of 30 samples to accommodate the QRS complex. It is known that symlets family of wavelets give details more accurately than others. Also, these wavelets show similarity with the QRS complexes and similar to ECG signal, their energy spectra are concentrated around low frequencies [7]. Therefore, in the wavelet analysis, symlet 7 is selected as the mother wavelet. A 2-level wavelet decomposition tree with symlet 7 bases function is exploited for implementation.

B. Performance evaluation and comparison

We have evaluated the performance of our method by comparing it with the EMD soft thresholding [2], wavelet soft thresholding [9] and EMD-wavelet methods [5]. The simulations were carried out in MATLAB 7.6 environment.

The performance of the proposed method is compared with other methods based on three metrics : improvement in signal to noise ratio (SNR_{imp}), mean square error (MSE), and percent root mean square difference (PRD). The metrics are computed as follows,

$$SNR_{imp}[dB] = 10log_{10}\frac{\sum_{n=1}^{N}|y[n] - x[n]|^2}{\sum_{i=1}^{N}|\hat{x}[n] - x[n]|^2}, \tag{11}$$

$$MSE = \frac{1}{N}\sum_{n=1}^{N}(x[n] - \hat{x}[n])^2, \tag{12}$$

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x[n] - \hat{x}[n])^2}{\sum_{i=1}^{N}x^2[n]}} \times 100, \tag{13}$$

where, *x*[*n*] denotes the original ECG signal, *y*[*n*] means the noisy ECG signal, and $\hat{x}[n]$ denotes the reconstructed

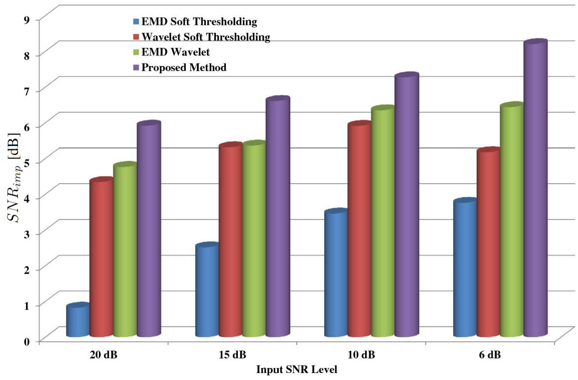

Fig. 3. Comparison of the mean improvement in SNR in dB for different denoising methods at different input SNR levels

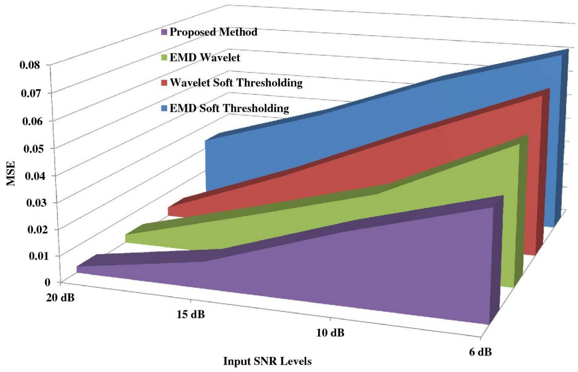

Fig. 4. Comparison of the mean MSE for different denoising methods at different input SNR levels

enhanced ECG signal, and N is the number of ECG samples. For a denoising method to be said better, it is desirable that the larger the SNR_{imp} is, the smaller the MSE and PRD are.

Fig. 3 shows SNR_{imp} [dB] at different input SNR levels in a bar diagram. In this figure, for a particular denoising scheme, the mean improvement is calculated by considering the SNR_{imp} for all ECG files under consideration. Over the range of input SNR levels (20 dB to 6 dB), the other methods show lower SNR_{imp}, whereas the SNR_{imp} for the proposed method is higher even at lower input SNRs as expected.

Fig. 4 shows MSE results for different input SNR levels in a 3-D area plot. At any SNR level, the mean of the MSE results are obtained from the MSE of all the ECG files for a particular denoising scheme. As SNR varies from high to low, the proposed method always outperforms all the comparison methods as the mean MSE for other methods are relatively higher, particularly at a low SNR.

TABLE I shows $PRD(\%)$ results at different input SNR levels for all the methods under consideration. The $PRD(\%)$ value for a denoising scheme at a particular SNR is the mean $PRD(\%)$ obtained from all the ECG files. It is clear from this table that along the range of input SNR levels considered, the other methods show comparatively higher $PRD(\%)$ with respect to the proposed method thus attesting the superiority of the proposed method.

TABLE I
COMPARISON OF THE MEAN $PRD(\%)$ FOR DIFFERENT DENOISING METHODS AT DIFFERENT INPUT SNR LEVELS

Input SNR Level [dB]	EMD Soft Thresholding [2]	Wavelet Soft Thresholding [9]	EMD Wavelet [5]	Proposed Method
6	64.73	58.46	51.87	48.44
10	54.23	47.96	43.38	40.52
15	35.26	32.98	30.40	25.68
20	28.92	20.65	17.55	13.46

IV. CONCLUSION

An effective method of ECG denoising based on enhancement algorithms employed in the EMD as well as wavelet domains is presented. In order to discard noise mainly existing in the initial IMFs that contain the most important information bearing part of the ECG signal, namely the QRS complex, we apply a window in the EMD domain that is capable of reducing noise while preserving the QRS complex. Then, considering the attractive features of the DWT in retaining the characteristics of the uncorrupted ECG signal even after reconstruction, an adaptive soft thresholding is performed in the DWT domain for further reduction of the noise remaining after the proposed EMD operation. A number of simulations is carried out and it has been shown that the proposed method outperforms other existing methods of ECG denoising.

V. ACKNOWLEDGEMENT

The authors would like to express their sincere gratitude towards the authorities of the Department of Electrical and Electronic Engineering, Bangladesh University of Engineering and Technology (BUET) for providing constant support throughout this research work.

REFERENCES

[1] R. M. Rangayan, *Biomedical Signal Analysis*. IEEE Press, 2002.
[2] G. Tang and A. Qin, "*ECG* de-noising based on empirical mode decomposition," in *Proceedings of the 9th International Conference for Young Computer Scientists*, Feb. 2008, pp. 903 – 906.
[3] T. He, G. Clifford, and L. Tarassenko, "Application of *ICA* in removing artefacts from the *ECG*," *Neural Processing Letters*, pp. 105–116, 2006.
[4] G. Clifford, L. Tarassenko, and N. Townsend, "One-pass training of optimal architecture auto-associative neural network for detecting ectopic beats," *IEE Electronic Letters*, vol. 37 no. 18, pp. 1126–1127, Aug. 2001.
[5] N. Li and P. Li, "An improved algorithm based on *EMD*-wavelet for *ECG* signal de-noising," in *Proceedings of the International Joint Conference on Computational Sciences and Optimization*, 2009, pp. 825 – 827.
[6] B. Weng, M. B. Velasco, and K. E. Barner, "*ECG* denoising based on the empirical mode decomposition," in *Proceedings of the 28th IEEE EMBS Annual International Conference New York City, USA*, Sept. 2006, pp. 1–4.
[7] Mahmoodabadi and S. Ahmadian, "*ECG* feature extraction based on multiresolution wavelet transform," in *Proceedings of the IEEE 27th Annual Conference on Engineering in Medicine and Biology Shanghai, China*, Sept. 2005, pp. 3902–3905.
[8] D. Donoho, "De-noising by soft-thresholding," *IEEE Transaction on Information Theory*, vol. 41, 3, pp. 613–627, 1995.
[9] M. Alfaouri and K. Daqrouq, "*ECG* signal denoising by wavelet transform thresholding," *American Journal of Applied Sciences*, vol. 5 (3), pp. 276–281, 2008.
[10] "*MIT-BIH* arrythmia database," Accessed on 21/05/2011. [Online]. Available: http://www.physionet.org/mitdb