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A Wavelet Based Technique for Suppression of EMG Noise and Motion Artifact in Ambulatory ECG

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Abstract— **A wavelet-based denoising technique is investigated for suppressing EMG noise and motion artifact in ambulatory ECG. EMG noise is reduced by thresholding the wavelet coefficients using an improved thresholding function combining the features of hard and soft thresholding. Motion artifact is reduced by limiting the wavelet coefficients. Thresholds for both the denoising steps are estimated using the statistics of the noisy signal. Denoising of simulated noisy ECG signals resulted in an average SNR improvement of 11.4 dB, and its application on ambulatory ECG recordings resulted in L_2 norm and max-min based improvement indices close to one. It significantly improved R-peak detection in both the cases.**

I. INTRODUCTION

BASELINE wander, powerline interference, electromyogram (EMG), and motion artifact are some of the common disturbances in the ECG signals [1], [2]. Powerline interference and baseline wander can be reduced by a careful design of the ECG hardware. Motion artifact and EMG noise can be reduced by restricting the motion of the patient during signal recording, but this is not possible in ambulatory ECG recording. Signal processing techniques, known as ECG denoising, are generally employed for suppressing these disturbances [3]–[11].

Motion artifact and EMG noise have a spectral overlap with ECG and they cannot be effectively suppressed by filtering [2]–[7]. Tong *et al.* [4] used adaptive filtering for reducing motion artifact with the output of an accelerometer, placed on the ECG electrode on the right arm, as the reference input. He *et al.* [5] used a method based on independent component analysis (ICA) on 3-lead ECG. The components representing noise were located and set to zero and the remaining components were used to get the denoised signal. Dai and Lian [6] used modified moving window averaging to estimate and remove baseline wander from ECG, by applying the moving average on samples separated by intervals rather than on consecutive samples and by removing the samples corresponding to the R-peaks. Blanco-Velasco *et al.* [7] used empirical mode decomposition for denoising ECG. The input ECG was decomposed into its fundamental oscillations, called intrinsic mode functions (IMFs). The initial IMFs were related to high frequency noise and QRS complexes. The noise in the initial IMFs was separated by windowing out the R-peak locations. A low-pass filter bank was used to extract the baseline wander from final IMFs. The extracted disturbances were subtracted from the input ECG to get the denoised signal.

Several techniques using wavelet-based multi-resolution analysis have been reported for denoising ECG signals [3], [8]–[11]. Zhang [8] applied wavelet decomposition using Symlet (order 10), which has a shape similarity to the QRS complex, for removing the baseline wander from the ECG signal sampled at 360 Hz, by subtracting its 8^{th} scale approximation. It resulted, at times, in a distortion in the ST segments. The EMG noise was removed by wavelet thresholding. Out of the several methods studied, the best results were obtained by using EBayes threshold. Denoising was found to be better for piecewise thresholding than for processing the whole record together. Li and Lin [11] reported that EMG noise could be consistently suppressed by hard thresholding with EBayes threshold with 5-level decomposition using Symlet (order 4). Features of both the hard thresholding and soft thresholding can be combined by suitably designing the thresholding function [9], [12]. It has been reported that thresholding the wavelet coefficients may result in oscillations at sharp transitions in the signal due to Gibbs phenomenon, and that these can be reduced by using translation-invariant denoising [8], [9].

The wavelet-based denoising techniques generally employ hard, soft, or improved thresholding functions with the thresholds obtained using SURE, EBayes, Donoho's universal threshold, *etc* [8]–[11]. These techniques produce good signal enhancement for noises which are uniformly present throughout the signal, but they are not effective in suppressing EMG noise. The motion artifact is generally suppressed by eliminating approximation at a particular scale, but it may cause signal distortion or improper artifact correction. To overcome these problems, a technique using an improved thresholding function for suppressing the EMG noise and limiting of the wavelet coefficients for suppressing the motion artifact is investigated. Thresholds for both the denoising steps are estimated using the statistics of the noisy signal itself. The technique is validated by applying it on noisy ECG signals generated using the records from the MIT/BIH database and on ambulatory ECG recordings.

II. DENOISING METHOD

Several wavelet bases, *e.g.* Daubechies (db4,db8), Symlets (sym4,sym7,sym8,sym10), Coiflets (coif5), discrete Meyer (dmey), and Biorthogonal (bior4.4), have been used

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for ECG denoising [11]. The denoising is effective if the dilated version of the wavelet (or the scaling function) at some scale matches the shape of the signal or noise components. In ECG, the baseline wander and motion artifact components do not have a characteristic shape and all the above wavelet bases show a similarity with the ECG signal components at some scale. We have used dmey for denoising as it resulted in the least RMS error in reconstructing the noise-free ECG signals, sampled at 360 Hz, from the first ten details. The ECG is decomposed into details D_1 – D_{10} and approximation A_{10}. The slow baseline wander is suppressed by setting A_{10} to zero. The EMG noise and motion artifact are suppressed using non-linear modifications of the wavelet coefficients as described in the following two subsections.

A. EMG noise suppression

EMG noise is a non-stationary broadband noise. In ECG recordings with 360 Hz sampling, it gets predominantly represented in the initial four details and particularly in D_1, as indicated by a high average absolute value of D_1 in segments with significant EMG noise. For suppressing the EMG noise, a thresholding operation is applied on the wavelet coefficients. For each scale i, a time-varying threshold $\theta_i(n)$ is obtained by scaling the span of the coefficients as obtained from the long-term statistics of the noisy signal with a scaling factor $\gamma(n)$ obtained from a short-time estimate of the level of the EMG noise in the signal. For robustness against excessive noise in some segments, the 90th percentile of the coefficients is taken as the span, and the threshold is given as

$$\theta_i(n) = \gamma(n)\ \text{p90}\left[|D_i(n)|\right] \tag{1}$$

A moving-window average of absolute value of D_1, avgD1(n), is used as the short-time estimate of the level of the EMG noise. A 35-point window is used as it approximates the duration of typical short bursts of EMG noise. Its 5-percentile is taken as a lower threshold avgD1L and half of its 95-percentile is taken as the upper threshold avgD1H. These thresholds are used for thresholding, clipping, and normalizing the short-time average to get the time varying scaling factor

$$\gamma(n) = \begin{cases} 0, & \text{avgD1}(n) < \text{avgD1L} \\ \dfrac{\text{avgD1}(n) - \text{avgD1L}}{\text{avgD1H} - \text{avgD1L}}, & \text{avgD1L} \le \text{avgD1}(n) \le \text{avgD1H} \\ 1, & \text{avgD1}(n) > \text{avgD1H} \end{cases} \tag{2}$$

As D_1 has insignificant contribution from ECG, it is totally removed. Before using it for thresholding, $\theta_i(n)$ is resampled to match its number of points to that in D_i.

As D_2–D_4 have significant contributions from the signal as well as from EMG noise, hard thresholding may introduce significant signal distortion and soft thresholding may not effectively suppress the artifact. Hence D_2–D_4 are modified by using an improved thresholding function, combining the features of hard thresholding and soft thresholding as

$$\hat{D}_i(n) = \begin{cases} 0, & |D_i(n)| < \theta_i(n) \\ \text{sgn}(D_i(n))\left(|D_i(n)| - f(n)\right), & \theta_i(n) \le |D_i(n)| \le \theta_i(n) + S_i/2 \\ \text{sgn}(D_i(n))\left(|D_i(n)| - g(n)\right), & \theta_i(n) + S_i/2 < |D_i(n)| < \theta_i(n) + S_i \\ D_i(n), & \theta_i(n) + S_i \le |D_i(n)| \end{cases} \tag{3}$$

where

$$f(n) = \theta_i(n)\left[1 - 0.5(e^{ar} - 1)/(e^{a} - 1)\right], \quad r = (|D_i(n)| - \theta_i(n))/(S_i/2) \tag{4}$$

$$g(n) = \theta_i(n)\left[0.5 - 0.5(1 - e^{-ar})/(1 - e^{-a})\right], \quad r = (|D_i(n)| - \theta_i(n) - S_i/2)/(S_i/2) \tag{5}$$

The factor a controls the transition between soft and hard thresholding. Setting $a \approx 3$ and the transition span as

$$S_i = 0.75\ \text{p95}[\,|D_i(n)|, \quad |D_i(n)| > \theta_i(n)] \tag{6}$$

results in a thresholding which combines the features of hard and soft thresholding without showing disadvantages of either of them.

B. Motion artifact suppression

Most of the noise suppression techniques using wavelet thresholding are based on the assumption that the noise is always present and has low amplitude, and that the signal is present in specific time segments and has relatively high amplitude [13]. In ECG corrupted with non-stationary motion artifact, ECG signal is always present and the motion artifact occurs intermittently and it generally has high amplitude. Hence limiting of the wavelet coefficients is investigated for suppressing the motion artifact. The operation, using threshold ϕ_i, on $D_i(n)$ is carried out as

$$\hat{D}_i(n) = \begin{cases} D_i(n), & |D_i(n)| \le \phi_i \\ \text{sgn}(D_i(n))\phi_i, & |D_i(n)| > \phi_i \end{cases} \tag{7}$$

The threshold ϕ_i is an estimate of the maximum value of the wavelet coefficients of the ECG signals at scale i. It should be high enough to exclude the possibility of reducing the coefficients representing noise-free ECG, and low enough to significantly suppress the motion artifact. The thresholds are estimated by dividing the ECG record into segments of two average cardiac cycles. At each scale i, the maximum absolute values of coefficients in these segments are used to calculate the average μ_i and standard deviation σ_i. The limiting threshold for scale i is calculated as $\phi_i = \mu_i - \eta\sigma_i$, A value of η close to 0.1 resulted in effective denoising without causing signal distortion, while a larger value caused distortion in artifact-free ECG segments.

III. Method of Evaluation

A quantitative estimate of the performance of a denoising technique can be obtained as the SNR improvement for ECG inputs with different levels and types of simulated noise [4], [5], [9]–[11]. For real ECG records, noise reduction is generally assessed by visual inspection [3], [7], [8]. Tong *et al.* [4] used improvement indices based on signal excursion (max-min) and L_2 norm to quantify the enhancement.

The denoising was carried out by applying EMG noise reduction followed by motion artifact reduction. The technique was evaluated by applying it on simulated noisy ECG records and on ambulatory ECG records. The simulated noisy records were obtained by adding ECG records from the MIT/BIH arrhythmia database and ECG-free noise records from the MIT/BIH noise stress test database, having waveforms with 360 Hz sampling and 11-bit resolution. From each of the 48 two-channel ECG records in the database, single channel ECG signals of one min. duration were taken as noise-free ECG. Segments from the EMG noise ("ma") and motion artifact ("em") were taken as the noise. All the records were scaled to have the same RMS value. Simulated noisy records with different values of SNR were generated by scaling the noise and adding it to the signal. The noises used were EMG noise, motion artifact, and a mix of EMG noise and motion artifact in 1:2 ratio (approximating the occurrence in ambulatory recordings). Ambulatory ECG signals were recorded using a Holter monitor (ECIL, Hyderabad, India) at 200 Hz with 8-bit resolution. The recordings were resampled to 360 Hz (the sampling rate used in the MIT/BIH database). The recordings were taken from five healthy volunteers in resting condition and during common ambulatory activities like hand movements, walking, and climbing stairs.

A qualitative evaluation of the denoising on both types of records involved a visual examination of the output for suppression of the artifact and presence of distortion. A quantitative evaluation involved calculation of improvement in the SNR for the simulated noisy records. Another quantitative evaluation, as used by Tong *et al.* [4], involved the improvement indices (I.I.) based on L_2 norm and excursion (max-min) of the signal and calculated as

$$\text{I.I.} = \frac{\left|(\text{Pre-denoising value}) - (\text{Post-denoising value})\right|}{\left|(\text{Pre-denoising value}) - (\text{Artifact-free value})\right|} \quad (8)$$

An index value close to one indicates an effective denoising and a small value indicates ineffective noise suppression. A value larger than one indicates signal distortion. Improvement in automated R-peak detection using Pan-Tompkins algorithm [14] was also used as a measure of denoising.

IV. Results

A. Denoising of Simulated Noisy ECG

The improvements in SNR obtained by denoising are given in Table 1. The technique was effective in suppressing all the three types of simulated noise, with a mean improvement of 11.4 dB for mixed noise at –10 dB input SNR. At this input SNR, the improvement indices, as calculated using (8), were close to one indicating a significant noise reduction without introducing distortion. In automated R-peak detection, the errors (failures and false detections) reduced from 14.5 % to 2.2 %. In many of the segments with EMG noise, Gibbs oscillation produced by the thresholding operation, could be observed in the vicinity of the QRS complexes. Translation-invariant [8], [9] application of the denoising, with 1-sample shift and 125 iterations, reduced these oscillations and resulted in SNR improvement of up to 1 dB. It did not result in any change in improvement indices and errors in the automated detection of R-peaks.

TABLE I
MEAN (AND STD. DEV.) OF SNR IMPROVEMENT (dB) FOR SIMULATED NOISY ECG (N = 48).

Noise type	Input SNR (dB)		
	-10	-5	0
EMG noise	12.1 (1.7)	8.8 (2.0)	5.1 (2.3)
Motion artifact	11.5 (0.9)	8.3 (1.4)	4.8 (2.1)
Mixed	11.4 (0.9)	8.3 (1.5)	4.9 (2.2)

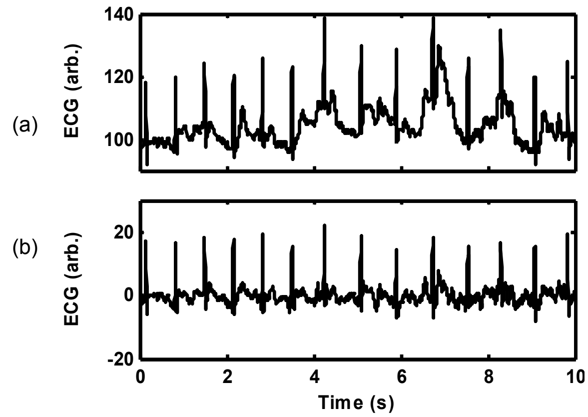

Fig. 1. Suppression of motion artifact in ambulatory ECG: (a) Input. (b) Output.

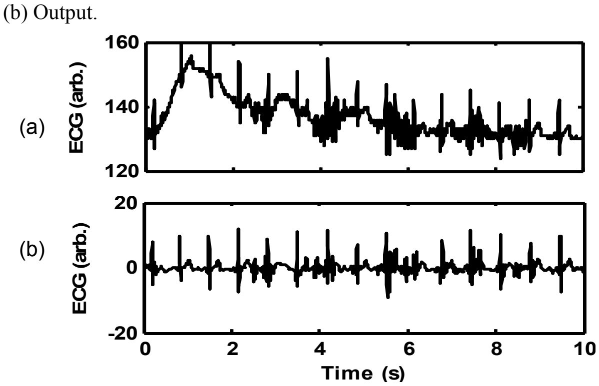

Fig. 2. Suppression of EMG noise in ambulatory ECG: (a) Input, (b) Output.

B. Ambulatory ECG

A visual examination of the processed outputs showed that the denoising technique was effective in suppressing the EMG noise and motion artifact, and it did not result in any visible distortions in the clean segments. In Fig. 1, the motion artifact during 6–8 s is attenuated without affecting the nearby QRS complexes. In Fig. 2, the EMG noise is

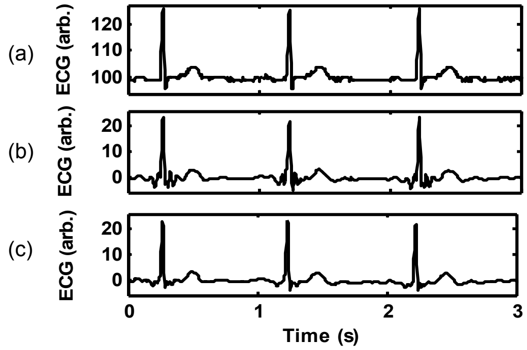

Fig. 3. Suppression of Gibbs oscillations in the vicinity of QRS complexes: (a) Input ECG, (b) ECG after EMG denoising, (c) ECG after translation-invariant EMG denoising.

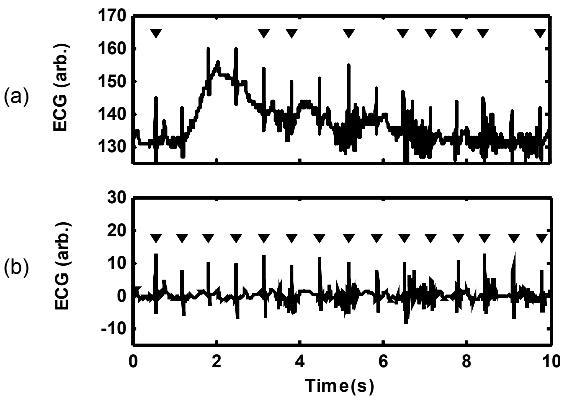

Fig. 4 Automated R-peak detection applied on (a) input ECG, (b) ECG after denoising.

attenuated while the EMG-free region is unaffected and the initial artifact is suppressed. The R-peak overlapping with the EMG noise (the first R-peak after 6 s) is attenuated. An occurrence of Gibbs oscillations and its suppression using translation invariant denoising is shown in Fig. 3. In the example of the automated R-peak detection in Fig. 4, it is seen that the denoising resulted in the detection of all the R-peaks. Its application on ambulatory ECG recordings (10-s segments from the recordings from five volunteers, different leads, and different ambulatory activities) with a total of 551 cardiac cycles resulted in L_2 norm and max-min based improvement indices close to one. Application of the automated R-peak detection on these records resulted in an error of 12.3 % (54 failures and 14 false detections). Denoising significantly reduced the error to 1.5 % (4 failures and 4 false detections).

V. Discussion

The wavelet-based denoising technique for suppressing EMG noise and motion artifact in ECG does not require a reference as in adaptive filtering techniques. It does not need multi-channel signals as required by ICA-based techniques. Further, identification of R-peaks or other characteristic points as required in the cubic spline and EMD-based techniques are not needed. The discrete Meyer wavelet was chosen as the wavelet basis function for this application after studying the effectiveness of several wavelet bases. EMG noise was reduced by thresholding combining the features of hard and soft thresholding. Motion artifact was reduced by limiting the wavelet coefficients. Thresholds for both the denoising steps were estimated from the statistics of the wavelet coefficients of the noisy signal in an automated manner. Gibbs oscillations due to thresholding, occasionally occurring in the vicinity of QRS complexes, were suppressed by translation-invariant application of denoising. Effectiveness of the technique was validated by applying it on simulated noisy ECG records as well as on ambulatory recordings from a Holter recorder. Its application significantly reduced the EMG noise and motion artifact without introducing any visible distortions in ST segments. Its performance needs to be further evaluated with respect to some of the other techniques and particularly on ECG records from patients with different cardiac disorders.

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