A UNIFIED SPARSE SIGNAL DECOMPOSITION AND RECONSTRUCTION FRAMEWORK FOR ELIMINATION OF MUSCLE ARTIFACTS FROM ECG SIGNAL

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ABSTRACT

Removal of muscle artifacts from the ECG signals is crucial for a reliable and accurate measurement of local features of ECG signals. In this paper, we present an automatic method for removal of muscle artifacts from ECG signals, based on four steps: decomposing ECG signal using sparse signal decomposition on mixed dictionaries; obtaining QRS complex signal; determining time-instants of R-peak; and removal of muscle artifacts from ECG signal. The noise reduction performance of the proposed method is tested and validated using ECG signals taken from a standard MIT-BIH Arrhythmia database. The reconstructed signals are assessed using both subjective quality assessment test and objective quality assessment metrics. Performance evaluation results show that the proposed method outperforms other existing ECG denoising methods inadequately removing the muscle artifacts without significantly distorting the morphologies of P-wave, QRS-complex and T-wave of the ECG signals.

Index Terms— Electrocardiogram (ECG), ECG denoising, QRS detection, ECG arrhythmias, muscle artifacts

1. INTRODUCTION

The electrocardiogram (ECG) is often contaminated by muscle artifacts [1]- [6]. The ECG signal is a widely used diagnostic tool for analysis and diagnosis of heart abnormalities related with different types of arrhythmias. Generally, muscle artifacts are ubiquitous in wearable health care monitoring and holter monitoring which distort both temporal-spectral characteristics of ECG signal [1]. In wearable ambulatory monitoring conditions, it has been observed that the local waves of the ECG signal are often masked by muscle artifacts. In most clinical evaluation cases, the cardiac diagnosis must be made more accurately. Therefore, the detection and removal of muscle artifacts from the ECG signal poses a real challenge and is crucial for the reliable interpretation of ECG-based quantitative measures. Numerous methods have been developed for detection and removal of artifacts in the ECG signals [1]- [12]. The existing methods are based on the signal processing techniques including, empirical mode decomposition (EMD) [1, 2], singular value decomposition (SVD) filter [4], morphological operators [5], independent components analysis [6], ensemble empirical mode decomposition (EEMD) [7], nonlinear Bayesian filtering framework [8], wavelet transforms [9, 10], EMD and wavelet transform [9, 10], and Genetic algorithm and wavelet scheme [11].

A variety of discrete wavelet transform (DWT) and EMD based filtering methods have been presented for removal of artifacts from ECG signal. Many wavelet-based ECG denoising methods were reported by exploiting the multiresolution characteristics of the ECG signals and different types of noises. Most DWT based methods include the following steps: wavelet decomposition of ECG signal using predefined wavelet filters and decomposition level, selection of characteristics subbands for discriminating artifacts and local waves of ECG signal using the frequency ranges of wavelet subband for the fixed sampling rates; the detection of artifacts using the statistical parameters; and suppression of artifacts and the reconstruction of enhanced ECG signal. In [1], Lee Jinseok *et al.* reported a method for automatic motion and noise artifact detection in holter ECG data using EMD and statistical approaches [1]. The method consists of two stages: determining the first mode of intrinsic mode function (F-IMF) of the EMD of ECG signal and calculation of signal complexity and variability statistics such as Shannon entropy, mean, and variance. This method assumes that the F-IMF of clean ECG segments have periodic patterns whereas the MN-artifact-corrupted ECG segments have highly varying irregular dynamics with lower magnitudes. In general, the EMD based ECG denoising methods include the following steps: decomposition of ECG signal using EMD/EEMD algorithm, selection of intrinsic mode functions (IMFs) for detection and removal of artifacts; and reconstruction of denoised ECG signal [1, 2]. The wavelet denoising method attempts to separate clean and noisy wavelet coefficients, but it can be difficult to use since it requires identification of the location of each local waves including P-wave, QRS complex, and T wave. Furthermore, the noise may be spread over different levels of detail coefficients in wavelet decomposition. Hence, we cannot fix the level of decomposition required for exact removal of muscle artifacts. In EMD based decomposition approach, muscle artifacts and impulsive noises may be distributed over a number of IMFs. Thus, it is difficult to automate the process of denoising because the number of IMFs required to be estimated for denoising a particular noisy

ECG signal cannot be determined by any off-line processing. Therefore, in this paper, we investigate the sparse signal decomposition and reconstruction on mixed dictionaries which can effectively capture the local waves of ECG signal and artifacts, in particular muscle artifacts and impulsive noises.

An automated method to separate clean ECG portions from segments with muscle artifacts is most essential for more accurate diagnosis and treatment of clinically important atrial arrhythmias. In this paper, we present sparse signal decomposition and reconstruction framework for removal of muscle artifacts from the ECG signal. The proposed method consists of four major steps: decomposing ECG signal using sparse signal decomposition on mixed dictionaries; obtaining QRS complex feature signal; determining time-instants of R-peak; and removal of muscle artifacts from ECG signal. The performance of the proposed method is tested and validated using the clean and noisy ECG signals taken from the standard MIT-BIH Arrhythmia database. The reconstructed signals are assessed using both subjective quality assessment test and objective quality assessment metrics. Performance evaluation results show that the proposed sparse signal decomposition and reconstruction framework outperforms other existing ECG denoising methods in adequately removing the muscle artifacts without significantly distorting the morphological features (including, amplitude, duration, polarity, and shape) of local waves such as P-wave, QRS-complex, and T-wave of ECG signal. The rest of the paper is organized as follows. Section 2 describes the proposed framework. In Section 3, the method is validated using real ECG signals and ECG signal corrupted with synthetically generated with muscle artifacts taken from MIT-BIH arrhythmia database. Finally, conclusions are drawn in Section 4.

2. PROPOSED DENOISING FRAMEWORK

In this section, we present a sparse representation framework for removal of muscle artifacts from the ECG signals. The proposed framework consists of following steps: decomposing ECG signal using sparse signal decomposition on mixed dictionaries, obtaining QRS complex signal, determining time-instants of R-peak, extracting QRS complex portion within the duration of 100 ms centered at the identified R-peak instant and reconstruction of the denoised ECG signal using the subsignals obtained for the dictionaries of P/T waves, QRS complexes and the extracted QRS complex portions using the previous step. The signal processing steps of the proposed algorithm are described in the table of Algorithm 1.

In this subsection, we first introduce sparse representation of ECG signals and different noises on mixed dictionaries for extracting the ECG local waves and different noises simultaneously. An ECG signal **x** can be represented with time-localized and frequency-localized elementary waveforms on hybrid mixed dictionary matrix $\mathbf{\Psi} \in \mathbb{R}^{P\times Q}$ such that $P < Q$ is given as $\mathbf{x} = \mathbf{\Psi}\alpha = \sum_{i=1}^{Q} \alpha_i \psi_i$, where $\alpha = [\alpha_1, \alpha_2, \cdots \alpha_Q]$ is the sparse vector for an overcomplete dictionary. Analytic basis functions or beat patterns can be obtained from the temporal and spectral characteristics of ECG and noise for constructing the overcomplete mixed dictionaries. The frequency-domain localized components (like low-frequency components, baseline wander (BW) and power line interference (PLI)) and time domain localized spiked components (like muscle artifact and high frequency (HF) components of QRS) can be effectively modeled using sinusoidal waveforms and impulses respectively. Therefore, the mixed dictionary can be constructed using time-localized and frequency-localized elementary waveforms to capture the additive components of the ECG signal and background noises. In this work, the ECG signal is decomposed using the predefined overcomplete mixed dictionary matrix with a size of $P \times Q$ as

Algorithm 1 Proposed muscle artifacts removal algorithm

```
Input: Fs = 360 Hz, N_1 = T * Fs, shift=50 ms.
x ← Input ECG signal
Fs ← Sampling frequency
T ← Time in sec
k=1;
for i = 1 : N_1 : length(x) do
Step0: Read ECG signal corrupted with muscle artifacts
Step1: Decompose the signal using SSD into x_BW, x_PL, x_PT, x_QRS and x_SPK.
Step2: Detect R-peak from x_QRS
    Rpeak = RPeakDetector(x_QRS,x,Fs); // Using algorithm 2
Step3: Add QRS portion from x_SPK to x_PT and x_QRS
    shift = 50*Fs;
    q=1;
    xptqrs=x_PT + x_QRS;
    sig = [zeros(shift,1); x_SPK; zeros(shift,1)];
    sig1 = [zeros(shift,1);; xptqrs; zeros(shift,1);];
    Rpeak = Rpeak+shift;
    for jj=1:length(Rpeak) do
        WI = Rpeak(k)-shift;
        WE = Rpeak(k)+shift;
        wsig = sig(WI:WE);
        wsig1=sig1(WI:WE);
        w=wsig+wsig1;
        sig1(WI:WE)=w;
        q = q+1;
    endfor
    x̂=sig1;
    x̂=x̂(NW+1:end-NW); // EMG removed signal
    k=k+1;
endfor
```

$$\mathbf{\Psi} = [\mathbf{\Psi_{BW}}|\mathbf{\Psi_{PT}}|\mathbf{\Psi_{QRS}}|\mathbf{\Psi_{SPK}}|\mathbf{\Psi_{PLI}}], \quad (1)$$

where, P is length of the ECG signal **x** and Q is the number of elementary waveforms. $\mathbf{\Psi_{BW}}$, $\mathbf{\Psi_{PT}}$, $\mathbf{\Psi_{QRS}}$, $\mathbf{\Psi_{SPK}}$ and $\mathbf{\Psi_{PLI}}$ denote matrices of elementary waveforms to capture BW, local P & T wave, LF components or wide portions of QRS complexes, spiky components (HF component of QRS and HF noises), powerline interference respectively. $\mathbf{\Psi}_{BW}$, $\mathbf{\Psi}_{PT}$, $\mathbf{\Psi}_{QRS}$ and $\mathbf{\Psi}_{PLI}$ contain elementary discrete sine and cosine basis functions as

$$[\mathbf{S}]_{kl} = \sqrt{\frac{2}{P}}[a_k sin(\frac{\pi(2l+1)(k+1)}{2P})] \quad (2)$$

where, $a_k = 1/\sqrt{2}$ for $k = P-1$, otherwise $a_k = 1$ and $k, l = 0, 1, 2, \cdots P-1$.

$$[\mathbf{C}]_{kl} = \sqrt{\frac{2}{P}}[a_k cos(\frac{\pi(2l+1)k}{2P})] \tag{3}$$

where, $a_k = 1/\sqrt{2}$ for $k = 0$, otherwise $a_k = 1$ and $k, l = 0, 1, 2, \cdots P-1$. Both sine and cosine waveforms are used to avoid discontinuities at the block boundaries. The dictionary matrix's size and the number of iterations determine the computational complexity of the algorithm [15]. The characteristics of the signals can be used to learn the dictionaries for applications like feature parameter estimation, event detection, compression, and denoising. In this work, our goal to subtract the muscle artifact while preserving the shape of the signal. Therefore, time-frequency information of ECG local waves and different noise components helps to construct the mixed dictionary. The dominant frequency of BW and PLI noises lie between 0-0.8 Hz (upto 1 Hz during stress test) [14] and 57-63 Hz or 47-53 Hz respectively. On the other hand, most of the energy of local P/T wave and QRS complex lie below 1-5 Hz and 5-20 Hz [16] respectively. Hence, sinusoidal dictionary matrices $\mathbf{\Psi}_{BW}$, $\mathbf{\Psi}_{PT}$, $\mathbf{\Psi}_{QRS}$ and $\mathbf{\Psi}_{PLI}$ constitute dominant frequency ranges 0-1 Hz, 1-2 Hz, 2-20 Hz and 57-63 Hz respectively. If the frequency is f, the column number will be $\lfloor \frac{2Af}{f_s} \rfloor$ (f_s being sampling rate and P being length of the signal). The sine and cosine waveforms in the dictionary are calculated using (2) and (3) for required frequency ranges.

The sparse coefficients can be estimated by solving l_1 -norm convex optimization [17], [18].

$$\hat{\alpha} = argmin. \|\mathbf{\Psi}\alpha - \mathbf{x}\|_2^2 + \lambda\|\alpha\|_1 \tag{4}$$

λ is the regularization parameter. It adjusts relative weights between reconstruction fidelity $\|\mathbf{\Psi}\alpha - \mathbf{x}\|_2^2$ and sparsity term $\|\alpha\|_1$. The estimated sparse coefficients vector $\hat{\alpha}$ includes,

$$\hat{\alpha} = [\hat{\alpha}_{BW}|\hat{\alpha}_{PT}|\hat{\alpha}_{QRS}|\hat{\alpha}_{SPK}|\hat{\alpha}_{PLI}] \tag{5}$$

$\hat{\alpha}_{BW}$, $\hat{\alpha}_{PT}$, $\hat{\alpha}_{QRS}$ and $\hat{\alpha}_{PLI}$ are the coefficients corresponding to sinusoidal elementary waveform for $\mathbf{\Psi}_{BW}$, $\mathbf{\Psi}_{PT}$, $\mathbf{\Psi}_{QRS}$ and $\mathbf{\Psi}_{PLI}$ respectively. The ECG signal can be represented as

$$\begin{aligned} \hat{\mathbf{x}} &\approx \mathbf{\Psi}\hat{\alpha} = [\mathbf{\Psi}_{BW}|\mathbf{\Psi}_{PT}|\mathbf{\Psi}_{QRS}|\mathbf{\Psi}_{SPK}|\mathbf{\Psi}_{PLI}]\hat{\alpha} \\ \hat{\mathbf{x}} &= \mathbf{\Psi}_{BW}\hat{\alpha}_{BW} + \mathbf{\Psi}_{PT}\hat{\alpha}_{PT} + \mathbf{\Psi}_{QRS}\hat{\alpha}_{QRS} \\ &\quad + \mathbf{\Psi}_{SPK}\hat{\alpha}_{SPK} + \mathbf{\Psi}_{PLI}\hat{\alpha}_{PLI} \end{aligned} \tag{6}$$

The reconstructed ECG signal $\hat{\mathbf{x}}$ can be computed as $\hat{\mathbf{x}} \approx \hat{\mathbf{x}}_{BW} + \hat{\mathbf{x}}_{PT} + \hat{\mathbf{x}}_{QRS} + \hat{\mathbf{x}}_{SPK} + \hat{\mathbf{x}}_{PL}$ where, $\hat{\mathbf{x}}_{BW}$, $\hat{\mathbf{x}}_{PT}$, $\hat{\mathbf{x}}_{QRS}$, $\hat{\mathbf{x}}_{SPK}$ and $\hat{\mathbf{x}}_{PL}$ are reconstructed BW signal, local P/T wave signal, wide QRS complex, spiky events including HF noises and HF QRS and PLI signal respectively. The effectiveness of R-peak detection algorithm is illustrated in Fig. 1 for the noisy ECG signal.

Algorithm 2 Proposed R peak detection algorithm

Function:Rpeak = RPeakDetector($\mathbf{x}_{QRS}$,**x**,Fs);
Input:
$\mathbf{x}_{QRS} \leftarrow$ Reconstructed QRS signal
Fs $\leftarrow$ Sampling frequency
x $\leftarrow$ Input ECG signal
Output: Rpeak = location of R peaks
Procedure:
Step0: Initialization n= 0, 1, 2, . . . $N-1$
Step1: Perform derivative and squaring operation
d=[0 diff($\mathbf{x}_{QRS}$)]
$\mathbf{d} = \frac{\mathbf{d}}{max(|\mathbf{d}|)}$
$\mathbf{d} = \mathbf{d}^2$
Step2: Apply adaptive thresholding, $\bar{\mathbf{d}} = (|\mathbf{d})| > \sigma_d) * \mathbf{d}$, σ_d denotes the standard deviation of **d**.
Step3: Compute Shannon energy followed by smoothing to obtain envelope
See = -$\bar{\mathbf{d}}. * log(\bar{\mathbf{d}})$
$\mathbf{s} = filtfilt(b, a, \mathbf{See})$; b=ones(1,WS)/WS; and a=1; WS=floor(0.1*Fs)
Step4: Peak finding logic using Gaussian derivative operator
$\mathbf{z} = conv(\mathbf{s}, \mathbf{h})$ //convolution of **s** and **h**;
h[k]=w[k] - w[k 1]; $w = e^{\frac{1}{2}\frac{(2\epsilon l)}{L}}$
L is the window length, L=floor(2.5*Fs) for interval of 2.5 s;
ϵ=floor(0.05*Fs) for duration of 50 ms;
r=$(sign(z[n]) > 0)\&\&(sign(z[n+1]) < 0)$; // store locations of negative zero-crossing points in $z[n]$
Step5: Perform peak adjustment procedure
nw=floor(0.05*Fs); //searching window size to find true R-peaks
for p=1 to length(r) **do**
[Rmax Rpeak]=max {**x**[r(p) nw : r(p) + nw]} //store current location of a detected R-peak
endfor
EndProcedure

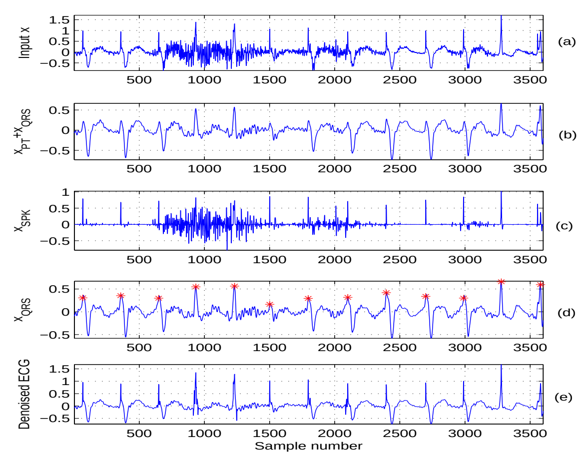

Fig. 1. Illustrates the outputs of the proposed sparse decomposition approach (a) Original ECG signal taken from a mit-biha record 104 corrupted with MA (b) Addition of reconstructed P/T wave $\hat{\mathbf{x}}_{PT}$ and wide QRS signal $\hat{\mathbf{x}}_{QRS}$ (c) Spiky signal $\hat{\mathbf{x}}_{SPK}$ (QRS and muscle artifact) reconstructed from identity basis (d) R-peak detection result on $\hat{\mathbf{x}}_{QRS}$ (e) Denoised ECG signal

3. RESULTS AND DISCUSSION

In this section, the noise reduction performance of the proposed method is tested and validated using ECG signals taken from a standard MIT-BIH Arrhythmia database. The recon-

Table 1. Performance evaluation of denoising methods using different objective quality metrics including root mean squared error (RMSE), signal to noise ratio (SNR), maximum absolute error (MAX), normalized cross correlation (NCC) and wavelet energy based diagnostic distortion (WEDD)

	EMD [3]					**EMD+Wavelet[10]**					**Proposed Method**				
Rec.	**RMSE**	**SNR**	**MAX**	**NCC**	**WEDD**	**RMSE**	**SNR**	**MAX**	**NCC**	**WEDD**	**RMSE**	**SNR**	**MAX**	**NCC**	**WEDD**
100	0.07	8.80	0.59	0.938	37.23	0.07	8.57	0.62	0.934	37.04	0.04	13.21	0.41	0.979	18.22
101	0.06	11.17	0.46	0.967	27.90	0.06	10.81	0.52	0.963	28.14	0.03	16.48	0.20	0.992	13.29
102	0.05	11.44	0.31	0.967	26.72	0.05	11.06	0.39	0.963	27.18	0.03	15.48	0.22	0.986	14.51
104	0.06	12.42	0.54	0.971	26.32	0.06	11.27	0.61	0.963	22.56	0.03	16.44	0.48	0.989	14.36
106	0.07	12.13	0.87	0.969	29.78	0.07	12.10	0.85	0.969	29.68	0.04	17.63	0.20	0.993	10.72
107	0.12	16.59	0.73	0.989	13.50	0.12	16.41	0.73	0.988	13.52	0.06	22.03	0.48	0.997	6.04
109	0.10	12.46	0.58	0.970	27.22	0.10	12.45	0.58	0.970	21.32	0.03	22.08	0.20	0.997	6.92
111	0.06	9.92	0.44	0.948	36.20	0.09	11.09	1.00	0.948	32.89	0.03	14.68	0.21	0.984	16.23
117	0.04	14.38	0.26	0.981	35.63	0.04	14.38	0.25	0.981	35.82	0.03	15.22	0.18	0.985	17.44
118	0.05	9.57	0.61	0.943	39.76	0.05	9.60	0.60	0.944	39.64	0.03	14.24	0.20	0.982	19.25
119	0.09	13.16	0.90	0.974	22.76	0.09	13.19	0.89	0.974	22.49	0.05	19.38	0.48	0.996	9.19
123	0.11	8.56	1.10	0.927	39.59	0.11	8.60	1.06	0.928	38.72	0.04	17.73	0.18	0.994	11.02
124	0.08	13.64	0.71	0.974	20.33	0.08	13.62	0.73	0.974	20.34	0.04	18.89	0.45	0.994	12.05
203	0.09	13.60	0.57	0.978	24.40	0.09	13.58	0.58	0.978	24.28	0.04	19.77	0.37	0.995	8.24
207	0.04	14.45	0.34	0.980	23.48	0.04	14.44	0.34	0.980	23.47	0.04	15.83	0.27	0.987	14.02
208	0.09	13.54	0.76	0.978	17.04	0.09	13.40	0.80	0.978	17.25	0.05	18.28	0.64	0.993	11.27
Avg.	**0.07**	**12.24**	**0.61**	**0.97**	**27.99**	**0.08**	**12.16**	**0.66**	**0.96**	**27.15**	**0.04**	**17.34**	**0.32**	**0.99**	**12.67**

structed signals are assessed using both subjective quality assessment test and objective quality assessment metrics including the root mean square error (RMSE), signal to noise ratio (SNR), normalized cross correlation (NCC), maximum absolute error (MAX), and wavelet energy based diagnostic distortion (WEDD) [19]. In this work, the existing denoising methods based on the EMD, DWT and EMD, high-pass filter (HPF), and moving average filter (MAF) are implemented for performance comparison. The noise reduction performance of EMD, and DWT and EMD method is summarized in Table 1. From the values of different objective quality metrics, it is noted that the proposed method has lower values of the RMSE, MAX and WEDD metrics and higher values of SNR, NCC and WEDD metrics for most of tested ECG signals. The original and reconstructed ECG signals are shown in Figs. 1 and 2 for visual inspection of morphological features of the local waves of the ECG signal. It is evident from Fig. 2 that proposed method outperforms other existing methods. Due to the lack of space, the performance evaluation results are presented in Table 1 and Figs. 1 and 2 for demonstrating the noise reduction capability of the proposed denoising method.

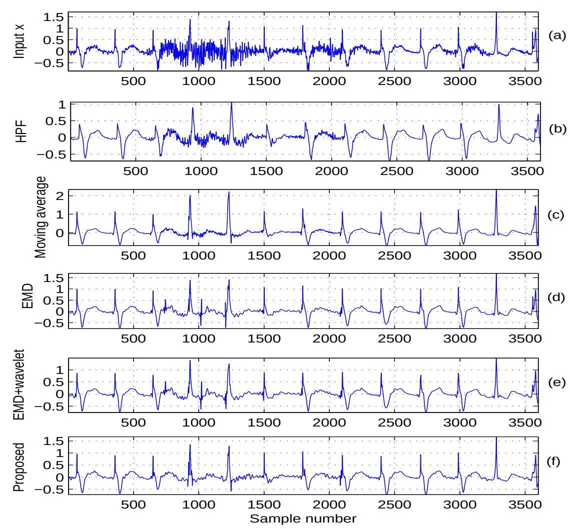

Fig. 2. Results of the five denoising methods (a) Original ECG taken from a mitbiha record 104 (b) HPF-based denoised signal [13], (c) MAF-based denoised signal [9], (d) EMD based denoised signal [3], (e) EMD + wavelet based denoised signal [10], (f) the proposed method.

4. CONCLUSION

This paper presents an automatic method for removal of muscle artifacts from ECG signals using the sparse signal decomposition and R-peak information. The noise reduction capability of the proposed method is tested and validated using ECG signals taken from a standard MIT-BIH Arrhythmia database. The reconstructed signals are assessed using both subjective quality assessment test and objective quality assessment metrics. Performance evaluation results show that the proposed method outperforms other existing ECG denoising methods in adequately removing the muscle artifacts without significantly distorting the morphologies of P-wave, QRS-complex and T-wave of the ECG signals.

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