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Denoising Baseline Signal of Electrocardiogram using Separable Wavelets Bases

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***Abstract*—The electrocardiogram signals are affected by the baseline wandering noise. In this paper, the separable wavelet transform method is used for denoising of the baseline wandering signals. To that end, the one-dimensional signal is set to the two-dimensional matrix via lexicographic ordering. And then, adaptive wavelet filtering is used to remove baseline wandering noise. The proposed method is applied to the wide range of data set from the MIT-BIH arrhythmia database. The performance of the method is assessed by common quantitative metrics.**

Anahtar Kelimeler*—*electrocardiogram, denoising, seperable wavelet transform.

I. Introduction

Electrocardiogram (ECG) signals are the measure of heart electrical activity that is useful in the cardiovascular system for diagnosis and treatment. The signal that oscillates in the 0 - 100 Hz frequency range that is indicative of heart disorders. The ECG signal must be recorded neatly and cleanly in order to be a useful marker for heart disorders. The ECG signals is distorted by artifacts while recording. This can lead to misdiagnoses or different interpretations. There are various interference and noise that degrade the ECG signals during the data recording. This degradation factors that corrupt the morphology of the ECG data are caused by nature of the human body such as movement of the body, breathing cause baseline wandering and electromyographic interference and noises that caused by data acquisition systems e.g. electrode contact noise, the interaction between electrodes. For a well-defined diagnosis and correct determination of cardiac disorders, the source of the noises and interference should be identified for a developing a robust noise removal algorithm.

Baseline wandering is common artifact that caused by patients body muscle and respiratory movements, mismatch impedance between electrode, and skin [1]. This causes the problem in detection of the ECG features. In the literature, baseline wandering can be removed by applying a frequency or time domain filtering [7], [9]. The methods have been evaluated under two main heading as the non-adaptive and adaptive approach [3], [10]. Finite/infinite impulse response and notch filters are the non-adaptive solutions. Due to that the baseline wandering occurs in frequency under 0.5 Hz, finite or infinite impulse response (FIR/IIR) high pass filter can remove the baseline frequency. Baseline wandering noise occurs in a narrow 0 - 0.5 Hz frequency. The noise can be eliminated by well-defined high pass filter with low-frequency bandwidth below 1 Hz cut-off frequency. Non-adapting high pass filter approach may cause deformation on the morphology of the signal that leads a deformation on the diagnostic feature of the ECG signals [1]. Adaptive or non-adaptive filter solutions have been designed for removing baseline wandering [2], [6]. Due to the non-stationary nature of the ECG signal, non-adaptive filters have limited performance on noise removing while adaptive filters outperform the techniques that used non-adaptive approach [11]. In the recent study, the term of baseline wandering is estimated by merging the local trend based on signal segments [1]. Besides the baseline wandering, noises are contaminated in ECG signals. This kind of noises appears in the wide range of frequency. Various approaches have been developed to eliminate ECG noises [16].

The most common methods used in ECG signal denoising are determination threshold for discrete wavelet coefficients, fuzzy logic algorithms, FIR/IIR filtering [8], empirical mode decomposition. Due to the non-stationary characteristic of the ECG signal, the classical methods do not give satisfactory results. The Wavelet transform becoming an efficient tool for analysis of the non-stationary signals [20]. The Wavelet transform localized in both time and frequency, therefore, non-stationary signal components are well-defined as a few numbers of coefficients [17]. Proposed method consists of combined adaptive filter and wavelet transform for baseline wandering noise. The data is transformed to wavelet space for removing the additive noise. The data is represented in wavelet sparsity and detail and approximation coefficients are used for reconstructed of the denoised data. The method has been tested on MIT-BIH arrhythmia database, 48 half-hour excerpts of the two-channel ECG signal. The database was digitized at 360 samples/second per channel with 11-bit resolution over a 10 mV range of amplitude.

II. Baseline Wandering and Noise in ECG Signals

ECG signals are contaminated by the noise signals while recording or acquisition process. Digital ECG signal is defined as $s(n) \in \mathbb{R}$ with M sample length. Additive normal distribution noise and low frequency BW noise are set to $N^r(n) \in \mathbb{R}$ and $N^{BW}(n) \in \mathbb{R}$, respectively. The noisy ECG signal $g(n)$ is expressed as,

$$\bar{g}(n) = s(n) + N^{BW}(n) \tag{1}$$

$$g(n) = \bar{g}(n) + \sigma N^r(n) \tag{2}$$

In the (1) and (2), the ECG signal has two different type of noises. The coefficient σ is amplitude parameter of standard normal distributed white noise. The ECG signal without noise and noisy signal is given in Fig. 1.

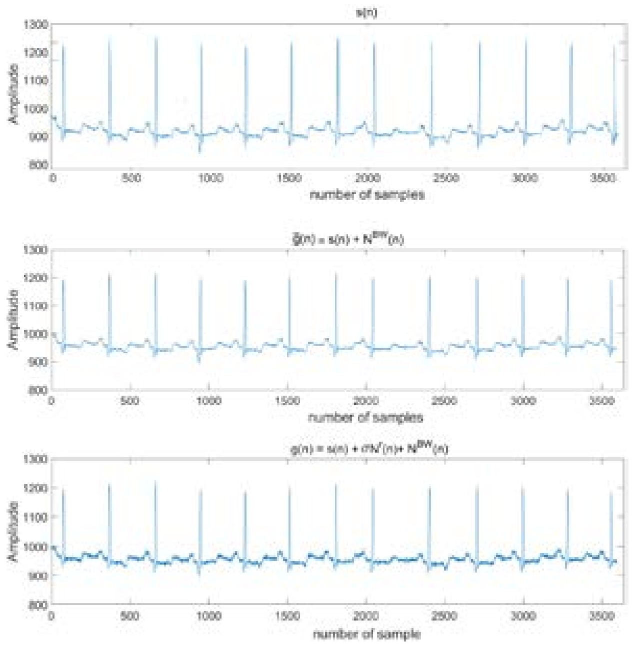

Figure 1: ECG signal without noise, contaminated with BW and additive noise with $\sigma = 0.8$

The aim of the study is to remove BW noise $N^{BW}(n)$ and additive white noise $N^r(n)$ noises using adaptive filter and separable wavelet transform, respectively. The noise removed signal is assigned $\tilde{s}(n)$. The method seeks for minimum error between clear signal $s(n)$ and corrupted $g(n)$ signals.

III. Proposed Method

In this paper, baseline wandering (BW) and zero-mean Gaussian noise are removed from the ECG signal afterwards. The block diagram of the proposed method is given at Fig. 2 in general.

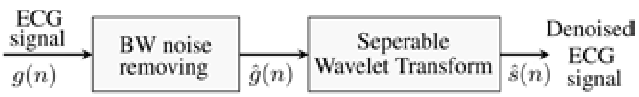

Figure 2: Generic block diagram of proposed method

BW noise removing process where adaptive wavelet transform filtering is applied is the first block of the proposed algorithm. Adaptive filter and wavelet transform are used to remove low frequency BW noise. In adaptive block, Recursive Least Square (RLS) filter is used. The block is elucidated in following subsection III-A.

Elimination of additive noise is processed with wavelet based denoising techniques in the second block of proposed method given in Fig. 2. The first step of separable wavelet transform is to re-form 1D ECG signal to the two-dimensional (2D) form via lexicographic ordering. Secondly, the matrix is exposed to separable wavelet transform. In the last stage, wavelet coefficients belonging to noise are eliminated by applying threshold value.

By lexicographic ordering, 1D ECG data is transformed to the two-dimensional matrix. The matrix consists of BW noise-removed data is transformed wavelet space. The wavelet transform is exposed by a separable structure [15].

Considering of a large class of signals, the number of wavelet coefficients is diminishing rapidly. This property is called unconditional basis that makes wavelets so effective in data denoising [5]. Additionally, it is shown that wavelets in fields of denoising are near optimal for a wide class of signals. Motivated by the theory of sparsity, coefficients of noise in wavelet domain can be eliminated [4].

A. *Adaptive Wavelet Filtering for Baseline Wandering*

Baseline wandering noise is removed by the wavelet transform based adaptive filtering. Since baseline wandering noise frequency is occurs in the low frequencies, approximation coefficients of the wavelet transform can be filtered by an adaptive filter. The filtered and high frequencies (details) coefficients are exposed to the inverse wavelet transform [12]. In the adaptive filter block, RLS algorithm, which is recently

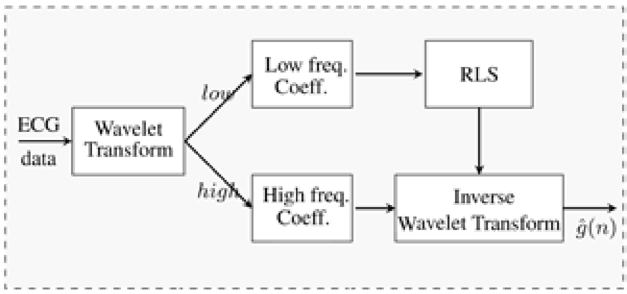

Figure 3: BW signal removing pipeline

used for prediction [18], is used to eliminate low-frequency components. The approximation coefficients are filtered to remove low-frequency components. Having filtered the low-frequency components, filtered approximation, and the high-frequency coefficients are exposed to the inverse wavelet transform for the reconstruction of the baseline wandering removed signal..

B. *Separable Wavelet Transform*

Separable Wavelet Transform (SWT) based noise removed method is performed in the second stage of generic block diagram . The first step of SWT stage is to set 1D ECG signals to 2D matrix. This stage is a pre-operation for SWT which is a tensor product of approximation and detail coefficients of 1D ECG data [13]. The ECG matrix is obtained by lexicographic ordering. Then the matrix is mapped to wavelet space by applying SWT. Having been performed SWT to the matrix, hard threshold applied to the coefficients. Lastly, the remaining coefficients are exposed to Inverse Separable Wavelet Transform (ISWT) to obtain noise removed signal. Any orthonormal

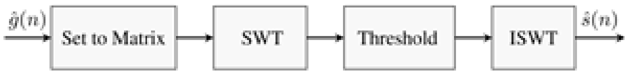

Figure 4: Additive white noise removing block diagram

basis of wavelet has been defines as $\psi_{j,k}$ where $(j,k) \in \mathbb{Z}^2$ from $\mathbf{L}^2(\mathbb{R})$ can regarded as a separable wavelet orthonormal basis of $\mathbb{Z}^2$ [14]:

$$\{ \psi_{j_1,k_1}(\hat{g}_2(n))\psi_{j_2,k_2}(\hat{g}_1(n))\}_{(j_1,j_2,k_1,k_2)\in\mathbb{Z}^4} \tag{3}$$

where ψ_{j_1,k_1} and ψ_{j_2,k_2} are functions at two scales 2^{j_1} and 2^{j_2} along $\hat{g}_1(n)$ and $\hat{g}_2(n)$. In SWT block, the signal is mapped to two-dimensional wavelet coefficients space: details and approximation regarding principle given expression (3). Having defined the wavelet transform for 1D data, it can be adapted to the function of two-dimensional matrix by applying the same process to rows and columns analogously. Wavelet transform for one-dimensional discrete $g(n)$ signal with M length is expressed as follows,

$$W_\phi(j_0,k) = \frac{1}{\sqrt{M}}\sum_n \hat{g}(n)\phi_{j_0,k}(n), \qquad j \le j_0 \tag{4}$$

$$W_\psi(j,k) = \frac{1}{\sqrt{M}}\sum_{j=j_0}^{\infty} \hat{g}(n)\psi_{j,k}(n), \qquad j \le j_0 \tag{5}$$

where $\phi_{j_0,k}(n)$ and $\psi_{j,k}(n)$ are basis function that defines in range of $[0, M-1]$. The signal $\hat{g}(n)$ can be reconstructed by operating inverse wavelet transform as described,

$$\hat{s}(n) = \frac{1}{M}\sum_k W_\phi(j_0,k)\phi_{j_0,k}(n) + \sum_{j=j_0}^{\infty} W_\psi(j,k)\psi_{j,k}(n) \tag{6}$$

where $W_\phi(j_0,k)$ states for the low frequency component (approximation coefficients) and $W_\psi(j,k)$ states for high frequency components (detail coefficients). $g(n)$ is reconstructed by approximation and detail coefficients.

IV. Simulation Results

The algorithm is tested on a public domain ECG data set. Firstly, adaptive filter based baseline wandering noise removing algorithm is applied on the dataset of Arrhythmia Database MIT-BIH. Low-frequency components are eliminated by RLS filter applying on approximation coefficients of wavelet transformed ECG signals. The result of the dataset for BW filtering that is compared with the signal 1 and signal-2 samples with BW noise shown in Fig. 5 and Fig. 6

Secondly, process to remove additive white noise for different level of σ amplitude coefficients is applied to signals. Before applying SWT, one-dimensional ECG signals are transformed to the two-dimensional matrix. Then the matrix is mapped to wavelet space by applying separable wavelet transform where the coefficients that belong to noise is eliminated by applying the hard threshold. Signal to Noise Ratio (SNR) and Peak Signal-to-Noise Ratio (PSNR) are used as

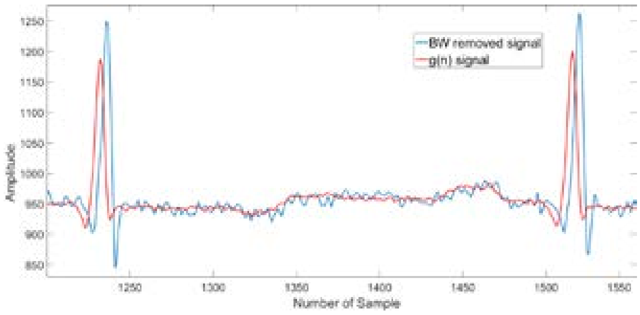

Figure 5: Adaptive baseline wandering filter result (Signal-1)

quantitative assessment metrics. The algorithm is tested on 7 seven ECG signals taken from MIT-BIH dataset, namely, $100.dat...107.dat$ samples.

Quantitative assessment of these signals are given in Table 1 for $\sigma = 0.08$ and $\sigma = 0.8$ values.

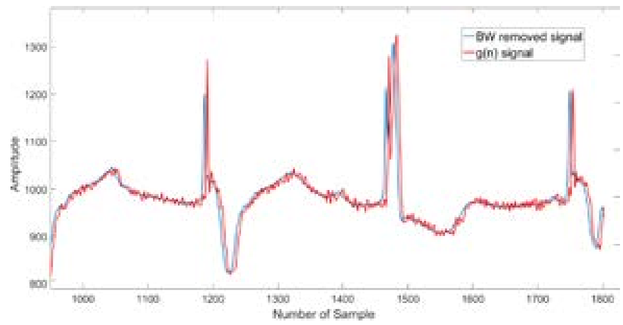

Figure 6: Adaptive baseline wandering filter result (Signal-2)

Table I: PSNR and SNR of noise-removed signals

$\sigma = 0.08$	S-1	S-2	S-3	S-4	S-5	S-6	S-7
PSNR	77,6	81,6	80,3	79,3	82,6	80,6	81,4
SNR	22,8	26,7	25,4	24,4	27,6	25,8	26,5
$\sigma = 0.8$	S-1	S-2	S-3	S-4	S-5	S-6	S-7
PSNR	77,6	81,6	80,3	79,3	82,6	80,6	81,4
SNR	22,8	26,7	25,4	24,4	27,6	25,8	26,5

In Figure 7, the results are shown for different level of σ values in terms of SNR and PSNR values. It obvious that performance of the method decrease with increasing level of noise.

V. Conclusion

The discrete wavelet transform is becoming an essential tool for processing of non-stationary signals such as ECG signals. The SWT is an extension of DWT that is regarded as a tensor product of wavelet coefficients. In this study, the wavelet transform is used to eliminate two basic noise type, baseline wandering, and Gaussian noise. To remove noise with the low-frequency component, baseline wandering noise, the signal is mapped to the wavelet domain and approximation coefficients are filtered by the RLS algorithm. The noise occurs

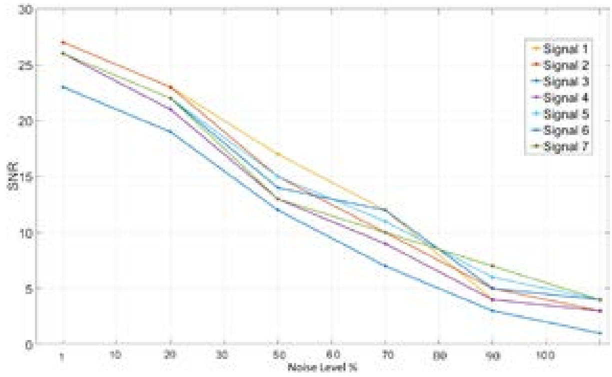

Figure 7: Separable wavelet based noise removing results

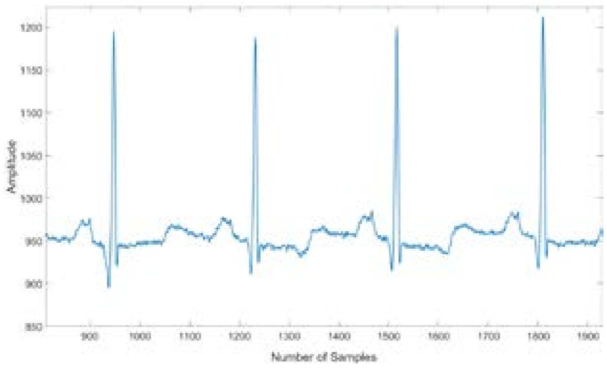

Figure 8: BW and Gaussian noise removed signal, $\sigma = 0.08$

in a wide range of frequency is modeled as Gaussian noise. The frequency component that belongs to the noise signal is removed by thresholding the wavelet transform coefficients. The algorithm is applied to the various sample of ECG signal with a different level of additive noise. Simulation results show that the frequency component of the baseline wandering is eliminated.

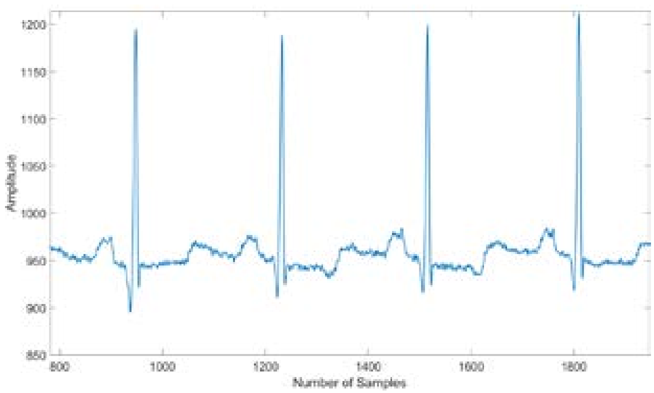

Figure 9: BW and Gaussian noise removed signal, $\sigma = 0.8$

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