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ORIGINAL ARTICLE

Time–frequency localization using three-tap biorthogonal wavelet filter bank for electrocardiogram compressions

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Abstract

A joint time–frequency localized three-band biorthogonal wavelet filter bank to compress Electrocardiogram signals is proposed in this work. Further, the use of adaptive thresholding and modified run-length encoding resulted in maximum data volume reduction while guaranteeing reconstructing quality. Using signal-to-noise ratio, compression ratio (C_R), maximum absolute error (E_{MA}), quality score (Q_s), root mean square error, compression time (C_T) and percentage root mean square difference the validity of the proposed approach is studied. The experimental results deduced that the performance of the proposed approach is better when compared to the two-band wavelet filter bank. The proposed compression method enables loss-less data transmission of medical signals to remote locations for therapeutic usage.

Keywords Electrocardiogram · Biorthogonal wavelet transform · Wavelet filter bank · Electrocardiogram compression

1 Introduction

Clinical procedures have a prominent and important space for transmission techniques of biomedical signals. To make a remote clinical assessment using biomedical signals, signal transmission techniques have paramount importance. Healthcare processes generate heavy data thus demand a huge data transmission. Using data compression techniques in bio-signal transmission can make the remote clinical assessment cost-effective. For example, while monitoring cardiac activity using an ECG, data is recorded using multiple channels for several hours thus making it imperative for a system to be equipped with sufficient storage capacity clubbed with channel bandwidth. As real-time monitoring requires a huge memory and large bandwidth to transfer raw data, a proper compression technique should enable the data storage and transmission with minimal requirements. Further, to enable secure off-line data storage through ECG archives, the ECG data needs to be compressed for a cost-effective solution. Thus, there is an obvious requirement for data compression in biomedical signals.

Literature has supported several compression ratios ranging from 2:1 to 50:1 [1]. The literature differentiates the compression techniques into two categories namely, direct time-domain (the turning point, cycle-to-cycle, scan along polygonal approximation to name a few) and transformed frequency-domain techniques (Discrete cosine transform, wavelet transform to name a few). Considering the trade-off between simplicity, compression ratio, preserve clinical information and insensitive to noise, wavelet transform based compression methods have provided a significant advancement in the last few years [2].

2 Selection of wavelet transform and filter bank architecture

The main limitation of Fourier transform lies in dealing with the non-stationary type of signals. The wavelet transform enables both time and frequency domain analysis thus allowing the analysis of non-stationary signals. The wavelet transform is the mathematical tool that deals with joint time–frequency analysis to reveal the features hidden within the signal. With the help of variable window size, wavelet transform enables analyzing different frequency components

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within a signal. Oscillating wave-like characteristics of a wavelet transform resembling band like spectrum makes it a better choice in removing noises from signals. Wavelet transform can decompose a signal into two separate series, namely, scaling function and wavelet function. Out of the existing thirteen different wavelet families, only few can be applied to compress an ECG signal.

Properties of a wavelet transform play a significant role in the selection of a wavelet transform for ECG compression. Different properties of wavelet transform are listed in Table 1. Based on orthogonality; wavelet transforms are categorized into orthogonal, semi-orthogonal, biorthogonal and shift orthogonal wavelet transforms. Biorthogonal wavelet transform satisfies all the following essential properties of ECG compression: (i) allows transmission between spline of zero order and spline of infinite order; (ii) provides an optimal natural signal interpolant that has least oscillating energy; (iii) has minimum MSE (mean square error) at every decomposition level; (iv) highest degree of shift variance; (v) generates possibilities to construct symmetrical wavelet functions. In this work, the biorthogonal wavelet transform is applied to compress the ECG signal. In the analysis of non-stationary signals, the wavelet filters and bases for attaining optimal joint time–frequency localized wavelet filter banks (WFBs) are designed [3].

Current literature uses two-band WFBs to analyze ECG signals [4–10]. Poor resolution ($\Delta\omega = \pi/2$) of low and high-frequency bands during signal decomposition is the major drawback of two-band WFBs. In two-band WFBs, cascading and wavelet packet decomposition is required to improve the resolution of lower and higher frequency bands, respectively. Cascading increases the computation complexity of the design. To reduce the computation complexity, Three-band WFBs with linear phase, lesser computational complexity, higher energy in high -frequency bands and better frequency resolution of ($\Delta\omega = \pi/3$) in lower and higher frequency bands are preferred over two-band WFBs [3]. Literature has supported the involvement of three-band time–frequency localized WFBs in numerous applications, namely, classification of EEG signals [11], digital watermarking [12], and image denoising [13]. The advantages of joint time–frequency localized three-band biorthogonal WFB motivates us to compress the ECG signal using three-band WFBs. The objective of the present scheme is to evaluate the performance of joint time–frequency localized three-band biorthogonal WFBs on different performance evaluation indexes, namely, C_R, Q_S, C_T, RMSE, SNR, E_{MA}, and PRD and to develop a computer-aided ECG compression scheme which can be used in the real systems.

Table 1 Comparison of different wavelet families

Wavelet family	Support width	Filter length	Number of vanishing moments
Haar	1	2	1
Coiflets	6 N – 1	6 N	2 N – 1
Daubechies	2 N – 1	2 N	N
Biorthogonal/reverse biorthogonal	2 Nr + 1, 2 Nd + 1	Max (2Nr, 2Nd) + 2	Nr
Symlets	2N – 1	2N	N

*Nr reconstruction order, Nd decomposition order

3 Proposed method

The signal processing flow of the proposed ECG compression scheme, the corresponding three-tap wavelet filter bank, and decomposition of ECG signal up to the fourth level, respectively are shown in Figs. 1, 2 and 3. Initially, ECG data is recorded using iworx® IX-TA (a portable 3-channel device) at a frequency of 360 Hz. The recorded analog ECG signal is digitized using an analog-to-digital converter (ADC). The process used to compress the ECG signal is same as used in [14] except some modifications done in the proposed work which are as follows: a novel joint time–frequency localized three-band biorthogonal WFB is utilized to decompose the

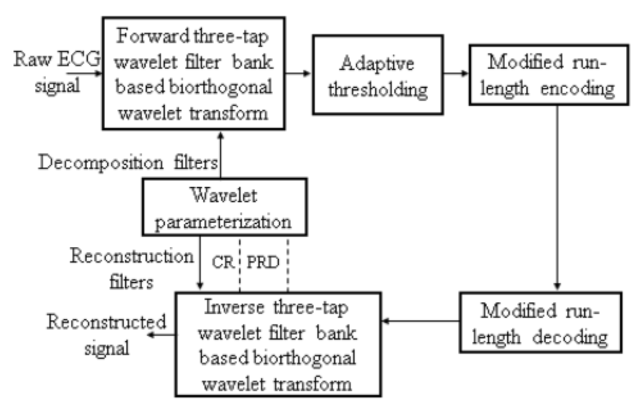


Fig. 1 Proposed three-tap biorthogonal wavelet filter bank-based ECG compression scheme

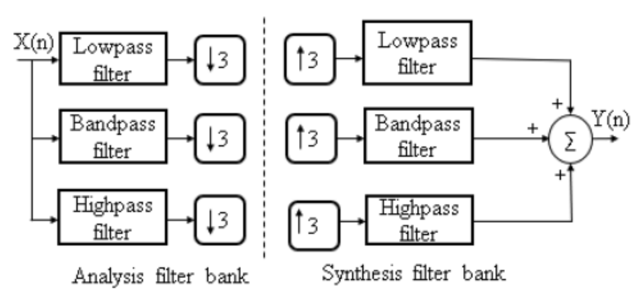
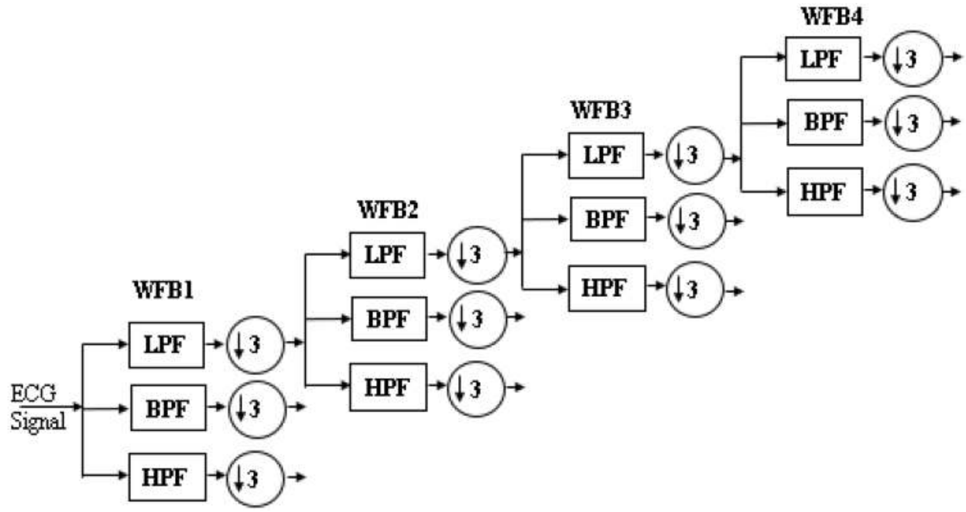


Fig. 2 Proposed three-tap biorthogonal wavelet filter bank

Fig. 3 Decomposition of ECG signal up to the fourth level



digitized ECG signal into four sub-bands. The transfer function of different filters namely, lowpass, bandpass and highpass, respectively, are obtained as shown in Eqs. (1)–(3).

$$H_0(z) = -0.0074 + 0.4559z^{-1} + 0.7292z^{-2} + 0.4559z^{-3} - 0.0074z^{-4} \tag{1}$$

$$H_1(z) = -0.0178 - 0.3588z^{-1} + 0 - 0.3558z^{-3} - 0.0178z^{-4} \tag{2}$$

$$H_2(z) = 0.0098 - 0.4125z^{-1} + 0.1179z^{-2} - 0.4125z^{-3} + 0.0098z^{-4} \tag{3}$$

The decomposed ECG signal is adaptively thresholded, and the absolute values greater than the threshold are considered as digital high (logic high and represented as "1") and all the other remaining values are considered as digital low (logic low and represented as "0"). The digitized data is then compressed using run-length encoding scheme.

4 Experimental results

C_R, E_{MA}, Q_S, RMSE, C_T and PRD are the parameters used to demonstrate the validity of the proposed approach. Parameters listed above are mathematically expressed using Eqs. (4)–(8).

$$Compression\,Ratio\,(C_R) = \frac{NB_o}{NB_c} \tag{4}$$

$$PRD = 100\sqrt{\left\{\frac{\sum_{n=1}^{N}\left[h(n) - \hat{h}(n)\right]^2}{\sum_{n=1}^{N}[h(n)]^2}\right\}} \tag{5}$$

$$Q_S = \frac{C_R}{PRD} \tag{6}$$

$$E_{MA} = \max\left[h(n) - g(n)\right] \tag{7}$$

$$RMSE = \sqrt{\sum_{n=1}^{N}\frac{\left[\hat{h}(n) - h(n)\right]^2}{N}} \tag{8}$$

where NB_0 is the total bits in the input ECG, NB_c is the total bits in the compressed signal, h*(n)* is the ECG signal, *g(n)* is the reconstructed output, $\hat{h}$(n) is the denoised output. C_R is the ratio of size of the raw signal to the size of the compressed signal. PRD estimates the quality of the reconstructed signal by measuring the inaccuracy between original signal and reconstructed signal. Q_S is the C_R divided by the PRD which estimates the behavior of the C_R. Performance results of the proposed ECG compression approach is summarized in Table 2, where the proposed approach achieve a better result compared to the latest literature [15–19]. Proposed design achieves a highest average C_R, average Q_S, respectively, of 22.61 and 20.81. Further, the proposed design has a minimum average C_T, average E_{MA}, average RMSE and PRD, respectively of, 327.29 ms, 0.013, 0.0016 and 1.60.

Error between the original ECG signal and the reconstructed ECG signal is determined with the help of PRD. Lowest the value of PRD signifies the better performance. Figure 4 compare the PRD values obtained by the proposed method with the existing literature [15–19]. The proposed method obtains the lowest average PRD value of 1.28 amongst all of the existing methods.

A comparison of C_R and PRD between the proposed scheme and the existing Refs. [15–19] is presented in Fig. 5. From Fig. 5, a highest C_R and lowest PRD of the proposed scheme has been observed and compared with [15–19].

Signal-to-noise ratio (SNR) is an objective measure to evaluate the performance of the system which undergoes the noise. Higher SNR value leads to better quality of the signal

Table 2 Performance evaluation of the proposed approach

Performance parameters	Proposed method	[15] (*)	[16] (*)	[17] (*)	[18] (*)	[19] (*)
Average C_R	22.61	18.89	11.52	13.19	18.76	21.19
Average Q_S	27.81	20.47	7.83	11.81	20.76	26.76
Average C_T (ms)	327.29	494.22	491.27	421.08	459.87	398.24
Average E_{MA}	0.0013	0.0002	0.016	0.032	0.100	0.006
Average RMSE	0.0016	0.029	0.021	0.020	0.020	0.032

For the fair comparison, 9th level of wavelet decomposition is utilized

*Performance of the given references is calculated by generating the similar environment as described in the original paper

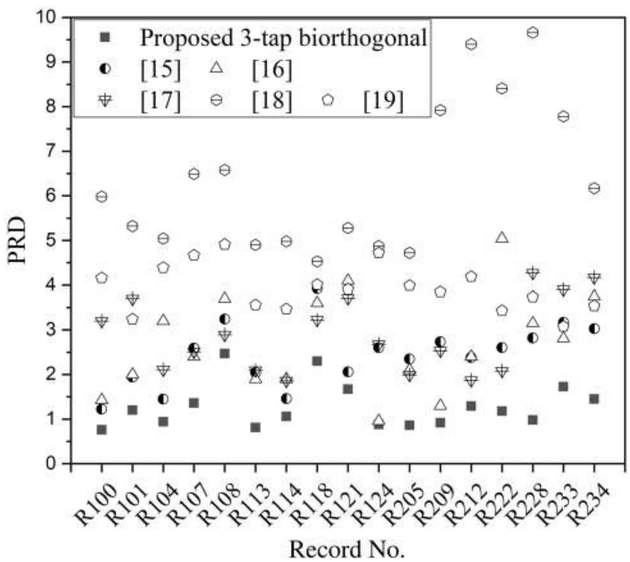


Fig. 4 Comparison of PRD with existing schemes for different ECG records (indicted as R100 and others) taken from MIT-BIH database

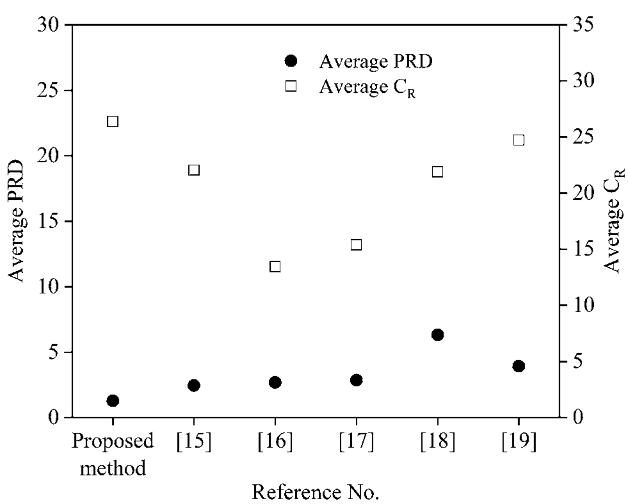


Fig. 5 Comparison of the C_R and PRD between the proposed scheme and the existing schemes

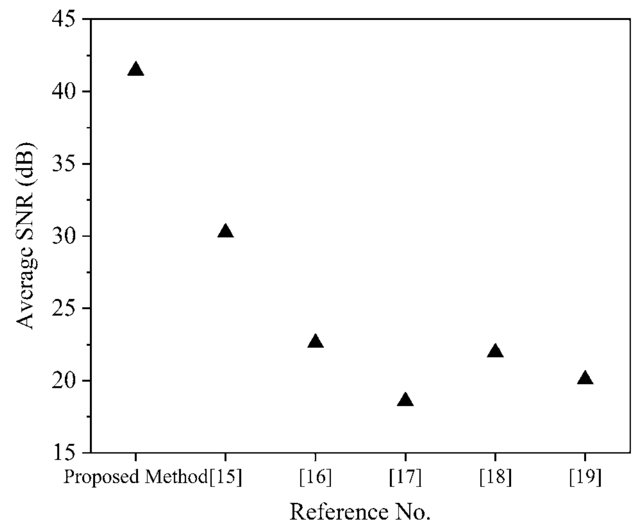


Fig. 6 SNR comparison of the proposed method with the existing methods

and hence, it is easy to decode the signal without errors. A comparison of output SNR between the proposed scheme and the existing schemes has been represented in Fig. 6 and a highest SNR of the proposed scheme compared to the Refs. [15–19] has been observed.

The output of the proposed joint time–frequency localized three-band biorthogonal WFBs based ECG compression approach is shown in Fig. 7. Figure 7(a) is an input ECG signal having a sampling frequency of 360 Hz. Figure 7(b) represents the reconstructed ECG signal.

5 Conclusion

A novel joint time–frequency localized three-tap biorthogonal wavelet filter bank for ECG compression is proposed in this article. The proposed time–frequency localized three-tap biorthogonal WFB for biosignals achives a losless compression ratio of 22.6. Simulations results demonstrate that the proposed three-tap biorthogonal WFB results in a higher compression ratio of the biosignals when compared to

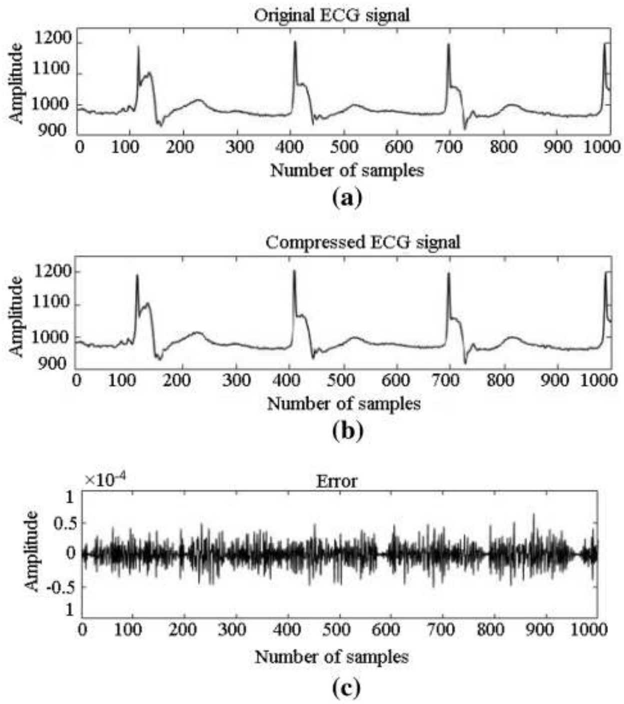


Fig. 7 (**a**) Original ECG signal, (**b**) compressed ECG signal and (**c**) error

two-tap biorthogonal WFB. The better frequency resolution at both lower and higher frequency of three-tap biorthogonal WFB leads to a better compression of the signal. Thus time–frequency localized three-tap biorthogonal WFB can enable loss-less compress with a high compression ratio to transmit biosignals for therapeutic use to assist in remote clinical assessment.

Compliance with ethical standards

Conflict of interest All authors declare that they have no conflicts of interest.

Ethical approval This article does not contain any studies with human participants or animals performed by any of the authors.

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