Beat Reordering for Optimal Electrocardiogram Signal Compression using SPIHT

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***Abstract*—An effective electrocardiogram (ECG) signal compression method based on two-dimensional wavelet transform which employs set partitioning in hierarchical trees (SPIHT) and beat reordering technique is presented. This method utilizes the redundancy between adjacent samples and adjacent beats. Beat reordering rearranges beat order in 2D ECG array based on the similarity between adjacent beats. This rearrangement reduces variances between adjacent beats so that the 2D ECG array contains less high frequency component. The experiments on two datasets from MIT-BIH arrhythmia database revealed that the proposed method is more efficient for ECG signal compression in comparison with several previous proposed methods in literature. The experimental results show that the proposed method yields relatively low distortion at high compression rate.**

ECG compression; set partitioning in hierarchical trees (SPIHT); wavelet transform; multirate signal processing

I. INTRODUCTION

ECG signal is a very important source of information for cardiologist in diagnosing their cardiac patients. Long term ECG monitoring is recommended for patients who have been diagnosed with mild version of a cardiac disorder but still maintain active lifestyle [1]. This long term ECG monitoring is called ambulatory monitor. An ambulatory monitor with the sampling rate of 360 Hz, 11bit/sample data resolution, a 24-hour recording requires about 43 Mbytes of storage per channel. Recent advances in sensor technology allow ambulatory monitor to record ECG signal at higher sampling rate and data resolution. As the sampling rate, data resolution, and observation time increase, the amount of storage requirement also increases. The amount of transmission time and bandwidth also increases when the ECG signal needs to be transmitted. Therefore, ECG signal compression becomes an important issue in biomedical engineering and signal processing research area.

SPIHT is a wavelet-based coding technique, which supports progressive coding capability. In progressive coding, signal quality can be improved gradually as the compressed bit rate increases. The encoded bit stream can be stopped when desired quality is met [2]. Several ECG signal compression methods based on SPIHT and its modification has been presented recently. Lu et al. proposed 1D SPIHT coding for single/multi-lead ECG signal compression [3]. Pooyan et al. divided ECG signal into non-overlapped frames and applied 1D SPIHT coding on each frame of ECG signal [4]. Goudarzi et al. proposed SPIHT coding on multiwavelet transformed 2D ECG array [5]. Rezazadeh et al. applied similar technique to Goudarzi to construct 2D ECG array with the implementation of sub-band energy compression before SPIHT coding [6]. Tai et al. also used similar technique to construct 2D ECG array and proposed modified SPIHT coding that divided wavelet transformed image into three partitions [7]. Sharifahmadian presented enhanced SPIHT coding that limits redundant evaluation in the sorting pass of SPIHT for multi-lead ECG signal compression [8]. Sharaeian and Fatemizadeh applied vector quantization on residual image obtained from SPIHT coding [9]. Nayebi et al. proposed run length coding on SPIHT. Nayebi used similar 2D ECG array to Goudarzi, as an input for SPIHT coding [10]. Wang et al. applied lifting wavelet transform and adopted different threshold value for high frequency subband in SPIHT coding [11].

In this paper, we proposed a beat reordering technique to optimize SPIHT coding for ECG signal compression. Beat reordering rearranges beat order in 2D ECG array based on similarity among adjacent beats. The rearrangement will reduce variances among adjacent beats so that the 2D ECG array contains less high frequency. SPIHT coding work more efficiently on the signal with less high frequency component [12]. This paper is organized as follows: wavelet-based baseline wander removal technique, beat normalization, 2D ECG array construction, beat reordering, and short introduction to the SPIHT coding are presented in section II. The evaluation of the proposed method using the selected records from MIT-BIH arrhythmia database and the comparison with other methods are explained in section III. Finally, the conclusion will be given in section IV.

II. METHODOLOGY

The schematic diagram of compression and decompression stage of the proposed method is shown in Fig. 1. First, we used wavelet-based baseline wander removal proposed by Sargolzaei to remove baseline wander from ECG signal [13]. The duration of each beat then calculated from RR interval of detected QRS complexes. Since the duration of each beat is different, we applied beat normalization based on period and amplitude normalization (PAN) method [14]. Next, the output of beat normalization process is reorganized into 2D array

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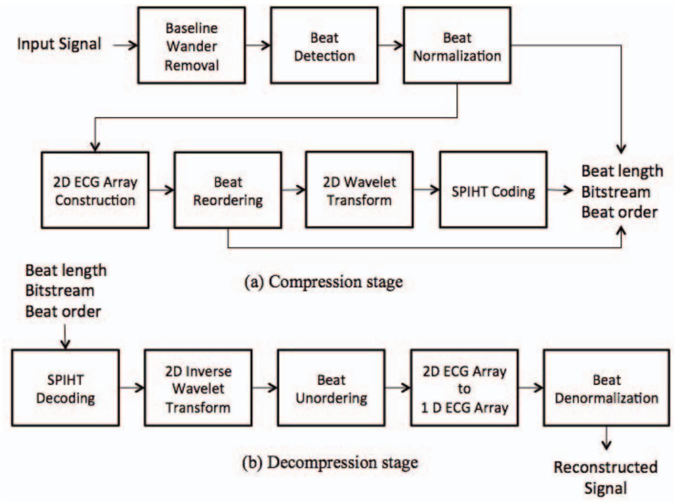


Figure 1. Schematic diagram of the proposed method

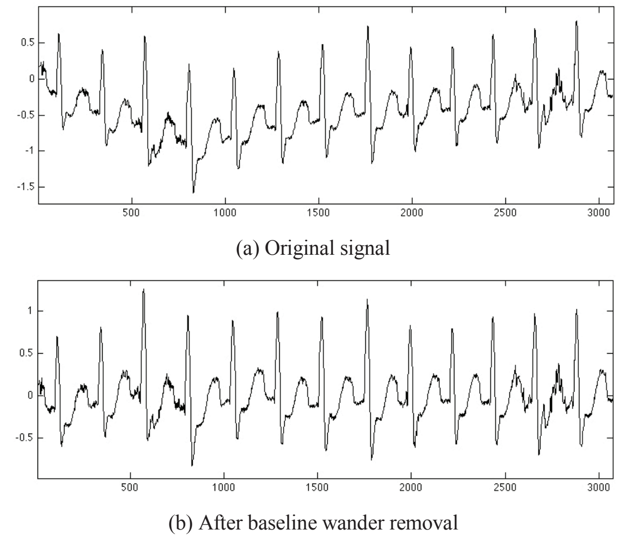


Figure 2. Signal plot of first 3072 samples from record 109

form. Beat reordering technique is employed to optimize SPIHT coding by rearranging beat order in 2D ECG array based on their similarities. Beat reordering is done by grouping similar beats in 2D ECG array into the same cluster using fuzzy c-means clustering, the order of each beat on each cluster then sorted by their distance to the centroid. We applied 2D wavelet transform to transform 2D ECG array into the time-frequency domain. Finally, SPIHT coding is applied to the beat reordered of 2D ECG array. Detail explanation of each stage will be covered in the next part of this paper.

A. Wavelet Based Baseline Wander Removal

Baseline wander is a common phenomenon in biomedical electric recording such as ECG. The baseline wander appears as significant drift from the baseline of the ECG signal mainly caused by patient breathing, body movement, bad electrodes and improper electrode site preparation, etc. [15]. Removing baseline wander is essential preprocessing step to enhance ECG signal characteristics for clinical diagnoses.

In this paper, we applied adaptive baseline wander removal method that constructs a model of baseline wander with multiresolution analysis of the ECG signal using discrete wavelet transform [13]. Sargolzaei et al. indicates that the spectrum of the baseline is below the spectrum of the ECG signal, therefore its energy concentration in corresponding time-scale plane does not change as much as the scale is changed in the wavelet based decomposition procedure, but the energy of the ECG signal decreases as the scale is changed. Therefore, baseline wander can be estimated from inverse wavelet transform of approximation coefficients when the energy of detail coefficient in certain level of decomposition reaches local minima. Fig. 2 shows the original signal of record 109 from MIT-BIH arrhythmia database and the result of baseline wander removal.

B. 2D ECG Array Construction

There are two types of correlation in the ECG signal, which are correlation in a single ECG cycle (intrabeat correlation) and the correlation among ECG cycles (interbeat correlation). An optimal ECG signal compression needs to decorrelate both types of correlations to achieve high compression rate at low distortion. The original ECG signal needs to be arranged into two-dimensional ECG array, which consists of one or more normalized heartbeats. The intrabeat correlation can be seen in each column, while the interbeat correlation can be shown in each row of the 2D ECG array. For this purpose, the peaks of ECG signal should be detected to obtain each heartbeat duration. Different QRS complex detection techniques can be used to find the peaks of ECG signal [16][17]. Since each heartbeat can have a different duration, it should be normalized into constant number in order to construct 2D ECG array. Our experimental result on MIT-BIH arrhythmia database shows that the optimal duration of each heartbeat consists of 256 samples. We used PAN method [14] to normalize each heartbeat duration without amplitude normalization step since this step does not give a substantial contribution to optimize overall compression stage.

To perform beat normalization, the variable beat vector is first interpolated by a factor L. The signal is then downsampled by the appropriate factor, so that the length of all heartbeat becomes constant. If $x(n)$ is the input to an interpolation filter with an upsampling factor L and impulse response $h(n)$, then the output $y(n)$ is defined as,

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)h(n - kL) \quad (1)$$

The upsampler inserts L-1 zeros between successive samples. The filter $h(n)$, which operates at a rate L times higher than input signal, replaces the inserted zeros with the interpolated values. Polyphase implementation of this filter ensures efficient interpolation. The output $y(n)$ of a decimation filter with an impulse $h(n)$ and a downsampling factor M is defined as,

$$y(n) = \sum_{k=-\infty}^{\infty} x(k)h(nM - k) \quad (2)$$

The antialiasing effect caused by the downsampling of the signal is removed by lowpass filter $h(n)$. The change of sampling rate is a reversible process. If the resampled beat is brought back to the original sampling rate by multirate processing, there will be no distortion. The output of overall normalization process is,

$$Y_i(n) = \sum_{k=0}^{P_i-1} X_i(k) h(nM_i - kL) \qquad (3)$$

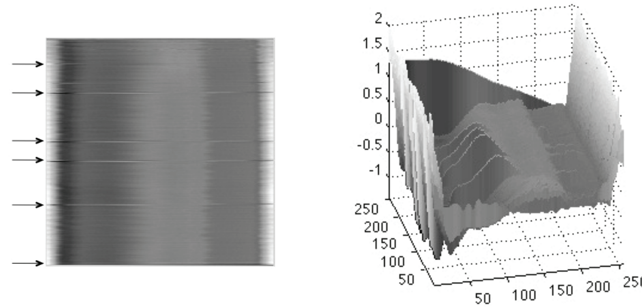
Where $X_i(n)$, $Y_i(n)$ are n-th samples of the i-th input beat and output of normalized beat respectively, $h(n)$ is the impulse respose of the filter, P_i is the number of samples in i-th original beat. L and M_i are the upsampling and downsampling factor for the i-th beat vector.

We applied different strategy to construct 2D ECG array than those applied in [5]. Each row of 2D ECG array in our method extracted start from the peak of ECG signal or R wave to the next R wave, instead of P wave to the next P wave. R wave is more preferred than P wave, since R wave easier to detect than P wave. There are some cases on ECG recordings where no P wave on particular ECG cycle. P wave detection on this kind of ECG signal could lead to some inaccuracies. Fig. 3 shows 2D ECG array of record 109 from MIT-BIH arrhythmia database. Each of 2D ECG array is composed of 256 columns, which contains the amplitude of each ECG cycle, and 256 rows or 256 ECG cycles.

C. Beat Reordering

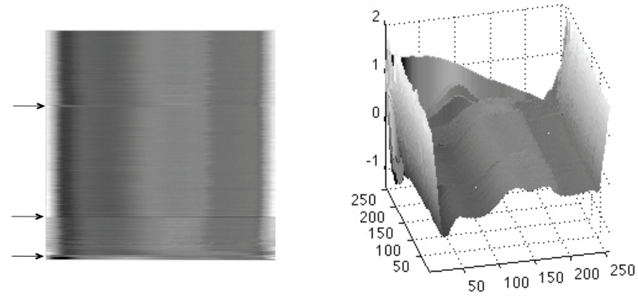
To achieve high compression rate at low distortion, an optimal ECG signal compression needs to decorrelate intrabeat and interbeat correlation. Most of data compression methods have taken advantage of high correlation among the adjacent samples. The higher correlation between adjacent samples, the easier to predict the next samples of data. Therefore, the higher compression rate is easier to achieve on high predictable data. Some of the data have high predictable properties naturally, such as the population growth in the city. But, other data such as electroencephalography (EEG) signal does not have this predictable property. ECG is a pseudo-periodic signal in the sense that the cardiac cycle repeats according to heart rate [1]. However, several ECG cycle could have different signal characteristics from the others. This particular ECG cycle reduces overall predictability properties of ECG signal. Rearranging the order of each ECG cycle could increase the predictability of this kind of ECG signal, so that similar ECG cycle placed in a close position.

In this paper, we proposed beat reordering technique to optimize SPIHT coding by rearranging beat or ECG cycle order in 2D ECG array based on their similarities. The first step of beat reordering is to cluster similar beats using fuzzy c-means clustering. The next step is rearranging the order of beats inside each cluster based on their distance to the centroid. Since the frequency distribution only affected by the order of beats inside each cluster, so that the order of each cluster does not affect to the beat ordering efficiency. Fig. 4 shows the result of beat reordering on record 109 from MIT-BIH arrhythmia database. The arrows on Fig. 3 and Fig 4. indicates the position of spikes on 2D ECG array. Compared to Fig. 3, beat-reordered 2D ECG array is smoother. There are less strips or fluctuations on Fig. 4 than those on Fig. 3. Beat reordering reduces the variances among adjacent beats. Consequently, this rearrangement of beat order reduces the high frequency component of 2D ECG array. This leads to higher efficiency of



(a) Top view (b) 3D view

Figure 3. 2D ECG array of record 109



(a) Top view (b) 3D view

Figure 4. 2D ECG array of record 109 after beat reordered

wavelet-based data compression methods such as SPIHT coding [12].

D. Wavelet Transform

Wavelet is a wave-like oscillation signal of limited duration that starts out at zero, increases, and then decreases back to zero. A family of wavelets can be constructed from a function $\psi(t)$, sometimes known as a "mother wavelet," which is confined in a finite interval. "Daughter wavelets" $\psi_{a,b}(t)$ are then formed by translation (b) and contraction (a),

$$\psi_{a,b}(t) = \frac{1}{\sqrt{a}} \psi\left(\frac{t-b}{a}\right) \qquad (4)$$

Discrete Wavelet Transform (DWT) that is based on sub-band coding is found to yield a fast computation of Wavelet Transform. DWT uses the set of dyadic scales and translates from the mother wavelet to form an orthonormal basis for signal analysis. DWT decomposes the signal into an approximation and detail coefficients. The approximation coefficients is subsequently divided into new approximation and detailed coefficients. Decomposition of a signal $x(t)$ can be expressed in (5).

$$x(t) = \sum_{J-M\le j<J} \sum_{k\in Z} d_{j,k}\phi_{j,k}(t) + \sum_{k\in Z} c_{j,k}\psi_{j,k}(t) \qquad (5)$$

$\phi(t)$ is the scaling function, $\psi(t)$ is the wavelet functions. The decomposition formula of $x(t)$ for the wavelet transform is,

$$c_{j,k} = \sum_n h_{n-2k} c_{j+1,n} \qquad (6)$$

$$d_{j,k} = \sum_n h_{n-2k} d_{j+1,n} \quad (7)$$

h_n and g_n are the wavelet transform conjugate mirror filter of $\phi(t)$ [11].

E. Overview of SPIHT

Set partitioning in hierarchical trees (SPIHT) is one of the "state of the art" wavelet-based coding techniques, which orders the transform coefficients using a set partitioning algorithm based on the sub-band pyramid. The information required to reconstruct signal is very compact since SPIHT sends only the most important ordered coefficients information first. SPIHT is also one of the codecs that provides user selectable bitrate and progressive transmission of encoded bit stream. Encoding process can be terminated at any point, allowing a bitrate or distortion parameter to be met exactly. Embedded coding is comparable to binary finite precision representation of a real number. A string of binary digits can represent any real number. For each digit added to the right of binary digits, the precision of the real number becomes higher. Encoding can stop at any time and provide the best representation of the real number achievable within the framework of the binary digit representation. SPIHT encoder also can be terminated at any time and provide the best representation of the signal achievable within the framework [18].

SPIHT coding adopts a hierarchical quad-tree data structure on a wavelet-transformed signal. The energy of a wavelet-transformed signal is centered on the low frequency coefficients. Those coefficients are hierarchical ordered and have a parent-child relationship through subbands. SPIHT utilizes this relationship to save many bits from representing insignificant coefficients. Brief SPIHT algorithm described as follows.

1) Initialization: Set the list of significant points (LSP) as empty. Set the roots of similarity trees in the list of insignificant points (LIP) and the list of the in-significant sets (LIS). Set the threshold $T_0 = 2^n$ with $n = \lfloor log_2 (\max|c(i,j)|) \rfloor$, where $c(i,j)$ denotes the coefficient at position (i,j).

2) Sorting pass in LIP: Each coefficient in the LIP is checked and the significant coefficients are moved to the LSP. The sign bits of the significant coefficients are encoded.

3) Sorting pass in LIS: If an entry in the LIS is significant, a one is sent and then its two offspring are checked like an entry in the LIP. If an entry in the LIS is insignificant, a zero is sent.

4) Refinement pass: Each old entry of LSP is checked. If it is significant under current threshold, a one is sent and its magnitude reduced by the current threshold. If it is insignificant, a zero is sent.

III. Experimental Result and Discussion

To verify the effectiveness of the proposed method, we compared the performance of the proposed method with other previous methods. The proposed algorithm was tested and evaluated using two datasets from the MIT-BIH arrhythmia database. All records on this database were sampled at 360 Hz and 11 bits resolution. The first dataset consists of 15 records from the database, i.e. 100, 101, 102, 103, 107, 117, 118, 119, 201, 209, 212, 215, 217, 219, and 234. The first two-minute signal from each record on this dataset was used on three experiments: 1) to determined the most optimal wavelet basis; 2) to verify the effectiveness of beat reordering process; 3) to compare the performance of the proposed method with SPIHT-based ECG signal compression proposed by Goudarzi [5]. Goudarzi used the same records as the first dataset in the experiment. The second dataset consists of 11 records from the database, i.e. 100, 101, 102, 103, 107, 109, 111, 115, 117, 118, 119. The first two-minute signal from each record on this dataset was used to compare the performance of the proposed method with four other previous methods proposed by Alshamali [19], Benzid [20], Blanco [21], Lu [3]. They used the same records as this dataset in their experiment.

The performance of the proposed method is measured according to its percent root mean square difference (PRD) for each experiment. Although PRD does not exactly relate to the result of a clinical subjective test, it is widely used in the ECG data compression literature and facilitates the comparison of various schemes. The PRD is defined by,

$$\text{PRD} = \sqrt{\frac{\sum_{i=1}^{n}[x_{ori}(i) - x_{rec}(i)]}{\sum_{i=1}^{n} x_{ori}(i)^2}} \text{ x } 100 \quad (8)$$

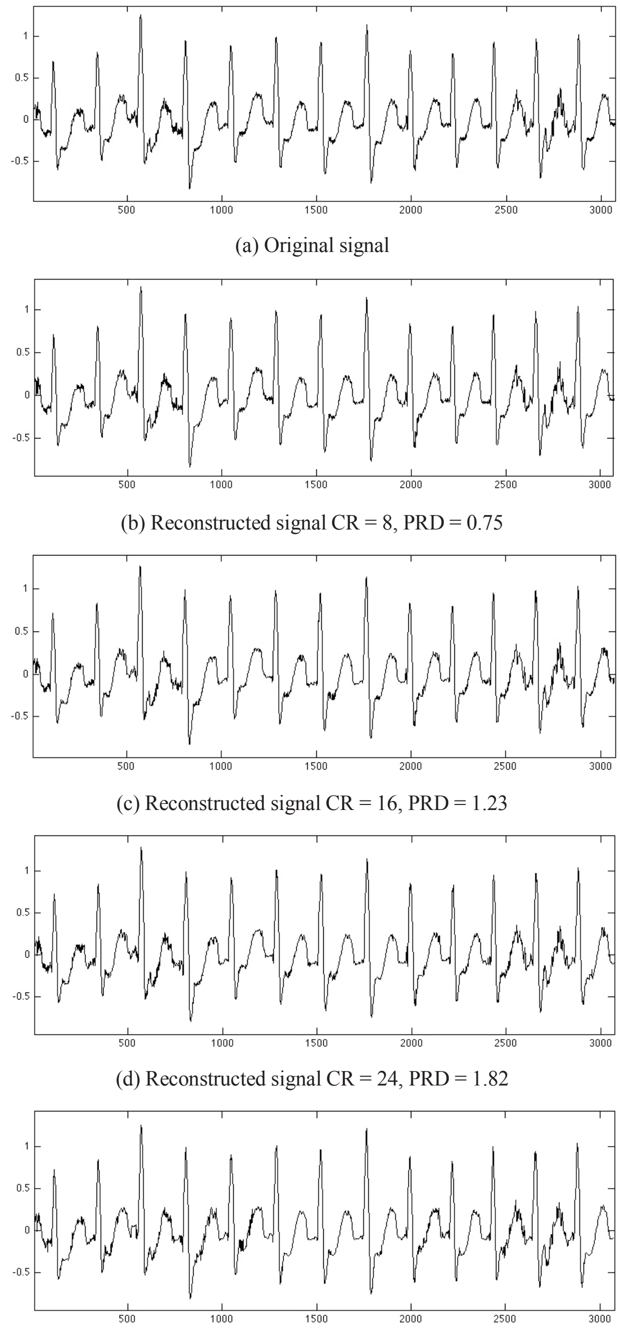
Where x_{orig} and x_{rec} are the original and reconstructed ECG signal, respectively. n is the number of samples. To compare the PRD, each experiment should be performed at the same compression rate (CR).

A. The Optimal Wavelet Basis

In this experiment we compressed all of the records from the first dataset using different wavelet basis, i.e. db6, db14, db22, sym6, sym8, sym10, coif2, coif3, coif4, bior2.2, bior4.4, and bior6.8 at 8, 16, 24, and 32 compression rates. 2D wavelet transform was calculated with 8 level of decomposition. The mean of PRD from each experiment scenario then compared to determine optimal basis wavelet on the proposed method. Fig. 5 shows the plot of the first 3072 samples of original and reconstructed signal of record 109 at various compression rates. There is no notable difference between the original and reconstructed signals at all compression rates. The mean of PRD at 8, 16, 24, and 32 compression rates are less than 2, which is considered as a very good reconstructed signal [22]. The mean of PRD from each experiment scenario is shown on Table I. The smallest mean of PRD at 16 and 24 compression rates was achieved by bior6.8 wavelet basis, while at 8 and 16 compression rates was achieved by sym8 and coif4, respectively. Based on this fact, bior6.8 was chosen as the wavelet basis for the entire experiments.

B. The Effect of Beat Reordering to Reconstructed Signal Accuracy

We compared the performance of the proposed method with and without beat reordering by compressing all of the records from the first database using bior6.8 wavelet basis at 8, 16, 24, and 32 compression rates. Table II shows the mean of



(a) Original signal

(b) Reconstructed signal CR = 8, PRD = 0.75

(c) Reconstructed signal CR = 16, PRD = 1.23

(d) Reconstructed signal CR = 24, PRD = 1.82

(e) Reconstructed signal CR = 32, PRD = 1.97

Figure 5. Original and reconstructed signal of record 109 at various CR

PRD from each experiment scenario. The result shows that beat reordering significantly reduces the mean of PRD. The range of the mean of PRD without beat reordering at different compression rates is 4.16, this value reduced to 2.93 after beat reordering applied. The differences between the mean of PRD from the proposed method with beat reordering and without beat reordering become larger as the compression rate higher. This fact indicates that the effect of beat reordering also effective for higher compression rate.

TABLE I. THE MEAN OF PRD OF RECONSTRUCTED SIGNAL USING DIFFERENT WAVELET BASIS

Wavelet basis	CR			
	8	*16*	*24*	*32*
db6	2.02	3.52	4.84	5.93
db14	2.07	4.22	5.47	6.21
db22	2.04	4.24	5.92	7.24
sym6	1.90	3.60	4.76	5.68
sym8	**1.89**	3.43	4.71	5.74
sym10	1.99	3.94	4.73	5.86
coif2	1.96	3.61	4.55	5.90
coif3	1.94	3.53	4.83	5.49
coif4	1.92	3.57	4.54	**5.43**
bior2.2	2.06	3.69	5.22	6.04
bior4.4	1.99	3.61	4.71	5.75
bior6.8	1.94	**3.29**	**4.50**	6.10

TABLE II. THE MEAN OF PRD OF RECONSTRUCTED SIGNAL WITH AND WITHOUT BEAT REORDERING

Beat reordering	CR			
	8	*16*	*24*	*32*
without	1.94	3.29	4.50	6.10
with	1.71	3.08	3.79	4.64
difference	0.23	0.21	0.71	1.46

TABLE III. THE MEAN OF PRD OF RECONSTRUCTED SIGNAL COMPARED TO GOUDARZI [5]

Method	CR							
	8	*10*	*14*	*18*	*22*	*26*	*28*	*30*
Goudarzi	2.12	2.52	3.33	4.20	5.08	5.93	6.34	6.72
Proposed	1.71	2.05	2.73	3.18	3.64	4.05	4.29	4.39
difference	0.41	0.47	0.60	1.02	1.44	1.88	2.05	2.33

C. Performance Comparison with Other Methods

To compare the performance of the proposed method with other methods, we performed two different experiments. First, the performance of the proposed method compared to the 2D multiwavelet transform compression for ECG signal proposed by Goudarzi [5]. In this experiment, we used the first dataset which includes the same records from MIT-BIH arrhythmia database as used in [5]. We also used the same compression rates for this comparison, i.e. 8, 10, 14, 18, 22, 26, 28, and 30. The second experiment was intended to compared the performance of proposed method with four other previous methods proposed by Alshamali [19], Benzid [20], Blanco [21], Lu [3]. For the second experiment, we used the second dataset, which includes the same records from MIT-BIH arrhythmia database as used in their experiment.

The result of the first experiment is shown on Table III. This result suggests that the performance of the proposed method is better than [5]. The mean of PRD of the proposed method at all compression rates are smaller than [5]. The mean of PRD of the proposed method increased gradually at higher compression rates, these increment levels are smaller than those in [5]. The differences of the mean of PRD at different compression rates become more noticeable at higher compression rates, i.e. 0.41 at compression rates of 8 and 2.33 at compression rate of 30.This fact suggests that the proposed

TABLE IV. THE MEAN OF PRD OF RECONSTRUCTED SIGNAL OF PROPOSED METHOD COMPARED TO OTHER METHODS

Method	*CR*	*PRD*
Proposed	13 16 24	2.49 2.82 3.46
Alshamali [19]	12.75 14.46	3.80 4.83
Benzid [21]	12.6 15.95	3.51 4.84
Blanco [22]	11.62 14.13	3.73 4.79
Lu [3]	12 16	3.57 4.85

method maintains lower distortion even at the higher compression rate.

Table IV shows the result of the second experiment. This result indicates that the performance of the proposed method also better than the other four methods [19], [20], [21], and [3]. The mean of PRD of the proposed method at the similar (not exact) compression rate is lower than those other four methods. At the range of 11~13 compression rates, the mean of PRD of the proposed method is 2.49, which is significantly lower than the other methods, i.e. 3.8, 3.51, 3.73, and 3.57, proposed by [19], [20], [21], and [3], respectively. The same fact occurred at the range of 14~16 compression rates, the mean of PRD of the proposed method is 2.82, while the other methods generate higher distortion, i.e. 4.83, 4.84, 4.79, and 4.85 for methods proposed by [19], [20], [21], and [3], respectively. At a higher compression rate, i.e. 24, the mean of PRD of the proposed method is 3.46, this value still smaller than the distortions from those other methods at the lower compression rate.

IV. CONCLUSION

We proposed an ECG signal compression method based on two-dimensional wavelet transform which employs SPIHT coding and beat reordering technique. The performance of the proposed method was compared with the other five previous proposed ECG signal compression methods using two datasets from MIT-BIH arrhythmia database. The result shows that the proposed method was performed better than the other methods. The experiment also reveals that the beat reordering technique gives significant performance improvement to the SPIHT-based ECG signal compression. The experiments showed that the proposed method gives lower distortion at a higher compression rate. Further improvement would be the implementation of an optimal weight initialization in fuzzy c-means clustering to optimize beat reordering technique.

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