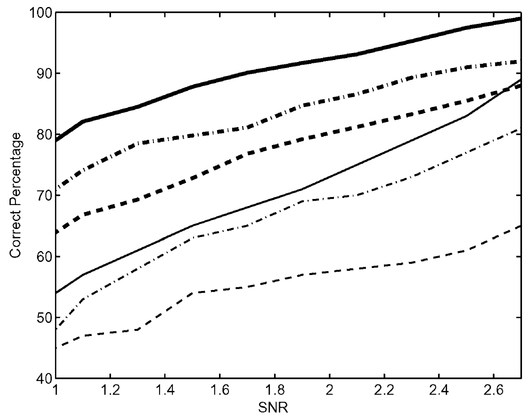
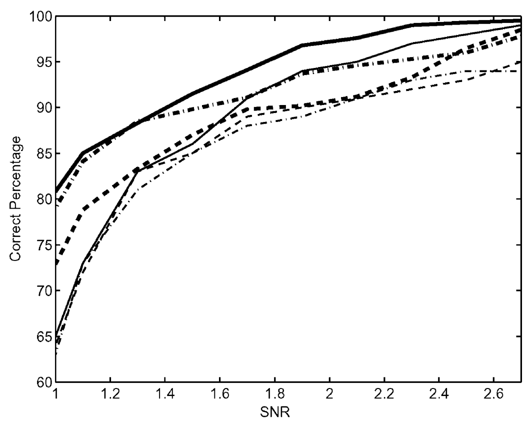


(a)



(b)

Fig. 2. The percentage of correct classification for single spikes (thick curves) and overlap (thin curves) decomposition (solid lines for our method, dashed lines for method [4] and dash-dotted lines for method [7]). (a) three-class case under various SNR levels. (b) two-class case under various SNR levels.

is feasible to use this proposed system, without any *a priori* knowledge about the background noise. Moreover, the proposed RELAX method achieved better performance than other methods [4], [7] in our application. However, there is still some limitation—the K-means algorithm is optimal classification method if the classes are normally distributed with spherical and equal covariance matrices, but it will cause suboptimal result if the noise deviates significantly from the above conditions.

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An Effective and Efficient Compression Algorithm for ECG Signals With Irregular Periods

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***Abstract*—This paper presents an effective and efficient preprocessing algorithm for two-dimensional (2-D) electrocardiogram (ECG) compression to better compress irregular ECG signals by exploiting their inter- and intra-beat correlations. To better reveal the correlation structure, we first convert the ECG signal into a proper 2-D representation, or image. This involves a few steps including QRS detection and alignment, period sorting, and length equalization. The resulting 2-D ECG representation is then ready to be compressed by an appropriate image compression algorithm. We choose the state-of-the-art JPEG2000 for its high efficiency and flexibility. In this way, the proposed algorithm is shown to outperform some existing arts in the literature by simultaneously achieving high compression**

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TABLE I
COMPARISON OF 2-D ECG COMPRESSION ALGORITHMS

Algorithm	QRS Detection	Period Normalization	Amplitude Normalization	Mean Removal	Period sorting	Block/Frame Based	Transform and Coefficient Encoding
Lee [1]	Yes	No	No	No	No	Block	DCT
Wei [4]	Yes	Yes	No	Yes	No	Frame	SVD
Tai [7]	Yes	No	No	No	No	Block	Modified SPIHT
A. Bilgin [15] [16]	Yes	Yes	No	No	No	Frame	JPEG2000
Proposed Approach 1	Yes	No	No	No	Yes	Frame	JPEG2000
Proposed Approach 2	Yes	Yes	No	No	Yes	Frame	JPEG2000

* Some of the comparisons are quoted from reference [7].

ratio (CR), low percent root mean squared difference (PRD), low maximum error (MaxErr), and low standard derivation of errors (StdErr). In particular, because the proposed period sorting method rearranges the detected heartbeats into a smoother image that is easier to compress, this algorithm is insensitive to irregular ECG periods. Thus either the irregular ECG signals or the QRS false-detection cases can be better compressed. This is a significant improvement over existing 2-D ECG compression methods. Moreover, this algorithm is not tied exclusively to JPEG2000. It can also be combined with other 2-D preprocessing methods or appropriate codecs to enhance the compression performance in irregular ECG cases.

***Index Terms*—Compression, irregular ECG, JPEG2000, period sorting, 2-D correlation.**

I. INTRODUCTION

Because modern electrocardiogram (ECG) monitoring devices generate vast amounts of data and require huge storage capacity, many ECG compression methods were proposed to process, transmit, and store the data efficiently. They could be classified [1] into the following four categories.

1) Parameter extraction techniques (e.g., prediction [2] and vector quantization (VQ) methods [3]).
2) Transform-domain techniques (e.g., two-dimensional (2-D) discrete cosine transform (DCT) [1], singular value decomposition (SVD) [4], and wavelet transforms [5]–[8]).
3) Direct time-domain techniques (e.g., amplitude zone epoch coding (AZTEC) [9], scan-along polygonal approximation (SAPA) [10], and FAN algorithm [11]).
4) Other compression methods. (Other new techniques have evolved which need new classifications such as the filter bank based algorithm [12].)

Among the categories listed above, most of the methods adopt one-dimensional (1-D) representations for 1-D ECG signals. However, since the ECG signals have both sample-to-sample (intra-beat) and beat-to-beat (inter-beat) correlations, some 2-D compression approaches have been proposed for better compression performances. Most of the 2-D ECG compression methods consist of following steps [7]: 1) QRS detection; 2) preprocessing; 3) transformation. For example, Lee [1] used "cut and align beats approach and 2-D DCT" to get good compression results in regular ECG. Wei [4] used "period normalization and truncated SVD algorithm" to compress 2-D ECG arrays. Recently, wavelets are widely used for both 1-D and 2-D ECG compression [5]–[8]. Most of the papers showed good ECG compression performances for regular ECG cases. However, their compression performance dropped in irregular ECG signals. In order for the 2-D ECG compression algorithms to accommodate irregular ECG signals, we propose below a novel preprocessing procedure that converts (1-D) ECG signals to smooth, easier-to-compress 2-D representations. As for the codec, the wavelet-based JPEG2000 [13], [14], which is the latest international standard for still image compression, is chosen because it can handle more than-8-bits-per-pixel images. Moreover, it performs better at moderate to high compression ratios than conventional ones such as the DCT-based JPEG standard that can suffer from blocking artifacts. Furthermore, the inherent multi-resolution nature of wavelets allows both localized details and large smooth regions of the ECG to be well preserved. In fact, some authors have begun to use JPEG2000 to compress ECG [15], [16] and obtained pretty good PRD. Although we choose JPEG2000 in this paper, the proposed preprocessing method can be combined with other preprocessing methods such as period normalization or codecs like set partitioning in hierarchical tree (SPIHT) [7], [17]. The comparison of some 2-D ECG compression algorithms is listed in Table I.

The paper is organized as follows. Section II describes the performance measures, the overview of our algorithm, and the preprocess that transforms 1-D ECG signals to 2-D images. Section III demonstrates experimental results of two approaches using the algorithm we propose with related discussions given in Section IV. Section V concludes the paper.

II. PROPOSED 2-D ECG COMPRESSION ALGORITHM

A. Performance Measures

Before describing the algorithm, four measures are first introduced for comparing the compression performance with other algorithms: the compression ratio (CR), the percent root mean squared difference (PRD), the maximum error (dubbed MaxErr), and the standard derivation of errors (dubbed StdErr).

The CR is calculated as the number of bits in the original 1-D ECG signal over the total number of bits in the compressed data.

$$\mathrm{CR} = \frac{\text{The number of bits in the original 1−D ECG signal}}{\text{The total number of bits in the compressed data}}. \tag{1}$$

In our method, some side information should be added into the compressed data losslessly including:

1) size of the 2-D array;

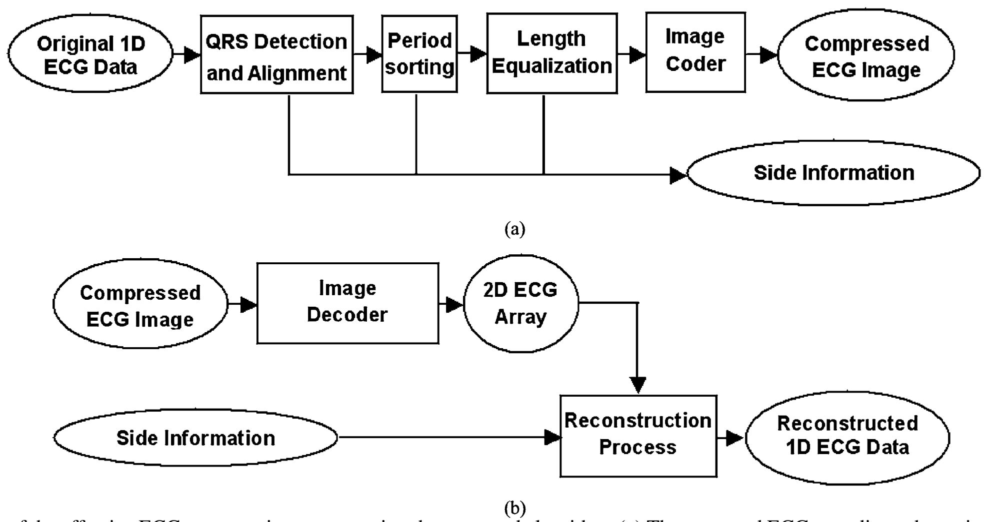

Fig. 1. Block diagram of the effective ECG compression system using the proposed algorithm. (a) The proposed ECG encoding scheme including the QRS detection and alignment, period sorting, length equalization, and image coder. (b) The ECG decoding scheme including image decoder for ECG image and reconstruction process.

2) original heartbeat lengths;
3) ordering of heartbeats.

The PRD measures normalized root mean squared difference between the compressed and original ECG sequences. Depending on the choice of normalization, there have been various "flavors" of PRD in the literature, for example, those with mean-offset [8] or with 1024-offset [1], [4], [7], [15], [16]. The effects of various offsets on PRD values will be discussed in Section IV-A. It is meaningless to compare PRD's with different offsets. Because most of the papers using 2-D methods on MIT-BIH arrhythmia database [18] adopt the 1024-offset, we choose the same one for fair comparison but also provide PRD with mean-offset for readers' reference. The corresponding PRD with 1024-offset is given by

$$\mathrm{PRD} = \sqrt{\frac{\sum_{n=1}^{N} [y(n) - \hat{y}(n)]^2}{\sum_{n=1}^{N} [y(n) - 1024]^2}} * 100\%. \tag{2}$$

where $y(n)$ is the original signal of length N from the MIT-BIH arrhythmia database, and $\hat{y}(n)$ is the reconstructed signal. The dynamic range of the database is 11 bits with 360-Hz sampling rate.

The CR and PRD are global performance indicators. For local effects, the MaxErr and StdErr are found useful.

First, the errors are defined as the difference between the original signal and the reconstructed signal

$$\mathrm{error}(n) = y(n) - \hat{y}(n). \tag{3}$$

The MaxErr is the largest absolute value of errors

$$\mathrm{MaxErr} = \max_{n=1}^{N}(|\mathrm{error}(n)|). \tag{4}$$

The standard derivation of errors StdErr is given by

$$\mathrm{StdErr} = \sqrt{\frac{\sum_{n=1}^{N} [\mathrm{error}(n) - \overline{\mathrm{error}}]^2}{N - 1}} \tag{5}$$

where $\overline{\mathrm{error}}$ is the mean of the errors.

B. Overview of the Algorithm

Having defined the performance measures, we are now ready to describe the proposed algorithm in the following sections. The block diagram of the 2-D ECG compression system using the proposed algorithm can be found in Fig. 1. Fig. 1(a) shows the 1-D to 2-D process including the QRS detection and alignment, period sorting, length equalization (which can be mean extension or period normalization in this paper), and an image codec (which we choose to be JPEG2000). The side information needs to be recorded losslessly for signal reconstruction but the corresponding overhead is negligible compared to the size of the original ECG data. Fig. 1(b) shows the signal reconstruction process, where the (intermediate) 2-D ECG array is obtained by decoding the compressed ECG image. With the necessary side information, the reconstructed 1-D ECG is obtained.

C. QRS Detection and Alignment

To map 1-D ECG signals to 2-D arrays, the peaks of QRS waves should be detected first to identify each heartbeat. Many QRS detection algorithms [19] have been proposed and we choose "A simple real-time QRS detection algorithm" [20] for its high detection accuracy (99.5%). Others with high enough detection accuracy would also work. After each QRS peak of heartbeat segments is identified, the original 1-D ECG signal is cut at every 130th sample before each QRS peak (a 130-sample shift from the QRS peak, a smooth region estimated from human physiology [21]). Note that we choose not to use the QRS peaks to delimit each heartbeat segment because we want to avoid large boundary values, which tend to result in discontinuities and make the 2-D arrays hard to compress. As shown in Fig. 2(a), if the ECG is cut directly at each detected QRS peak, after each heartbeat segment is aligned, sharp boundaries will result from the discontinuity at each end in the 2-D arrays. To avoid the discontinuity at each QRS peak, a 130-sample shift from the QRS peak is applied. This step produces a smoother 2-D array as shown in Fig. 2(b).

D. Period Sorting

The 2-D array resulting from QRS detection and alignment already exhibits the inter-beat correlation of the original ECG signals. However, the period irregularity presents a challenge to 2-D compression algorithms. To exploit more inter-beat correlation and simultaneously obtain a superior performance, we propose an additional period sorting

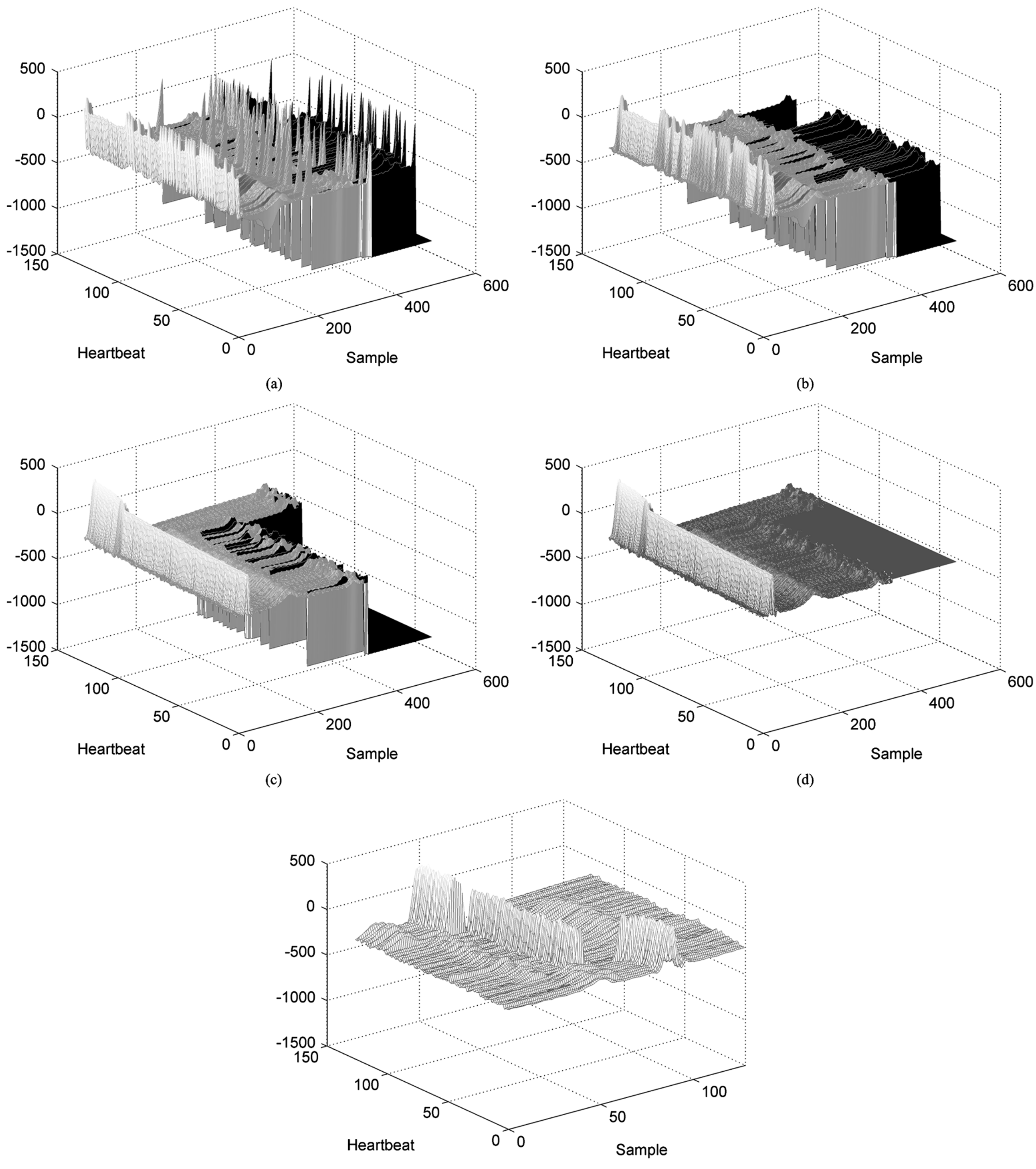

Fig. 2. ECG segments. (a) Cutting at QRS peaks followed by zero-extension. (b) Cutting with 130-sample shifts from the QRS peaks followed by zero-extension. (c) Period sorting applied to (b). (d) Period sorting applied to (b) with mean extension. (e) Period sorting applied to (b) with period normalization.

step which sorts the heartbeat segments according to their periods in ascending or descending order [Fig. 2(c)]. This is a novel and powerful method for irregular ECG compression because it reduces the period differences among the adjacent heartbeats effectively, resulting in improved CR, PRD, MaxErr, and StdErr. Note for regular ECG, it can be skipped because the period differences among regular heartbeats are negligible for the current purpose, but period sorting will increase the compression overhead (by a small amount) to record the sorting ordering for regular ECG.

Comparing to the literature, we see that existing 2-D ECG compression methods [1], [4] show good results for normal ECG signals but not for irregular ones. Namely, these algorithms have poor PRD on irregular ECG signals. However, clinically, irregular signals are more significant for diagnosis than normal ones. It is very desirable that a compression algorithm can process abnormal ECG signals very well. The proposed period sorting step effectively addresses this issue and better exposes the 2-D correlation structure. Then one appropriate length equalization method can be adopted to form a proper 2-D image. We choose two length equalization methods to demonstrate the performances of our algorithm in this paper.

E. Length Equalization

Approach 1—By Mean Extension: One popular length equalization method is by extending the signals. Several extension methods have

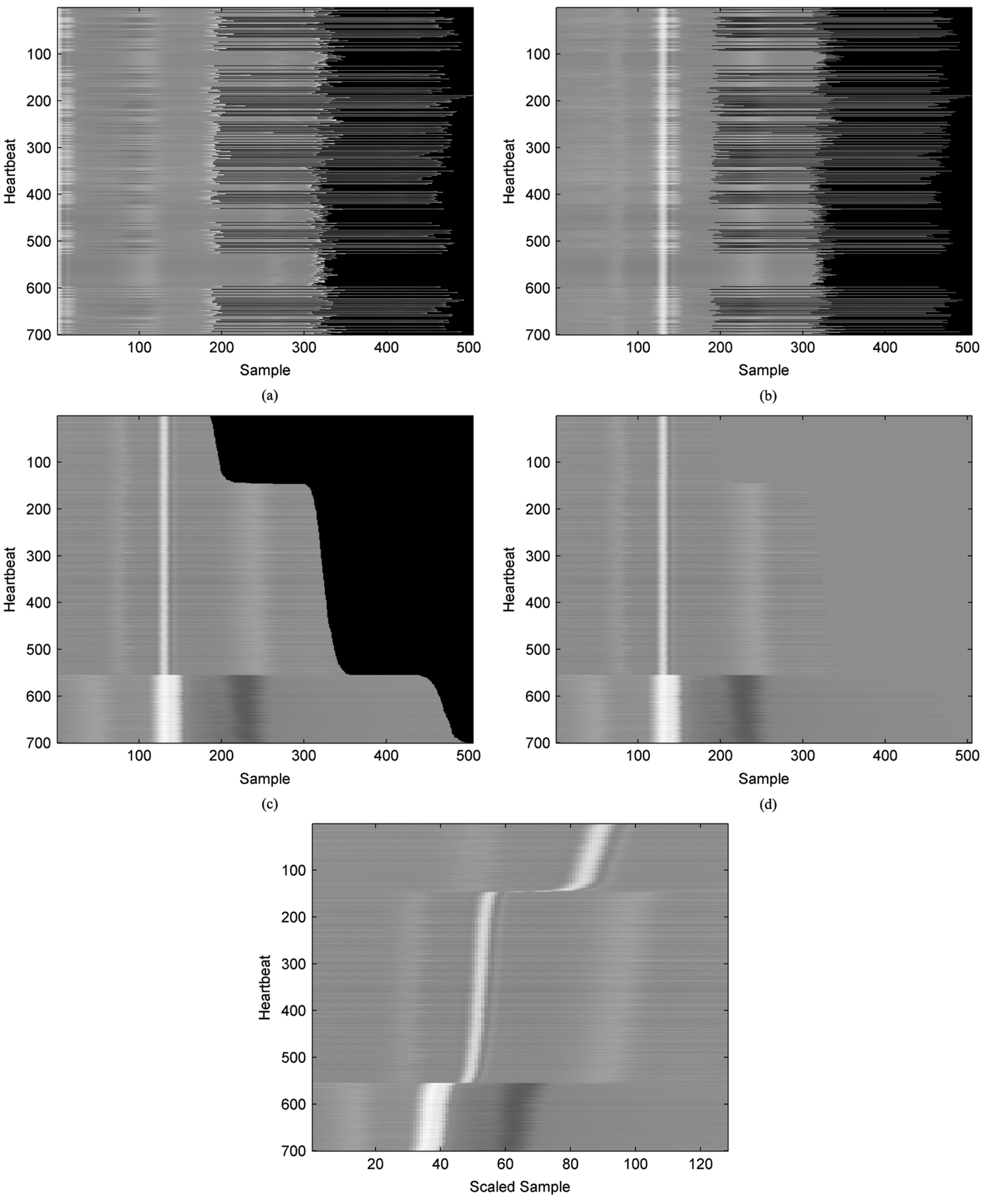

Fig. 3. Step-by-step illustrations of the 2-D grayscale arrays resulting from the proposed approaches showing that the 2-D arrays become smoother and smoother as the algorithm progresses. (a) Cutting at QRS peaks followed by zero-extension, illustrated here only for comparison. (b) Cutting with 130-sample shifts from the QRS peaks followed by zero-extension. (c) Period sorting applied to (b). (d) Period sorting applied to (b) with mean extension. (e) Period sorting applied to (b) with period normalization.

been considered in the literature, including zero-extension which pads the short segments with zeros, zero-order extension that extends a segment by repeating its last sample, and mean extension which pads short segments with the mean of the last samples of heartbeat segments. In summary, this step equalizes the length of each heartbeat segment to form a proper 2-D array. The original ECG signal can be converted "losslessly" to this array.

We choose mean extension [1], [7] because it can reduce the sharp boundaries at the ends of the rows and among the heartbeats [Fig. 2(d)].

Approach 2—By Period Normalization: For effective length equalization, Wei [4] proposed the period normalization method that scales the periods to form a 2-D array. It is adopted by Bilgin [15], [16] with JPEG2000 for good compression performance. However, it is a lossy preprocessing step and cannot process extremely irregular ECG very

TABLE II
COMPRESSION RESULTS OF VARIOUS 2-D ECG COMPRESSION ALGORITHMS.

Algorithm	Record	CR	PRD (%) with 1024 offset	PRD (%) with mean offset	MaxErr	StdErr
Lee et. al [1]	100	24:1	8.10	NA	NA	NA
Proposed Approach 1	100	24:1	5.21	10.56	26	3.65
Proposed Approach 2	100	24:1	4.06	8.22	17	2.90
Wei et. al [4]	117	10:1	1.18	NA	NA	NA
A. Bilgin et. al [15][16]	117	10:1	1.03	NA	NA	NA
Proposed Approach 1	117	10:1	0.98	3.77	6	1.44
Proposed Approach 2	117	13:1	1.18	4.36	12	1.99
Lee et. al [1]	119	24:1	10.5	NA	NA	NA
A. Bilgin et. al [15][16]	119	21.6:1	3.76	NA	NA	NA
Tai et.al [7]	119	20:1	2.17	NA	NA	NA
Proposed Approach 1	119	21.6:1	2.81	5.31	41	5.54
Proposed Approach 2	119	20.9:1	1.81	3.42	24	3.58
Period normalization and JPEG2000	119	10:1	1.37	2.59	23	2.68
Proposed Approach 1	119	10:1	1.15	2.17	20	2.03
Proposed Approach 2	119	10:1	1.03	1.95	22	1.98
Period normalization and JPEG2000 in 30% QRS false-detection case	119	21.6:1	13.9	29.3	433	31.12
Proposed Approach 1 in 30% QRS false-detection case	119	21.6:1	3.40	6.10	54	6.32
Proposed Approach 2 in 30% QRS false-detection case	119	21.6:1	3.76	7.14	107	7.50

well. In this paper, we will show that its performance can be enhanced when combined with the period sorting step we propose [Fig. 2(e)].

III. EXPERIMENTAL RESULTS

The proposed algorithm was applied to records 100–234 in MIT-BIH arrhythmia database. Record 119 with extremely varying periods is taken for an example.

First, the QRS peaks are detected, cut and aligned. Fig. 3(a) would be the 2-D grayscale array if we were to cut the ECG at QRS peaks. Note the undesirable large values near the segment boundaries as pointed out earlier. By taking the proposed sample shift method with zero-extension (but no period sorting yet), we obtain Fig. 3(b). Then, by the proposed period sorting step, Fig. 3(c) is formed.

The following two approaches using different length equalization methods are chosen to demonstrate the performance of our algorithm.

Approach 1—By Mean Extension: By mean extension with the mean of the last samples of heartbeat segments, Fig. 3(d) is obtained.

These 2-D representations are compressed by the image coder JPEG2000. The compression performances are shown in Fig. 4. It shows that CR and PRD results are improved step by step, i.e., QRS detection and alignment reveal the inter-beat correlation; the period sorting enhances the order of irregular periods; and the mean extension step smoothes the boundaries of the end of each heartbeat segment. The comparison results of various 2-D ECG compression algorithms are summarized in Table II. In addition, we provide MaxErr and StdErr for readers' reference. It is clear that the proposed Approach 1 perform better than [1], [4], [15], [16], especially in irregular ECG record 119.

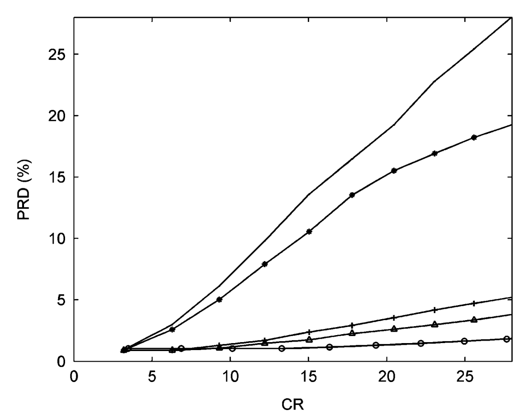

Fig. 4. The CR and PRD pairs for the 2-D compressions of the intermediate 2-D arrays by JPEG2000, showing that CR and PRD results are improved step by step as the algorithm progresses. Record 119 is taken for an example. Legend "-": Corresponding to Fig. 3(a), Legend "*": Corresponding to Fig. 3(b), Legend "+:": Corresponding to Fig. 3(c), Legend " △ ": Corresponding to Fig. 3(d), Legend "o": Corresponding to Fig. 3(e).

Approach 2—By Period Normalization: Another option of length equalization is period normalization. By this step, Fig. 3(e) is obtained. The compression performance is also shown in Fig. 4. The comparison results in Table II show that it enhances PRD more than Approach 1 in most records except the QRS false-detection case that will be discussed in Section IV. Moreover, by combining period sorting step, it enhances the performance of the algorithm that uses period normalization only.

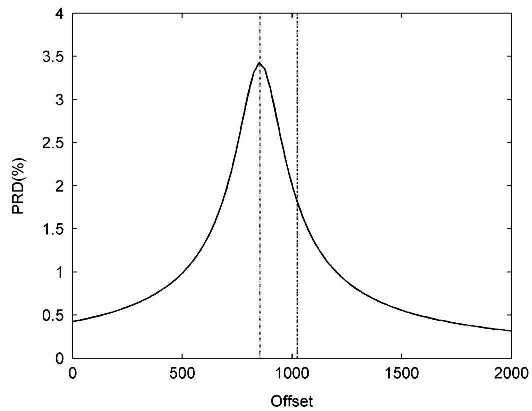

Fig. 5. The effects of offsets on PRD values. The record 119 with CR 21.6 by Approach 2 is taken for an example. The largest value of PRD appears when mean-offset is taken. . .: Mean of original ECG, -.: 1024

IV. Discussion

A. Offset in PRD Calculation

Various offsets of PRD have been assumed in the literature. Fig. 5 shows an example of how the offsets affect the PRD values, where the record 119 with CR 21.6 by Approach 2 is taken. From Fig. 5 we see why it is important to clearly specify the offset used when computing or comparing PRDs. Large or small offsets result in small PRD values, while the maximum of PRD occurs when the offset equals the mean.

As for other records using the 1024-offset, the larger the distance between the ECG mean and 1024, the smaller the PRD. It will be more pertinent if mean-offset is adopted. Because many authors use 1024 -offset, we provide 1024-offset PRD, too.

B. Overhead of Side Information

Although the side information including the image size, the heartbeat lengths, and the ordering need to be recorded losslessly in the compressed data for signal reconstruction, the corresponding overhead is negligible, for example, $1/207$ of the original data size of record 119 by Approach 2. Thus the CR varies from 24.0 to 21.6, but PRD is improved from 16.44% to 1.81%, which justifies the slight reduction in compression ratio.

C. Sensitivity to Accuracy of QRS Detection

An interesting question to ask is what will happen when QRS peaks are not detected correctly or when the irregular ECG signals do not have obvious QRS peaks in some heartbeats. The following test case demonstrates how this algorithm performs with QRS false detections that happen frequently in abnormal ECG cases. Again, record 119 is taken for an example. We force the QRS detection to deliberately false-detect large P or T waves and miss some QRS peaks. Thus we make a 30% QRS false-detection case and form a 2-D array with high aspect ratio. This case is analogous to extremely irregular ECG. When period normalization and JPEG2000 described in [16] are taken to compress this case, the CR and PRD are 21.6% and 13.9%, respectively. However, the proposed Approach 1 sorts and rearranges the irregular ECG segments to form a much smoother image. Its sensitivity to period irregularity is small. The CR and PRD obtained are 21.6% and 3.40%, respectively.

As for Approach 2, its performances are better than Approach 1 in most cases but worse in this case. Because the period variation is too large for tuning a proper scaling resolution, its errors are larger than Approach 1. The compression results are summarized in Table II.

TABLE III
Lossless Compression Results of Approach 1

Algorithm	Record	CR	PRD (%)
JPEG2000 Lossless Mode	100	3.08	0
JPEG2000 Lossless Mode	119	2.85	0

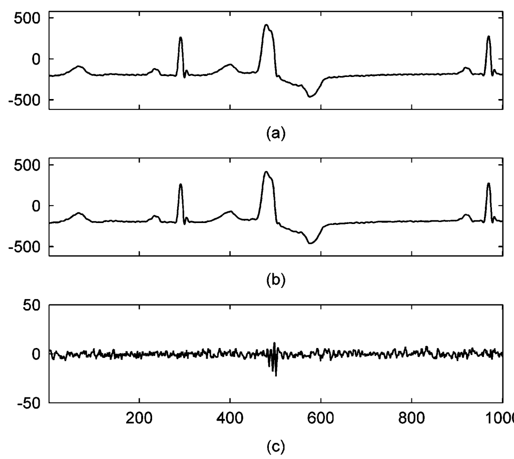

Fig. 6-1. Original signal, reconstructed signal, and errors of record 119 by period normalization with CR 10. Notice the difference in the y-scales. (a) Original ECG signal. (b) Reconstructed ECG signal. (c) Reconstruction errors around the point where the MaxErr occurs.

D. Performance Comparison of the Algorithms

Approach 1 retains the lengths of original heartbeat segments instead of using the period normalization method [4], [15], [16]. Thus, this method keeps the possibility to do lossless compression but period normalization method cannot. The lossless performance of Approach 1 is listed in Table III. The effective period sorting step in Approach 1 is more efficient than the period normalization method because the latter requires some calculations to scale and recover each point of each heartbeat segment, which is more compute-intensive. Moreover, Approach 1 compresses ECG with extremely irregular periods (the 30% false-detection case) better than Approach 2.

As for Approach 2, our period sorting is combined with the period normalization step. Although period normalization cannot retain the ECG losslessly and it cannot handle ECG with extremely irregular periods very well, its global performance indicator PRD is better than Approach 1 and other works [1], [4], [15], [16] in most cases. In record 119, Approach 2 even outperforms Tai's modified SPIHT algorithm [7].

For local effects, the MaxErr and StdErr may reveal more local information than PRD. Here three algorithms, period normalization, period sorting (Approach 1), and period sorting combined with period normalization (Approach 2) are taken for examples. Their compression results of record 119 with CR 10 are listed in Table II. In this case, for the global indicator PRD, Approach 2 is the best of the three algorithms. However, the MaxErr shows that Approach 1 is the best algorithm for local performance. Figs. 6-1, 6-2, and 6-3 show the original signal, the reconstructed signal, and the errors around the point where the MaxErr occurs by the three algorithms. It is clear the errors are small and even distributed by Approach 1.

E. Time Latency

Just like most 2-D ECG compression algorithms, the proposed algorithm needs to collect at least one period of ECG data to form a 2-D image (one frame), i.e., it will delay at least one 2-D array collection

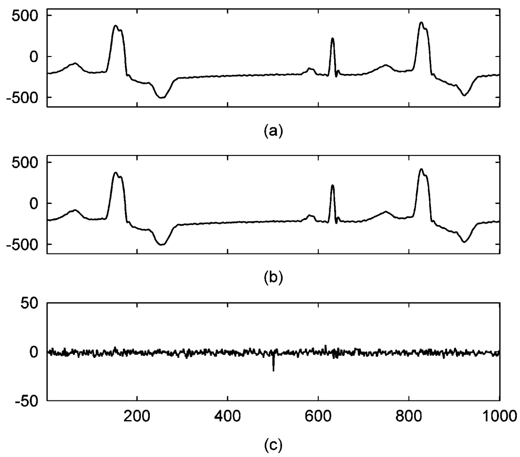

Fig. 6-2. Original signal, reconstructed signal, and errors of record 119 by period sorting with CR 10 (Approach 1). Notice the difference in the y-scales. (a) Original ECG signal. (b) Reconstructed ECG signal. (c) Reconstruction errors around the point where the MaxErr occurs.

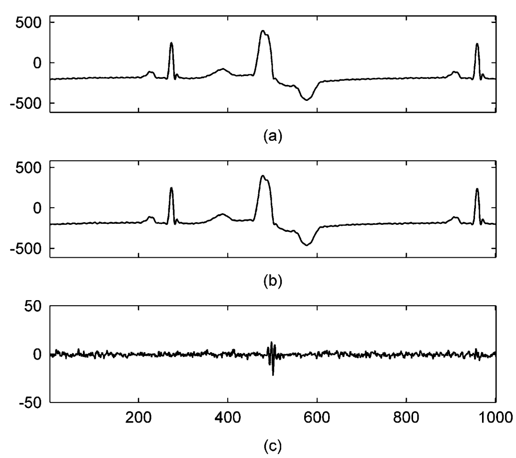

Fig. 6-3. Original signal, reconstructed signal, and errors of record 119 by period sorting combined with period normalization with CR 10 (Approach 2). Notice the difference in the y-scales. (a) Original ECG signal. (b) Reconstructed ECG signal. (c) Reconstruction errors around the point where the MaxErr occurs.

time. Therefore, it is an off-line algorithm. For example, if one frame includes 600 seconds of ECG data, the latency will be at least 10 minutes. However, except for real-time transmission, it is acceptable for most clinical compression and storage purposes.

V. Conclusion

The main contribution in this paper is to provide an effective and efficient 2-D ECG preprocessing algorithm for better compressing the ECG with irregular periods, in which the period sorting step is a novel and powerful method to reduce the period differences among the heartbeats effectively. This algorithm is not tied exclusively to the codec JPEG2000 chosen in this paper. It can also be combined with other 2-D preprocessing methods and/or appropriate codecs. Therefore, we provide two approaches to demonstrate how it works when combined with other methods such as mean extension and period normalization to enhance the compression performance in irregular ECG cases.

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