A 2-D ECG compression algorithm based on wavelet transform and vector quantization

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Abstract

In this paper, we proposed a new two-dimensional (2-D) wavelet-based electrocardiogram (ECG) data compression algorithm. A 1-D ECG data is first segmented and aligned to a 2-D data array, thus the two kinds of correlation of heartbeat signals can be fully utilized. And then 2-D wavelet transform is applied to the constructed 2-D ECG data array. A modified vector quantization (VQ) is employed to the wavelet coefficients. This modified VQ algorithm constructs a new tree vector (TV) which well utilizing the characteristics of the wavelet coefficients. Records selected from the MIT/BIH arrhythmia database are tested contrastively using the proposed algorithm, some compression algorithms based on wavelet transform and the other 2-D ECG compression algorithms. The experimental results show that the proposed method is suitable for various morphologies of ECG data, and that it achieves higher compression ratio with the characteristic features well preserved.

1. Introduction

Electrocardiogram (ECG) compression has an important role in diagnosis. Many ECG compression methods have been proposed in the literature, including direct compression techniques such as amplitude-zone-time epoch coding (AZTEC), coordinate reduction time encoding system (CORTES), scan-along polygonal approximation (SAPA), and differential pulse code modulation (DPCM); and transformational approaches such as Fourier transform (FT), Karhunen–Loeve transform (KLT), discrete cosine transformation (DCT), and wavelet transform (WT) (see Refs. [1,2] and references therein).

For a long period of time, lossless compression methods have been the main methods for coding ECG signals [3–6]. But because of the low compression ratios, they cannot suit the increasing tasks of compressing and transmitting ECG signals. In practice, people often use lossy compression methods [1]. In order to avoid false diagnosis, lossy compression methods should not introduce obvious errors to ECG signals. The main goal of lossy compression methods is to reduce the redundancy of ECG signals as much as possible while preserving the necessary diagnosis features. The redundancy mainly consists of the statistical correlation between adjacent samples, the asymmetry distribution of the
quantitative amplitudes and the similarity between heartbeats. The diagnostic information mainly lies in the P-QRS-T waves [7].

Several ECG data compression algorithms have been proposed in recent years. Hilton proposed wavelet and wavelet packet-based compression algorithms based on embedded zerotree wavelet (EZW) [8]. Lu et al. modified the set partitioning in hierarchical tress (SPIHT) algorithm for the one-dimensional case and applied it to the ECG compression [9]. Miaou et al. presented lossy and lossless compression algorithms based on vector quantization (VQ) [10,11]. Moghadam et al. proposed an ECG compression algorithm using 2-D wavelet packet transform [12]. Moazami-Goudarzi et al. applied the SPIHT algorithm to 2-D multiwavelet transform of ECG signals [13].

By studying the ECG waveforms, it can be concluded that the ECG signals generally show two types of correlation, namely correlation between adjacent samples within each ECG cycles (intrabeat correlation) and correlation between adjacent heartbeats (interbeat correlation) [7,12–14]. However, most existing ECG compression techniques [8–16] did not utilize such correlation between adjacent heartbeats. Therefore, on the basis of the aforementioned compression algorithms, a 2-D compression method of ECG signals is proposed in this paper, which fully utilizes both interbeat correlation and intrabeat correlation and thus can further improve the compression efficiency. In the proposed algorithm, the QRS complex in each heartbeat is first detected for segmenting and aligning a 1-D ECG signal to a 2-D data array, and then wavelet transform is applied to the constructed 2-D data array. Finally, according to the characteristics of the wavelet coefficients, a modified VQ algorithm is applied to the wavelet transformed coefficients for better compression performance.

2. Theory and methods

2.1. Wavelet transform

Wavelet transform is a landmark in the phylogeny of mathematics. Compared with the traditional Fourier analysis, wavelet transform shows an idea to observe signals with different scales and to analyze signals with multi-resolution. It has fine frequency resolution and coarse time resolution at lower frequency, and coarse frequency resolution and fine time resolution at higher frequency. Since this matches the characteristic of most signals, the wavelet transform is treated as a powerful implement for digital signal processing.

The traditional wavelet, which is called the first generation of wavelet, is a dilated and translated version of the mother wavelet. In 1996, Sweldens et al. [17,18] proposed the lifting scheme to form the second generation of wavelet. It contains three steps, i.e., split, prediction and update. Compared with the first generation of wavelet, the second generation of wavelet has the following advantages. (1) It can finish wavelet transform in the current position, which can save the memory. (2) The computation complexity decreases by a half, compared with the normal Mallat algorithm. (3) It can realize integer wavelet transform.

In wavelet-based data compression, the following should be considered to choose the optimal wavelet [19–21]: orthogonal character, linear phase, regularity and vanishing moment. Orthogonal wavelets cannot satisfy the orthogonal character and linear phase simultaneously, so biorthogonal wavelets are usually used for data compression. Here and throughout this paper, we adopt the 9/7 tap biorthogonal integer wavelet based on the lifting scheme (Fig. 1). It is popular in data compression because it is symmetrical, regular and has high vanishing moment [19,20,22]. The integer wavelet transform is as follows (see [17,18]):

\[ d_{1,j}^{(1)} = s_{0,2j+1} + \left[ \alpha (s_{1,2j} + s_{1,2j+2}) + 1/2 \right], \quad s_{1,j}^{(1)} = s_{0,2j} + \left[ \beta (d_{1,j}^{(1)} + d_{1,j-1}^{(1)}) + 1/2 \right], \]

Fig. 1. Lifting separation scheme of wavelet 9/7.
\[ d_{1,l} = d^{(1)}_{1,l} + \left[ \gamma \left( s^{(1)}_{1,l} + s^{(1)}_{1,l+1} \right) + 1/2 \right], \quad s_{1,l} = s^{(1)}_{1,l} + \left[ \delta (d_{1,l} + d_{1,l-1}) + 1/2 \right]. \]

The constants are given by \( \alpha = -1.586134342, \beta = -0.05298011854, \gamma = 0.8829110762, \delta = 0.4435068522, K = 1.149604398. \)

2.2. Principle of VQ

VQ is a very effective data compression technique [23]. It has been widely applied in such domains as image compression, video compression and pattern recognition. VQ is the multi-dimension extension of scalar quantization. It can adequately utilize the correlation between the components of a vector to reduce the redundancy. According to Shannon’s rate-distortion theory, a better performance is always achieved by coding vectors instead of scalars. If the vectors have sufficiently large codebook size and sufficiently large dimension, the errors of VQ can reach the bottom limits defined by Shannon. In VQ, a \( k \)-dimensional vector is formed using the samples and then the vector is quantized. Only the index of the vector is transmitted or stored, thus can improve the compression ratios greatly. Figure 2 shows the encoding and decoding process of VQ.

VQ is a mapping \( Q : \mathbb{R}^k \rightarrow C \) from a \( k \)-dimensional vector \( x \), in an Euclidean space \( \mathbb{R}^k \), into a finite set \( C \). The set \( C = \{ c_1, c_2, \ldots, c_N \} \) is called the VQ codebook of size \( N \), and \( e_l = \{ e_{l1}, e_{l2}, \ldots, e_{lk} \} \) is a \( k \)-dimensional codeword of the codebook. The process of VQ is usually composed of three phases, namely codebook design, encoding and decoding. Let \( x_t = \{ x_{(1)}, x_{(2)}, \ldots, x_{(k)} \} \) be a \( k \)-dimensional input vector for VQ at some time \( t \). The distortion measure between \( x_t \) and \( c_i \) is defined by the mean square error

\[ d(x_t, c_i) = \| x_t - c_i \|^2 = \sum_{j=1}^{k} (x_{(j)} - c_{ij})^2. \]  

(1)

According to Eq. (1), the encoder finds the best-matched codevector \( c_{i*} \) in codebook \( C \) for \( x_t \), and the index \( i^* \) is stored and transmitted instead of \( x_t \). The VQ decoder can easily find the corresponding codeword from the codebook according to the received index.

2.3. Modified VQ based on wavelet transform

After 2-D wavelet transform, the energy of the data concentrates in the low-frequency subband \( LL_M \). In the three directions, i.e., horizontal, vertical and diagonal, the high-frequency subbands have similarity under different resolution. Except the subband \( LL_M \) at the lowest resolution and the subbands \( LH_1, HL_1, \) and \( HH_1 \) at the highest resolution, a point in a lower resolution subbands correspond to four points at the same spatial position in a higher resolution subbands. High-frequency subbands in the three directions contain different high-frequency information, e.g., subbands \( LH_i \) contain more high-frequency information of the vertical direction. Therefore, we modified the VQ algorithm according to the distribution characteristic of wavelet coefficients. Form codebooks \( C_{LH}, C_{HL} \) and \( C_{HH} \) respectively in the three directions after wavelet transform. The codevector of the codebooks is a tree vector (TV), where wavelet transformed coefficients in the vector are arranged in the order of a hierarchical tree. Figure 3
shows the structure of a TV, taking the codebook $C_{\text{LH}}$ as an example. As the subbands LH$_i$ represent the horizontal texture information of the original data, choose the two coefficients adjacent in the horizontal direction as the root point of $C_{\text{LH}}$. Similarly, for the subbands HL$_i$, choose the two coefficients adjacent in the vertical direction as the root point of the TV. Some advantages can be achieved in this way. It fully utilizes the differences of the wavelet transformed coefficients in the three directions and respectively forms the codebook space bearing individual directional characteristic, which can improve the capability of codebooks in some degree. The correlation inside a vector is enhanced. It is obvious that the modified VQ method cannot only improve the compression ratio, but also cut the range and the time of searching during the decoding. The time for computing the relative error changes is also decreased.

Furthermore, to guarantee the quality of the reconstructed data, a distortion constrained codevector replenishment (DCCR) (see [10]) is introduced to the vector quantizer. The DCCR mechanism is as follows. If $d(x_t, c_{i^*}) \leq d_{\text{th}}$ ($d_{\text{th}}$ is the distortion limit or threshold), the index $i^*$ is transmitted or stored. At the same time, the codebook $C_t$ at time $t$ is updated to $C_{t+1}$ in the following manner: $c_{i^*}$ is promoted to the first position of $C_t$ and all the codevectors in front of it, i.e., $c_1 \sim c_{i^*-1}$, are pushed down by one notch. If $d(x_t, c_{i^*}) > d_{\text{th}}$, $x_t$ or its approximation must be transmitted or stored as $\hat{x}_t$. In this case, $x_t$ or the approximation is treated as a new codevector and is inserted to the first position of the codebook $C_t$, all the original codevectors are pushed down by one notch and the last one is discarded.

3. Algorithm description

According to the intrabeat correlation and the interbeat correlation of ECG signals, we propose a 2-D ECG signal compression algorithm. Figure 4 shows the encoding process of the proposed algorithm. The proposed algorithm is generally implemented in the following steps. (1) QRS complex detection of the 1-D ECG signal. (2) 2-D ECG data array construction. (3) 2-D wavelet decomposition and coefficients encoding.
3.1. QRS complex detection

In order to fully utilize the interbeat correlation, the input 1-D ECG signal has to be QRS complex detected and the original 1-D signal can be segmented and aligned according to the results of QRS detection. By comparing several typical QRS detection algorithms [24–27], we find that the QRS detection scheme based on wavelet transform, proposed by Kadambe et al. [27], has robust noise performance. It employs the multi-resolution analysis and bears flexibility in analyzing the time-varying morphology of ECG data. Therefore, the Kadambe algorithm is adopted in this paper to detect QRS complex.

3.2. 2-D ECG data array construction

The construction of a cut and aligned 2-D ECG data array after the QRS detection is illustrated in Fig. 5. Figure 5c is the gray scale mapping of Fig. 5b. The white strap in Fig. 5c corresponds to the QRS complex.

Segment the 1-D ECG signal according to the heartbeat period (namely the R–R interval). The length of each heartbeat has to be preserved or sent to the decoder for signal reconstruction. An appropriate number of zeros is padded to the end of each heartbeat data sequence, so that the length of each segment becomes uniform (Fig. 5b). Because the length of each heartbeat is coded, the number of padded zeros need not be preserved for decoding process. To further improve the coding efficiency, estimate the mean heartbeat period from some initial cycles of the ECG data and preserve or send it to the decoder. The difference between the mean heartbeat period and each heartbeat period is coded.

Amplitude normalization brings about further similarity between the ECG data. Each sample of a heartbeat is divided by the magnitude of the largest sample of that beat. This makes the highest amplitude sample of each beat equal to one. Thus, the variations between the magnitudes of different segments are decreased, which enhances the similarity of the vectors in VQ. To further improve the coding efficiency, estimate the mean R-peak value from some initial values of R peaks and preserve or send it to the decoder. The difference between the mean R-peak value and the value of each R peak is coded.

3.3. 2-D wavelet decomposition and coefficients encoding

Apply 2-D wavelet decomposition to the constructed 2-D ECG data array. According to the characteristic of the wavelet transformed coefficients, adopt different coding methods to different subbands respectively. The energy after wavelet transform centers in the low-frequency subband LL_M. In order to guarantee the quality of the reconstructed data, apply lossless DPCM to the coefficients in the low-frequency subbands. Each high-frequency subband, LH_i, HL_i,
and HH_i (i = 1, 2, ..., M), contains different directional texture information and represents similarity of different
directions. Apply the modified VQ algorithm to these subbands. The original codebook can be obtained using the
LBG training algorithm which is proposed by Linde et al. [28].

In order to reconstruct the ECG waveforms, the compressed data must include the following items: (1) mean
heartbeat period and the difference between mean heartbeat period and each heartbeat period; (2) mean R-peak value
and the difference between mean R-peak value and the value of each R-peak; (3) encoded bit stream of wavelet
coefficients.

4. Experimental results and analysis

Take all records in full length of Lead II data set from the MIT/BIH arrhythmia database [29] as the test data in this
paper. There are 48 records in the data set and each record is slightly more than 30 min long. The sampling frequency
and the resolution are 360 Hz and 11 bits, respectively.

At present, the percent root-mean-square difference (PRD) remains to be the most widely accepted and convenient
evaluation criterion for ECG compression methods [30]. It can be formulated as

$$\text{PRD} = \sqrt{\frac{\sum_{i=1}^{N} (x_{\text{org}}(i) - x_{\text{rec}}(i))^2}{\sum_{i=1}^{N} x_{\text{org}}^2(i)}} \times 100\%,$$

where \(x_{\text{org}}(i)\) is the original signal, \(x_{\text{rec}}(i)\) is the corresponding reconstructed signal, \(N\) is the number of samples. In
order to verify the compression performance of the proposed algorithm, the numerical values of the data are in the
range from −1024 to 1023, i.e., subtracting 1024 from the original data ranging from zero to 2047, in order to comply
with the PRD definition in Eq. (2).

4.1. Determining coding parameters

In VQ, the vector dimension has large effect on the whole quantization scheme. Larger vector dimension seems to
increase the compression ratio, but it does not in practice. The computational complexity of VQ increases exponen-
tially with the vector dimension and codebook size. In this paper, we implement 3-level wavelet transform to the 2-D
ECG signals using the 9/7 tap biorthogonal integer wavelet based on the lifting scheme, which forms 10 coefficient
subbands. The root point of a TV contains two coefficients, so the dimension of a vector is 42. In order to reduce the
computational complexity and increase the coding efficiency as much as possible, we select and use the codebook
size \(N = 1024\) throughout this paper. Given the vector dimension and the codebook size, we generate the correspond-
ing initial codebooks using the LBG algorithm and a training set taken from the wavelet transformed coefficients of
record 100.

4.2. Compression results and discussions

We test the propose method using all the 48 records of the MIT/BIH arrhythmia database. The PRD-CR (CR is the
compression ratio) results of ten typical ECG records, including records 100, 101, 102, 103, 107, 109, 111, 115, 117,
and 119, are depicted in Fig. 6. We can see in Fig. 6 that the results of all the records are close to each other. This
implies that the proposed method is suitable for various morphologies of ECG data.

Recently, some scholars have proposed compression methods based on wavelet transform and have achieved ex-
cellent compression performance. There are some representative methods. Lu et al. [9] applied the SPIHT algorithm
for ECG signal compression. Eleven MIT/BIH records were tested using the SPIHT methods, including records 100,
101, 102, 103, 107, 109, 111, 115, 117, 118, and 119. Miaou et al. [10] introduced dynamic VQ and modified the
SPIHT method. We compare the two compression methods with the proposed method using the above 11 records with
full length. The comparison results are listed in Table 1. As can be seen from Table 1, the compression performance of
the proposed algorithm is better than the SPIHT method and the dynamic VQ method. This is mainly because that the
proposed algorithm has cut and aligned the 1-D ECG signal to 2-D data array, which can further utilize the correlation
between the adjacent heartbeat cycles.
In 1999, Lee and Buckley [14] proposed an ECG compression method based on the 2-D DCT. In 2003, Bilgin et al. [31] applied the image coding standard—JPEG to ECG signal compression. In 2005, Tai et al. [32] adopted a modified SPIHT method to compressing ECG signals. The above three 2-D ECG signal compression methods are representative and have obtained excellent compression effect. Figure 7 shows the PRD-CR curves of the three methods and the proposed method tested by the same record 101. As is demonstrated in Fig. 7, the proposed algorithm has lower PRDs than the Lee, JPEG, and Tai algorithms at the same CRs. This indicates that the compression performance of the proposed algorithm is more excellent than the other three.

Figure 8 shows the compression performance of the proposed algorithm tested by the MIT/BIH records 100, 109, 117, and 119. As can be seen from Fig. 8, the characteristic features are well preserved in the reconstructed signals, i.e., the clinical diagnosis information in the original ECG signals are well preserved in the reconstructed signals, and the error signals are almost uniformly distributed.

### Table 1

<table>
<thead>
<tr>
<th>CR</th>
<th>PRD</th>
<th>Dynamic VQ [10]</th>
<th>Proposed algorithm</th>
</tr>
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<tr>
<td>12</td>
<td>2.9 ± 1.03</td>
<td>2.7 ± 1.35</td>
<td>1.6 ± 0.98</td>
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<tr>
<td>20</td>
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<td>4.3 ± 1.72</td>
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<tr>
<td>36</td>
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<td>5.8 ± 2.60</td>
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<tr>
<td>45</td>
<td>17.5 ± 3.70</td>
<td>10.1 ± 3.26</td>
<td>7.5 ± 3.17</td>
</tr>
</tbody>
</table>

5. Conclusions

(1) In this paper, we proposed a new 2-D ECG signal compression algorithm based on wavelet transform and VQ, which fully utilized the interbeat correlation and the intrabeat correlation of ECG signals. The codevector in VQ is chosen as a TV. According to the characteristic of wavelet transformed coefficients, TVs in different directions have adopted different construction methods, which adequately utilized the directional features of the wavelet coefficients. Records selected from the MIT/BIH arrhythmia database are tested comparatively using the proposed algorithm, some wavelet-based compression methods and the other 2-D ECG signal compression methods. The
experimental results proved the validity of the proposed algorithm. As was shown in Section 4, the proposed algorithm can obtain high CRs with low distortions and it has more excellent performance than the traditional wavelet-based algorithms and 2-D methods.

(2) The QRS complex detection algorithm was applied in the proposed algorithm. The accuracy of the QRS complex detector may greatly affect the performance of the proposed algorithm. So, how to find an accurate QRS detection algorithm is the continuing research work in theory and in practice.

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References


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