Computational efficient method for ECG signal compression based on modified SPIHT technique

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Abstract: In this paper, an improved method for electrocardiogram (ECG) signal compression using Set Partitioning in Hierarchical Trees (SPIHT) algorithm is proposed. ECG signals are compressed based on different transform such as discrete cosine transform and discrete wavelet transform with modified SPIHT. The modified SPIHT algorithm yields good compression with controlled quantity of signal degradation and requires computational time as compared to earlier published SPIHT algorithms. The proposed algorithm is suitable for the ECG signal compression for telemedicine or e-health system due to minimum computational time.

Keywords: ECG compression; SPIHT; DCT; discrete cosine transform; DWT; discrete wavelet transform; modified SPIHT; compression ratio.


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R. Kumar et al.

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1 Introduction

An electrocardiogram (ECG) is a physiological signal of cardiac functionality due to ionic activity in the cardiac muscles of human heart. ECG signals are recorded from patients for monitoring and diagnostic purposes. Therefore, the storage of computerised ECG is become necessary. Recording of ECG signal requires huge amount of data that increases with different sampling rates, number of channels, and time, etc. However, the storage has limitation which made ECG signal compression as an important issue of research in biomedical signal processing. In addition, the transmission speed of real-time ECG signal is also improved and is also economical due to ECG signal compression. Hence, data compression plays an important role in managing the data capacity and provides effective solution to the problem of storing and transmission bandwidth. It is also useful for ECG database management, transmission and telemedicine as well as real-time ECG processing.

In the real-time ECG compression and telemedicine or e-health monitoring, computational time is a key feature of real-time biomedical signal processing. There are so many different methods developed for ECG processing (Londhe et al., 2012; Jegan and Anusuya, 2013; Chatterjee et al., 2013; Bansal, 2013; Kamath, 2013) as well as ECG signal compression. In early stage of ECG compression research, several methods have been developed such as Amplitude Zone Time Epoch Coding (AZTEC) and Coordinate Reduction Time Encoding System (CORTES); both methods are referred as direct compression scheme. In this method, compression is achieved by eliminating redundancy.
Computational efficient method for ECG signal compression

between different ECG samples in the time domain. A detailed review on these techniques is presented in the work of Jalaleddine et al. (1990), Nave and Cohen (1993) and Zigel et al. (2000).

In the past two decades, a substantial progress has been made in the field of data compression. Several efficient ECG compression techniques have been developed such as Linear Predictive Coding (LPC), waveform coding and sub-band coding. In all these techniques, sophisticated signal processing techniques are employed. Linear predictive coding is a robust tool widely used for analysing speech and ECG signal in various fields such as spectral estimation, adaptive filtering and data compression (Hamilton and Tompkins, 1991; Al-Shroud et al., 2003). Several efficient methods (Aydin, 1991) have been reported in the literature based on linear prediction. While in sub-band decomposition, spectral information is divided into a set of signals that can be encoded by using a variety of techniques. Based on sub-band decomposition, various techniques (Huso and Gjerde, 1996; Cetin et al., 1993) have been devised for ECG signal compression.

In the past, marked progress has been made in ECG compression application based on transformation methods such as Discrete Cosine Transform (DCT), Fast Fourier Transform (FFT) and Discrete Wavelet Transform (DWT), which are extensively used in data compression (Ranjeet et al., 2011; Kumar and Ranjeet, 2011; Kumar and Ranjeet, 2012; Kumar et al., 2012; Kumari and Sadasivam, 2007; Blanco-Velasco et al., 2004; Shao-Gang and Shu-Nien, 2005). Recently, a lot of works have been done in the area of wavelet transform-based ECG compression using Set Partitioning in Hierarchical Trees (SPIHT) algorithm, which gives higher performance as compared to earlier techniques. As time complexity has not been computed in the works already reported based on SPIHT. In view of the above, there is a strong need to modify the SPIHT and reduce the time complexity. Also, SPIHT only works for integer values due to which loss of data is very high, further this loss is overcome by the modified works (Lu et al., 2000; Mohammad et al., 2005).

In this context, SPIHT-based method works efficiently with very low distortion in recovered signal from compressed data. Lu et al. (2000) proposed a 1-D SPIHT-based method for ECG signal compression and tested the reconstruction performance with different compression scores. Therefore, many authors reported different algorithms based on SPIHT and modified SPIHT for different types of data processing such as 1-D and 2-D. Here, SPIHT-based methods explore the new dimension for researcher in field of ECG signal processing.

In this continuity, several techniques have been proposed based on 2-D transformation to achieve better compression using concept of image processing on ECG signals; wavelet analysis and its encoding techniques are frequently applied by the several researchers. Here, most popular image techniques such as Embedded Zerotree of Wavelet (EZW) coding and SPIHT are applied on ECG signal (Hilton, 1997; Lu et al., 2000). In order to 2-D ECG compression, JPEG and JPEG2000 techniques are applied (Lee and Buckley, 1999; Alexandre et al., 2006; Lukin et al., 2008; Ahmad et al., 2001), but, due to blocking artefacts, JPEG is not much popular compare to the wavelet-based JPEG2000. Several techniques are presented based on the JPEG2000 standard such as modified vector quantisation (VQ) (Wang and Meng, 2008; Sahraeian and Fatemizadeh, 2007), wavelet focation and wavelet packets (Ciocoiu, 2009; Ahmed et al., 2001), ROI masking and conditional entropy coding (Huang and Wang, 2009), modified SPIHT (Tai et al., 2005; Wang and Chen, 2008) and other coding techniques like arithmetic,
run-length coding (Srinivasan et al., 2011; Nayebi et al., 2008; Mohammadpour and Mollaci, 2009), which are basically applied on 2-D ECG image form using the interbeat correlation and alignment.

In this paper, MSPIHT algorithm-based ECG compression is carried out with the help of DWT and DCT. The ECG compression was achieved in minimum computational time as compared to earlier developed methods. The minimum process time is an advantage for the minimum delay in telemedicine application, and enhances the system performance, etc.

2 Transformation-based analysis

In the biomedical signal processing or other areas of digital signal processing, mathematical manipulation or transformation of signal becomes popular for extraction or encryption of the signal information. Here, transform techniques give solution for such type of analysis, transforms the spatial or time-domain information into frequency, phase or other domain representations of signal. In signal processing, many transform techniques are reported such as Discrete Fourier Transform (DFT), DCT, Karhunen–Loève transform (KLT) and DWT, which provide transformation analysis to extracting or hiding the signal information.

Let a signal $X(n)$ of $N$ length is represented in the spatial domain where $n$ is spatial variable. Then the signal is represented in transform domain using the forward (analysis) discrete transform $Y(k)$, it can be describe by equation (1).

$$
Y(k) = \sum_{n=0}^{N-1} X(n) g_k(n)
$$

where $k$ is transform domain variable. The $Y(k)$ can be obtained by the forward discrete transform and its inverse transform give the original signal sequence $X(n)$, it is define in equation (2).

$$
X(n) = \sum_{k=0}^{N-1} Y(k) h_k(n)
$$

where $g_k(n)$ and $h_k(n)$ are known as forward (analysis equation) and inverse (synthesis equation) transform kernel, respectively. The energy of original signal is also preserved in the transform coefficients $Y(k)$ due to energy compaction property of transforms; it is defined by Parseval’s relation, as in equation (3)

$$
\sum_{n=0}^{N-1} E \left| X(n) \right|^2 = \sum_{k=0}^{N-1} E \left| Y(k) \right|^2
$$

The average energy $E \left| Y(k) \right|^2$ of transform coefficients $Y(k)$ and $E \left| X(n) \right|^2$ is the average energy of input sequence $X(n)$ (Mitra, 2006). In this paper, signal data compression analysis done based on the DCT and DWT techniques, due to energy compaction property of transforms, both are the most suitable for the compression application.
2.1 Discrete cosine transform

A discrete cosine transform expresses a sequence of finitely many data points in terms of a sum of cosine function. If the input data consists of correlated quantities, then most of the \( n \) transform coefficients produced by the DCT are zeros or small numbers and preserve the significant information in only few starting transform coefficients. The early coefficients contain the important (low-frequency) signal information and the later coefficients contain the insignificant (high-frequency) signal information. DCT also gives support to the some degrees of localisation in time, but the resolution is fixed. Compressing a set of correlated pixels with the DCT is therefore done by (a) computing the DCT coefficients of the pixels, (b) quantising the coefficients, and (c) encoding them with variable-length codes. DCT has widely used for the data compression, it is transform as in equation (4):

\[
Y(k) = \sum_{n=0}^{N-1} 2X(n) \cos \left( \frac{\pi k (2n + 1)}{2N} \right)
\]

While, the inverse IDCT is defined as in equation (5):

\[
X(n) = \frac{1}{N} \sum_{k=0}^{N-1} Y(k) \cos \left( \frac{\pi k (2n + 1)}{2N} \right)
\]

DCT gives the decomposed coefficient of the original signal and it also gives the more weight to low-pass coefficients to high-pass coefficients (Mitra, 2006), as illustrated in Figure 1a.

**Figure 1** ECG signal decomposition (a) using the DCT and (b) using DWT (see online version for colours)
2.2 Discrete wavelet transform

The wavelet transform has emerged as a powerful mathematical tool in many areas of science and engineering, more so in the field of data compression. The concept of wavelets was first introduced by Grossman and Morlet in 1984 to analyse signal structures of very different scales in the framework of seismic signals. Wavelets transform is a method to analyse a signal in time and frequency domain, it is effective for the analysis of time-varying non-stationary signal like ECG (Husoy and Gjerde, 1996; Cetin et al., 1993; Ranjeet et al., 2011). The basic principle of wavelet transform is that it decomposes the given signal in too many functions by using property of translation and dilation of a single prototype function, called a mother wavelet \((\psi(t))\), as define in equation (6):

\[
\psi_{ab}(t) = \left|a\right|^{-1/2} \psi\left(\frac{t-b}{a}\right) \quad a, b \in \mathbb{R}, \quad a \neq 0
\]  

(6)

When the parameters \(a\) and \(b\) are restricted to discrete values as: \(a = 2^{-m}, b = n2^{-m}\), then, a new family of discrete wavelets is derived as in equation (7):

\[
\psi_{mn}(t) = 2^{-m/2} \psi\left(2^m t - n\right), \quad m, n \in \mathbb{Z}
\]  

(7)

where the function, \(\psi\), the mother wavelet, satisfies \(\int_{-\infty}^{\infty} \psi(t) dt = 0\).

A continuous-time wavelet transform of a signal \((f(t))\) is defined in equation (8) as:

\[
W_f(b,a) = \left|a\right|^{-1/2} \int_{-\infty}^{\infty} f(t) \psi^*\left(\frac{t-b}{a}\right) dt
\]  

(8)

where the asterisk denotes a complex conjugate and the multiplication of \(\left|a\right|^{-1/2}\) is for the energy normalisation purposes, so that the transformed signal will have the same energy at every scale. Hence, the wavelets have adaptive nature, present a large time base for analysing the low frequency components, and have a better time resolution for analysing phenomena that are more transitory.

As \(a\) and \(b\) are continuous over \(\mathbb{R}\) (over the real number), there is often redundant in CWT representation of the signal. A more compact representation can be found with a special case of WT, called the DWT, where only the required wavelet coefficients for the reconstruction of \(x(t)\) are kept. Substituting equation (8) into equation (7), DWT of a signal \(f(t)\) is obtained as:

\[
DWT_{\psi_{mn}}f(m,n) = \int_{-\infty}^{\infty} f(t) \psi_{mn}^*(t) dt
\]  

(9)

where \(\psi_{mn}(t) = 2^{-m/2} \psi\left(2^m t - n\right)\).

However, for computing equation (9), an infinite number of terms are required. Therefore, to overcome this problem, a new family of basis functions, called scaling functions, \((\phi_{mn}(t))\), was introduced in equation (10), which is derived just similar to the wavelets:

\[
\phi_{mn}(t) = 2^{-m} \phi\left(2^m t - n\right)
\]  

(10)
These scaling functions are complementary basis for wavelet function. Due to this, the Multiresolution Analysis (MRA) of signal is possible. There are three basic concepts of multiresolution: sub-band coding, vector space and pyramid structure coding. DWT decomposes a signal at several $n$ levels in different frequency bands. Each level decomposes a signal into approximation coefficients (AC: low-frequency band of processing signal) and detail coefficients (DC: high-frequency band of processing signal) (Aydin, 1991; Husoy and Gjerde, 1996; Cetin et al., 1993; Ranjeet et al., 2011; Kumar and Ranjeet, 2011), as demonstrated in Figure 1b.

The algorithm of wavelet signal decomposition is illustrated in Figure 2, where $X$ is original sequence decomposed in two bands at single level $cA_1$ and $cD_1$. At higher level of decomposition, $cA_1$ is again divided in two bands $cA_2$ and $cD_2$ using the wavelet analysis and the same for next levels of decompositions.

Figure 2  Algorithm of wavelet decomposition as spatial tree orientation (see online version for colours)

At each step of DWT decomposition, there are two outputs: scaling coefficients $x^{j,i}(n)$ and the wavelet coefficients $y^{j,i}(n)$. These coefficients are given as:

$$x^{j,i}(n) = \sum_{i=0}^{2^n} g(2n-i)x^j(n)$$  \hspace{1cm} (11)

and

$$y^{j,i}(n) = \sum_{i=0}^{2^n} h(2n-i)x^j(n)$$  \hspace{1cm} (12)

where the original signal is represented by $x^0(n)$ and $j$ shows the scaling number. Here, $g(n)$ and $h(n)$ represent the low-pass and high-pass filters, respectively, as shown in Figure 3 and equations (11) and (12).
3 Set partitioning in hierarchical trees

The set partitioning in hierarchical trees entropy coding algorithm is fast and efficient; it was designed for optimal progressive transmission, as well as for compression. It generates a fully embedded bit stream and is highly competitive with other entropy coding algorithms. The basic working principle of SPIHT algorithm is: (a) using the self-similarity of transform coefficients, i.e. if the magnitude of coefficient on a certain location of the scale in transform domain is large or small, the magnitude of the coefficient on the same location of the adjacent scale is also large or small; (b) transmitting the coefficient is started with significant coefficient (large magnitude) and (c) transmitting the encoded coefficient chronologically (Lu et al., 2000; Mohammad et al., 2005).

3.1 SPIHT definition

A transform coefficient of signal will be considered as an insignificant coefficient; if its absolute value is smaller than a given threshold \( T \), besides it is considered to be significant coefficient. The following are some basic definitions and explanations used in SPIHT (Lu et al., 2000; Mohammad et al., 2005). LSP: List of Significant Points; LIP: List of Insignificant Points; LIS: List of Insignificant Sets; \( O(i) \): set of direct descendants of a tree node defined by point location \( I \); \( D(i) \): set of descendants of node defined by point location \( i \); \( L(i) \): set defined by \( L(i) = D(i) - O(i) \).

The SPIHT algorithm is applied on transform coefficient of the input signal and firstly initialised. The output of SPIHT is encoded bit of transformed signal. The amplitude of original signal is \( x \) by \( x(n) \). Transform the signal values to some different domains from time-domain is denoted by (transform coefficients) \( c(k) \). The algorithm for the signal compression based on the SPIHT is shown in Figure 4.
In the SPIHT encoding technique, firstly coefficients are needed to sorting as coefficients with higher energy have to be passing first. These resultant spatial-orientation tree in Figure 2 formation is obtained to reduce the insignificant sets in this case.

4 Modified SPIHT

The basic principle of SPIHT (Lu et al., 2000; Mohammad et al., 2005) remains the same as in Section 3, i.e. transmission of most significant bit first and then continuing with decreasing priority of position of bits and transmission of values with higher energy. SPIHT only works for integer values due to which loss of data is very high. In order to include decimal values of data for encoding, time complexity has to be reduced. This is done through removing spatial tree formation concept from the SPIHT. Therefore, the modified version of SPIHT works on real-transform coefficient values. In this, MSPIHT only two arrays have been used. Array List of Insignificant Coefficients (LIC) is used for storing all the data values of transform coefficients and another array List of Significant Coefficients (LSC) is used for storing the significant values.

4.1 Modified SPIHT (MSPIHT) algorithm

Step 1: Separate integer and decimal part of transformed coefficients. Then multiply decimal part by $10^m$ ($m = 2$, in case two places after decimal) and contain the integer part only.

Step 2: Initialise the set LIC_I to all integer part of transformed coefficients. Set LIC_D to all decimal part of transformed coefficients. Set LSC_I and LSC_D to an empty set. Set the significance threshold $2^n$ with $n = \lceil \log_2 \max |c_i| \rceil$, where $c_i$ denotes the transform coefficient.

Step 3: Sorting pass: check the significance of all coefficients in LIC_I and LIC_D:

A: If significant, output 1, output a sign bit and move the coefficient to the LSC_I and LSC_D, respectively.

B: If not significant, output 0.
**R. Kumar et al.**

**Step 4:** Refinement pass: for each entry in the LSC_I and LSC_D, except those included in the last sorting pass, output the \( n \)-th most significant bit of transformed coefficient.

**Step 5:** Loop decrement the threshold and go to step 3 if needed.

The proposed technique used hard threshold criteria for selecting the significant wavelet transform coefficient as define in Step 2. Here, multiplication by \( 10^m \) factor enhances the coefficient magnitude; therefore, some of significant coefficients are passed through threshold level. This helps to preserve significant coefficient and reducing reconstruction error.

### 4.2 Proposed approach

Firstly, the sign of the coefficients values are passed to decoder and then most significant bits of the values present in LSC. Now in order to make it work for decimal value also, values of ECG signal transform coefficients are divided in two parts. First part consists of integer part of the coefficients values and the second part comprises decimal values. In these works, two decimal places have been taken care of transform coefficients. Two separate encodings are done for both the part and send to the decoder. The steps for encoding of both parts remain the same as stated earlier in SPIHT. In case of applying encoding scheme for decimal values, these values are first multiplied by \( 10^m \) \((m = 2, \) in case two places of decimal values\) and then all other steps for both the cases are the same. Finally, output comes in term of encoded data in compressed form with respect to transform coefficients. Further, compressed data are stored in the memory or transmitted over the channel for telemedicine applications. During the compression process, maximum value of \( m \) is 2, here \( m \) will be higher taken care at the cost of increased time complexity. Thus, a lot of flexibility in terms of taking values has been introduced in this work. So that signal process using MSPIHT obtained the loss of data values is reduced at minimum time complexity. Figure 5 shows the MSPIHT algorithm for the ECG signal compression.

**Figure 5** MSPIHT algorithm for the transformation-based signal compression
Computational efficient method for ECG signal compression

During the reconstruction of signal, the compressed data are decoded using the MSPIHT decoding techniques. Where, encoded data are divided by the 10\(^{th}\) to get the original transform coefficient. Then the inverse transformation is applied to obtain the original values of signal. Throughout the experiment, 1024 sample length of signals are utilised and tested for proposed compression technique, where three levels of wavelet decomposition are chosen.

5 Results and discussion

In this section, a DWT-based methodology using MSPIHT has been used for ECG signal compression. The propose algorithm is tested on five different records from the MIT-BIH arrhythmia database, the test data sets are: 100, 112, 117, 118, 124 and 217. ECG records have been obtained from MIT-BIH Arrhythmia Database (see http://www.physionet.org) these data sets are used in earlier studies so that they make comparison easy with earlier methods. A modified SPIHT algorithm is used for ECG compression that gives enhanced performance as compared to SPIHT (Lu et al., 2000; Mohammad et al., 2005) in terms of computational time as well as compression factor. The performance of MSPIHT algorithms in the field of ECG signal compression can be evaluated by considering the fidelity of reconstructed signal to original signal. These three parameters are taken into consideration for performance evaluation. Compression of signal is measured in terms of compression ratio (CR) using equation (13) but there are so many issues that are involved after the compression, and are required to be observed and control it. Like, the Percent Root-Mean Square Difference (PRD) using equation (14) measures the distortion between original and reconstructed ECG signal. One more parameter used in this is Time Complexity (TC) or elapsed time.

Compression ratio (CR):

\[
CR = \frac{\text{Number of significant Encoded Transform coefficients}}{\text{Total number of Transform coefficients}} \times 100
\]  

(13)

Percent root-mean square difference (PRD):

\[
PRD = \sqrt{\frac{\text{Reconstructed noise energy}}{\text{Original signal energy}}} \times 100
\]  

(14)

Time Complexity (TC): time taken for the algorithm performance, its measured time unit is second (s)

Tables 1 and 2 show the comparison of both the algorithms SPIHT and MSPIHT that are applied on DCT and DWT coefficients. Here, methodology is implemented on MATLAB 7 with system specification Intel Quad Core processor (Q9550 @ 2.83 GHz) and 2.00 GB system memory on the 64-bit operating system. In this paper, analysis is described based on DCT and different wavelet filters’ families such as debauches,
biorthogonal wavelet and coiflet using the MSPIHT encoding technique. Table 1 contains the average performance of wavelet filters and DCT on the MIT-BIH ECG signal records (http://www.physionet.org).

**Table 1**  Performance of proposed SPIHT with DCT

<table>
<thead>
<tr>
<th>Signal</th>
<th>Compression Ratio (CR)</th>
<th>Percent root-mean difference (PRD)</th>
<th>Time Complexity (TC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rec. 100</td>
<td>58</td>
<td>12.4</td>
<td>0.48</td>
</tr>
<tr>
<td>Rec. 112</td>
<td>65</td>
<td>9.3</td>
<td>0.58</td>
</tr>
<tr>
<td>Rec. 117</td>
<td>44</td>
<td>9.4</td>
<td>0.60</td>
</tr>
<tr>
<td>Rec. 118</td>
<td>37</td>
<td>11.04</td>
<td>0.61</td>
</tr>
<tr>
<td>Rec. 124</td>
<td>49</td>
<td>8.04</td>
<td>0.59</td>
</tr>
<tr>
<td>Rec. 217</td>
<td>34</td>
<td>13</td>
<td>0.73</td>
</tr>
</tbody>
</table>

**Table 2**  Performance of SPIHT and proposed algorithms with DWT

<table>
<thead>
<tr>
<th>Signal</th>
<th>Compression Ratio (CR)</th>
<th>Percent root-mean difference (PRD)</th>
<th>Time Complexity (TC)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPIHT</td>
<td>11.5</td>
<td>15.1</td>
<td>2.3</td>
</tr>
<tr>
<td>MSPIHT</td>
<td>15.2</td>
<td>15.1</td>
<td>1.08</td>
</tr>
<tr>
<td>SPIHT</td>
<td>14</td>
<td>12</td>
<td>9</td>
</tr>
<tr>
<td>MSPIHT</td>
<td>15</td>
<td>9</td>
<td>9</td>
</tr>
<tr>
<td>SPIHT</td>
<td>8</td>
<td>6</td>
<td>11</td>
</tr>
<tr>
<td>MSPIHT</td>
<td>9</td>
<td>9</td>
<td>2.3</td>
</tr>
<tr>
<td>SPIHT</td>
<td>7</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>MSPIHT</td>
<td>8</td>
<td>9</td>
<td>4.5</td>
</tr>
<tr>
<td>SPIHT</td>
<td>12</td>
<td>16</td>
<td>13</td>
</tr>
<tr>
<td>MSPIHT</td>
<td>22</td>
<td>34</td>
<td>5.26</td>
</tr>
</tbody>
</table>

Here, average performance in terms of compression ratio (CR), PRD and computational time taken by SPIHT and MSPIHT algorithms with DWT is 12.41%, 11.68% and 2.96 s and 15.86%, 10.38% and 0.68 s, respectively. On the other hand, performance of MSPIHT algorithm with DCT is 47.83%, 10.52% and 0.598 s. From the analysis of Tables 1 and 2, it is clearly shown that the computational complexities of modified SPIHT algorithms are 4.35 times and 4.93 times less than the earlier developed technique SPIHT with DWT and DCT, respectively, at the comparable compression of signal.

The other transform-based compression methods listed in the literature (Zhang et al., 2013; Chen et al., 2008; Miaou et al., 2000; Lu et al., 2000; Wang and Meng, 2008; Wang and Chen, 2008) are presented in Table 3. From the literature, these techniques are compared with the proposed algorithm in terms of CR, PRD and TC.

**Compression analysis:** In this paper, MSPIHT algorithm is applied on six ECG signal records. The algorithm have been applied on DCT and DWT coefficients and found that the average compression was 47.83% and 15.68%, respectively. In similar work, Zhang et al. stated that the compression performance of Sparse Bayesian learning technique was 40%. Similarly, Chen et al., Miaou et al., Lu et al., Wang and Meng and Wang and Chen stated that the average compression was 42%, 45%, 15%, 45% and 40%, respectively. As compare to other listed works, the proposed algorithm is good with DCT.
Computational efficient method for ECG signal compression

Percent Root-Mean Square difference (PRD) and Time COMPLEXITY (TC): Proposed algorithm achieved good amount of compression for ECG signal. Here, PRD represents the root-mean difference between the original signal and compressed signal. From the analysis DCT and DWT, the compression with control amount of root-mean difference using MSPIHT is 10.52 and 10.83, respectively, in minimum computational time as compare to Zhang et al. (2013) and Lu et al. (2000).

Table 3 clearly shows that the MSPIHT is better in all respect especially with the DCT for ECG signal compression as well as in controlled quality of distortion in signal. Figure 6 illustrates the reconstruction of compressed signal MIT-BIH Rec. 100 using the proposed MSPIHT approach with DCT and DWT techniques.

Table 3 Performance comparison of SPIHT and MSPIHT with other techniques

<table>
<thead>
<tr>
<th>Signal</th>
<th>CR (%)</th>
<th>PRD (%)</th>
<th>TC (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed + DCT</td>
<td>47.83</td>
<td>10.52</td>
<td>0.60</td>
</tr>
<tr>
<td>Proposed +DWT</td>
<td>15.68</td>
<td>10.38</td>
<td>0.68</td>
</tr>
<tr>
<td>DWT + SPIHT</td>
<td>12.41</td>
<td>11.68</td>
<td>2.96</td>
</tr>
<tr>
<td>Zhang et al. (2013)</td>
<td>65</td>
<td>–</td>
<td>0.70</td>
</tr>
<tr>
<td>Zhang et al. (2013)</td>
<td>40</td>
<td>–</td>
<td>1.10</td>
</tr>
<tr>
<td>Chen et al. (2008)</td>
<td>42</td>
<td>9.89</td>
<td>–</td>
</tr>
<tr>
<td>Miaou et al. (2002)</td>
<td>45</td>
<td>10.1</td>
<td>–</td>
</tr>
<tr>
<td>Lu et al.(2000)</td>
<td>20</td>
<td>6.49</td>
<td>6.48</td>
</tr>
<tr>
<td>Wang et al. (2008) [AQ3]</td>
<td>45</td>
<td>7.5</td>
<td>–</td>
</tr>
<tr>
<td>Wang et al. (2008)+SPIHT [AQ3]</td>
<td>40</td>
<td>13.6</td>
<td>–</td>
</tr>
<tr>
<td>Wang et al. (2008)+MSPIHT [AQ3]</td>
<td>40</td>
<td>12.5</td>
<td>–</td>
</tr>
</tbody>
</table>

Figure 6 ECG signal (a) original signal, (b) reconstructed using DCT and (c) reconstructed using DWT (see online version for colours)

AQ3: Please specify whether Wang et al. (2008) should be Wang and Meng, 2008 or Wang and Chen, 2008 in Table 3.
The proposed method has been tested on different MIT-BIH ECG signal records and evaluated for compression as well as reconstruction efficiency. In this work, SPIHT plays a key role to encode the wavelet coefficient and identifies the significant value from computed transform coefficients. Here, SPIHT technique contains implication related to identify significant coefficient. Therefore, proposed method has two different LSC indexes for integer and decimal values of transform coefficient to select the most significant values, as discussed in Section 4.2. Moreover, the proposed method decreases compression efficiency at the cost of efficient reconstruction due to selection of significant coefficient as compare to SPIHT. The proposed method has good reconstruction efficiency with low-computational time as reported in Tables 1–3 as well as in Figure 6. The proposed method is easily adoptable in practice for remote healthcare, data management system in healthcare, etc.

6 Conclusions

The electrocardiogram signal is very important feature of human cardiac system for diagnosis and observation. In telemedicine, base treatment is based on the medical signal information and quality. The best compression algorithm helps to contain the clinical information in compressed signal form as well as overcome many other limitations such as data storage and transmission bandwidth. In this paper, MSPIHT algorithm is described for ECG signal compression which gives better results as compared to its earlier version of SPIHT in terms of compression ratio and signal quality as well as minimum time. The MSPIHT is not only efficient in respect of these two parameters, but also takes less computational time as compared to SPIHT. The results clearly reflect that the proposed algorithm is very efficient for ECG signal compression as well as telemedicine or e-health system.

References

Computational efficient method for ECG signal compression


