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 (DCT) and discrete wavelet transform (DWT) 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 computation time is required.

Keywords: ECG compression, SPIHT, DCT, DWT, modified SPIHT, compression ratio.

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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 computerized ECG has 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 has 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 economical due to ECG signal compression. Hence, data compression plays an important role in managing the data capacity, and provides effective solution against 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 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 like 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 between different ECG samples in the time domain. A detailed review on these techniques is presented in listed references (Jalaleddine et al., 1990; Nave and Cohen, 1993; 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 analyzing 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 literature based on linear prediction. While in sub-band decomposition, spectral information is divided into a set of signals that can then be encoded by using a variety of techniques. Based on sub-band decomposition, various techniques (Husoy 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., 2013; Kumar et al., 2012; Kumari and Sadasivam, 2007; Blanco et al., 2004; Shaou-Gang and Shu-Nien; 2005). Recently, lot of work has 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 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 has work efficiently with very low distortion in recovered signal from compressed data. Lu et al., 2000 proposed 1-D SPIHT based method for ECG signal compression and test the reconstruction performance with different compression score. Therefore, many authors reported different algorithm based on SPIHT and modified SPIHT for different type of data processing such as 1-D and 2-D. Here, SPIHT based methods explore the new dimension for research 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 are embedded zerotree wavelet (EZW) coding and set partitioning in hierarchical trees (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 Buckely, 1999; Alexandre et al., 2006; Lukin et al., 2008; Ahmad et al., 2001), but due to blocking artifacts JPEG not much popular than the wavelet based JPEG2000. There are
several techniques are presented based on the JPEG2000 standard such as modified vector quantization (VQ) (Wang and Meng, 2008; Sahraeian and Fatemizadeh, 2007), wavelet foeation and wavelet packets (Ciocoin, 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 the manuscript, MSPIHT algorithm based ECG compression is carried out with the help of discrete wavelet transforms (DWT) and discrete cosine transform (DCT). The ECG compression was achieved in minimum computation 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 area of digital signal processing, mathematical manipulation or transformation of signal become popular for extraction or encryption of the signal information. Here, transform techniques are given solution for such type of analysis, its transform the spatial or time domain information into frequency, phase or other domain representation of signal. In signal processing, there are many transform techniques are reported such as discrete Fourier transform (DFT), discrete cosine transform (DCT), Karhunen–Loève transform (KLT), discrete wavelet transform (DWT) etc., which are 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 the Eq. (1).

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

(1)

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’s define as in Eq. (2)

\[
X(n) = \sum_{k=0}^{K-1} Y(k) h_k(n)
\]

(2)

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

\[
\sum_{n=0}^{N-1} E[|X(n)|^2] = \sum_{k=0}^{K-1} E[|Y(k)|^2]
\]

(3)
The average energy \( E |Y(k)|^2 \) of transform coefficients \( Y(k) \) and \( E |X(n)|^2 \) is average energy of input sequence \( X(n) \) (Mitra, 2006). In this manuscript, 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 (DCT) expresses a sequence of finitely many data points in term 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 is also give support the some degree of localization in time, but the resolution is fixed. Compressing a set of correlated pixels with the DCT is therefore done by (1) computing the DCT coefficients of the pixels, (2) quantizing the coefficients, and (3) encoding them with variable-length codes. DCT has widely used for the data compression, it is transform is defined as in Eq. (4):

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

(4)

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

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

(5)

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

### 2.1 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 principal 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 \((\psi(t))\), defined as in Eq. (6)

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

(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 are derived in Eq. (7) as:

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

(7)

where, the function $\psi$, the mother wavelet, satisfies $\int_{\mathbb{R}} \psi(t)dt = 0$.

A continuous-time wavelet transform of a signal $(f(t))$ is defined in Eq. (8) as

$$
W_f(b,a) = \left\{ \frac{1}{a} \right\} \int_{-\infty}^{\infty} f(t) \psi^* \left( \frac{t-b}{a} \right) dt
$$

(8)

where, the asterisk denotes a complex conjugate and multiplication of $|\psi|^2$ is for the energy normalization 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 Discrete Wavelet Transform (DWT), where only the required wavelet coefficients for the reconstruction of $x(t)$ are kept. Substituting Eq. (8) into (7), DWT of a signal $f(t)$ is

$$
\text{DWT}_\psi f(m,n) = \int_{-\infty}^{\infty} f(t) \psi^*_{(m,n)}(t)dt
$$

(9)

where,

$$
\psi_{mn}(t) = 2^{-m} \psi(2^m t - n)
$$

However, for computing Eq. (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 Eq. (10), which is derived just similar to the wavelets:

$$
\phi_{mn}(t) = 2^{-m} \phi(2^m t - n)
$$

(10)

These scaling functions are complementary basis for wavelet function basis. Due to this, the multiresolution analysis (MRA) of signal is possible. There is three basic concept of multiresolution: sub-band coding, vector space and pyramid structure coding. DWT decompose 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), it is demonstrated in Fig. 1 (b).
The algorithm of wavelet signal decomposition is illustrated in Fig. 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 same for next levels of decompositions.

At each step of DWT decomposition, there are two outputs: scaling coefficients \( x^{j+1}(n) \) and the wavelet coefficients \( y^{j+1}(n) \). These coefficients are given as

\[
  x^{j+1}(n) = \sum_{i=1}^{2^n} g(2n-i)x^j(n) \tag{11}
\]

and

\[
  y^{j+1}(n) = \sum_{i=1}^{2^n} h(2n-i)x^j(n) \tag{12}
\]
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 in Fig. 3 and Eq. (11) and (12).

3 Set Partitioning in Hierarchical Trees

The set partitioning in hierarchical trees (SPIHT) 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: (i) using the self-similarity of transforms 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. (ii) Transmitting the coefficient is start with significant coefficient (large magnitude) (iii) 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 \( L(i) = D(i) - O(i) \).

![Fig. 4.SPIHT Algorithm for the transformation based Signal Compression](image)

The SPIHT Algorithm is applied on transform coefficient of the input signal and firstly initialized. The output of SPIHT is encoded bit of transformed signal. The amplitude of original signal \( x \) by \( x(n) \).
Transform the signal values to some different domain from time domain denoted by (transform coefficients) $c(k)$. The algorithm for the signal compression based on the SPIHT follows as Fig. 4.

In the SPIHT encoding technique, firstly coefficients are needed to sorting as coefficients with higher energy have to be passing first. These resultants that spatial orientation tree in Fig.2 formation is obtain 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 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. One array List of Insignificant Coefficients (LIC) is used for storing all the data values 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:** Initialize 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 $2^n$, $n = \lceil \log_2 \max |c_i| \rceil$, 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.

**Step4:** 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;

**Step5:** 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 defined 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 is divided in two parts. First part consists of integer part of the coefficients values and the second part comprises of decimal values. In these work, two decimal places has been taken care of from transform coefficients. Two separate encoding is 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 place of decimal values) and then all other steps for both the cases are same. Finally, output are comes in term of encoded data in compressed form as respect to transform coefficients. Further, compressed data are stored to 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 but 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 are reduced at minimum time complexity. Here, Fig. 5 shows the MSPIHT algorithm for the 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 \( 10^m \) 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 utilized and tested for proposed compression technique, where three level of wavelet decomposition is chosen.

### 5 Results and Discussion
In this section, a Discrete wavelet transform based methodology using MSPIHT has been used for ECG signal compression. The propose algorithm is tested on 5 different records from the MIT-BIH arrhythmia database, the test dataset are 100, 112, 117, 118, 124 and 217. ECG records have been obtained from MIT-BIH Arrhythmia Database (http://www.physionet.org) because of these data sets are used in earlier studies, its 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 computation 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 term of compression ratio (CR) using Eq.(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 Eq. (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):

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

Percent root mean square difference (PRD):

\[
PRD = \left( \frac{\text{Reconstructed noise energy}}{\text{Original signal energy}} \right)^{1/2} \times 100
\]

\[
= \sqrt{\frac{\sum (x(n) - y(n))^2}{\sum x(n)^2}} \times 100
\]

Time Complexity (TC): Time taken for the Algorithm performance, its measured time unit second (sec.)

Table. 1 and Table.2 show the comparison of both the algorithm SPIHT and MSPIHT 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 manuscript, analysis is described based on discrete cosine transform (DCT) and different wavelet filters families such as deauches, biorthogonal wavelet and coiflet using the MSPIHT encoding technique. Table.1 contain the average performance of wavelet filters and DCT on the MIT-BIH ECG signals records (http://www.physionet.org).

Here, average performance in term of compression ratio (CR), PRD and computation time taken by SPIHT and MSPHIT algorithms with DWT is 12.41%, 11.68% and 2.96sec. and 15.86%, 10.38% and 0.68sec. respectively. On the other hand performance of MSPIHT algorithm with DCT is 47.83%, 10.52% and 0.598sec. From the analysis in Table.1 and Table. 2, its clearly shown that the computation
complexity 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.

<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></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MSPIHT</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rec. 100</td>
<td>11.5</td>
<td>15.2</td>
<td>2.3</td>
</tr>
<tr>
<td>Rec. 112</td>
<td>14</td>
<td>15</td>
<td>1.9</td>
</tr>
<tr>
<td>Rec. 117</td>
<td>8</td>
<td>9</td>
<td>1.5</td>
</tr>
<tr>
<td>Rec. 118</td>
<td>7</td>
<td>8</td>
<td>2.3</td>
</tr>
<tr>
<td>Rec. 124</td>
<td>12</td>
<td>14</td>
<td>4.5</td>
</tr>
<tr>
<td>Rec. 217</td>
<td>22</td>
<td>34</td>
<td>5.26</td>
</tr>
</tbody>
</table>

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 (sec.)</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)</td>
<td>45</td>
<td>7.5</td>
<td>-</td>
</tr>
<tr>
<td>Wang et al. (2008) + SPIHT</td>
<td>40</td>
<td>13.6</td>
<td>-</td>
</tr>
<tr>
<td>Wang et al. (2008) + MSPIHT</td>
<td>40</td>
<td>12.5</td>
<td>-</td>
</tr>
</tbody>
</table>
There are other transform based compression methods are listed in literature (Zhang et al., 2013; Chen et al., 2008; Miaou et al., 2000; Lu et al., 2000; Wang et al., 2008; Wang et al., 2008) in Table. 3. From the literature, these techniques are compared with the proposed algorithm in term of CR, PRD and TC.

*Compression Analysis:* In this manuscript, MSPIHT algorithm is applied on six numbers of ECG signal records. The algorithm have been applied on DCT and DWT coefficient and found the average compression is 47.83% and 15.68% respectively. In similar work, Zhang et al. state the compression performance of Sparse Bayesian Learning technique is 40%. Similarly, Chen et al., Miaou et al., Lu et al., Wang et al., and Wang et al. state that the average compression is 42%, 45%, 15%, 45% and 40% respectively. As comparison, proposed algorithm is good with DCT with respect to listed work in references.

Fig. 6 ECG Signal: (a) Original Signal, (b) reconstructed using DCT and (c) reconstructed using DWT

*Percent root-mean square difference (PRD) and Time complexity (TC):* Proposed algorithm achieved good amount of compression for ECG signal. Here, PRD represent the root-mean difference between the original signal and compressed signal. Form the analysis DCT and DWT give the compression with control amount of root-mean difference using MSPIHT, its 10.52 and 10.83 respectively in minimum computation time as compare to Zhang et al. (2013) and Lu et al. (2000).

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

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 play key role to encode the wavelet
coefficient and identify the significant value from computed transform coefficients. Here, SPIHT technique contains implication related to identify significant coefficient. Therefore, proposed method having two different LSC index for integer and decimal value of transform coefficient to select the most significant values as discussed in section 4.2. Moreover, the proposed method has decreases compression efficiency at cost of efficient reconstruction due to selection of significant coefficient as compare to SPIHT. The proposed method has good reconstruction efficiency with low computation time as reported in Table.1, 2 and 3 as well shown in fig.6. The proposed method has easily adoptable in practice for remote healthcare, data management system in health care etc.

5 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 help to contain the clinical information in compressed signal form a well as overcome many other limitation like data storage, transmission bandwidth etc. In this manuscript, MSPIHT algorithm is described for ECG signal compression which gives better results than 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 it also takes less computation time as compared to SPIHT. The results clearly reflect that the proposed algorithm is veryefficient for ECG signal compression as well telemedicine or e-health system.

6 References


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