High Performance Method for Electrocardiogram Compression Using Two Dimensional Multiwavelet Transform

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Abstract— In this paper, we introduce an effective ECG compression algorithm based on two dimensional multiwavelet transform. The SPIHT algorithm has achieved prominent success in signal compression [1]. Multiwavelets offer simultaneous orthogonality, symmetry, and short support, which is not possible with scalar two-channel wavelet systems. These features are known to be important in signal processing. Therefore multiwavelet offers the possibility of superior performance for image processing applications. This paper deals with beat variation periods and then exploits the correlation between cycles (inter-beat) and the correlation within each ECG cycle (intra-beat). We suggested applying the SPIHT algorithm to 2-D multiwavelet transform of ECG signals. Experiments on selected records of ECG from MIT-BIH arrhythmia database revealed that the proposed algorithm is significantly more efficient for compression in comparison with previously proposed ECG compression schemes.

Keywords— ECG signal compression; multirate processing, 2-D Multiwavelet; Prefiltering

Topic area— Multimedia Processing

I. INTRODUCTION

Biological signal Compression and especially ECG has an important role in diagnosis, taking care of patients and signal transfer through communication lines. Normally, a 24-hour recording is desirable to detect heart abnormalities or disorders. This long term ECG monitoring is called Holter monitoring in automated ECG analysis. As an example, with the sampling rate of 360 Hz, 11 bit/sample data resolution, a 24 hours record requires about 43 Mbytes per channel. Therefore, efficient coding of the ECG is an important issue in biological signal processing. In the past, many schemes have been presented for compression of ECG data. These techniques can be classified in two categories: (1) direct compression such as Amplitude-Zone-Time Epoch Coding (AZTEC), Turning Point (TP), Coordinate Reduction Time Coding System (CORTCS), Fan algorithm, Scan-Along Polygonal Approximation (SAPA), and the Long Term Prediction (LTP). (2) Transformational methods such as Fourier Transform, Walsh Transform, Karhunen-Loeve Transform (KLT), and Wavelet Transform (WT). In most cases, direct methods are superior to transform methods with respect to system simplicity and error. However, transform methods usually achieve higher compression rates and are insensitive to noise contained in the original ECG signal [2].

Among the methods mentioned above, wavelet transformation is an efficient tool in signal processing aimed to compressing ECG signals. Uniwavelets are well known for their reasonable approximation and data compression properties. Recently, a lot of interest has been focused on the study of multiwavelets. Multiwavelet, due to a larger flexibility in constructing smooth, compactly supported and symmetric scaling functions, have even better approximation and data compression properties, see the discussion in [3],[4] and [5]. Also applying multiwavelets in signal processing [6,7,8,9], compression [8,10,11] and noise elimination [8,11,12] indicate the superiority of multiwavelet to wavelet.

Since reasonable results have been achieved by SPIHT algorithm in image compression and subjects that mentioned above, in this paper we suggest the application of SPIHT algorithm to 2-D multiwavelet transform of ECG signals.

II. CONSTRUCTION OF TWO DIMENSIONAL ECG ARRAY

We used the technique reported in [13] for delineating cycles, period and amplitude normalization. The period of each beat is normalized using multirate techniques and set to a constant number, i.e. 128 samples. This produces beats with a constant period, eliminating the effect of heart rate variability. First interpolating by a factor L, which is the constant number chosen to be the fixed period and then by down sampling with the appropriate factor for each cycle, the length of each cycle becomes uniform hence period normalization is performed. The factor L is chosen to have a high value, so that there would be no error in down sampling.

Let \( x(n) \) be the input of an interpolation filter with an upper sampling factor \( L \) and an impulse response \( h(n) \). Then the output \( y(n) \) is given by:

\[
y(n) = \sum_{k=-\infty}^{\infty} x(k) h(n - kL)
\]  

(1)

The up sampler just inserts \( L-1 \) zeros between successive samples. The filter \( h(n) \), which operates at a rate \( L \) times higher than that of the input signal, replaces the inserted zeros.
with interpolated values. The polyphase implementation of this filter insures efficient interpolation. The output of a
decimation filter \( y(n) \) with a down sampling factor \( M \), is given by:

\[
y(n) = \sum_{k=-\infty}^{\infty} k x(k) y(nM - k)
\]  

(2)

Since down sampling causes aliasing, a lowpass filter \( h(n) \)
is used to remove it. If the signal does not contain frequencies
above \( \pi / M \), there is no need for the decimation filter and
only down sampling is enough. Thus the change of sampling
rate is a reversible process provided that the Nyquist condition
is satisfied. The original sampling rate taken back by multirate
techniques is recovered with no distortion. The output of the
system is given by:

\[
y_i(n) = \sum_{k=0}^{p_i-1} x_i(k) h \left( nM_i - kL \right)
\]  

(3)

Where \( x_i(n) \) and \( y_i(n) \) are the \( n \)th samples of the \( i \)th
input beat and output (PAN) beat, respectively. \( p_i \) is the total
number of samples in the \( i \)-th original beat, \( h(n) \) is the impulse
response of the filter and \( L \) and \( M_i \) are the up sampling and
down sampling factors respectively for the \( i \)-th beat vector
[13].

Amplitude normalization is performed in order to make the
beats as similar as possible, and minimizing the variations
between the magnitudes of the beats and setting the highest
amplitude equal to one. A 2-D ECG array created using this
approach is shown in Figure 1.

![Figure 1: Shows 2-D ECG array constructed for record 100 from MIT-BIH database, shown as a grayscale image.](image)

### III. Multiwavelet

#### A. A Short History of Multiwavelet

Multiwavelets constitute a new chapter which has been
added to wavelet theory in recent years. Recently, much
interest has been generated in the study of the multiwavelets
where more than one scaling functions and mother wavelet are
used to represent a given signal.

The first construction for polynomial multiwavelet was
given by Alpert, who used them as a basis for the
representation of certain operators. Later, Geronimo, Hardin
and Massopust constructed a multiscale function with two
components using fractal interpolation.

In [5], multiwavelets based on Cardinal Hermite splines
were constructed. In spite of the many theoretical results on
multiwavelets, their successful applications to various
problems in signal processing are still limited.

Unlike scalar wavelets in which Mallat's pyramid algorithm
have provided a solution for acceptable signal decomposition
and reconstruction, a reasonable framework for the application
of multiwavelets is still not available. Nevertheless, several
researchers have proposed methods of applying a given
multiwavelet filter to signal and image decomposition. For
example, Xia et al [14, 15] have proposed new algorithm to
compute multiwavelet transformation coefficients by using
appropriate pre and post filtering, and have indicated that the
energy compaction for discrete multiwavelet transform may
be better than that obtained using conventional discrete scalar
wavelet transforms.

#### B. Multiwavelet in Comparison with Wavelet

The multiwavelet idea originates from the generalization of
scalar wavelets. Instead of one scaling function and one
wavelet, multiple scaling functions and wavelets are used.
This leads to a more degree of freedom in constructing
wavelets. Therefore opposed to scalar wavelets, properties
such as compact support, orthogonality, symmetry, vanishing
moments and short support can be gathered simultaneously in
multiwavelets, which are fundamental in signal processing
[8,9].

The increase in degree of freedom in multiwavelets is
obtained at the expense of replacing scalars with matrices,
scalar functions with vector functions and single matrices with
block of matrices. However, prefiltering is an essential task
which should be performed for any use of multiwavelets in
signal processing [8, 14].

#### C. Prefiltering of the Data

One of the challenges in realizing multiwavelets is the
efficient prefiltering. In the case of scalar wavelets, the given
signal data are usually assumed to be the scaling coefficients
that are sampled at a certain resolution, and hence, we directly
apply multiresolution decomposition on the given signal.
But the same technique can not be employed directly in the
multiwavelet setting and same prefiltering has to be performed
on the input signal prior to multiwavelet decomposition. The
type of the prefiltering employed is critical for the success of
the results obtained in the application.

As mentioned above, multifilter banks require a vector valued
input signal. There is a number of ways to produce such a
signal from 2-D image data. Perhaps the most obvious method
is to use adjacent rows and columns of the image data; and
this has already been attempted. There could be infinitely
many ways to do such prefiltering. There exist well known
prefilters in literature [14-16]. The most obvious way to get
the second input row is just to repeat the first one and use two
identical rows of length \( n \).

A different way to get the input rows for the multiwavelet
filterbank is to preprocess the given scalar signal \( f(n) \). In our
implementation, we first refer to Repeated Row (RR) and
second we refer to Approximation prefilter (App). RR
representations have proven useful in feature extraction; however, they require more calculation than APP representations. Furthermore, in data compression applications, one is seeking to remove redundancy, and not to increase it. Thus in this paper we apply the multiwavelet with approximation prefiltering. Experimental results shows that in this case, SA4 multiwavelet based on APP prefiltering method, slightly outperforms the other multiwavelets used in this study that CL, GHM, BIGHM6 and Cardbal4 multiwavelets.

IV. SPIHT CODING ALGORITHM

A. Overview of SPIHT

In this paper we use SPIHT coding algorithm for coding wavelet transform of ECG signal. Set partitioning in hierarchical trees (SPIHT) is an embedded coding technique. In an embedded coding algorithm, all encodings of the same signal at lower bit rates (than target rate) are embedded at the beginning of the bit stream for the target bit rate. So we can use any amount of bits received for decoding, at a lower bit rate that can be achieved when using the whole bit stream of the coded signal. Effectively, bits are ordered in the order of importance. This type of coding is especially useful for progressive transmission and transmission over a noisy channel. Using an embedded code, an encoder can terminate the encoding process at any point, thereby allowing a target rate or distortion parameter to be met exactly. Typically, some target parameters, such as bit count, is monitored in the encoding process and when the target is met, the encoding simply stops. Similarly, given a bit stream, the decoder can cease decoding at any point and can produce reconstruction corresponding to all the lower rate encodings. Embedded coding is similar in spirit to binary finite precision representations of real numbers. All real numbers can be represented by a string of binary digits. For each digit added to the right, more precision is added. Yet, encoding can cease at any time and provide the best representation of the real number achievable within the framework of the binary digit representation. Similarly, the embedded coder can cease at any time and provide the best representation of the signal achievable within its framework.[4]

B. Proposed Compression Algorithm

To compress the 2-D array, there are many 2-D compression algorithms available, which are mostly used in image compression. In this paper, the 2-D multiwavelet transform by SPIHT (Set Partitioning in Hierarchical Trees) coder is selected for implementing the 2-D transform. Figure 2 shows the block diagram of the proposed method. First, we make the 2-D array, which is a matrix. Then we apply 2-D multiwavelet on it. Then For assisting the SPIHT algorithm, we apply SPIHT codec over each rows of the coefficients transform same as [17].

V. RESULTS AND DISCUSSION

We used data from the MIT-BIH arrhythmia database to test the performance of our proposed algorithm. All ECG data used here are sampled at 360 Hz, 11 bits/sample.

We used PRD to measure distortion between the original signal and the reconstructed signal. PRD can be defined as:

$$PRD = \frac{\sum(x_{or} - x_{re})^2}{\sum(x_{or})^2} \times 100\%$$

where $x_{or}$ and $x_{re}$ are the original and reconstructed signals of length $N$, respectively. Since the data used in the literatures are usually different in the sampling frequency, and resolution, exact comparisons are inconclusive. Nonetheless, we compared the PRD result for similar compression ratios.

We used record numbers 100, 101, 102, 103, 107, 117, 118, 119, 201, 209, 212, 215, 217, 219 and 234 of MIT-BIH database which consist of different rhythms, QRS complexes and morphologies and entopic beats. We compressed 2 minutes of data from each of these records. We report compression ratios from actual compressed file sizes and PRDs from decompressed files. Figure 3 shows the PRD result value versus CR for each record of data and the average PRD values of this dataset are presented in Table 1.

![Figure 2 Block Diagram of the proposed algorithm.](image)

![Figure 3. The PRD results of MIT-BIH ECG data](image)

<table>
<thead>
<tr>
<th>CR</th>
<th>8</th>
<th>10</th>
<th>14</th>
<th>18</th>
<th>22</th>
<th>26</th>
<th>28</th>
<th>30</th>
</tr>
</thead>
<tbody>
<tr>
<td>PRD</td>
<td>2.14</td>
<td>2.52</td>
<td>3.33</td>
<td>4.20</td>
<td>5.08</td>
<td>5.93</td>
<td>6.34</td>
<td>6.72</td>
</tr>
</tbody>
</table>

TABLE 1. AVERAGE TEST RESULT FOR THE DATASET
From Figure 3 we see that the results for all data are approximately close to each other. This means the proposed algorithm is suitable for a variety of ECG data. For the sake of comparing our method with other methods in the literature for different CRs and records, the algorithm was applied to records 117 and 119 from MIT-BIH database. Hilton presented a wavelet and wavelet packet based EZW encoder [2]. He reported the PRD value of 2.6% with compression ratio 8:1 for record 117 and compared it with the best previous results. The PRD value of the proposed method here is 1.83% for the same record and compression ratio which is significantly better than the encoders in [18] and [19]. In order to compare to ASEC [20], for record 119, they reported PRD result 5.5% at bitrate 183 bps, compared to our PRD of 4.87% at the same bitrate. The summary of this comparison appears in Table II. The simulation result for selected records indicate that the proposed method has good progressive reconstruction quality, and that the reconstruction quality degrades gracefully all the way up to very high compression ratios, such as CR=90. Finally, to illustrate the progressive decompression quality of the presented method in order to investigate the effect of compressing ECG signals using proposed method from the clinical point of view, three waveforms including original, reconstructed waveforms and difference between original and reconstructed signal (error) of records 117, at the different CRs, are shown in Figure 4. Note that reconstructed ECG signals are smoothed versions of the original signals.

<table>
<thead>
<tr>
<th>Algorithm</th>
<th>Record</th>
<th>CR</th>
<th>PRD(%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hilton [18]</td>
<td>117</td>
<td>8:1</td>
<td>2.6</td>
</tr>
<tr>
<td>Djohan et al. [19]</td>
<td>117</td>
<td>8:1</td>
<td>3.9</td>
</tr>
<tr>
<td>Proposed</td>
<td>117</td>
<td>8:1</td>
<td>1.83</td>
</tr>
<tr>
<td>ASEC [20]</td>
<td>119</td>
<td>21.6:1</td>
<td>5.5</td>
</tr>
<tr>
<td>Lu et al. [17]</td>
<td>119</td>
<td>21.6:1</td>
<td>5</td>
</tr>
<tr>
<td>Proposed</td>
<td>119</td>
<td>21.6:1</td>
<td>4.87</td>
</tr>
</tbody>
</table>

VI. CONCLUSION

In this paper, we proposed a new ECG compression scheme which combines the efficiency of multiwavelet transform and SPIHT algorithm. It should be noted that a further improvement in results may be achieved with sophisticated implementation of multiwavelet transform by considering computationally cost and effective prefiltering methods.

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