World Academy of Science, Engineering and Technology
International Journal of Biomedical and Biological Engineering
Vol:3, No:11, 2009

A Novel Compression Algorithm for Electrocardiogram Signals based on Wavelet Transform and SPIHT

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Abstract**—**Electrocardiogram (ECG) data compression algorithm is needed that will reduce the amount of data to be transmitted, stored and analyzed, but without losing the clinical information content. A wavelet ECG data codec based on the Set Partitioning In Hierarchical Trees (SPIHT) compression algorithm is proposed in this paper. The SPIHT algorithm has achieved notable success in still image coding. We modified the algorithm for the one-dimensional (1-D) case and applied it to compression of ECG data.

By this compression method, small percent root mean square difference (PRD) and high compression ratio with low implementation complexity are achieved. Experiments on selected records from the MIT-BIH arrhythmia database revealed that the proposed codec is significantly more efficient in compression and in computation than previously proposed ECG compression schemes. Compression ratios of up to 48:1 for ECG signals lead to acceptable results for visual inspection.

Keywords**—**Discrete Wavelet Transform, ECG compression, SPIHT.

I. INTRODUCTION

MULTICHANNEL ECG data provide cardiologists with essential information to diagnose heart disease in a patient. In an ambulatory monitoring system, the volume of ECG data is necessarily large, as a long period of time is required in order to gather enough information about the patient. As an example, with the sampling rate of 360 Hz, 11 bits/sample data resolution, a 24-hours record requires about 43 Mbytes per channel. Therefore, an effective data compression scheme for ECG signals is required in many practical applications including:
(a) ECG data storage; (b) ambulatory recording systems; and (c) ECG data transmission over telephone line or digital telecommunication network.

Many lossless and lossy compression techniques have been presented in literature. The current compression methods can be classified into two classes: direct methods and transformational methods [1]. In the first class of methods, the signals are processed in a time domain where the samples that do not have important information for reconstruction are eliminated (polynomial predictor and polynomial interpolator). The ECG signals can also be compressed in a time domain by quantizing and entropy coding the differential values between the real and predicted samples.

In the second class of methods, the signal is processed and coded in the transformational domain, such as Fourier Transform (FT) and Karhunen- Loeve Transform (KLT), Fast Walsh transform, Discrete Cosine Transform (DCT) [2,3] and wavelet transform [4–8]. In [9], a review for the ECG compression methods that have been reported for about three decades is given.

Transform based compression techniques are based on the application of linear orthogonal transformation to a set of ECG samples. Among these, wavelet transform based ECG data compression techniques have received significant attention because of their good localization properties in the time and frequency domains, energy compaction ability, easy implementation and efficiency. Recently, many one-dimensional (1D) and two-dimensional (2D) wavelet transform based compression algorithms with low reconstruction error and smooth signal qualities are reported. It is important to find the best compression method for all different shapes of ECG signal regardless of heart disease of patient.

This paper presents a very effective transformational approach for ECG compression using wavelet transform and SPIHT coding. The SPIHT algorithm is a highly refined version of the Embedded Zerotrees of Wavelet (EZW) transforms algorithm. It was introduced in Said and Pearlman [10, 11] which has shown superior results in image compression and wavelet compression of ECG signals [12]. ECG reconstruction is accomplished by the inverse of the wavelet transform. The forward and inverse wavelet transforms are efficiently implemented by a pair of appropriately designed Quadrate Mirror Filters (QMFs).

The compression ratio depends on the parameters how ECG signal is digitized (sampling frequency and number of bits per sample) and the level of decomposition. In this paper, compression of ECG signal is quantized with 11 bits per sample and by sampling frequency of 360 Hz.

The remainder of this paper is structured as follows. In section 2 the compression method used in this work are presented. In section 3, the compression algorithm is detailed. In section 4 results and discussion are shown and finally, the

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conclusions are given in section 5.

II. Compression Method

In this section, we present a compression scheme. Here, the details of the encoding scheme are explained given that the incoming signal has been decomposed. This compressor does not need any signal pre-processing such as QRS complex detection and no a priori signal knowledge is required. The compression processing can be divided into subsequent (see Figure 1):

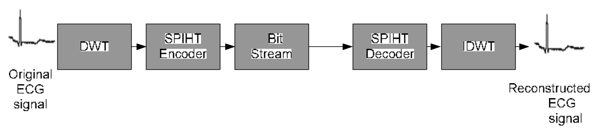

Fig. 1 Block diagram of a wavelet transform based ECG compression method using SPIHT algorithm

Every input block of N samples is decomposed using Discrete Wavelet Transform (DWT). DWT is one of the most powerful tools in digital signal processing. It is often used in compression methods because of its energy compaction ability. A signal can be represented by scaling and translating a short wave called wavelet. Discrete coefficients describing the scaling and translations are called wavelet coefficients. In the DWT decomposition algorithm, every coefficient at any scale is related with two other coefficients at the immediate lower scale. The set of wavelet coefficients gives a less redundant alter-native representation of the signal well suited for compression.

The DWT can be represented as a dyadic filter bank with level n. For most physical signals the signal energy is concentrated in the lower frequency bands, thus this representation gives energy compaction. So, based on problems mentioned above, finding a wavelet that has the most energy compaction is an important subject in signal compression. Many of the resulting wavelet coefficients, especially in the higher frequency bands, are either zero or close to zero. By coding only the larger coefficients, many bits are already discarded without loosing significant information.

After applying wavelet transform on ECG signal, we can represent it using trees because of the sub-sampling that is performed in the transform. A coefficient in a low subband can be thought of as having four descendants in the next higher subband (see Figure 2). The four descendants each also have four descendants in the next higher subband and we see a quad-tree emerge. Tree-based algorithm is set partitioning in hierarchical trees (SPIHT) algorithm. This is used for efficient quantization and coding of wavelet coefficients. We can now give a definition of the zerotree. A zerotree is a quad-tree of which all nodes are equal to or smaller than the root. The tree is coded with a single symbol and reconstructed by the decoder as a quad-tree filled with zeroes.

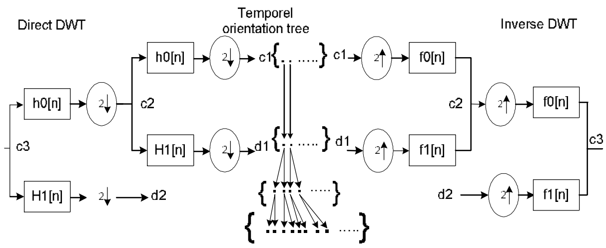

Fig. 2 The relations between wavelet coefficients in different subbands as quad-trees.

This correspondence is iterated through scale, giving the temporal orientation tree. In the encoding process, the whole set of coefficients of a zerotree can be referenced by its root, which is the first coefficient of the temporal orientation tree at the lower scale. Also, a coefficient is called significant if its magnitude is greater than a given threshold value. The method of setting the value of coefficient to zero if the absolute value of a coefficient is below the threshold defined, is calling "thresholding". It is very important to select appropriate value for threshold. Large threshold values lead to very good compression but distortion might appear in reconstruction. Small threshold values lead to low compression but reconstructed signal is very similar to the original one. ECG reconstruction is accomplished by inverting the compression operations through the use of the inverse of the SPIHT coding (SPIHT decoder) to reconstruct the wavelet coefficients, followed by the inverse of the wavelet transform to get the reconstructed ECG signal.

III. Details of SPIHT Algorithm

Here we explain the details of 1-D SPIHT based on 1-D DWT coefficients of a signal. We directly apply the 1D-SPIHT codec over the subband coefficients from wavelet decomposition up to three, four or five levels. There are three important definitions in the 1D- SPIHT parent-offspring relationship as shown in Figure 3:

1) $O(i)$: offspring $O(i)$ represents the set of the 2 coefficients (as pointed by arrows) of next higher subband from coefficient $X(i)$.

2) $D(i)$: the descendent $D(i)$ of coefficient $X(i)$ is the set containing all offspring in all later subbands.

3) $L(i)$: a set defined by $L(i) = D(i) - O(i)$

The 1D-SPIHT algorithm assumes that each coefficient $X(i)$ is a good predictor of the coefficients which are represented by the sub-tree rooted by $X(i)$, i.e. $D(i)$.

The overall procedure is controlled by an attribute, which gives information on the significance of the coefficients.

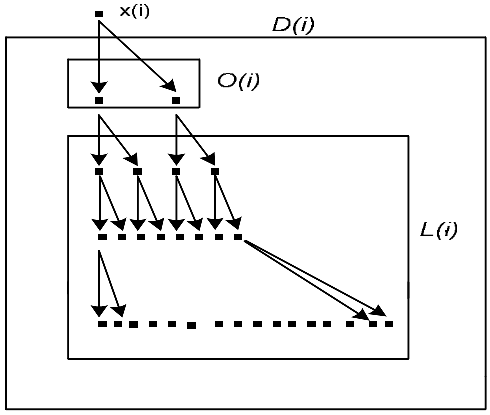

Fig. 3 The definition of parent-offspring relationship in 1-D SPIHT

The wavelet-transformed signal is searched for the largest magnitude which defines the threshold *k* with the highest significance.

$$k = \left\lfloor \log_2 \max_i |x_i| \right\rfloor, 0 \le i \le K, \qquad (1)$$

Where *k* denotes the number of DWT coefficients.

A coefficient of the wavelet transformed signal is significant with respect to a threshold *k* if its magnitude is larger than 2^k. Otherwise it's called insignificant with respect to the threshold *k*. it can described as:

$$S_k(x_i) = \begin{cases} 1, & \text{if } |x_i| \ \ge \ 2^k \\ 0, & \text{otherwise} \end{cases} \qquad (2)$$

Where $S_k(x_i)$ denotes the significance of x_i with respect to a threshold *k*.

In the 1D-SPIHT, the wavelet coefficients are classified in three sets, namely the list of insignificant points (LIP) which contains the coordinate of those coefficients that are insignificant with respect to the current threshold *k*, the list of significant points (LSP) which contains the coordinates of those coefficients that are significant with respect to *k*, and the list of insignificant sets (LIS) which contains the coordinates of the roots of insignificant sub-trees.

We use 22 steps to depict the overall 1D-SPIHT coding process as follows:

(0) *Initialization*

LIP= All elements in *H*, where *H* is a set of all roots coordinates in the top-most lowpass subband.

LSP = Empty

LIS = D's of Roots

The empty set is assigned to the LSP since no coefficient is significant yet. The tree roots *H* are added to the LIP and those with descendants to the LIS.

(1) *Sorting Pass*

(2) For each $i \in$ LIP

(3) Output $s_k(x_i)$;

(4) If $s_k(x_i)$=1, then

Move i to the LSP and Output sign of coeff(i): 0/1 = -/+

Endif

End loop over LIP

(5) For each $i \in$ LIS

(6) If type D, then

(7) Send $s_k(D(i))$;

(8) If $s_k(D(i))$ =1, then

(9) For each $j \in O(i)$

(10) output $s_k(x_j)$;

(11) If $s_k(x_j)$=1, then

add j to the LSP and output the sign of x_j;

(12) else append j to LIP;

End if

End for

(13) else (type L)

(14) Send $s_k(L(i))$

(15) If $s_k(L(i))$ =1, then

(16) add each $j \in O(i)$ to the end of the LIS as an entry of type D

(17) remove i from the LIS

(18) End if on type

(19) End loop over LIS

(20) Refinement Pass

(21) For each element $i \in$ LSP except those just added above Output the kth most significant bit of $|x_i|$

End loop over LIS

Update

(22) Decrement k by 1

Go to Significance Map Encoding Step (1)

In the 1D-SPIHT, wavelet coefficients are arranged in a parent-offspring orientation tree in order to exploit the spatial self-similarity property of wavelet coefficients across subbands. The property implies that if a node coefficient is insignificant with respect to a given threshold, probably all nodes descending from that are insignificant too.

IV. Results and Discussion

The ECG signals used in simulation are from MIT-BIH arrhythmia database. This database includes different shapes of ECG signals. The records used are 100, 101, 102, 103, 104, 105, 106, 107, 118, 119, 200, 201, 202, 203, 205, 207, 208, 209, 210, 212, 213, 214, 215, 217 and 219 (25 records).

The distortion between the original and the reconstructed signal was measured by percent root mean square difference (PRD). PRD is easy to calculate and compare, and is widely used in the ECG compression literature. The PRD is given by:

$$PRD = \sqrt{\frac{\sum_{n=0}^{N-1}\left[x_{org}(n) - x_{rec}(n)\right]^2}{\sum_{n=0}^{N-1} x_{org}^{2}(n)}} \times 100\% \quad (3)$$

Where x_{org} denotes the original data, x_{rec} denotes the reconstructed data, and N, the number of samples.

The compression ratio (CR) is calculated as the number of bits in the original signal over the number of bits in the compressed signal.

$$CR = \frac{\text{number of bits in the original signal}}{\text{number of bits in the compressed signal}} \quad (4)$$

The comparison of compression ratios and quality of reconstructed signal is done by changing the following parameters: Level of decomposition and wavelet used, for DWT and number of filters and appropriate number of filter's coefficients. All of our tests are applied on the first 1024 samples from MIT-BIH records. We retain the same number of largest coefficients for each wavelet, and then invert the algorithm to reconstruct the signal and measure the performance of each wavelet.

The investigation of the obtained results shows that Daubechies (*D*4), symmetrical (sym6), biorthognonal (bior4.4) and coiflet (coif2) perform better than the other wavelets. They provide the minimum PRD and the maximum CR. The final results of 25 records from MIT-BIH database are shown in Figure 4.

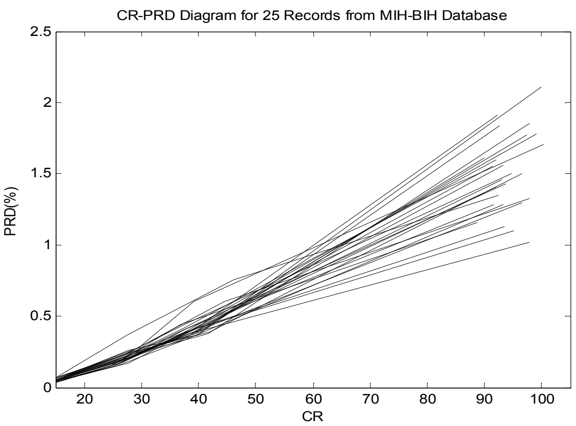

Fig. 4 CR-PRD results for 25 records from MIT-BIH database

The PRD slightly increases by increasing CR. Here, it should be mentioned that in ECG compression, not only we deal with normal ECG signals, but also we mostly deal with ECG signals with arrhythmia that in general have not a simple and common pattern.

The results of applying the Bior4.4 wavelet with SPIHT coding algorithm to records 117, 118, 119, 107, 102, and 203 are shown in Figures 5 to 9. In each figure, the original and reconstructed signals and difference between them (error) is plotted. The values of CR and PRD are also shown in figures.

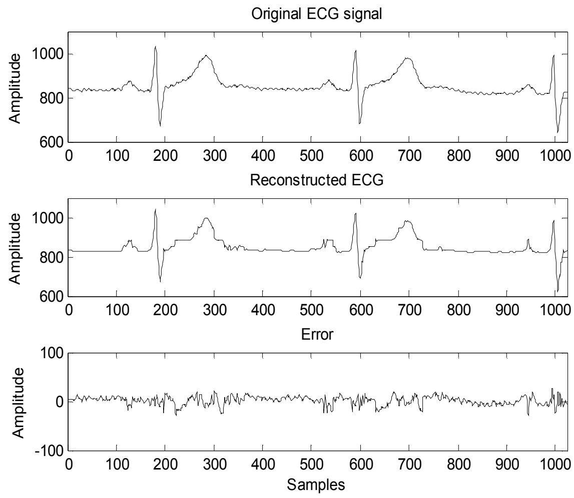

Fig. 5 ECG 117 with CR= 45, PRD=1.06
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

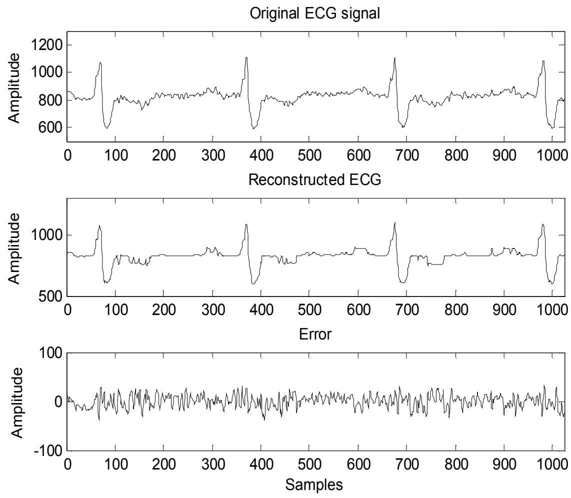

Fig. 6 ECG 118 with CR= 48.08, PRD= 1.53
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

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TABLE I
COMPARISON BETWEEN THE PROPOSED METHOD AND OTHER COMPRESSION ALGORITHMS (THE RECORD 117 AND 119)

Methods	Signals	CR	PRD (%)
Proposed method	117	45:1	1.06
	119	45.83:1	1.31
Wavelet and Huffman [10]	117	9.4:1	3.2
SPHIT [12]	117	8:1	1.18
	119	21.6	5
Hilton [11]	117	8:1	2.6
Djohn [11]	117	8:1	3.9
AZTEC [9]	117	10:1	28
TP [9]	117	2:1	5.3
CORTES [9]	117	4.8:1	7
JPEG2000 [13]	117	10:1	1.03

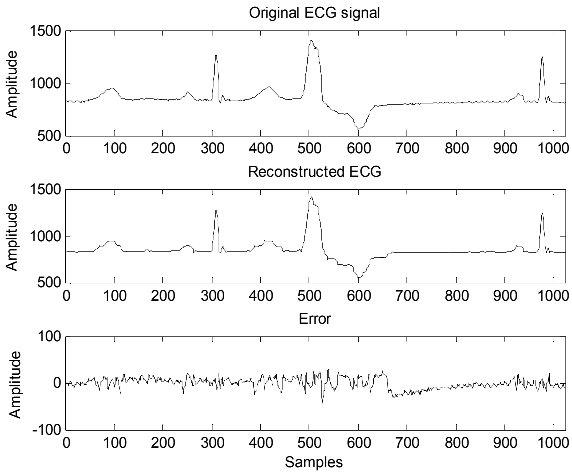

Fig. 7 ECG 119 with CR= 45.83, PRD=1.31
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

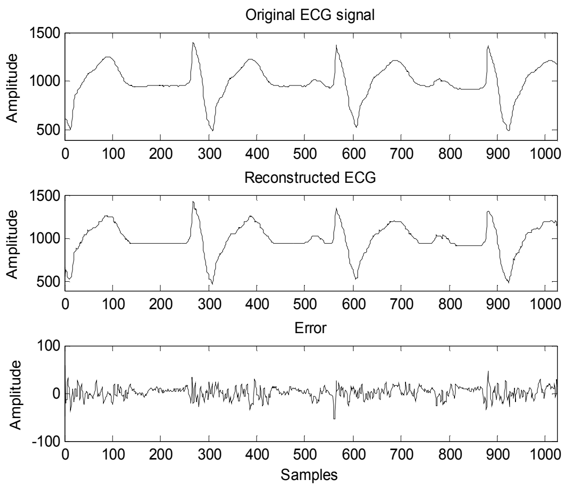

Fig. 8 ECG 107 with CR= 48.15, PRD= 1.18
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

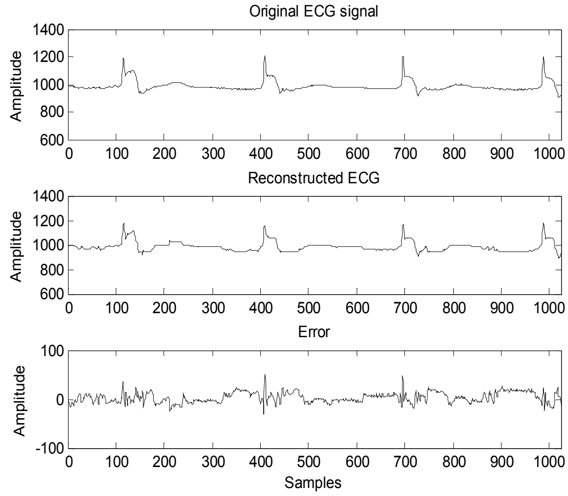

Fig. 9 ECG 102 with CR=46.41, PRD= 1.10
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

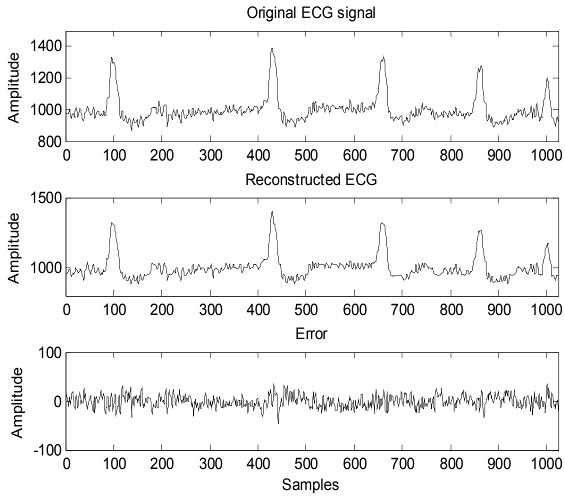

Fig. 10 ECG 203 with CR= 48.38, PRD= 1.18
Top figure is original signal, the middle is reconstructed signal and bottom signal is error

The figures indicate that the characteristic features of the signal are preserved well in the reconstructed signals and the main effect of the proposed method is the smoothing of background noise.

The results showed that our coding algorithm has following features: Our algorithm compresses all kinds of ECG data very efficiently, perhaps more efficiently than any previous ECG compression method.

The proposed method has been compared with some other compression techniques [9], [10], [11], [12] for the records 117, 119 and the results are presented in Table 1.

In Table I, the proposed method is compared to other methods in literature for different CR's and records. The methods in this table include other wavelet-based coders, as well as the parametric ECG signal coder AZTEC [9].

Although the proposed method compares favourably with other methods in terms of PRD, it should be noted that a diagnostic quality assessment would be required to compare the clinical utility of different methods.

V. Conclusion

We proposed an ECG data compression codec based on 1-D SPIHT coding algorithm. Discrete Wavelet Transform, mentioned, samples of signals are transformed to groups of transformation coefficients. Almost all coefficients below the determined threshold are rounded to zero values and by inverse transform the similar signal to original one is created. In this way small number of coefficients is stored, and compression is obtained. The proposed method is rather fast and easy to implement and leads to high CR with a good reconstructive quality. We test its performance by coding several records in MIT-BIH ECG arrhythmia database and compared the results to other methods.

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