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:

$$y(n) = \sum_{k=-\infty}^{\infty} x(n)\, h(n-KL) \tag{1}$$

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 :

$$y(n) = \sum_{k=-\infty}^{\infty} x(k) y(nM - k) \tag{2}$$

Since down sampling causes aliasing, a lowpass filter h(n) is used to remove it. If the signal does not contain frequencies above π / 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 :

$$y_i(n) = \sum_{k=0}^{p_i - 1} x_i(k) h(nM_i - KL) \tag{3}$$

Where $x_i(n)$ and $y_i(n)$ are the nth samples of the ith 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.

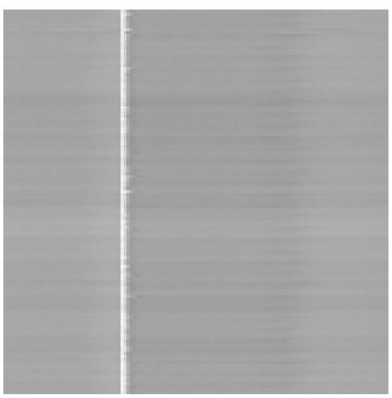


Figure 1.Shows 2-D ECG array constructed for record 100 from MIT-BIH database, shown as a grayscale image.

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 multiscaling 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 prefilter. 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.

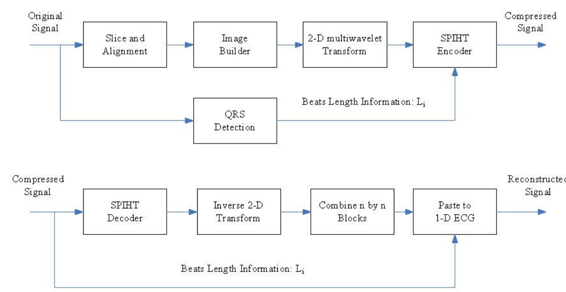


Figure 2 Block Diagram of the proposed algorithm.

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

$$PRD = \sqrt{\frac{\Sigma\left(x_{or} - x_{re}\right)^2}{\Sigma\left(x_{or}\right)^2}} \times 100\% \qquad (4)$$

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.

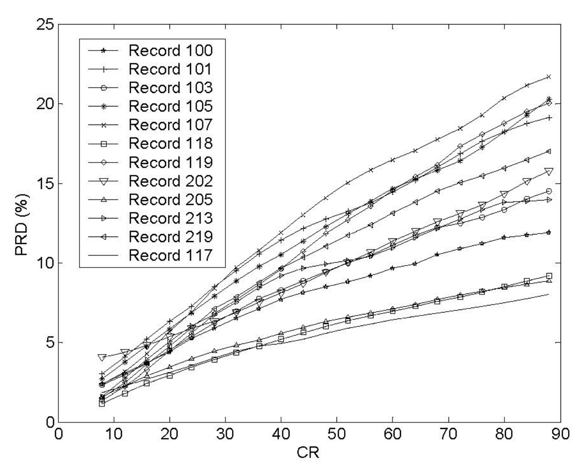


Figure 3. The PRD results of MIT-BIH ECG data

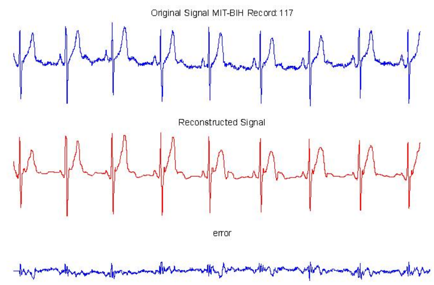
TABLE I. AVERAGE TEST RESULT FOR THE DATASET

CR	***8***	***10***	***14***	***18***	***22***	***26***	***28***	***30***
PRD	***2.14***	***2.52***	***3.33***	***4.20***	***5.08***	***5.93***	***6.34***	***6.72***

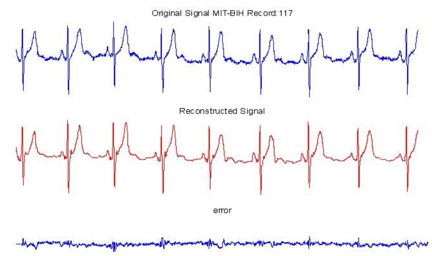
From Figure 3 we see that the results for all data are approximately close to each other. This means the proposed algorithm is suitable for a variety of ECG data. For the sake of comparing our method with other methods in the literature for different CRs and records, the algorithm was applied to records 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 II. PRD COMPARISON OF DIFFRENRENT ALGORITHM

Algorithm	Record	CR	PRD(%)
Hilton [18]	*117*	*8:1*	*2.6*
Djohan et al. [19]	*117*	*8:1*	*3.9*
Proposed	*117*	*8:1*	*1.83*
ASEC [20]	*119*	*21.6:1*	*5.5*
Lu et al. [17]	*119*	*21:6:1*	*5*
Proposed	*119*	*21.6:1*	*4.87*



(a)



(b)

(c)

Figure 4.Compressing ECG using the SA4 with App prefiltering method. The above figure shows the original signal, the middle shows reconstructed signal after compression and the bottom shows the error between them. The first 2048 samples of MIT-BIH record 117 are showed. CR=8, PRD=1.83%

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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REFRENCES

[1] A. Said, W. A. Pearlman, "A New, Fast and Efficient Image Coder Based on Set Partitioning in Hierarchical Trees," IEEE Trans. On Circuits and System for Video Technology., vol. 6, pp. 243-250, June 1996.

[2] S. M. S. Jalaleddine, C. G. Hutchens, R. D. Strattan, and W. A. Coberly, "ECG data compression techniques- a unified approach," IEEE Trans. Biomed. Eng., vol. 37, no. 4, pp. 329-343, Apr. 1990.

[3] T. D. Bui and G.Chen, "Translation-invariant denoising using multiwavelets," IEEE Trans. Signal Processing. vol. 46, pp. 3414-3420, Dec. 1999.

[4] S. Mallat, "A Wavelet Tour of Signal Processing," New Yourk: Cambridge Univ. Press, 1999.

[5] V. Strela and A. T. Walden, "Signal and image denoising via wavelet thresholding: Orthogonal and biorthogonal, scalar and multiple wavelet transforms," in Nonlinear and Nonstationary Signal Processing, W. J. Fitzgerald, R. L. Smith, A. T. Walden, and P. C. Young, Eds. Cambridge, U.K.: Cambridge Univ. Press, 2001, pp. 124-157.

[6] M. Cotronei, L. B. Montefosco, and L. Puccio, " Multiwavelet analysis and Signal Processing," IEEE Trans. Circuit and System, vol.45,no.8, pp. 970-987, Aug.1998.

[7] V. Strela, P.N. Heller, G. Strang, P. Topiwala, C. Heil, "The application of multiwavelet filter banks to image processing," IEEE Trans. Image processing, vol. 8(4), pp.548-563, April 1999. (Also Technical Report, MIT, Jan. 1996)

[8] V. Strela, Multiwavelets: Theory and Application, PhD. Thesis, MIT, 1996.

[9] H. Soltanian- Zadeh and K. Jafari-khouzani," Multiwavelet gradind of prostate pathological images," Processings of SPIE Medical Imaging conference, San Diago, CA, feb.2002.

[10] P. N. Heller, V. Strela, G. strang, P. Topiwala, C. Heil, and L. S. Hills, " Multiwavelet filter banks for data compression," IEEE proc. of the Int. symp. on Circuits and System, pp. 1796-1799, 1995.

[11] M. Cotronei, D. Lazzaro, L. B. Montefusco, and L. Puccio,"Image Compression Through Embedded Multiwavelet Transform Coding ," IEEE Trans. Image Proc., vol. 9, No. 2, pp.184-189,Feb. 2000.

[12] T. R. Dowine, and B. W. silverman," The discrete multiple wavelet transform and thresholding methods," Technical Report, University of Bristol, November 1996. (Also in IEEE Trans. On Signal Processing, vol.46, pp. 2558-2561, 1998)

[13] Ramakrishnan AG,Saha S. "ECG Coding by Wavelet based Linear Prediction.," IEEE Trans. Biomed. Eng., vol. 44, No. 12, pp.1253-1261, 1997.

[14] T. N. T. Goodman and S. L. Lee, "Wavelet of Multiplicity r", Trans. Amer. Math Soc., vol. 342, pp. 307-329, 1994

[15] [X. G. Gia, " A New prefiter Design for Discrete Multiwavelet transforms," IEEE Trans. Signal Processing, vol. 46, No.6, pp.1558-1570, 1998.

[16] G. Plonka and V. Strela," From wavelet to multiwavelets," Math Methods for Curves and Surf. II., M. Dahlem, T. Lyche, L. Shumaker (Eds), Vanderblt University Press, pp.375-399, 1998.

[17] Zhito Lu, Dong Yong kim, Pearlman, W.A. "Wavelet compression of ECG signal by the set portioning in hierarchical trees algorithm," IEEE Trans. Biomed. Eng., vol. 47, No. 7, pp. -856, July. 2000.

[18] Michael L. Hilton, "Wavelet and Wavelet Packet Compression of Electrocardiograms," IEEE Trans. Biomed. Eng., vol. 44, pp. 394-402, May 1997.

[19] A. Djohan, T. Q. Nguyen, and W. J. Tompkins, "ECG Compression Using discrete symmetric wavelet transform," Cardinal multiwavelets and the sampling theorem," Proc. Of IEEE Int. Conf. in Medicine and Biology, 1995.

[20] Y. Zigel, A. Cohen, A. Abu-ful, and A.Katz,"Analysis by Synthesis ECG Signal Compression," Computer in Cardiology, Vol.24, pp. 279-282, 1997.