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Analysis of EZW compression scheme applied for ECG signal compression

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ABSTRACT
Although digital storage media is not expensive and computational power has exponentially increased in the recent years, the possibility of electrocardiogram (ECG) compression still attracts the attention, due to the huge amount of the growing data that has to be stored or transmitted. The data's growth depends on the factors like the sampling rate, quantization levels and number of sensors per minute per patient, depending upon the time and amplitude, sampling rate etc. Besides the increased storage capacity for archival purposes, ECG compression also allows real-time transmission over telephone networks, economic off-line transmission to remote interpretation sites etc. ECG compression methods attempt to reduce the dimensionality of the non stationary and quasi periodical ECG signal, while retaining all clinically significant features including P-wave, QRS complex and the T-wave. Wavelets have recently been emerged as powerful tools for signal compression. A two-dimensional (2-D) wavelet-based electrocardiogram (ECG) data compression method that employs embedded zero tree (EZW) based compression algorithm is proposed in this paper. The reconstruct signal guaranteed the same RR interval as the original signal which is the major attraction presented in this paper. Records selected from the MIT-BIH arrhythmia database are tested and the experimental results show that the proposed method not only achieves high compression ratio with relatively low distortion but also is effective for various kinds of ECG morphologies.

Index Terms: ECG Compression, EZW, wavelet transform, and compression ratio.

1. INTRODUCTION
An electrocardiogram (ECG) is a basic diagnosis method to analyze the functioning of the heart. Since huge amount of data are generated over the period, there arises the need for an efficient compression algorithm, which can be good enough to store the data efficiently and cater the needs of the clinical acceptance.

Out of the numerous wavelet based compression algorithms [1]-[4], the embedded zero tree wavelet concept (EZW) [5] is proposed to be more capable to compress the signal. The heart beat signal shows some similarity between the adjacent heart beat signal [6]. The EZW compression algorithm preserves this property by converting the ECG signal into 2-D or image [7]. The paper is organized in the following way:

(i) *Wavelet transform:*
The wavelet transform which converts the signal in time domain to frequency domain

(ii) *Embedded Zero tree:*
Zero tree algorithms, which detect the significant data based on their importance.

(iii) *EZW based encoding & decoding:*
Encoding and compression based on EZW algorithm

(iv) *Experimental Results:*
The reconstructed signal is analyzed based on the compression ratio and RR interval (heart rate).

2. WAVELET TRANSFORM
Discrete Wavelet Transform (DWT) transforms discrete signal from time domain to time-frequency domain. The transformation product is a set of coefficients organized in the way that enables not only spectrum analysis of the signal, but also spectral behavior of the signal in time. This is achieved by splitting the signal f(t) into different frequency resolution based on the mother wavelet ($\psi(t)$) and the scaling factor
(s (n)). [9]

$$\mathbf{W_{\Phi}\,(j, \overline{k}) = 1/\sqrt{M} \sum{}^{n} s\,(n)\, \Phi_{(j0,k)}(n)} \quad \text{----------(1)}$$

$$\mathbf{W_{\psi}\,(j, k) = \overline{1}/\sqrt{M} \sum{}^{n} s\,(n)\, \psi_{(j,k)}(n)} \quad \text{-----(2)} \quad j \geq j0$$

The original signal is now transformed into two different coefficients (W_{Φ}, W_{ψ}) where the scaling function coefficient (W_{Φ}) is obtained by the series of transformation function with different scaling factors. The wavelet coefficient (W_{ψ}) is obtained from the mother wavelet. The scaling operation either dilates or compresses the signal. The low scale (high frequency) corresponds to the detailed information of the signal and vice versa. The normalization factor (M) is used to restore the energy level of the transformed signal as the original signal. The above mathematical function of the wavelet transform can be computed by recursively averaging and differencing coefficients called filter banks [10] which is shown in Fig [1]

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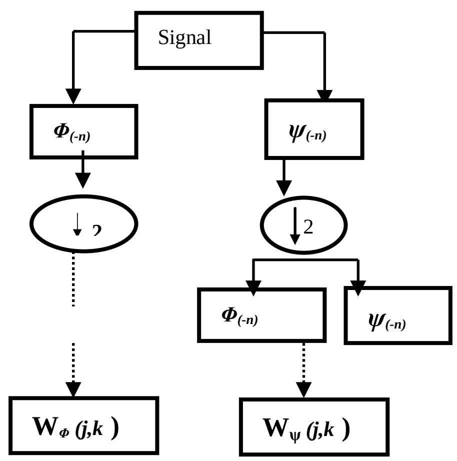
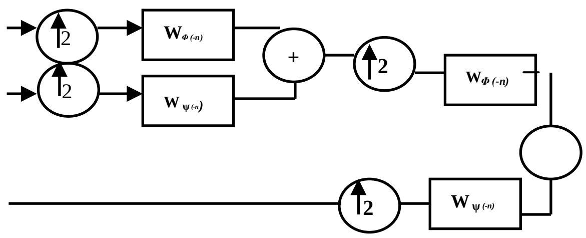


Fig[1] Discrete Wavelet Transform

The filters of different cutoff frequencies are used to analyze the signal at different scales. The signal is passed through a series of high pass filters to analyze the high frequency components and to a low pass filter to analyze the low frequency components. The reconstruction of the signal can be done by reversing the above process. In this reconstruction process, bank of synthesis filters are used, in which the wavelet coefficients and scaling function coefficients are given as an input to the filter. Inverse DWT is given by:

$$s(n)= 1/\sqrt{M} \sum_{k} W_{\Phi}(j,k)\Phi_{(j0,k)}(n)+ \sum^{\infty}_{j=j0} \sum_{k} W_{\psi}(j,k)\, \psi_{(j,k)}(n) \quad ---(3)$$

The inverse DWT filter bank is shown in the Fig(2)



Fig[2].Inverse DWT filter bank

3. EMBEDDED ZERO TREE (EZW)

Embedded zero tree introduced by Shapiro [5] is one of the promising encoding techniques that encodes the bits in the signal based on the importance of the bit. The embedded coder works in the heuristic manner, that it learns the details of the bit in the progressive steps. The Zero tree data structure [11] store the importance of the bits as significant and insignificant coefficients across the scales. This tree is constructed by the prioritized ordering whereby ordering is done based upon the wavelet coefficients scales, the magnitude and spatial location. The largest coefficients are considered to be more important than smaller since the energy level is high and are more important in the reconstruction. The encoding is done in several passes by selecting a different threshold in each pass. Initial thershold T_0 to be

$$T0= 2log2\ (max(Ci)) \quad -------- \quad (4)$$

where Ci is the wavelet coefficient. In each pass the encoding takes place in two steps. In the first step (also called as dominant pass) every coefficient is scanned and assigned one symbol according to the importance of the bit. In this pass, the wavelet coefficient is checked against the threshold. The scanning process begins from the lowest frequency sub bands LL, HL, LH and HH. If the coefficient is greater than the threshold, the bit is marked as significant; otherwise, it is marked as insignificant. The successive scanning process proceeds as per the above-mentioned method with the different threshold T1 (T_0 /2). A parent-child relationship is set between the wavelet coefficients under different sub band frequencies in the hierarchical manner. In the tree, in addition to the significant and insignificant bits, two more symbols are also used. (1) In the tree structure, if the coefficient of the root as well as all the descendents is insignificant then, that root is called ZERO tree roots. (2) ISOLATED zero means the root coefficients are insignificant and the descendants are significant. The significant bit may be positive or negative based on its sign of the bit. The dominant pass is followed by the subbordinate pass in which the significant bits from the dominant pass is encoded as one and the remaning bit as zero.The scanning process ends when the threshold reaches the minimum value.

4. COMPRESSION

The compression of the ECG data is practically implemeted as the following step based on the above techniques.

(i) Noise removal of the 1-D ECG data by Linear digital filtering and 2-D array construction.
(ii) EZW encoding and Decoding.
(iii) QRS detection .

(i) Linear Digital filtering and 2-D array construction:

This is a preprocessing step in the compression process. In this stage, the signal is characterized that is specific to QRS complex by suppressing the irrelevant information.This preprocessing step identifies the nonsignal artifacts, the noise form and its charcteristics. Proper filter has to be designed based upon the characteristcs of the noise. This step employs low pass and high pass filters which remove unwanted information in the ECG data. These filters not only remove the noise but also improve the signal to noise ratio that enhances the QRS complex.The heart beat shows some similarities with the adjacent beat. This correlation is employed for the compression technique which gives better reconstructed signal. In order to restore the adjacent heart beat correlation the 1-D ECG signal have to be fragmented properly and 2-D array is constructed of any size((32 *32),(64 *64),(256 *256) etc). In order to map the 1-D signal to 2-D array, first the QRS peaks of the signal (RRinterval) are to be detected.[12].

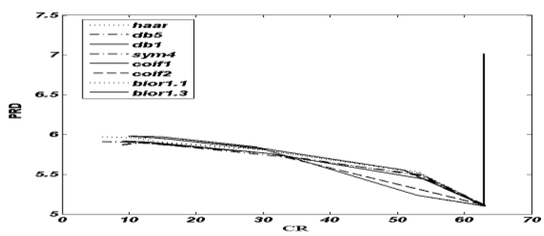
(ii) EZW encoding

The 2-D array of the ECG data block in the time domain is transformed into frequency domain by wavelet transform. The discrete wavelet transform (DWT) decomposes the data into approximation coefficients and detailed coefficient. The transformation is applied by properly selecting the mother wavelet and the filters. The encoding has will be identified according to their importance. To store these data two different arrays have to be maintained (significant array (SA) and insignificant array (ISA)). The encoding algorithm begins with the selection of threshold.

(1) Initial threshold for the encoding is given by

$$T0=2log2\ (max(Ci)$$

(2) Scan the data array against the initial threshold. For each Ci do the following
(3) If Ci< $T_{0,}$ then add it to ISA.Else if Ci ≥ $T_{0,}$ and Ci ≥ - T_0 then, add it to SA and output P and N respectively. Also mark the position of the data as zero so that it won't be scanned in the further passes.If the desecendent of Ci is not significant with respect to the threshold then output R and also remove it from the ISA.Else output as Z.
(4) Encoding of the bits in the SA is done by taking the absolute value of the coefficients. Create an array (EA) which stores the encoded data. For the current



Fig[3] : Performance analysis compression algorithm for the file 121 on the MIT-BIH database using Method I

threshold, scan the SA array and make the index of SA as 1 and 0 for P and N respectively.

(5) Set the new threshold value Ti($T_0/2$) *if* $T_0 > 0$.

Iteration goes on until the threshold reaches the minimum value. Any arithmatic coding like Humann encoding is applied to compress the data[13].

The decoding process is done in the reverse manner of the encoding. For each block of data array, the data is decoded and inverse wavelet transform is applied to recover the data. The decoding process is as follows

(1) Set the initial threshold and set the SA array as empty.
(2) Set the cofficient Ci as zero.
(3) Scan the ISA array and for each data (D) do the following.
If value of D is P, then set Ci =threshold. Else if value of D is N, then set Ci=-threshold. Else if value of D is R, then delete all its descendents. Else if value of D is Z, then do nothing.
(4) Set the new threshold T1 as (threshold /2) until new threshold is greater than zero.

(iii) QRS peak detection:

Various techniques are available to detect the QRS peak. Modified PAN &TOMKINS algorithm[14] is used to find the peak.The reconstructed signal is preprocessed and from the processed signal the discerete derivates are extracted.

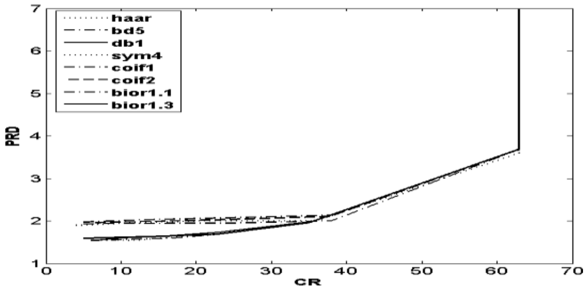
in order to emphasize the high slope of the QRS complex[15] which also supresses the P and T waves. The slope information obtained from the derivaties are given to the moving window integrator which gives the QRS characteristics waveform.The absolute value of the data samples are taken and from this the peaks are detected.The peak selection is done using the threshold method.To set the threshold the whole sample is scanned to find the maximum peak value and set the threshold from this value. Every sample is tested against the threshold. If the sample value is greater than the threshold, then next 100 consecutive samples are checked for the peak(maximum value).This method is applied for various threshold values ,out of this 20% of the maximum value of the integrator gives the better result which is shown in the table[1].

5. EXPERIMENTAL RESULTS

The compression algorithm is tested against the data taken from MIT-BIH arrhythmia database. The signals were acquired at 360 samples per second per channel with 11-bit resolution over a 10 mV range.The total duration of each record is 30 minutes and 5.556 seconds[16]. The compression ratio and percent root mean square difference (PRD) are taken into account to measure the performance of the compression algorithm. The PRD is given by

$$PRD = \sqrt{\frac{\sum_{i=1}^{n} (\text{original}(i) - \text{recon}(i))^2}{\sum_{i=1}^{n} (\text{ori}(i))^2}}$$

where original(i) is the original signal and recon(i) is the reconstructed signal The above technique can be applied to any dimensional array. In this paper, the compression is applied over 64 *64 array. The algorithm is applied over 14 files(100,101,103,105, 107,109,111, 112,113, 116, 117, 118, 121, 122) in the database for 60,000 samples. The compression over the data is done with preprocessing and without preprocessing.In the first method (Method I), the test data is preprocessed to remove the noise.For this preprocessing proper low pass and high pass filters are selected to remove the unwanted information and then the preprocessed data is compressed .In the second method(Method II)compression is done without any preprocessing. In both the methods the compression is done with various motherwavelets(both orthogonal and biorthogonal) and by varying the threshold values (5 to 4000).In method I the compression ratio on an average varies from 5:1 to 63 :1 with the PRD percentage from 5 % to 18% .Fig 5 shows the original and the reconstructed ECG signal of the file 121 and from the Fig it is observed that the PRD is more or less same for

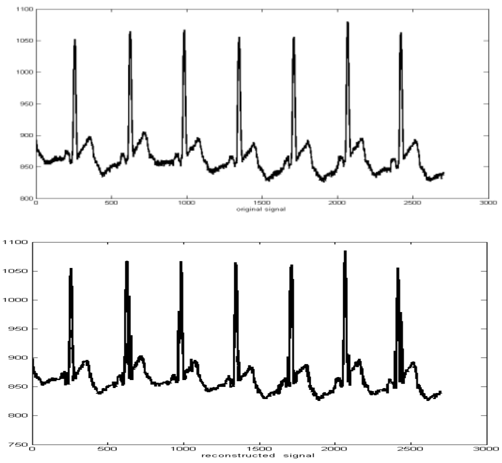


Fig[4] : Performance analysis compression algorithm for the file 121 on the MIT-BIH database using Method II

various compression ratios. The encoder performs poor for the file 103 with the same compression ratio and the PRD percentage varies from 8 % to 18 %.Fig (3) shows the performance analysis of the compression algorithm for the file 121.The graph shows that the original signal deviates almost linearly with the reconstructed signal for various thresholds. After certain threshold value(i.e.>4000) the PRD value changes rapidly with constant compression ratio (63:1).Method II also preserves the same compression ratio but the PRD on an average it varies from 1% to 8 %. In this method the PRD value increases as the compression ratio increases which is shown in Fig 4. The distortion curves show that the selection of different wavelets won't seriously affect the compression ratio. Most of the wavelets perform in the same manner. Clinical property is preserved visually upto the certain threshold values. Whenever the signal reaches the compression ratio 63:1 the reconstructed signal fails to retain its clinical property visually. To evaluvate the compressed data clinically the heart rate from the original and the reconstructed signal is calculated. To calculate the heart rate the QRS peaks are extracted and the heart rate is calculated from the RR interval using the formula

Heart rate=60/R-R interval(in seconds) **-------(5**

The resultant heart rate is compared with the heart rate variability (HRV) parameter in th MIT-BIH arrythmia [16] Database.The above mentioned QRS detection algorithm is used to find out the peaks (QRS) in the given range of samples and this algorithm is applied for both the methods.Method I and II shows the same number of peaks for all the compression ratios.The detected peaks before and after compression is analysed and the result is shown in Fig[6]. The heart rate is calculated from the detected intervals and it is compared with the HRV database. The result is shown in Fig [7] . From the analysis HRV value for the original and reconstrcuted signal obtained from various files are same .File 103 shows more deviation in the predicted range.The result is summarized in the table [1].The analysis shows that this compression method perverse its QRS property even with a high compression ratio (63:1).



Fig[5] Original and reconstructed ECG signal for 121 file (8:1)

The experimental result shows the percentage of correctness is above 92%.This may also increase if the number of samples are increased.

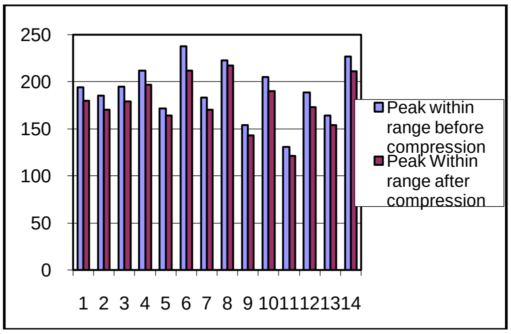
6. CONCLUSION

The 2-dimensional EZW ECG signal compression algorithm described in the paper. The data are compressed with and without processing. The algorithm works well for the processed data with the compression ratio ranges from 5:1 to 63:1 for various mother wavelets. The PRD for this process ranges from 5% to 18 %. The later techniques show the same compression ratio as the previous method but the PRD is much better than the previous one. Clinical analysis shows that the algorithm preserves more or less the same compression ratio for various motherwavelets and for various thresholds. Even though the compression algorithm gives higher compression ratio and perfect heart rate, the time complexity to do this process is slightly high due to various factors such as QRS peak detection.

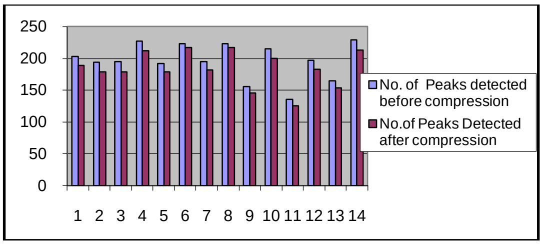
Table 1-Comparison of heart rate for various files. The heart rate is calculated for 60,000 samples and the calculated heart rate is same for the entire compression ratio (5:1 to 63:1)

S.No	FILE	Actual HRV	HRV obtained before compression	HRV obtained after compression	No. of Peaks detected before compression	No.of Peaks Detected after compression	Peak within range before compression	Peak Within range after compression	% of correctness for the detected peak	% of correctness for the heart rate within range
1	100	70 - 89	70-80	70-80	203	189	194	180	93.10	92.78
2	101	55 - 79	60-78	62-78	194	179	185	170	92.27	91.89
3	103	62 - 92	64-78	64-92	195	179	195	179	91.79	91.79
4	105	78 -102	78-89	78 -89	227	212	212	197	93.39	92.92
5	107	68 -82	68-71	68-81	192	179	172	164	93.23	95.35
6	109	77-102	77-97	77-97	223	217	238	212	97.31	89.08
7	111	64 -82	64-80	64-80	195	182	183	170	93.33	92.90
8	112	74 -91	80-90	80-90	223	217	223	217	97.31	97.31
9	113	48 -87	50-76	50-76	156	146	154	143	93.59	92.86
10	116	74 -86	74-83	74-83	215	200	205	190	93.02	92.68
11	117	48-66	48-53	48 -57	136	126	131	121	92.65	92.37
12	118	54-91	56-90	56 -90	197	183	189	173	92.89	91.53

13	121	55-83	55-69	55 -77	165	154	164	154	93.33	93.90
14	122	67-97	67-95	67-95	229	213	227	211	93.01	92.95



Fig[6] Comparison of peaks detected before and after compression.



Fig[7] Comparison of peaks within range before and after compression

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