Analysis of Transform Based ECG Compression Techniques

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***Abstract*— Electrocardiogram storage is of utmost importance to enable the correct diagnosis of a patient. This storage demands large quantities of memory as the records increase by the millions each year. Hence, the compression of these waveforms is of great significance. This paper proposes to compare various transform based techniques used to compress an ECG waveform. The performance of these techniques is measured through various parameters to obtain the most efficient one.**

***Keywords*-- ECG Compression, DCT, DCT-II, DST, FFT, Wavelet, Walsh Transform**

I. Introduction

Electrocardiogram (ECG) is the most performed electrophysiological test worldwide. The ECG signal is the electrical interpretation of the heart activity and is used to measure the rate, regularity of heartbeats, and the presence of any damage to the heart. The etymology of the word is derived from the Greek word *electro*, because it is related to the electrical activity; from *kardio*, Greek for heart; and *graph*, a Greek root meaning 'to write'.

All previous ECG records need to be stored, as one of the most important uses of the ECG data is in the comparison of records obtained over a long range period of time. However, memory requirement for this storage is huge. This makes the use of compression techniques a prerequisite.

Compression generally takes place by detecting and eliminating redundancies in a given data set. The paper seeks to find a compression technique that achieves maximum reduction in the volume of data while preserving the significant features of the ECG waveform.

The topic of ECG signal compression attracted considerable attention over the last two decades. Several examples of ECG compression algorithms have been described in literature. These compression techniques can be broadly classified into three categories.

A. Direct Time-Domain Techniques

These were the earlier approaches to biomedical signal compression which included methods such as AZTEC [1], CORTES [2] and FAN algorithms. They are based on heuristics in the sample selection process but they all suffer from sub-optimality. In addition, they are highly sensitive to sampling rate, quantization levels, and high frequency interference.

B. Parametric Extraction Techniques

These include Prediction and Vector Quantization (VQ) methods [3]. Here, the signal is analyzed and some important features such as typical cycles and extreme locations are determined before storing them. Reconstruction is then carried out by the use appropriate interpolation schemes. But as the modelling emphasizes more on the high amplitude region, the low amplitude region, which is crucial for the reconstruction of small significant components such as the Q and S waves and the QRS notches get neglected.

C. Transform based methods

They divide the signal into frequency components and allocate bits in the frequency domain efficiently. The input signal is divided into blocks of data and then stored in the frequency domain in the form of a vector. Then the entries in the vector are de-correlated which helps one to retain only the useful information. Their main focus is to minimize the number of addition and multiplication operations by using the symmetry property of the waveforms.

Transform methods provide higher coding results as compared to the time-domain and parametric extraction methods [4]. Hence, in this paper we have compared six of the most widely used transform based techniques for ECG compression.

II. Fundamental ECG Waveform

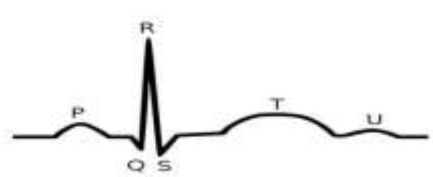

Fig. 1 Fundamental ECG waveform

A typical scalar electrocardiographic (ECG) lead is shown in Figure 1. It consists of a set of successive waves denoted by P, Q, R, S, and T waves. Study of each part of the waveform is vital to understand and later exploit the redundancies in the signal. The P-wave indicates the period when the atria are electrically stimulated to pump the blood into the ventricles. The QRS is a complex region which indicates that the ventricles are electrically stimulated to pump the blood out. The ST portion indicates the amount of time from the end of contraction of the ventricles to the beginning of the T-wave whereas the T-wave is the recovery period of the ventricles. The final portion, that is, the U-wave is the re-polarization of the papillary muscles. But it is rarely seen.

III. Transform-Based Compression Techniques

A. *Discrete Cosine Transform*

The discrete cosine transform (DCT) is a well known frequency-domain digital waveform compression method [5]. A DCT expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. The DCT of a vector ‘m’ is defined through (1).

$$V = \frac{1}{\sqrt{n}} \sum_{n=0}^{N-1} m_n \tag{1}$$

The algorithm calculates the DCT coefficients of the ECG signal based on the time period between two samples. It then proceeds to find the coefficients within a certain range and sets that particular index to zero, to achieve compression. Counters are used to measure the coefficients having a zero value before and after compression. Lastly IDCT is calculated to obtain the reconstructed waveform.

DCT uses cosine as basic functions and performs compression on DCT coefficients. The DCT-I is exactly equivalent to a Discrete Fourier Transform (DFT) of 2N-2 real numbers with even symmetry. This correlation and compaction property is the basic concept used for compression.

B. *Discrete Cosine Transform-II*

Unlike traditional algorithms which have fixed computation complexity, the DCT II algorithm depends on the statistical properties of the input data [6]. The DCT-II of a vector ‘m’ is achieved through (2). It is exactly equivalent to a DFT of 2N-2 real numbers with even symmetry.

$$V = \sum_{n=0}^{N-1} m_n \cos \frac{\pi}{N(n+0.5)k} \tag{2}$$

Here the data sequence is divided into blocks and the DCT-II coefficient of each block is calculated. The main advantage of this division is an improved compression ratio. These coefficients are quantized to obtain the compressed waveform. DCT-II can be viewed as special case of the DFT with real inputs of certain symmetry. Thus DCT of size N is equivalent to a DFT of size 4N.

C. *Discrete Sine Transform*

Discrete sine transform (DST) expresses a signal in terms of a sum of sinusoids with different frequencies and amplitudes [7]. It is equivalent to the imaginary parts of a DFT of roughly twice the length, operating on real data with odd symmetry. The DST of a vector ‘m’ is given in (3).

$$V = \sum_{n=0}^{N-1} m_n \sin \frac{\pi(n+1)(k+1)}{\mathrm{N}+1} \tag{3}$$

A DST-I is exactly equivalent to a DFT of a real sequence that is odd around the zero-th and middle points, scaled by 0.5. Here we find the frequency and time period between two samples and then calculate the DST of the ECG signal. The coefficients obtained in the transform are used for compression. If the coefficients have a zero value before compression then counter 1 is not changed but if it lies below a certain threshold then it is incremented. And if they have a zero value after compression then counter 2 is incremented. Lastly IDST is calculated to obtain the reconstructed waveform.

D. *Fast Fourier Transform*

A Fast Fourier transform (FFT) is a fast and more efficient algorithm to compute the discrete Fourier transform (DFT) and obtains the same result. FFT is computed from the formula shown in (4).

$$V = \sum_{n=0}^{N-1} m_n e^{\frac{-2\pi i k n}{N}} \tag{4}$$

Computing a DFT of N points in the traditional way takes N^2 arithmetical operations while an FFT can compute the same result in only NlogN operations. The difference in speed can be huge when the data sets are very large. This huge improvement has made many DFT based algorithms more practical [8].

Here we find the frequency and time period between two samples and then calculate the FFT of the ECG signal. This method also achieves compression upon computation of transform coefficients which represent the signal.

E. Walsh-Hadamard Transform

The Walsh-Hadamard transform is a non-sinusoidal, orthogonal transformation that decomposes the signal into a set of basis functions, known as Walsh functions. These are very similar to the orthogonal sinusoids used to perform the Fourier transform [9].

The WHT for a signal 'm' is defined in (5), where WAL (n, i) are the Walsh functions.

$$y_n = \frac{1}{N}\sum_{i=0}^{N-1} m_i WAL(n,i) \tag{5}$$

The transform generates sequency values, which can be further used to estimate the signal [10]. For compression, only a few of the coefficients are stored and the signal is later reconstructed from them. The number of coefficients depends on the user. Storing more coefficients will lead to increased resolution and noise, but a lower compression ratio. However, storage of less coefficients might cause loss of data and increase the distortion.

F. Wavelet Transform

Wavelet Transform (WT) is a powerful time-frequency signal analysis tool and it is used in a wide variety of applications including signal and image coding [11]. Discrete Wavelet transform has an orthogonal basis function and exhibits zero redundancy. It expresses the waveform in the form of a dyadic grid arrangement, using (6).

$$\varphi_{a,b}(t) = \frac{1}{\sqrt{x^a}}\varphi\left(\frac{t - byx^a}{x^a}\right) \tag{6}$$

Where, 'a' and 'b' control the wavelet dilation and translation respectively, 'x' is a fixed dilation step parameter and 'y' is a location parameter.

The result of the DWT is a multilevel decomposition, in which at each level the signal is decomposed in approximation and detail coefficients. One can choose the level of decomposition based on a desired cut-off frequency. The basic idea behind decomposition and reconstruction is low-pass and up-sampling respectively [12].

Initially, the signal components are localized in time and scale which helps to compress efficiently the different zones of the time-scale plane, according to the coefficient values obtained in each case. When the signal is segmented appropriately and the WT is applied to it, the WT coefficients that have low absolute values are equated to zero, resulting in compression. The original signal can then be recovered by an IWT.

IV. PARAMETERS FOR COMPARISON

The performance of the different techniques is done on the basis of the following parameters: Compression Ratio (CR), Compression Factor (CF), Space Savings (SS) and Percent root mean square difference (PRD).

A. Compression Ratio

It is defined as the ratio of the size of compressed file to that of the source file (7). In data compression, it represents one of the most important parameters for performance.

$$CR = \frac{\text{size of compressed file}}{\text{size of source file}} \tag{7}$$

B. Space Savings

Space Savings (8) is defined as the reduction in size relative to the uncompressed size.

$$SS = 1 - \frac{\text{Compressed Size}}{\text{Uncompressed Size}} \tag{8}$$

C. Compression Factor

Compression Factor (9) is the inverse of the compression ratio. It is defined as the ratio of size of source file to that of size of compressed file.

$$CF = \frac{\text{Size of Source File}}{\text{Size of Compressed File}} \tag{9}$$

D. Percent root mean square difference

Percent Root mean square Difference (PRD) is the most prominently used distortion measure. It is calculated as per (10).

$$PRD = \sqrt{\frac{\sum_{n=1}^{L}[x(n) - x'(n)]^2}{\sum_{n=1}^{L}[x(n)]^2}} \tag{10}$$

Where x(n) is the original signal, x'(n) is the reconstructed signal and L is the length of the block or sequence over which PRD is calculated. PRD provides a numerical measure of the residual root mean square (RMS) error.

V.RESULTS AND DISCUSSIONS

In order to test the performance of the compression techniques, we have taken the data from the MIT-BIH online database. The sampling frequency is kept at 340 Hz. The results of compression are shown in Fig. 2-7. In each figure, the first signal is the input ECG waveform. The second displays the reconstructed signal after compression and the third signal represents the reconstruction error. The reconstruction error is measured by computing the difference between the original and reconstructed signal at each sampled point.

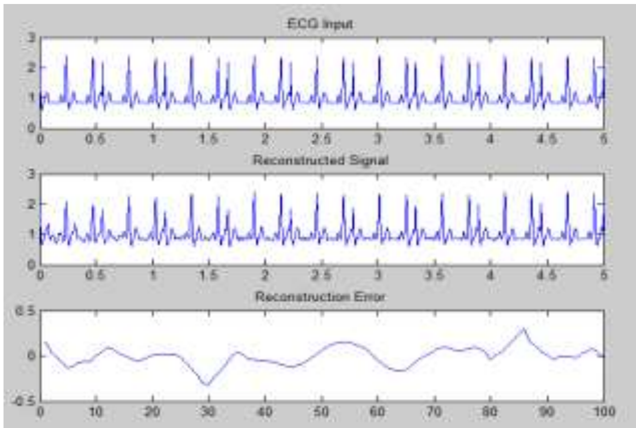

Fig. 2 DCT

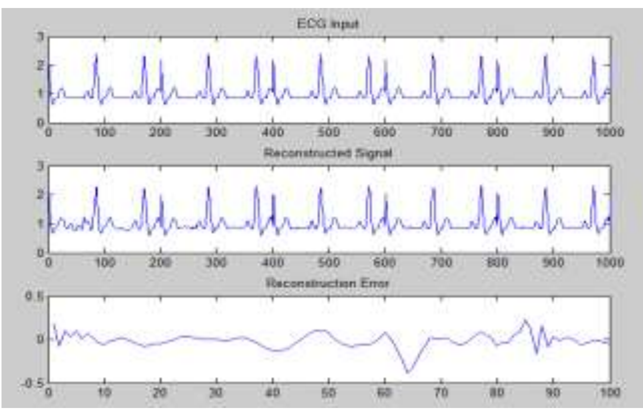

Fig. 3 DCT-II

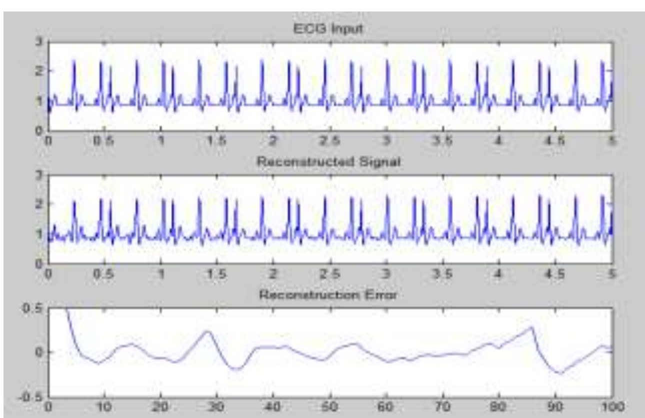

Fig. 4 DST

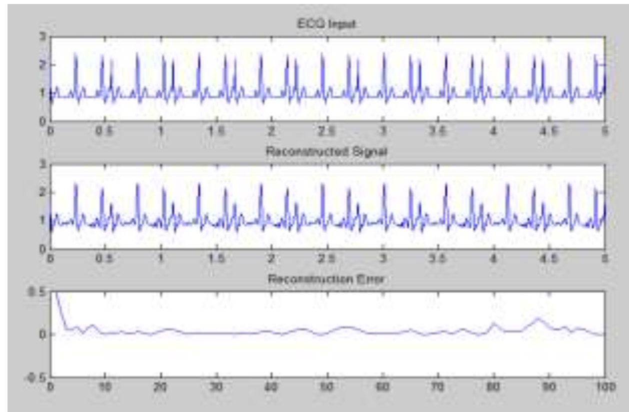

Fig. 5 FFT

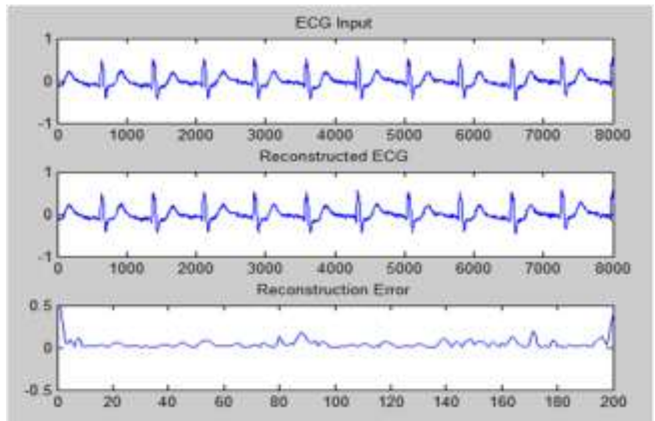

Fig. 6 Walsh Transform

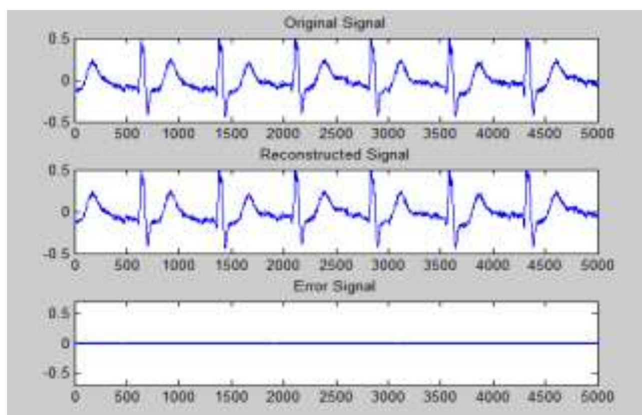

Fig. 7 Wavelet Transform

The result of comparison of the various techniques is shown in Table 1. The performance of each method is judged on the basis of four parameters.

The DCT-I and DCT-II provide a better compression ratio, however they suffer from high PRD value. Hence the reconstruction error is high. The FFT algorithm proved to be the most lossy compression technique, as seen from its PRD value of 7.05. The Walsh-Hadamard transform does not provide a suitable CR or PRD value. DST performs better compression than some of the others, but has a moderately high PRD value. The Wavelet method has exhibited a high degree of robustness, when compared to the others in the sense that the signal can be reconstructed without a significant loss by means of the PRD obtained.

TABLE 1.COMPARISON OF VARIOUS PARAMETERS

Method	CR	SS	CF	PRD
DCT-I	0.0500	0.9500	20.000	3.55
DCT-II	0.0480	0.9520	20.800	3.00
DST	0.0792	0.9208	12.626	3.95
FFT	0.1910	0.8090	05.230	7.05
Walsh	0.2501	0.7499	03.998	4.50
Wavelet	0.0739	0.9261	13.530	1.07

VI. Conclusion

Transform based techniques have gained popularity because of their high compression ability. This paper has compared various techniques for ECG signal compression. DCT-II was found to give the highest CR for the samples tested however the Wavelet Transform method gave the least distortion. Lossy compression methods require a good balance between the degrees of compression and residual distortion.

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