ECG Signal Compression for Diverse Transforms

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Abstract

Biological signal compression and especially ECG has an important role in the diagnosis, prognosis and survival analysis of heart diseases. Various techniques have been proposed over the years addressing the signal compression. Compression of digital electrocardiogram (ECG) signals is desirable for three reasons- economic use of storage data, reduction of the data transmission rate and transmission bandwidth conversation. ECG signal. In this paper a comparative study of Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Discrete Cosine compression is used for telemedicine field and re Transform (DCT) and Wavelet Transform (WT) transform based approach is carried out. Different ECG signals are tested from MIT-BIH arrhythmia database using MATLAB software. The experimental results are obtained for Percent Root Mean Square Difference (PRD), Signal to Noise ratio (SNR) and Compression ratio (CR). The result of ECG signal compression shows better compression performance in DWT compared to DFT, FFT and DCT.

Keywords: Electrocardiogram (ECG), Discrete Fourier Transform (DFT), Fast Fourier Transform (FFT), Discrete Cosine Transform (DCT), Wavelet Transform (WT).

1. Introduction

The ECG (electrocardiogram) is a biological signal which depicts the electrical activity of a heart. ECG is a quasi-periodical, rhythmically repeating signal, synchronized by the function of the heart. Analysis of ECG has been conducted with the data compression and reconstruction. The large amount of ECG data grows with the increase of number of channels, sampling resolution, sampling rate and recording time etc. For storage and transmission of large signal data, it is necessary to compress the ECG signal data [5].Data compression is the process of detecting and eliminating redundancies in a given data set. Compression techniques can be divided into classes: lossy and lossless methods. For ECG data compression, the lossy type has been applied due to its capability of a high data compression ratio [2]. Data compression techniques can be divided into three methods.

1. Direct Data Compression Method
2. Transform Method
3. Parameter Extraction Compression Method

The direct data compression method directly analyzes and compresses data in the time domain. This method depend on prediction or interpolation algorithms , which can decrease the redundancy in a sequence of data using by consecutive samples. Prediction algorithm apply a prior knowledge of previous samples, on the other hand interpolation algorithm uses a prior knowledge of both previous and future samples. The direct data compression methods base their detection of redundancies on direct analysis of actual samples. For example turning point (TP), amplitude zone time epoch coding (AZTEC), coordinate reduction time encoding system (CORTES) , delta algorithm and fan algorithm[3],[4].

Transform method, converts the time domain signal to the frequency or other domains and analyzes the energy distribution. Transformation methods involve processing of the input signal by a linear orthogonal transformation and encoding of the output using an appropriate error criterion. For signal reconstruction an inverse transformation is carried out and the signal is recovered with some error [5][6]. For example Fourier transform (FT), Fourier descriptor, Karhunen-Loeve transform (KLT) , The Walsh transform, discrete cosine transform (DCT) , and Wavelet transform (WT).

Parameter extraction compression method, extract the features and parameters of the signal. The extracted parameters are subsequently utilized for classification based on a prior knowledge of the signal features. For example peak detection method, linear prediction method, syntactic method or the neural network method. Direct and transformation methods are reversible, while parameter extraction method is irreversible.

In this paper various transforms like DFT, FFT, DCT and DWT are used for signal reconstruction for compression techniques. Threshold is a value where the transformed coefficients are set to zero without significantly changing in signal. If threshold value is high then more zeros can be set where as more retained energy is wasted. Two thresholding methods: Hard thresholding and Soft thresholding.

Hard thresholding is the process of setting to zero the elements whose the absolute values are lower than the threshold.

Soft thresholding is an extension of hard thresholding, first setting to zero the elements whose absolute values are lower than the threshold and then shrinking the nonzero coefficients toward zero [12]. Threshold is high, compression ratio will be high and vice versa.

A fix percentage threshold is based on maximum values of the transformed coefficient algorithm to get better compression. The paper is organized as follows: Section II provides different transform techniques. Section III explains the performance evaluation parameters. Section IV presents coding algorithm and test performance of different transforms. The experimental results are reported in Section V.

2. Transform Techniques

2.1. Discrete Fourier Transform

The Discrete Fourier Transform (DFT), that is, Fourier Transform as applied to a discrete complex valued series. The fundamental transform in digital signal processing is Discrete Fourier Transform which has the applications in frequency analysis, signal analysis etc. As the DFT transform can be applied to any complex valued series, in practice for large series it can take considerable time to compute, the time taken being proportional to the square of the number on points in the series[9]. The k^{th} DFT coefficient of length N sequence {f(x)} is defined as

$$F(k) = \sum_{n=0}^{N-1} x(n)\ e^{-\frac{j2\pi kn}{N}} \quad k = 0,1,\ldots\ldots N-1 \tag{1}$$

Where its inverse transform (IDFT) is given as

$$x(n) = \frac{1}{N}\sum_{k=0}^{N-1} F(k)\ e^{\frac{j2\pi kn}{N}} \quad n = 0,1,\ldots\ldots N-1 \tag{2}$$

2.2 Fast Fourier Transform

A much faster algorithm has been developed by Cooley and Tukey around 1965 called the FFT (Fast Fourier Transform). The number of complex multiplications and additions to compute DFT is N^2 .Although fast algorithms exist that makes to compute DFT efficiently. This algorithm is popularly known as Fast Fourier Transform (FFT) which reduces the computations to $N \log_2 N$.

A Fast Fourier Transform of N sample is defined as:

$$F(k) = \sum_{n=1}^{N} x(n)\ e^{-j2\pi\frac{(k-1)(n-1)}{N}} \quad 1 \le k \le N \tag{3}$$

Inverse Fast FourierTransform (IFFT)

$$x(n) = \frac{1}{N}\sum_{k=1}^{N} F(k)\ e^{\frac{j2\pi(k-1)(n-1)}{N}} \quad 1 \le n \le N \tag{4}$$

If x(n) is real, the above equation can be rewritten in terms of a summation of sine and cosine functions with real coefficients:

$$x(n) = \frac{1}{N}\sum_{k=1}^{N} a(k)\cos\left[\frac{2\pi(k-1)(n-1)}{N}\right] + b(k)\sin\left[\frac{2\pi(k-1)(n-1)}{N}\right] \tag{5}$$

Where

a(k)=real F(k) , b(k)= -imag F(k), $1 \leq n \leq N$

For example a transform on 1024 points using the DFT takes about 100 times longer than using the FFT, a significant increase in speed.

Major disadvantage of FFT is that it can not provide the information regarding the exact location of frequency component in time.

Fig.1 shows original signal, reconstructed signal using by FFT and error signal which is from original signal (record 117).

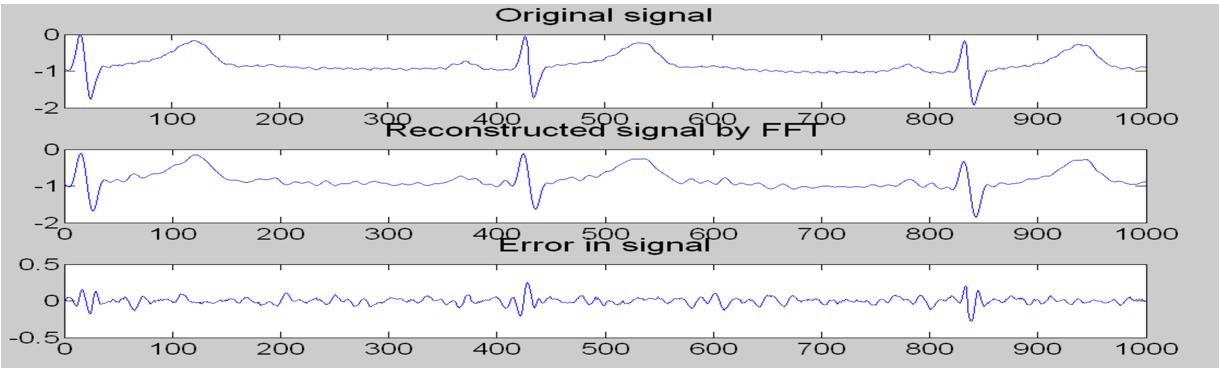

Figure.1 FFT Compression of MIT-BIH record 117

2.3 Discrete Fourier Transform

The Discrete Cosine Transform is closely related to DFT but only uses only real numbers, it express a function or a signal in terms of a sum of sinusoid with different frequencies and amplitudes. DCT implies different boundary conditions than the DFT or other related transforms.

DCT is often used in signal and image processing, especially for lossy data compression, because it has a strong "energy compaction" property .Signal can be reconstructed fairly accurately from only few DCT coefficients. Application is requiring data reduction [1][10].

A DCT is defined as:

$$F(k) = w(k)\sum_{n=0}^{N-1} x(n)\cos\left[\frac{\pi(2n+1)k}{2N}\right] \tag{6}$$

k=0,1,……………N-1,

w (k) = $\sqrt{1/N}$, for k=0

= $\sqrt{2/N}$, for $k \neq 0$

Fig.2 shows original signal, reconstructed signal using by DCT and error signal which is from original signal (record 117).

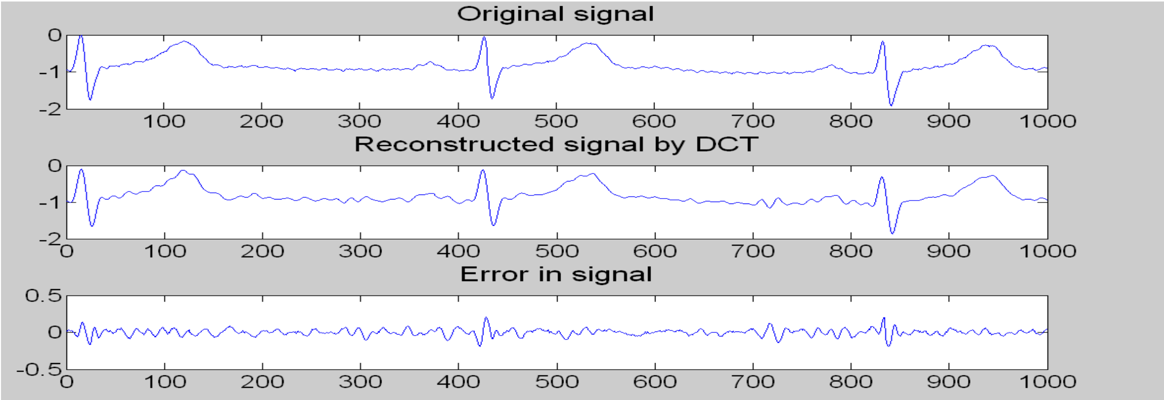

Figure.2 DCT Compression of MIT-BIH record 117

2.4 Discrete Wavelet Transform

Wavelet transform analyzes signals in both time and frequency domain simultaneously .Therefore it is suitable for the analysis of time-varying non-stationary signals such as ECG. It is an efficient tool in many applications especially in coding and compression of the signals because of multi-resolution and high energy compaction properties. A mother wavelet ψ (t) is a function of zero average:

$$\int_{-\infty}^{+\infty} \psi(t)\, dt = 0 \qquad (7)$$

When this function is dilated by a factor of 'a' and translated by an other scalar 'b' represented as in (8):

$$\psi_{a,b}(t) = \frac{1}{\sqrt{|a|}}\,\psi\left[\frac{t-b}{a}\right] \qquad (8)$$

If a and b are discredited then discrete wavelet can be represented as in (9):

$$\psi_{j,k}(t) = a_0^{-j/2}\,\psi\left(a_0^{-j}\,t - kb_o\right) \qquad (9)$$

Where for dyadic sampling $a_0 = 2$ and $b_0 = 1$

$$\psi_{j,k}(t) = a_0^{-j/2}\,\psi\left(a_0^{-j}\,t - kb_o\right) \quad j,k \in Z \qquad (10)$$

This multi-resolution wavelet algorithm decomposes a signal *x(t)* with the help of $\phi(t)$ and wavelet function by $\psi(t)$ .These functions resolves the signal into its coarse and detail components. Therefore using multi-resolution , the signal x(t) is defined in terms of scale and wavelet coefficients, *c(k)* and *d(k)* ,respectively[8].

$$x(t) = \sum_{k=-\infty}^{\infty} c(k)\,\phi_k(t) \sum_{j=0}^{\infty} \quad \sum_{k=-\infty}^{\infty} d(j,k)\,\psi_{j,k}(t) \qquad (11)$$

The first summation gives a function that is a low resolution or a coarse approximation of *x(t)*; the second one represents the higher or finer resolution to give detailed information of the signal[4].

DWT gives the better compression compare to DCT.

Fig.3 shows original signal, reconstructed signal using by DWT and error signal which is from original signal (record 117).

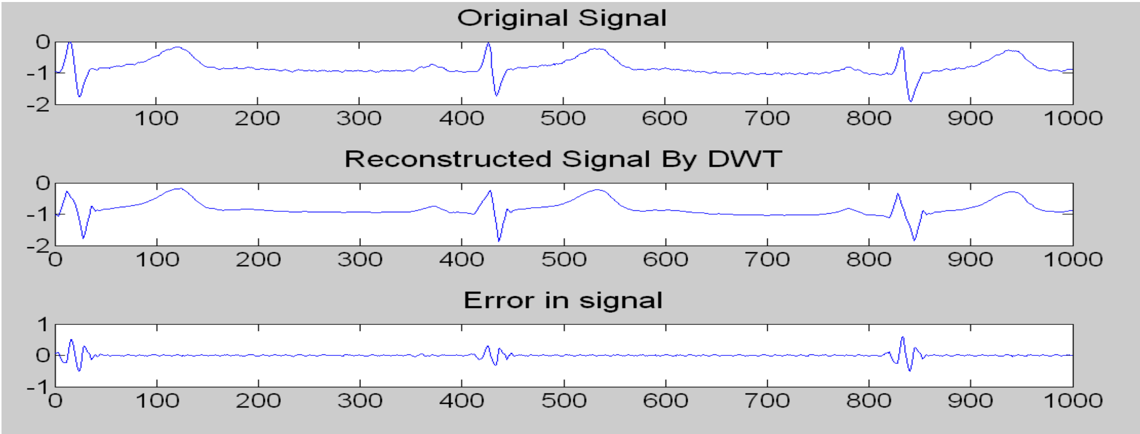

Figure.3 DWT Compression of MIT-BIH record 117

Figure.4 shows the compressed signal by DWT of record117.

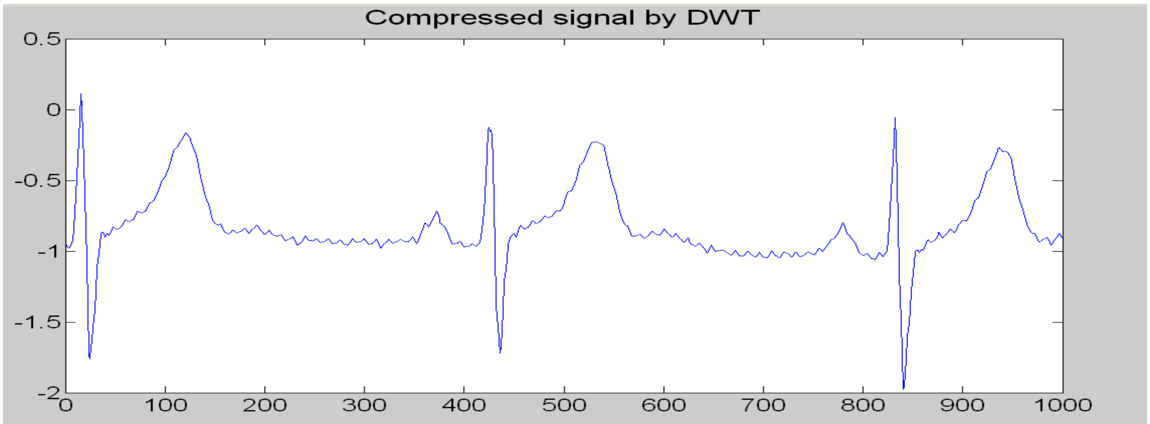

Figure.4 Compressed Signal by DWT record 117

3. *Performance Measurement*

3.1 Distortion Measurement: PRD

Percentage root mean difference (PRD) to measure distortion between the original signal and the reconstructed signal .PRD can be defined as:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N} [x[n] - \hat{x}[n]]^2}{\sum_{n=1}^{N} [x[n]]^2}} \times 100 \qquad (12)$$

where x[n] and $\hat{x}$[n] are the original and reconstructed signals of length N , respectively. The PRD indicates reconstruction fidelity by point wise comparison with the original data

3.2 Compression Ratio: CR

The compression ratio (CR) is defined as the ratio of the number of bits representing the original signal to the number of bits required to store the compressed signal. All data compression algorithm, used to minimize data storage by eliminating the redundancy wherever possible to increase the compression ratio. Compressed data must also represent the data with better fidelity while achieving high compression ratio [1].

$$CR = \frac{B_{original}}{B_{compressed}} \qquad (13)$$

Where $B_{original}$- Bit rate of the original signal

$B_{compressed}$- Bit rate of the compressed signal

3.3 Signal to Noise Ratio: SNR

Basically signal to noise ratio (SNR) is an engineering term for the power ratio between a signal and noise. It is expressed in terms of the logarithmic decibel scale.

$$SNR = 10\ \log_{10}\left(\frac{E_{signal}}{E_{noise}}\right)^2$$

$$SNR = 20\ \log_{10}\left(\frac{E_{signal}}{E_{noise}}\right) \qquad (14)$$

Where E_{signal}: Root mean square amplitude of the signal

E_{noise}: Root mean square amplitude of the noise

4. Proposed algorithm

BEGIN

Step 1: Loading of signal
The signal which is taken from MIT-BIH arrhythmia data base

Step 2: Transform the original signal using by DFT, FFT, DCT and WT

Step 3: Find the maximum value of the transformed coefficients and apply a fix percentage based hard threshold.

Step 4: Apply inverse transform to get the reconstruct signal.

Step 5: Calculation of Percent Root Mean Square Difference (PRD).

Step 6: Calculation of Signal to Noise Ratio (SNR).

Step 7: Calculation of Compression Ratio (CR).

Step 8: Displaying the result

END

5. Experimental results

The experimental data from MIT-BIH arrhythmia database is used to analyze and test the performance of coding scheme. Various ECG signal records are used for experiments and algorithm is tested for 1024,2048 and 4096 samples from each record 100,101,102,105,110,113,117,119,205,209 and 210. The database is sampled at 360Hz and the resolution of each sample is 11 bits/sample. Equation 12, 13 and 14 are used for evaluation of PRD, SNR and CR. Fig.5 shows the number of samples versus signal-to-noise ratio. Fig.6 shows the number of samples versus PRD and Fig7 shows the number of samples versus compression ratio. These findings will be a great help in the telemedicine field and remote diagnosis system.

5. Conclusion

Results are obtained from different transformations on various sets of data taken from MIT-BIH arrhythmia database and are shown in Table1.

For DFT algorithm the PRD is around 0.378 to 1.098%, SNR 56.76 to 68.54 with the corresponding CR 10.24:1 to 15.54:1.

For FFT algorithm the PRD is around 0.458 to 0.987%, SNR 59.76 to 85.88 with the corresponding CR 10.78:1 to 17.02:1.

For DCT algorithm the PRD is around 0.178 to 0.894%, SNR 8.76 to 13.87 with the corresponding CR 12.42:1 to 19.69:1.

For DWT algorithm the PRD is around 0.524 to 0.589%, SNR 36.30 to 51.12 with the corresponding CR 18.21:1 to 38.72:1. ECG signal compression using DWT algorithm can achieve better CR than other transforms. CR is increased as the number of samples increased.

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Table 1: Results of different transforms

No. of Samples/Transforms		Record 100			Record 117			Record 119			Record 210		
		SNR	PRD	CR	SNR	PRD	CR	SNR	PRD	CR	SNR	PRD	CR
1024	DFT	57.21	0.395	10.24	57.41	0.402	10.34	57.24	0.382	10.49	56.79	0.378	10.27
	FFT	59.76	0.458	10.78	59.87	0.476	11.02	59.83	0.492	10.87	60.15	0.478	11.23
	DCT	8.76	0.178	12.29	8.82	0.180	12.26	8.78	0.186	12.42	8.98	0.192	12.29
	DWT	36.56	0.524	18.87	36.30	0.557	18.21	36.58	0.564	18.86	36.59	0.535	18.91
2048	DFT	60.23	0.576	11.81	60.19	0.589	11.32	60.67	0.606	11.56	61.12	0.498	11.79
	FFT	74.34	0.610	12.02	74.56	0.618	12.20	74.68	0.622	12.35	74.90	0.613	12.52
	DCT	11.46	0.645	14.26	11.35	0.678	14.23	11.78	0.698	14.41	11.89	0.706	14.56
	DWT	42.48	0.549	22.67	42.67	0.551	22.88	42.69	0.602	22.92	42.73	0.610	22.27
4096	DFT	68.54	1.010	15.87	67.98	1.043	15.39	67.78	1.076	15.68	68.45	1.098	15.54
	FFT	85.25	0.932	17.02	86.21	0.945	16.88	85.79	0.987	16.98	85.88	0.965	16.76
	DCT	13.87	0.868	19.21	13.45	0.856	19.43	13.76	0.879	19.65	13.68	0.894	19.69
	DWT	50.78	0.578	38.19	51.12	0.575	38.53	50.98	0.597	38.64	50.76	0.589	38.72

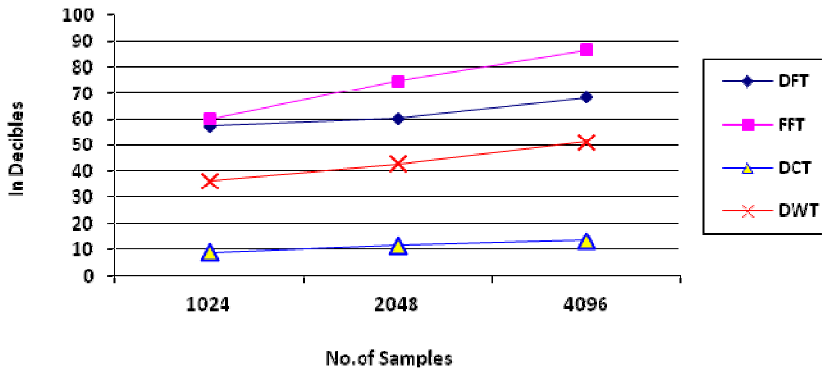

Figure.5 Signal to Noise Ratio (record 117)

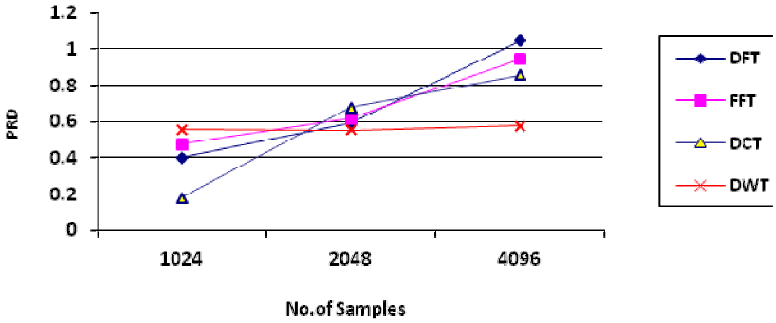

Figure.6 Percent Root Mean Difference (record 117)

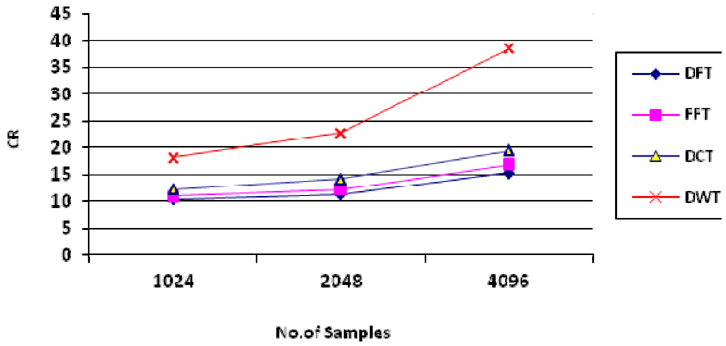

Figure.7 Compression Ratio (record 117)