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Performance Analysis of Various Types of ECG Compression Techniques In Terms of CR

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***Abstract*— In this paper, we compared the performance of various types of ECG compression techniques. These techniques are essential to reduce the size of data to be transmitted without losing the clinical information. We also studied Computerized Electrocardiogram(ECG), electroencephalogram (EEG), and magneto encephalogram (MEG) processing systems have been widely used in clinical practice. These schemes are based on transformation methods such as Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Fast Fourier Transform (FFT), and the improved method Discrete Cosine Transform- II (DCT-II). The comparative study is made in terms of Compression Ratio (CR) and Percent Root mean square Difference (PRD)**

***Index Terms*— Electrocardiogram (ECG), Discrete Cosine Transform (DCT), Discreet Sine Transform (DST), Fast Fourier Transform (FFT), Discrete Cosine Transform- II (DCT-II).**

I. Introduction

The ECG is a one of the important physiological signal which depicts the electrical activity of a heart. ECG processing is a topic of great interest in the scientific community because based on the ECG's a diagnosis is done for detecting abnormalities in the heart functioning [1]. Basically, a data coding algorithm seeks to minimize the number of code bits stored by reducing the redundancy present in the original signal. The design of data compression schemes therefore involves trade-offs among various factors including the degree of compression, the amount of distortion introduced (if using a lossy compression scheme) and the computational resources required to compress and uncompress the data. To deal with the huge amount of electrocardiogram (ECG) data for analysis, storage and transmission; an efficient ECG compression technique is needed to reduce the amount of data as much as possible while pre-serving the clinical significant signal for cardiac diagnosis, for analysis of ECG signal for various parameters such as heart rate, QRS-width, etc. An effective data compression scheme for ECG signal is required in many practical applications such as ECG data storage, ambulatory recording systems and ECG data transmission over telephone line or digital telecommunication network for telemedicine. The main goal of any compression technique is to achieve maximum data volume reduction while preserving the significant features [2] and also detecting and eliminating redundancies in a given data set. Data compression methods can be classified into two categories: 1) lossless and 2) lossy coding methods. Lossy compression is useful where a certain amount of error is acceptable for increased compression performance. Loss less or information preserving compression is used in the storage of medical or legal records. In lossless data compression, the signal samples are considered to be realizations of a random variable or a random process and the entropy of the source signal determines the lowest compression ratio that can be achieved. In lossless coding the original signal can be perfectly reconstructed. For typical biomedical signals lossless (reversible) compression methods can only achieve Compression Ratios (CR) in the order of 2 to 1. On the other hand lossy (irreversible) techniques may produce CR results in the order of 10 to 1.In lossy methods; there is some kind of quantization of the input data which leads to higher CR results at the expense of reversibility. In lossy methods, there is some kind of quantization of the input data which leads to higher CR results at the expense of reversibility. But this may be acceptable as long as no clinically significant degradation is introduced to the encoded signal. The CR levels of 2 to 1 are too low for most practical applications. Therefore, lossy coding methods which introduce small reconstruction errors are preferred in practice. In this paper we review the lossy biomedical data compression methods. When we compare these methods we find that direct data compression is a time domain compression algorithm which directly analyses samples where inter-beat and, intra-beat correlation is exploited. These algorithms suffer from sensitiveness to sampling rate, quantization levels and high frequency interference. It fails to achieve high data rate along with preservation of clinical information [6]. In Transform based technique [7] compressions are accomplished by applying an invertible orthogonal transform to the signal. Due to its de-correlation and energy compaction properties the transform based

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methods achieve better compression ratios [8]. In transform coding, knowledge of the application is used to choose information to discard, thereby lowering its bandwidth. The remaining information can then be compressed via a variety of methods. When the output is decoded, the result may not be identical to the original input, but is expected to be close enough for the purpose of the application. In parameter extraction methods a set of model parameters/features are extracted from the original signal (model based) which involves methods like Linear term prediction (LTP) and analysis by synthesis.

II. METHODOLOGY

In this section we studied about all the methods for ECG coding which is given below

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A. *Discrete Cosine Transform(DCT):*

The Discrete Cosine Transform (DCT) was developed to approximate Karhunen-Loeve Transform (KLT) when there is high correlation among the input samples, which is the case in many digital waveforms including speech, music, and biomedical signals. The DCT $V = [v_0\ v_1 \dots\dots. v_{N-1}]^T$ Of the vector **x** is defined as follows

$$v_0 = \frac{1}{\sqrt{N}} \sum_{n=0}^{N-1} x_n$$

$$v_k = \sqrt{\frac{2}{N}} \sum_{n=0}^{N-1} x_n cos \frac{(2n+1)k\pi}{2N},\ k = 1,2, \dots\dots. N-1$$

Where v_k is the *kth* DCT coefficient. The inverse discrete cosine transform (IDCT) of **v** is given by

$$x_n = \frac{1}{\sqrt{N}} v_0 + \sqrt{\frac{2}{N}} \sum_{k=1}^{N-1} v_k cos \frac{(2n+1)k\pi}{2N},$$
$$n = 0,1,2 \dots\dots\dots\dots. N-1$$

There exist fast algorithms, Order (*N* log *N*), to compute the DCT .Thus, DCT can be implemented in a computationally efficient manner. Two recent image and video coding standards, JPEG and MPEG, use DCT as the main building block. A discrete cosine transform (DCT) expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies. DCTs are important to numerous applications in science and engineering, from lossy compression of audio (e.g. MP3) and images (e.g. JPEG) (where small high frequency components can be discarded), to spectral methods for the numerical solution of partial differential equations. The use of cosine rather than sine functions is critical in these applications. For compression, it turns out that cosine functions are much more efficient whereas for differential equations the cosines express a particular choice of boundary conditions. In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample. Discrete Cosine Transform is a basis for many signal and image compression algorithms due to its high decorrelation and energy compaction property. A discrete Cosine Transform of *N* sample is defined as

$$F(u) = \sqrt{\frac{2}{N}} C(u) \sum_{x=0}^{N-1} f(x) \cos \frac{\pi(2x+1)u}{2N}$$
$$u = 0,1, \dots\dots\dots\dots\dots. N-1$$

$$\text{Where} C(u) = \begin{cases} \frac{1}{\sqrt{2}}, for\ u = 0 \\ 1,\quad otherwise \end{cases}$$

The function *f(x)* represents the value of *xth* samples of input signals. *F (u)* represents DCT coefficients. The inverse DCT is defined in similar fashion as

$$f(x) = \sqrt{\frac{2}{N}} \sum_{u=0}^{N-1} C(u) F(u) cos \frac{\pi(2x+1)u}{2N}$$
$$x = 0,1, \dots\dots\dots\dots\dots.. N-1$$

B. *Discrete Sine Transform*

Discrete sine transform (DST) is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using a purely real matrix. It is equivalent to the imaginary parts of a DFT of roughly twice the length, operating on real data with odd symmetry (since the Fourier transform of a real and odd function is imaginary and odd), where in some variants the input and/or output data are shifted by half a sample. Like any Fourier-related transform, discrete sine transforms (DSTs) express a function or a signal in terms of a sum of sinusoids with different frequencies and amplitudes. Like the discrete Fourier transforms (DFT), a DST operates on a function at a finite number of discrete data points. The obvious distinction between a DST and a DFT is that the former uses only sine functions, while the latter uses both cosines and sines (in the form of complex exponentials). However, this visible difference is merely a consequence of a deeper distinction: a DST implies different boundary conditions than the DFT or other related transforms.

Formally, the discrete sine transform is a linear, invertible function *F*: R^N -> R^N (where R denotes the set of real numbers), or equivalently an *N* × *N* square matrix. There are several variants of the DST with slightly modified definitions. The *N* real numbers $x_0, \dots. x_{N-1}$ are transformed into the *N* real numbers $X_0, \dots.. X_{N-1}$ according to

$$X_k = \sum_{n=0}^{N-1} x_n \sin\left[\frac{\pi}{N+1}(n+1)(k+1)\right]$$
$$k = 0,1, \dots\dots\dots\dots N-1$$

C. *Fast Fourier Transform (FFT)*

A fast Fourier transform (FFT)] is an efficient algorithm to compute the discrete Fourier transform (DFT) and it's inverse. There are many distinct FFT algorithms involving a wide range of mathematics, from simple complex-number arithmetic to group theory and number theory. A DFT decomposes a sequence of values into components of different frequencies but computing it directly from the definition is often too slow to be practical. An FFT is a way to compute the same result more quickly. Computing a DFT of *N* points in the naive way, using the definition, takes O(*N*2) arithmetical operations , while an FFT can compute the same result in onlyO(*N* log *N*) operations.

Fast Fourier Transform is a fundamental transform in digital signal processing with applications in frequency analysis, signal processing etc. The periodicity and symmetry properties of DFT are useful for compression. The *uth* FFT coefficient of length *N* sequence {*f(x)*} is defined as

$$F(u) = \sum_{x=0}^{N-1} f(x)e^{-j2\pi ux}/_{N}$$

$$u = 0,1, \ldots \ldots \ldots \ldots \ldots \ldots N-1$$

And its inverse transform is calculated from

$$f(x) = \frac{1}{N}\sum_{u=0}^{N-1} f(x)e^{j2\pi ux/N}$$

$$x = 0,1, \ldots \ldots \ldots \ldots . N-1$$

D. *Discrete Cosine Transform – II (DCT – II)*

The most common variant of discrete cosine transform is the type-II DCT [18]. The DCT-II is typically defined as a real, orthogonal (unitary), linear transformation by the formula

$$C_k^{II} = \sqrt{\frac{2-\delta_{k,0}}{N}} \sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}\left(n+\frac{1}{2}\right)k\right]$$

for N inputs x_n and N outputs C_k^{II} , where $\delta_{k,0}$ is the Kronecker delta (= 1 for k = 0 and = 0 otherwise). DCT-II can be viewed as special case of the discrete Fourier transform (DFT) with real inputs of certain symmetry. This viewpoint is fruitful because it means that any FFT algorithm for the DFT leads immediately to a corresponding fast algorithm for the DCT-II simply by discarding the redundant operations. The discrete Fourier transform of size *N* is defined by

$$X_k = \sum_{n=0}^{N-1} x_n$$

where $\omega_N = e^{-2\pi i/N}$ is an *Nth* primitive root of unity. In order to relate this to the DCT-II, it is convenient to choose a different normalization for the latter transform as

$$C_k = 2\sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{n}\left(n+\frac{1}{2}\right)k\right]$$

This normalization is not unitary, but it is more directly related to the DFT and therefore more convenient for the development of algorithms. Of course, any fast algorithm for *Ck* trivially yields a fast algorithm for C_k^{II} although the exact count of required multiplications depends on the normalization. In order to derive C_k from the DFT formula, we can use the identity

$$2\cos(\pi l/N) = \omega_{4N}^{2l} + \omega_{4N}^{4N-2l}$$

$$C_k = 2\sum_{n=0}^{N-1} x_n \cos\left[\frac{\pi}{N}(n+1)k\right]$$

$$C_k = \sum_{n=0}^{N-1} x_n \omega_{4N}^{(2n+1)k} + \sum_{n=0}^{N-1} x_n \omega_{4N}^{(4N-2n-1)k}$$

Thus, the DCT-II of size *N* is precisely a DFT of size 4*N*, of real-even inputs, where the even-indexed inputs are zero.

III. RESULT AND DISCUSSION

We used data in the MIT-BIH database to test the performance of the four coding techniques. The ECG data is sampled at 142Hz and the resolution of each sample is 11bits/samples. The amount of compression is measured by CR and the distortion between the original and reconstructed signal is measured by PRD. The comparison table shown in Table 1, details the resultant compression techniques. This gives the choice to select the best suitable compression method. A data compression algorithm must represent the data with acceptable fidelity while achieving high CR.

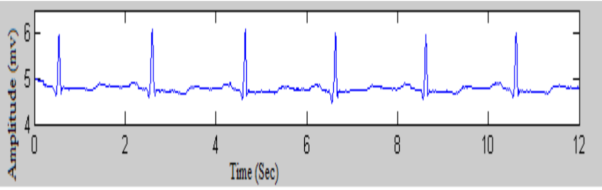

Fig:1 ECG Signal before Compression

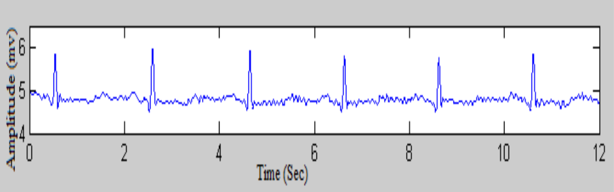

Fig:2 ECG signal after DCT Compression

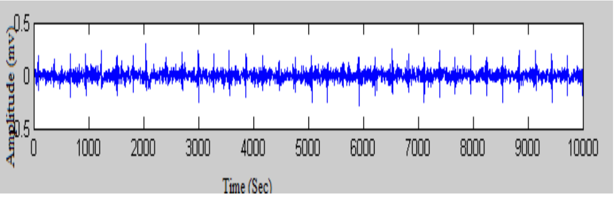

Fig:3 Error signal after DCT Compression

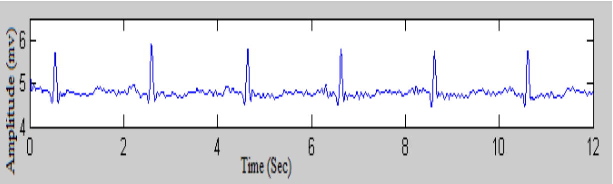

Fig:4 ECG signal after FFT compression

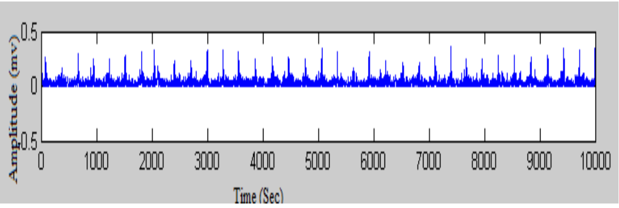

Fig:5 Error signal after FFT compression

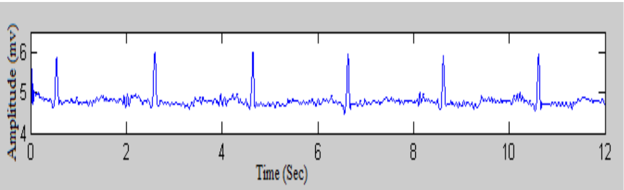

Fig:6 ECG signal after DST compression

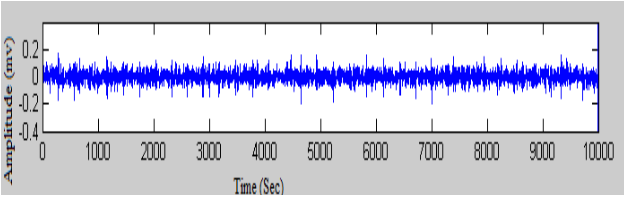

Fig:7 Error signal after DST compression

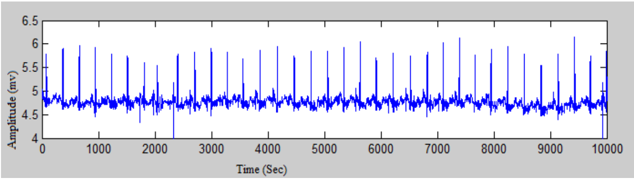

Fig:8 ECG signal after DCT 2 compression

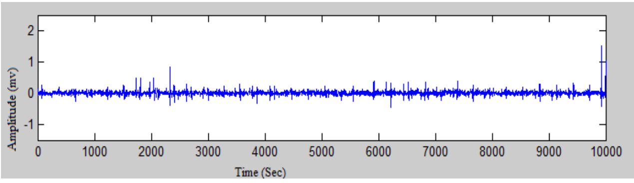

Fig:9 Error signal after DCT 2 compression

A data compression algorithm must represent the data with acceptable fidelity while achieving high CR. When we compare all the techniques CR of DCT 2 is high which is about 95.78 and it's PRS is also high which compensated by the CR.As the PRD indicates reconstruction fidelity; the increase in its value is actually undesirable. Although DCT-II provides maximum CR, but distortion is more. So a compromise is made between CR and PRD.

Table-1 Mathematical Values

Method	**Compression Ratio (CR)**	**PRD**
DCT	90.4600	0.9414
FFT	89.5900	1.1683
DST	85.1800	1.2584
DCT – II	95.7800	1.3320

IV. CONCLUSION

In this paper the preprocessed signal is transformed to get the decorrelated coefficients. Among the four techniques presented, DST provides lowest CR and distortion is also high. FFT improves CR and lowers PRD. So FFT is better choice than DST. Next is DCT which gives higher CR up to 91.68 with PRD as 0.8392. But DCT-II provides an improvement in terms of CR of 94.28 but PRD increases up to 1.5729. Thus an improvement of a discrete cosine transform (DCT) is presented as DCT-II. When we see the percentage of compression ratio DCT – II has fewer ratios of 20% which is very less than other techniques. The appropriate use of a block based DCT-II associated to a uniform scalar dead zone quantiser and arithmetic coding show very good results, confirming that the proposed strategy exhibits competitive performances compared with the most popular compressors used for ECG compression.

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