ECG Data Compression Analysis by Employing Different Transforms in Orthogonal Transformation Technique

Dhwani Kaushal
Department of Electronics and Communication
Delhi Technological University
Delhi, India
dhwanikaushal009@gmail.com

Vivek Singh
Department of Electronics and Communication
Delhi Technological University
Delhi, India
vsvivek1201@gmail.com

Priyanka Jain
Department of Electronics and Communication
Delhi Technological University
Delhi, India
priyankajain@dtu.ac.in

***Abstract* — This paper presents the performance analysis of FFT, DHT, DCT, and DST for ECG data compression using the orthogonal transformation method. The performance of each transform has been recorded by calculating compression ratio (CR) to measure the compression acquired, signal-to-noise ratio (SNR) to measure signal strength compared to background noise, and percent rms difference (PRD) for error measurement on Visual Studio (VS) Code using Python and has been compared with the literature. The Discrete Cosine transform performed well compared to the rest in the orthogonal transformation method.**

Keywords— DCT, DST, FFT, DHT compression ratio (CR), Percent rms difference (PRD), signal-to-noise-ratio (SNR)

I. INTRODUCTION

The Electrocardiogram (ECG) has been widely used to graphically display the electrical response generated due to the atria and ventricles' depolarization and repolarization. As ECG is a cost-effective and non-invasive technique, it is most commonly employed to diagnose heart diseases [1]. About 30 million ECGs are performed worldwide annually in acute care and ambulatory settings, but the problem of accurate retrieval of ECG data, and efficient storage deserves attention [2]. Also, data transmission has become much more convenient and faster by employing compression [3]. Algorithms that can provide a better CR and can cause less damage to the information in the recovered signal after compression, are in demand [4].

Transforms are used to shift signals in the time and frequency domain, for processing data. Over the years, many transforms have been introduced in literature and have also been employed in many real-life applications, a brief discussion of which is presented ahead. Some of them are Fast Fourier transform (FFT), Discrete Sine transform (DST), Discrete Cosine transform (DCT), and the latest, Discrete Hartley transform (DHT). Discrete Fourier transform (DFT), is similar to continuous Fourier transform of a given function. Fast Fourier transform is a more optimized algorithm than DFT, requiring fewer arithmetic operations for DFT computation. DST is a Fourier-related transform, that differs from DFT, as it uses only a sine function whereas DFT makes use of both sines as well as a cosine function. DCT on the other hand uses only the cosine function for calculating transform [5]. DHT, compared with DFT, requires no complex values and performs only real computations [6]. Fatma Abou–Chadi in [7] has presented an ECG data compression algorithm that uses the orthogonal transformation technique on the Fast Hartley Transform, and its comparison with Fast Fourier transform.

In [8], Kumar et al, presented that the ECG signal compression techniques developed so far are broadly categorized into three groups: (a) parameter extraction (b) direct method, and (c) transformation using orthogonal functions. The direct method openly analyzes the data points and reduces them in the time domain. The transformation method (using orthogonal transforms) performs an analysis of the energy distribution, by converting the signal from the time domain to another domain. The parameter extraction method does feature extraction from the original signal. Another recent method is ASCII-based encoding which incorporates the ECG data as ASCII characters in the existing technology [9,10]. The most commonly used techniques are (b) and (c), allowing for reconstruction of the compressed signal for future analysis. Initially, many algorithms were developed on the direct method [11], due to its simplicity and easy implementation on real-time systems. However, with increase in the calculating power of computers, later on, many algorithms [12] were developed for data compression using orthogonal transforms.

In this paper, using different transforms, we will be doing ECG data compression analysis, and comparing the performances based on CR, SNR, and PRD. The paper is organized as section 2 discusses the transforms used for analysis, in section 3 methodology has been presented, followed by a discussion on performance indexes in section 4, in section 5 a performance comparison of the transforms is made along with the results, and section 6 and 7 deals with the discussion and conclusion.

II. TRANSFORMS

A. Discrete Fourier Transform

The DFT X(k) for a given sequence x(m), length N is;

$$X(k) = \sum_{m=0}^{N-1} x(m)W^{mk} \quad (1)$$

Where, k = 0, 1, … N-1 and W = $e^{-j2\pi/N}$

B. Discrete Sine Transform

DST of a sequence with length N is defined as

$$X(k) = a_k \sum_{n=1}^{N} x[n] sin\frac{(2n-1)k\pi}{2N} \quad (2)$$

Where, k= 1, 2, … N

Here, $a_k = \sqrt{\frac{2}{N}}\varepsilon_k$ and $\varepsilon_k = \begin{cases} \sqrt{\frac{1}{2}}, & k = N \\ 1, & k = 1, ..N-1 \end{cases}$

C. Discrete Cosine Transform

DCT of a N point input sequence is given by

$$Y(k) = \sqrt{\frac{2}{N}} E_k \sum_{n=0}^{N-1} X[n] cos\frac{(2n+1)k\pi}{2N}$$
(3)

Where, k, n = {0, 1, 2, … N-1}

Here, $E_k = \begin{cases} \sqrt{\frac{1}{2}}, & k = 0 \\ 1, & k \neq 0 \end{cases}$

D. Discrete Hartley Transform

N point DHT is expressed as;

$$X[k] = \sum_{n=0}^{N-1} x[n] cas(\frac{2\pi nk}{N}) \quad (4)$$

Here k, n = 0, 1, 2 … N-1 and $Cas\theta = cos\theta + sin\theta$

III. METHODOLOGY

A. Data Acquisition

The data used for the experiment has been taken from the MIT-BIH arrhythmia database (117) [13].

B. Preprocessing of ECG Data

Before implementing the orthogonal transform technique, the collected ECG data was preprocessed using Python on Visual Studio Code. The data obtained from the MIT-BIH arrhythmia database is discrete and has a sampling frequency of 360 Hz.

C. Application of Orthogonal Transform Technique

Referring to (fig 1), the pre-processed ECG data is provided as an input signal to compute its N point transform. The N output coefficients are truncated to length L for a compression ratio (CR). It is noted from [13], that the total energy of the original signal in the time domain is distributed over all the samples, but after taking the transform the energy gets concentrated only in the first few coefficients (in case of DST and DCT), whereas it gets concentrated towards the extreme left and right side in case of FFT and DHT. All the coefficients that have energy less than the threshold energy, are removed. The threshold here has been calculated by plotting the energy spectrum, and removing certain coefficients and then observing the reconstructed signal. If the reconstructed signal is similar to original, then the threshold taken is correct, however if there is distortion then while removing coefficients, useful information has also been lost. The retained coefficients are lower-order harmonics, whereas higher-order harmonics have been discarded, as most of the information lies in lower harmonics. N-L zeroes are added for reconstruction, and the inverse transform is computed to get Xo(n).

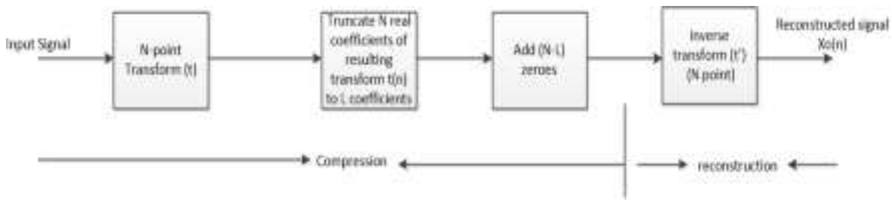

Fig 1. Detailed block diagram of the technique

IV. PERFORMANCE INDEX

We are using the following performance indexes to evaluate the performance of transforms on the technique adopted.

A. Compression Ratio: CR

The compression ratio is the ratio of the original data /signal size to the reconstructed data/signal size. It gives information about the degree to which the processed data has been compressed by removing unnecessary or repeated data. The more the CR, the lesser the number of bits of data to be stored or transmitted. The compression ratio (CR) is given by;

$$CR = N/L \tag{5}$$

N represents the number of coefficients of the original signal.
L represents the number of coefficients to be retained after compression.

B. *Percent rms Difference: PRD*

PRD measures the rms difference between the original ECG data and the compressed data. PRD is the most popular error measurement parameter, used to analyze ECG compression algorithms [14, 15, 16] and is gives as:

$$PRD = \sqrt{\frac{\sum(x[n]-x'[n])^2}{\sum(x[n]-\bar{x}[n])^2}} \times 100 \tag{6}$$

n varies from 1, 2 ,3 … N
Here, x[n] is representing the original signal
x'[n] is representing the reconstructed signal
$\bar{x}$[n] is representing the mean value of the original signal x[n]

It has been observed that in some papers, a different formula of PRD has been used with the denominator as $\sum_{n=1}^{N} x(n)^2$. While using this definition, one has to be careful since while defining PRD, one needs to check the DC level of the signal. MIT-BIH arrhythmia database has a baseline of 1024 that is added to the database for storage purposes [14]. If DC level is present in the original signal, then the PRD will give artificially low and perfect results. In order to have a fair comparison of ECG compression algorithms, the baseline needs to be flattened. With the fluctuated baseline, the variance of the reconstructed signal will be very high, and the PRD will be highly low, which can cover the original performance of the proposed algorithm [15].

C. *Signal-to-Noise-ratio: SNR*

SNR is an important parameter, used in many signals (audio, image, ECG, etc) that measures the level of a desired signal to the level of present background noise. The relationship between SNR and PRD according to [17] is given by:

$$SNR = -20\log(0.01PRD) \tag{7}$$

V. RESULTS

. It has been observed (referring to fig 2, fig 3, fig 4, and fig 5) that after reconstruction, some of the higher frequency components were removed, although the shape of the signal remains the same. The reconstructed signal, even after removal of high frequency components, looks similar to the original signal, as the presence and absence of these components is not visible to the naked eye. The values of calculated performance indexes has been compared with literature in table 1.

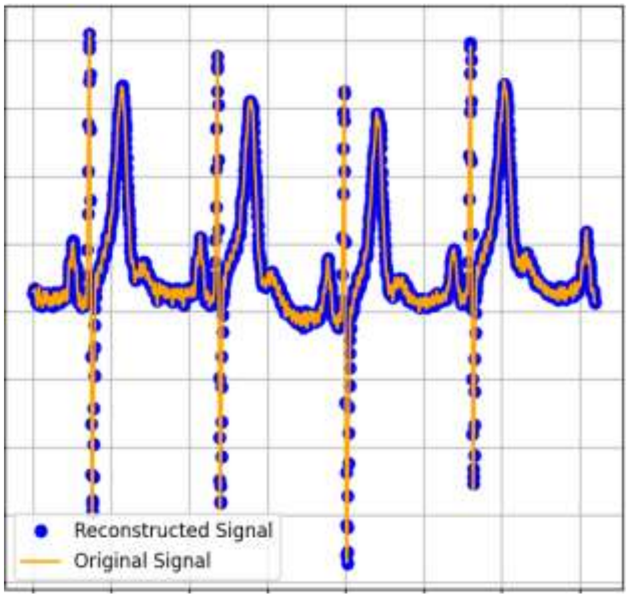

Fig 2. Overlap of Original and the ECG signal after compression using DCT

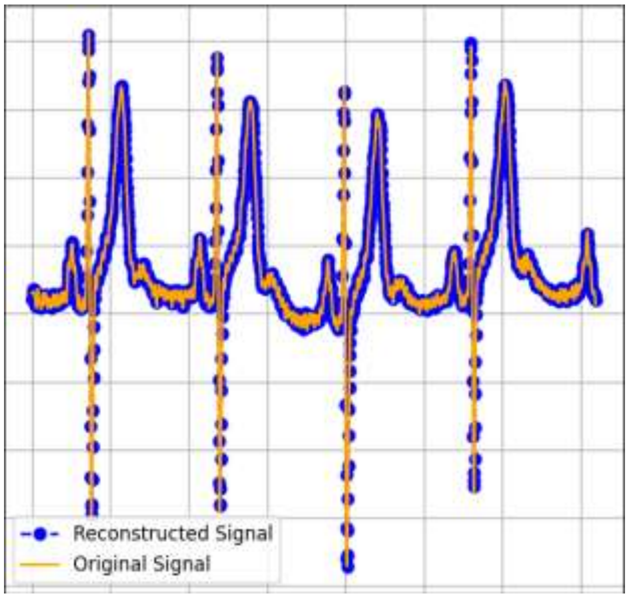

Fig 3. . Overlap of Original and the ECG signal after compression using FFT

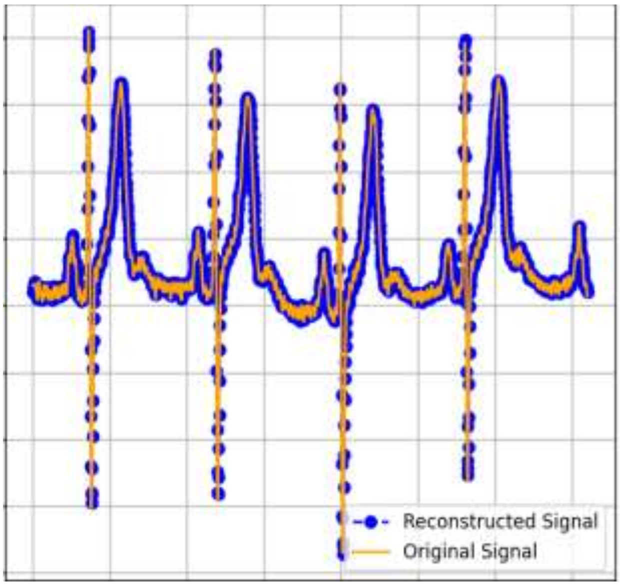

Fig 4. Overlap of Original and the ECG signal after compression using DHT

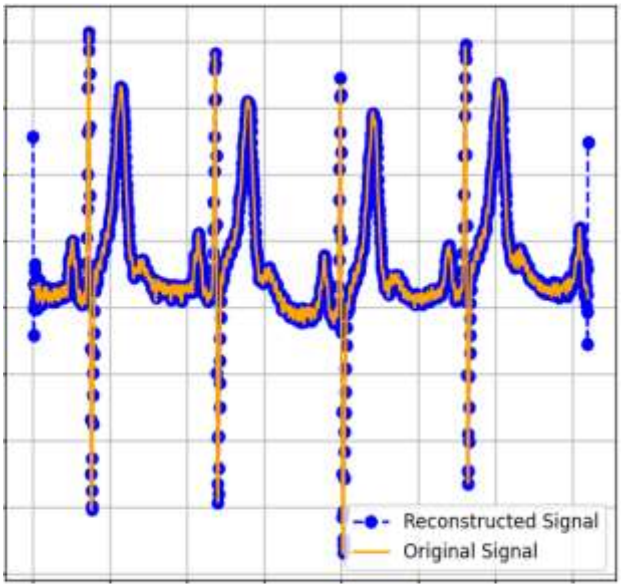

Fig 5 Overlap of Original and the ECG signal after compression using DST

Table1. Comparison of different transforms with literature

Reference	Performance Index	DCT	FFT	DHT	DST
Proposed	CR	5.14	5.14	5.14	5.14
	PRD	4.80	5.17	5.20	9.05
	SNR	26.36	25.71	25.67	20.86
Ref [1]	CR	68.8	3.66	-	-
	PRD	8.73	0.005	-	-
	SNR	9.99	73.97	-	-
Ref [5]	CR	90.43	89.57	-	85.18
	PRD	0.9382	1.661	-	1.2589

VI. Discussion

According to our results, we have found that the Discrete Cosine transform gives the best PRD of 4.80 at CR of 5.14 with an SNR of 26.36 compared to other transforms, when used in the orthogonal transformation technique. For highly correlated data sequences, DCT also has excellent energy compaction which makes it a better transform for compression. DHT and FFT have almost similar results, however, since in the case of DHT, the inverse has the same form as the forward DHT, except for the scaling factor, a single architecture or program can be used to calculate the forward and inverse, which saves hardware, and memory requirement is also reduced by half as compared to FFT, DCT, and DST. However, if considering the computational complexity, then FFT is a better choice since it has a complexity of O(N logN), but at the cost of complex hardware. By taking the same CR for all the transforms, we can get a clear picture of the performance parameters. By increasing CR, it was observed that after a certain value of CR, DCT gives more distortion as compared to DHT. If we consider individual thresholds of each transform by looking at their energy spectrum, then every transform has a different CR and its performance can be analyzed by observing the relation between CR and PRD i.e the quality score (CR/PRD). It can be noted from [1,5,7] that PRD comes out to be very low, when computed without removing the baseline value of the used database as discussed in section 4. According to [1], PRD comes out to be 0.005 with an SNR of 73.97 and CR of 3.66 for FFT. This is computed without removing the DC value of the database and hence gives false results. In case of [5] also it can be noted that PRD in the range of 0-1, cannot be achieved at a CR of 85-95 by using eq (6).

VII. Conclusion

In conclusion, we have carried out compression of ECG data using DCT, DST, FFT, and DHT for the orthogonal transformation technique and have simulated it on VS Code. It was found that Discrete Cosine transform has the best performance compared to the rest, and hence can be employed in compression techniques. However, other transforms also have advantages over DCT, which has been discussed.

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