IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)
e-ISSN: 2278-1676,p-ISSN: 2320-3331, Volume 15, Issue 4 Ser. I (Jul. – Aug. 2020), PP 46-56
www.iosrjournals.org

Development of Hybrid Lossless ECG Signal Compression Technique by Concatenation of Discrete Cosine with Fast Fourier Transforms

Adeleke, A. A. [1], Akingbade, K.F. , and Ponnle, A.A.
Electronics and Electrical Engineering Department, Faculty of Engineering and Technology, Federal University of Technology Akure,FUTA, Akure Ondo State, Nigeria.

Abstract: *The necessity of better Electrocardiogram (ECG) signal compression techniques is greater today than few years ago for several reasons. The quantity of ECG records is increasing in millions each year and previous records cannot be deleted since ECG signal is important for the comparison of records obtained over a long period of time to monitor the state of patients' heart. Therefore, it is imperative to ensure data generated is compressed as much as possible so that it takes up the least amount of space necessary and could be effectively transmitted despite the bandwidth limitation. In this research, hybrid lossless electrocardiogram signal compression algorithm using discrete cosine transform (DCT) and fast Fourier transform (FFT) was developed to find an optimal compression strategy for ECG data. The compression was carried out in two stages; DCT performed the first stage of compression while the FFT performed the second stage of compression. The algorithm was developed in MATLAB environment and the performance of the developed algorithm was tested in terms of the compression ratio (CR) and the percentage root mean difference (PRD) distortion metrics for the compression of data extracted from records 100 and 102 of the MIT-BIH database. The sampling rate and resolution were 360 Hz and 11-bit, respectively. The obtained results revealed that developed technique possesses higher compression ratios and acceptable reconstruction signal quality. For the record 100, the developed hybrid technique achieved a saving percentage (SP) of 95.03%, compression ratio (CR) of 45.60 with acceptable signal distortion (PRD) of 8.911%. For the record 102, the developed hybrid technique achieved SP of 98.08%, CR of 39.01 and PRD of 8.975% which are suitable for most monitoring and diagnoses applications.*

Keywords:*Electrocardiogram, Discrete cosine transform, fast fourier transform, saving percentage, compression ratio, percentage root mean difference.*

Date of Submission: 18-07-2020 Date of Acceptance: 02-08-2020

I. Introduction

The electrocardiogram (ECG) is a vital tool medical practitioner use to assess and diagnose a patient's heart condition; the accuracy of the signal is vital for correct diagnosis. Biomedical signals, such as electrocardiogram (ECG), electroencephalogram (EEG), surface electromyogram (SEMG) and bioacoustics signals generate large amounts of data when digitized for storage and analysis within a signal processing framework. It is an important physiological signal which is exploited to diagnose heart diseases because every arrhythmia in ECG signals can be related to a heart disease. ECG signals are recorded from patients for both monitoring and diagnostic purposes. Therefore, storage is very necessary. However, the storage has limitation which made ECG data compression an important issue of research in biomedical signal processing.In addition to these, there are other advantages of ECG compression such as enhancement of transmission speed of real-time ECG signal, and cost minimization. The ambulatory monitoring system usually requires continuous 12 to 24-hours ambulatory recording for good diagnostic quality. For example, with the sampling rate of 360 Hz, 11 bit/sample data resolution, a 24-h record requires about 43MB per channel. So, 12-channel system requires nearly 513.216 MB of storage disks daily [31]. As a result, data reduction and compression processes are of great interest in biomedical signal analysis, especially in the area of data transmission (e.g. in telemedicine applications) or where long-term recordings (e.g. in sleep laboratories, intensive care) are involved. With appropriate processing of biomedical signals, the redundant data stream could be reduced to the most significant parameters that could efficiently contribute to medical decision making. In this way, high density storage could be achieved. In the same vein, reduction of the number of bits required to describe a biomedical signal could facilitate the data transmission. Electrocardiograph is a combination of several Greek words. The Greek word electro, relates to electrical activities; *kardio,* means heart; and *graph* is a Greek root word meaning 'to write'.Electrocardiography is a commonly used, non-invasive procedure for recording electrical changes in the heart. The records, which are called an electrocardiogram (ECG), show the series of waves that relate to the electrical impulses which occur during each beat of the heart. An initial breakthrough came when Willem Einthoven, working in Leiden, the Netherlands, used the string galvanometer he invented in 1901. This device was much more sensitive than both the capillary electrometer Waller and String galvanometer that was invented by a French Engineer Clement Ader (1897). Rather than using self-adhesive electrodes, Einthoven's immerse each of patient's limbs into containers of salt solutions from which the ECG was recorded. Einthoven assigned the letters P, Q, R, S, and T to the various deflections, and described the electrocardiographic features of a number of cardiovascular disorders [26].

The ECG is the electrical manifestation of the contractile activity of the heart, and can be recorded fairly easily with surface electrodes on the limbs or chest. Due to its ease of measurement, ECG is perhaps the most commonly known, recognized, and used biomedical signal. The ECG recording diagnosis has a great variety of uses which are to find the cause of unexplained chest pain, which could be caused by a heart attack, inflammation of the sac surrounding the heart (pericarditis), or angina, find the cause of symptoms of heart disease, such as shortness of breath, dizziness, fainting, or rapid, irregular heartbeats (palpitations).Find out if the walls of the heart chambers are too thick (hypertrophied). It also used in check the effect of medication and whether they are causing side effects that affect the heart, monitors the operation of mechanical devices like pacemakers that are implanted in the patient's heart.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 and also detecting and eliminating redundancies in a given data set.Tarik *et al.* (2014) in their paper presented a hybrid technique for the compression of ECG signals based on DWT and exploiting the correlation between signal samples. It incorporates Discrete Wavelet Transform (DWT), Differential Pulse Code Modulation (DPCM), and run-length coding techniques for the compression of different parts of the signal. Mohamed *et al.* (2015) presented a hybrid ECG compression technique based on Discrete Wavelet Transform and reducing the correlation between signal samples and beats. The proposed scheme starts by segmenting the ECG signal into blocks; each of length 1024 samples. Duong *et al.* (2016) in their paper proposed a compression algorithm, called the advanced two-state algorithm. In this algorithm, the ECG pattern is divided into two categories: "complex" durations such as QRS complexes; labeled as low-state durations, and "plain" durations such as P or T waves, are labeled as high-state durations. Each duration type can be compressed at different compression ratios, and Piecewise Cubic Spline can be used for reconstructing the signal.The approach of combining multiple transformations i.e. DCT-FFT, has been successfully presented in this research work. The hybrid algorithm compensated the demerits of standalone DCT and FFT.

Research methodology

The developed algorithm is of two stages namely the Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) as shown in Figure 3.1. The first stage start at x(n) and end at IDCT while the second stage start at FFT and end at IFFT. x(n) is the input signal and x'(n) is the reconstructed signal after hybrid compression.

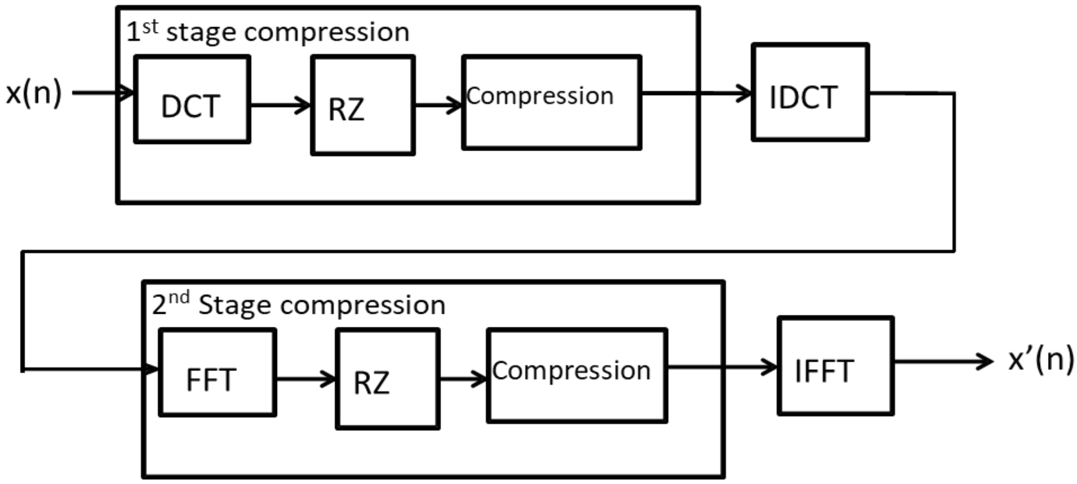


Figure 1: Block diagram of the developed hybrid algorithm.

The first stage compression is carried out by DCT algorithm, which compresses the data immediately the ECG stored file is loaded. Upon launching the algorithm, it read in ECG data and evaluates DCT of data. Thereafter, removing of zeroes is done in order to remove the redundancy in the data and to achieve a higher compression ratio. After removing of zeroes, the compression is done via DCT and inverse of discrete cosine transform (IDCT) is evaluated which served as input for the second stage of compression as shown in Figure 3.1. While the second stage compression, received the output of DCT algorithm i.e. IDCT as its input for further compression like in the first stage. The output of the IDCT which served as the input to the FFT was evaluated via FFT after which zeroes were removed purposely to achieve better and higher compression ratio with negligible distortion, then the compression through FFT and the Inverse of Fast Fourier Transform (IFFT) is then evaluated. The combination of the first stage with the second stage forms the hybrid method

Discrete Cosine Transform

Discrete Cosine Transform is a basis for many signal and image compression algorithms due to its high decorrelation and energy compaction property. DCT has many similarities to the FFT, for example, time-domain to frequency-domain conversion. However, the DCT only expresses the signal as a sum of cosine functions. A discrete Cosine Transform of N sample is defined as in Equation 1:

$$\mathbb{F}(u) = \sqrt{\frac{2}{N}}\,\mathrm{C}(u)\sum_{x=0}^{N-1} f(x)cos\left[\frac{\pi(2x+1)u}{2N}\right] \quad 1$$

where $u = 0, 1, \ldots, N-1,\ \mathrm{C}(u) = \frac{1}{\sqrt{2}} \quad for \quad u = 0$

$= 1 \qquad 0 < u \leq N-1$

The function f(x) represents the value of x^{th} samples of input ECG signals. F(u) represents a DCT coefficient. The inverse DCT is defined in similar fashion as follows in Equation 2

$$f(x) = \sqrt{\frac{2}{N}}\sum_{u=0}^{N-1} C(u)F(u)cos\left[\frac{\pi(2x+1)u}{2N}\right] \qquad 2$$

$x = 0$, 1,…, N-1 F(x) is the IDCT (reconstructed ECG signal)

Fast Fourier Transform (FFT)

A Fast Fourier Transform (FFT) is an efficient algorithm to compute the Discrete Fourier Transform (DFT) and its 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.

The difference in speed can be substantial, especially for long data sets where N may be in the thousands or millions in practice, the computation time can be reduced by several orders of magnitude in such cases, and the improvement is roughly proportional to N / log (N). This huge improvement made many DFT-based algorithms practical; FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers.

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 FFT are useful for compression. The u^{th} FFT coefficient of length N sequence {f(u)} is defined as in Equation 3

$$F(u) = \sum_{x=0}^{N-1} f(x)e^{-j2\pi ux/N} \qquad 3$$

where u=0, 1…N-1.

F (u) is Fast Fourier transform, f(x) is the reconstructed signal from DCT, N is uniform sample space, and $2\pi u/N$ is the frequency.

Its inverse transform (IFFT) as in Equation (4) is

$$f(x) = \frac{1}{N}\sum_{u=0}^{N-1} F(u)e^{j2\pi ux/N} \qquad 4$$

where x is 0, 1…N -1 f(x) is the IFFT (i.e. final reconstructed ECG signal)

Compression measurement

All data compression algorithms minimizes data storage by reducing the redundancy wherever possible, thereby increasing the compression ratio. 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. A high compression ratio is typically desired. A data compression algorithm must also represent the data with acceptable fidelity while achieving high CR.

It is given by:

$$CR = \frac{Original\ \ file\ size}{Compressed\ \ file\ size} \qquad 5$$

The definition is very obvious to reflect how much data is reduced during compression. The higher the compression ratio is, the smaller the size of the compressed file.

$$Saving\ Percentage = ((B-A)/B) * 100 \qquad 6$$

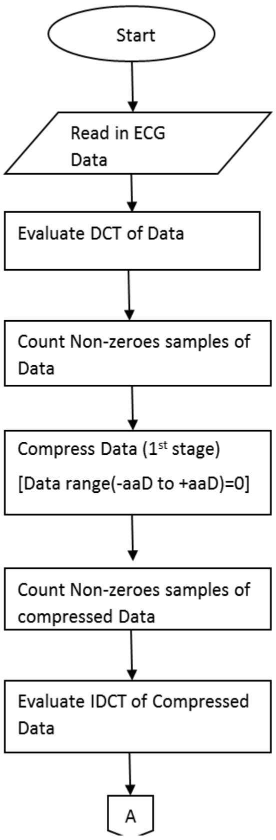
where B is the size before compression and A is the size after compression. The higher the saving percentage is, the more the efficient use of available bandwidth in telemedicine health care system, and subsequently the lower the cost of medical information transmission.

Distortion measurement

One of the most difficult problems in ECG compression and reconstruction is defining the error criterion that measures the ability of the reconstructed signal to preserve the relevant information. The reconstruction error is defined as the difference between the original signal and the reconstructed one. It measures the ability of the reconstructed signal to preserve the relevant diagnostic information; any slight loss or change of information canlead to wrong diagnosis. In the case of ECG compression, data that does not contain diagnostic information can be removed. The computational complexity component relates to practical implementation considerations and is desired to be as low as possible. Different objective error measures namely; root mean square error (RMSE), percentage root mean difference (PRD), signal to noise ratio (SNR) are used for calculation of reconstruction error. Among these error measures, the ECG processing is frequently measured by the percentage root mean difference (PRD). It is most commonly defined as: a measure of error loss. This error estimate is the one most commonly used in all scientific literature concerned with ECG compression techniques. The main drawbacks are the inability to cope with baseline fluctuations and the inability to discriminate between the diagnostic portions of an ECG curve. However, its simplicity and relative accuracy make it a popular error estimate among researchers. The globally standard of ECG signalreconstruction quality in terms of PRD is defined as PRD < 2%: very good reconstruction, PRD <2-5%: good reconstruction, PRD < 5-9%: acceptable quality of reconstruction and PRD > 9%: unacceptable quality. PRD calculation is as follows:

$$PRD = 100 \times \sqrt{\frac{\sum_{i=1}^{n}\left(ORG(i) - REC(i)\right)^2}{\sum_{i=1}^{n}\left(ORG(i)\right)^2}} \qquad (7)$$

where ORG is the original signal, REC is the reconstructed signal and N is the length of the window over which the PRD is calculated. The lower the PRD, the closer the reconstructed signal is to the original ECG data.



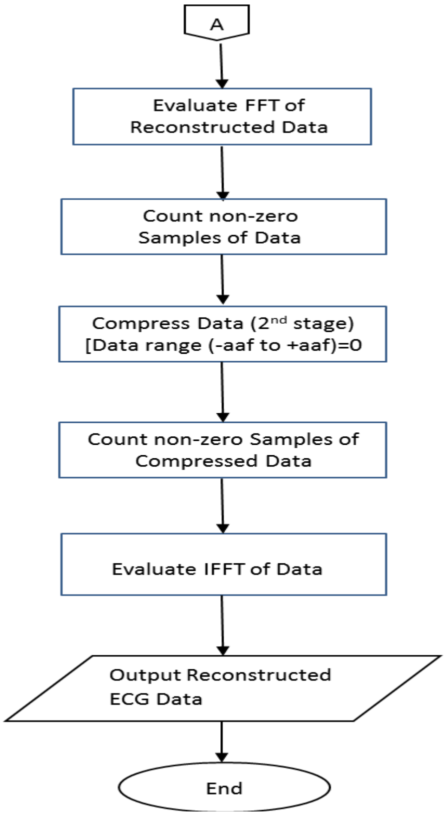


Figure 2: Flow chart of the developed hybrid compression algorithm.

II. Results and Discussion

The developed method was tested on the signals extracted from records 100 and 102 of the MIT-BIH database; for which the sampling rate is 360 Hz and the resolution is 11-bit. The results of the developed algorithm are obtained for record 100 and 102 MIT-BIH, and are shown in Figures 3 to 10.Figure 3 showsa time sample of the original ECG signal and DCT of the signal of MIT-BIH record 100. The DCT shows a sequence of finitely data point in terms of a sum of cosine functions. It shows that that ECG signal are quasi in nature (similar) means there is presence of redundancy and this property does not benefit compression, hence it need to be removed.Figure 4 comprises of wave forms of compressed DCT and recovered ECG signal. The compressed wave form clearly shows the removal of zeroes since it does not contain the clinical information. While the reconstructed ECG signal obtained by applying Inverse Discrete Cosine Transform.

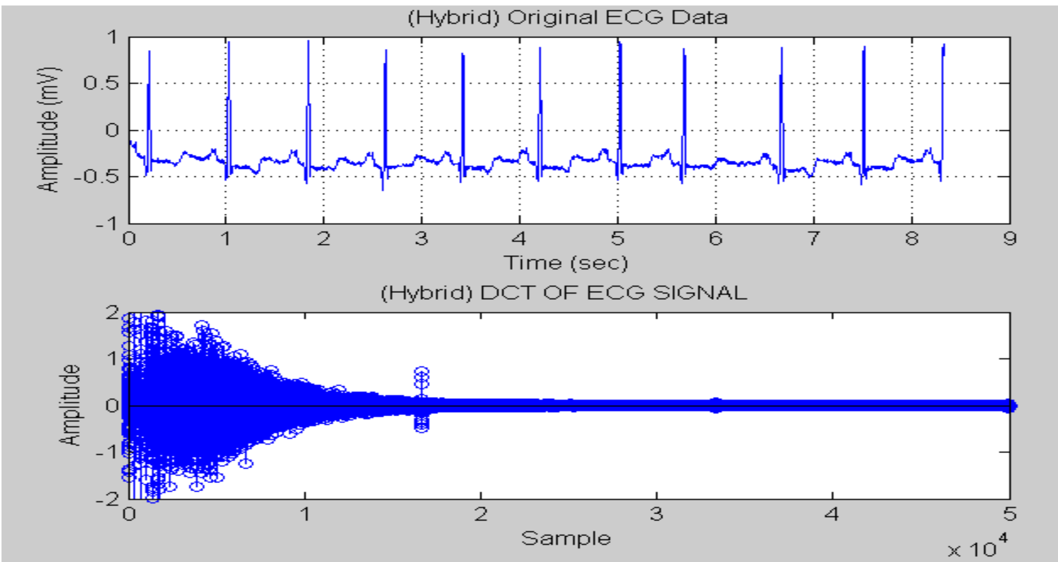


Figure:3: Original ECG Signal and DCT of the signal of MIT-BIH record 100.

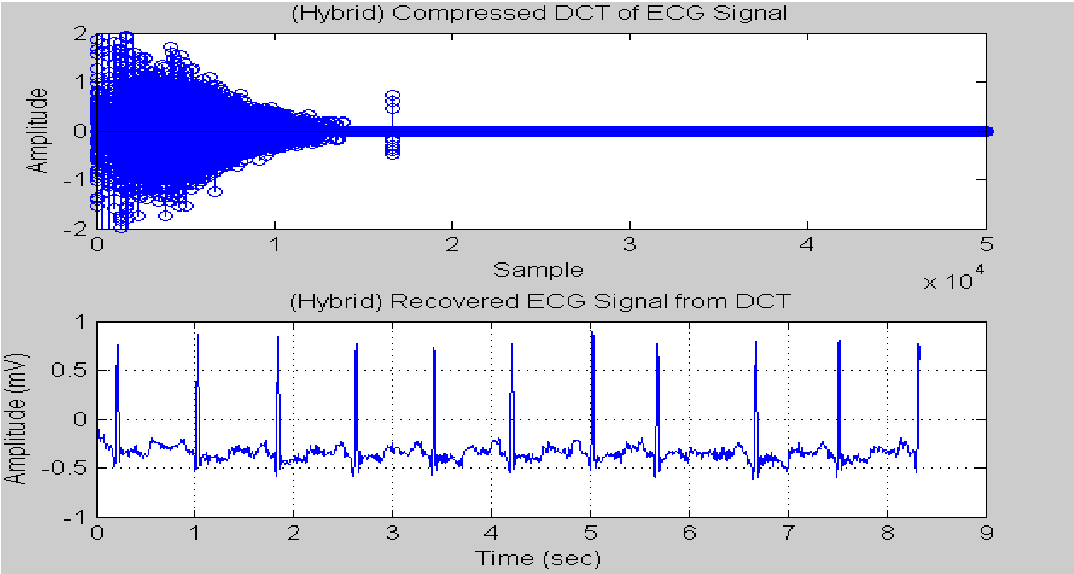


Figure: 4: Compressed DCT of ECG signal and recovered signal from DCT of MIT-BIH record 100

Figure 5 shows the FFT of IDCT and compressed FFT of IDCT of ECG signal of MIT-BIH record 100. The FFT of IDCT wave form shows the transform of recovered signal (IFFT) by means of FFT for further compression, while the compressed FFT of IDCT wave form shows the further removal of any redundancy that might present.Figure 6 shows the final recovered ECG signal and error due to hybrid compression of the ECG signal of MIT-BIH record 100. The first wave form of Figure 4.4 shows the reconstruction of the original ECG signal while the second wave form is the error due to hybrid compression, which indicates how extent the original signal has been distorted.The result of the Hybrid (DCT_FFT) Compression Analysis of MIT-BIH record 100 shows a high compression ratio (CR) of 45.56 with acceptable quality of reconstruction (PRD) of 8.91%.

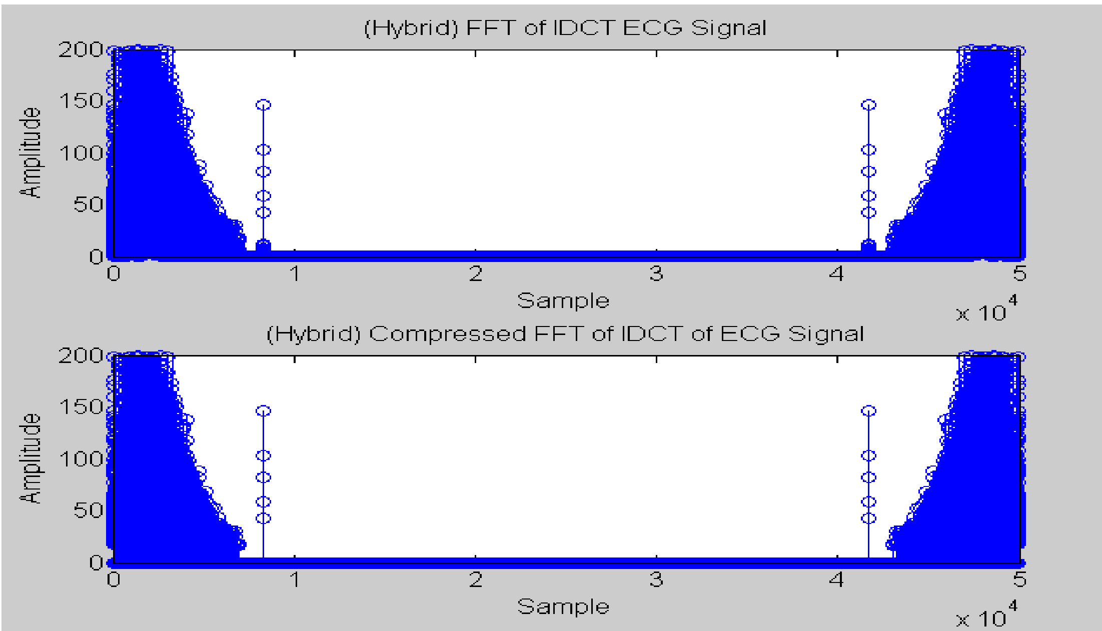


Figure: 5: FFT of IDCT and compressed FFT of IDCT of ECG signal of MIT-BIH record 100.

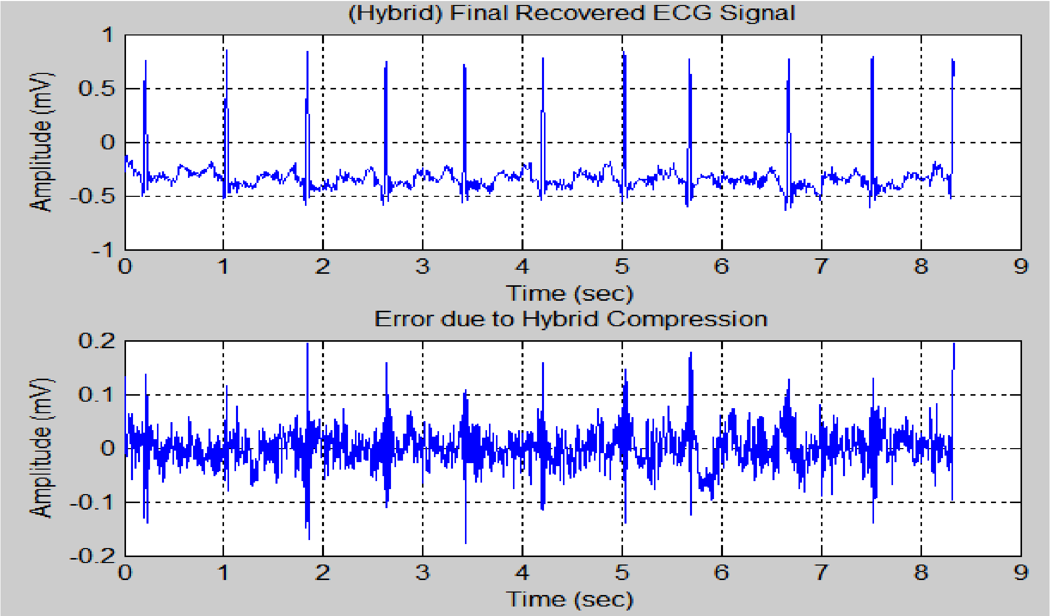


Figure: 6: Finalrecovered ECG signal and Error due to Hybrid Compression of ECG signal of MIT-BIH record 100.

Figure 7 shows a time sample of the original ECG signal and DCT of the signal of MIT-BIH record 102. The DCT wave form of Figure 6 shows a sequence of finitely data point in terms of a sum of cosine functions oscillating at different frequency. There is presence of redundancy in this wave form due to correlation between ECG data; hence it needs to be removed in other to archive high compression ratio.Figure 8 shows the wave forms of compressed DCT and recovered ECG signal. The compressed wave form clearly shows the removal of zeroes since it does not contain the clinical information. The reconstructed ECG signal was obtained by applying Inverse Discrete Cosine Transform.

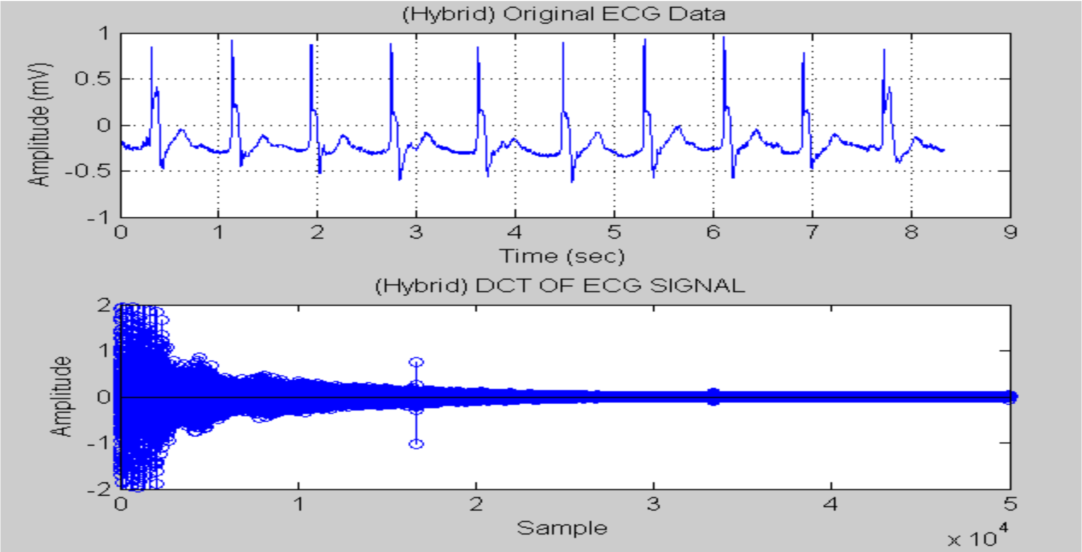


Figure: 7: Original ECG signal and DCT of ECG Signal of MIT-BIH record 102.

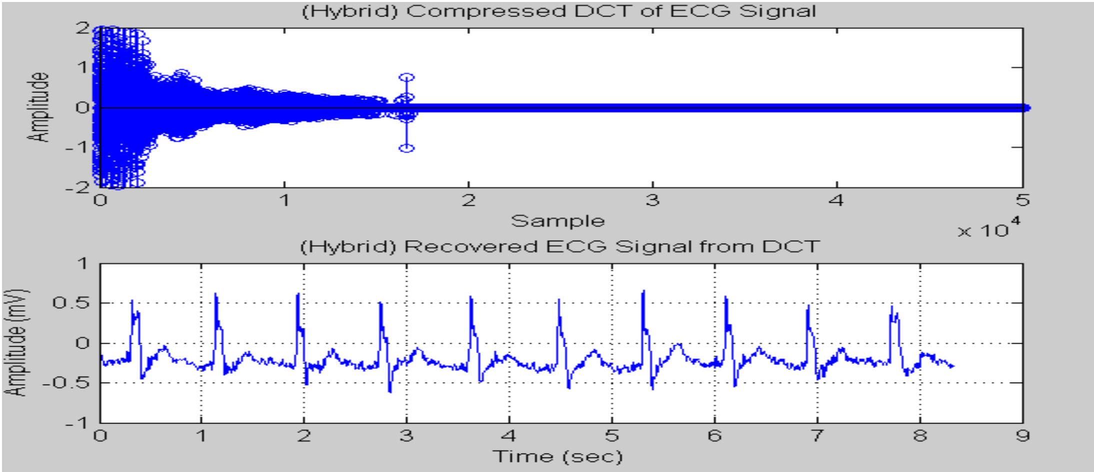


Figure: 8: Compressed DCT of ECG signal and recovered signal from DCT of MIT-BIH record 102.

Figure 9 shows the FFT of IDCT and compressed FFT of IDCT of ECG signal of MIT-BIH record 102. The first wave form of Figure 9 shows the transform of recovered signal for further compression. The second wave form is the compressed signal which shows the further removal of any redundancy that might present.Figure 10 shows the final recovered ECG signal and error due to hybrid compression of the ECG signal of MIT-BIH record 102. The first wave form of Figure 10 shows the reconstruction of original ECG signal after compression. The second wave form depicts error due to hybrid compression (the difference between the original signal and reconstructed signal), that shows how original signal has been distorted.The result of the Hybrid (DCT_FFT) Compression Analysis of MIT-BIH record 102 shows a compression ratio (CR) of 39.009 with acceptable quality of reconstruction (PRD) of 8.97%. By comparing the original signal with the reconstructed signal, it can be observed that the original and reconstructed ECG signals (signal after compression) are approximately matched.

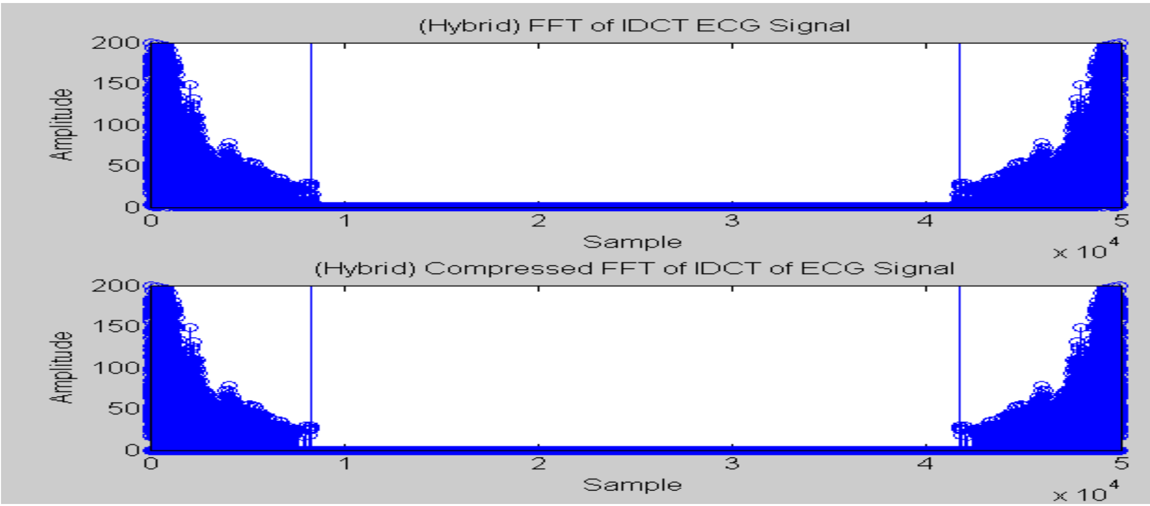


Figure: 9: FFT of IDCT and compressed FFT of IDCT of ECG signal of MIT-BIH record 102.

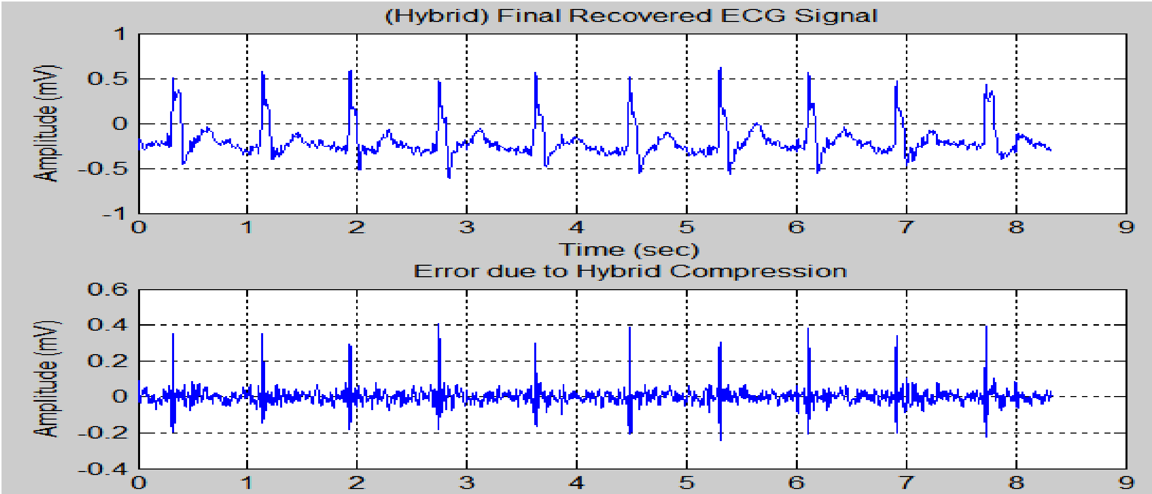


Figure: 10: Final recovered ECG signal and Error due to Hybrid Compression of ECG signal of MIT-BIH record 102.

Table 1: Performance of Compression Techniques for Record 100

No of Sample	Methods	Record 100		
		CR	PRD (%)	SP (%)
50,0000	Developed (HYBRID)	45.60	8.9113	95.03
	DCT	8.18	8.5923	90.43
	FFT	5.57	2.311	80.79

***SP-**

Table 2: Performance of Compression Techniques on MIT-BIH record 102

No of Sample	Methods	Record 102		
		CR	PRD (%)	SP (%)
	HYBRID	39.01	8.9785	98.08
	DCT	7.13	7.9902	94.18
	FFT	5.50	3.9816	81.43

For record 100, the developed technique has a CR of 45.60, acceptable PRD of 8.9113% with higher saving percentage of 95.03%. For record 102, a high compression ratio (CR) of 39.01 was achieved, and acceptable PRD of 8.9785% with higher saving percentage (SP) of 98.08%. In both comparisons, the HYBRID technique is very effective when compared with DCT and FFT compression methods.

Comparison with other existing algorithm

In the field of ECG signal compression, several techniques have been reported in the literature. In order to promote the developed algorithm, it is necessary to compare it with other acceptable published results. The comparison with the existing methods was made in term of compression performance and signal distortion. Table 4.3 shows the comparative performance of the developed method and some earlier published algorithms.

Table 3: Comparisons between the developed method and earlier published algorithms for MIT-BIH record 100.

Methods	**Record 100**	
	CR	PRD (%)
Tais *et al* (2005). SPIHT	10.0	1.48
Hung *et al* (2009). ROI mask.	20.9	0.185
Sangjoon *et al* (2011). A real-time compression and transmission algorithm.	27.9	2.93
Tarik *et al* (2014). DWT, Differential Pulse Code Modulation (DPCM), and Run-Length coding techniques, correlation between signal samples.	15.0	2.82
Mohamed *et al* (2015). DWT and QRS-Complex Estimation.	22.98	2.62
Duong *et al* (2016). Advance two stage compressions. (Piecewise Cubic Spline)	17.5	0.418
The developed method.	45.6	8.911

The results of Table 2 have clearly shown the effectiveness of the developed algorithm in getting high compression ratio of 45.6 with acceptable reconstruction signal quality compared to the indicated published results. Though the value of PRD of developed algorithm is higher than those of other published result indicated in the table, still it is acceptable since this value fall between globally standard of ECG signal reconstruction quality in terms of PRD. Therefore, the developed method has acceptable satisfactory performance in comparison with other existing methods.

III. Conclusion

Compression can significantly reduce the cost of medical information transmission through telecommunications channels. In this research, hybrid lossless electrocardiogram signals compression technique using Discrete Cosine Transform (DCT) and Fast Fourier Transform (FFT) methods was developed to find an optimal compression strategy for ECG data.The developed algorithm was tested adopting records extracted from MIT-BIH Arrhythmia Database (stored file) considering the compression ratio and the PRD distortion metrics. Simulation results have clearly shown the effectiveness of the developed algorithm in getting high compression ratios with acceptable reconstruction signal quality compared to recently published results. It is flexible in dealing with different types of applications; namely telediagnoses and telemonitoring of cardiac patients.The developed compression algorithm has some other features which are very important in the real-time environment. First, the reconstructed signal quality and the bit stream can be controlled by removing the spectral redundancy through the process of thresholding of data samples. Secondly, the computational complexity of the developed algorithm is very low.This hybrid compression can be implemented to save disk spaces for ECG signal storage, and to allow efficient use of available bandwidth in telemedicine-based health care systems.Hybrid approach is successful in compressing the ECG data samples using the approach detailed in this report. It can effectively detect and remove a considerable amount of redundancy by means of thresholding the ECG data samples thereby achieving the better compression ratio (CR) with acceptable reconstruction signal quality in terms percentage root mean square difference (PRD). A limitation of this method is that, as the value of threshold increases beyond the prediction limit, the more the distortion. To overcome this challenge, low threshold value was selected such that the quality of the ECG signal is not distorted on reconstruction and a good amount of data reduction is also achieved. Also, to improve on this, more complex algorithm like wavelet-based method can be studied. Since this thesis contains a study on the possibilities of lossless compression of ECG signals, there is plenty of further work to be done. In future, the compression study should be expanded to other biomedical signals, for instance phonocardiograph (PCG) signals, since mostly only ECG signals have been studied in this context.

References

[1]. Ahmed, S.M., Al-Zoubi, Q., and Abo-Zahhad, M. (2007): "A hybrid ECG Compression Algorithm based on Singular Value Decomposition and Discrete Wavelet Transform," Journal of Medical Engineering and Technology, Vol. 31, No. 1, pp. 54-61.

[2]. Al-Shrouf, A., and Ahmed, S. (2003): "A Novel Compression Algorithm for Electrocardiogram Signals based on the Linear Prediction of the Wavelet Coefficients," Digital Signal Processing, Vol. 13, pp. 604-622.

[3]. Benmalek, M. and Charef, A. (2009): "Digital Fractional Order Operators for R Wave Detection in Electrocardiogram Signal," IET Signal Processing, Vol. 3, pp. 381–391.

[4]. Berne, R.M., and Levy, M.N. (1990): Cardiovascular in Principle of Physiology, Wolfe Publications Ltd, London, pp. 212-213.

[5]. Cardenas, J., and Lorenzo, J. (1999): "Mean-Shape Vector Quantization for ECG Signal Compression," IEEE Transaction on Biomedical Engineering, Vol. 46, No. 1, pp. 62-70.

[6]. Chawla, M.P.S (2009): "A Comparative Analysis of Principal Component Technique for Electrocardiograms," Neural Compute and Application, Vol. 18, No. 1, pp. 54-61.

[7]. Claude, E. (1950): "Prediction and Entropy of Printed English", Bell System Technical Journal, Vol. 3, pp. 50-64.

[8]. Cochran, W.T. (1967): "What is the Fast Fourier Transform?" Proc. IEEE, Vol. 55, pp. 1664-1677.

[9]. Duong, T., Nguyen, M., Nguyen, I., and Nguyen, H. (2016): "Advanced Two-State Compression Algorithm," International Journal of Soft Computing Engineering, Vol.5, No. 6, pp. 2231- 2307.

[10]. Fozzard, A. and Oliver G. (1968): "AZTEC: A Preprocessing Scheme for Real Time ECG Rhythm Analysis", IEEE Transactions on Biomedical Engineering, Vol. 15, pp. 128-129.

[11]. Grauer, K., Cavallaro, D. (1997): Arrhythmia Interpretation: Advanced Cardiac Life Support Preparation and Clinical Approach. St.Louis,MO:Mosby.

[12]. http://library.med.utah.edu/kw/ecg/ecg_outline/Lesson3/index.html (Accessed on 21st March, 2013).

[13]. http://www.mauvila.com/ECG/ecg_intro.htm (accessed on 22nd Dec, 2014)

[14]. Ingels, F.M. (1971): Introduction and Coding Theory. Scranton, Pennyslavia.

[15]. Jalaleddine S. (1990): "ECG Data Compression Techniques-A Unified Approach", IEEE Transactions on Biomedical Engineering, Vol. 37, No .4, pp. 329-343.

[16]. Jane, R., Laguna, p., Thakor, N.V., and Cammal, P. (1992): "Adaptive base-line wander removal in the ECG; comparative analysis with Cubic Spline Technique". Computer in Cardiology, pp.143-148.

[17]. Klionski, D. M., Oreshko, N. I., Gepperzes, V.V., and Vasiljev, A.V. (2008): "Applications of Empirical Mode Decomposition for Processing Non Stationary Signals", ISSN 1054-6618, Pattern Recognition and Image Analysis, Vol. 18, No. 3, pp. 390–399.

[18]. Kumari, R., and Sridhar, A. (2013):"Analysis of ECG Data Compression Techniques" International Journal of Engineering Trends and Technology (IJETT) – Vol. 5, No 3. pp. 116-124.

[19]. Kumar, A., Ranjeet, K., and Pandey, R. (2011): "ECG Signal Compression Using Different Techniques," International Conference on Advances in Computing, Communication and Control. pp. 231-241.

[20]. Mengyl, P.I. (2005): "Fundamental Data Compression." Butterworth- Heinman Publication, Dhaka, Bangladesh.

[21]. MIT-BIH arrhythmia database http://www.physionet.org/Cgi-bin/atm/ATM

[22]. Netter, F.H. (1969): "The Ciba collection of Medical Illustrations", Ciba Pharmaceutical Company, Summit, Vol. 5, pp. 293.

[23]. Pranob, K. (2011): "A Contemporary Approach for ECG Signal Compression Using Wavelet Transforms", Signal and Image Processing: An International Journal (SIPIJ). Vol. 2, No 1), pp. 178 - 183.

[24]. Rao, K.R., and Yip, P. (1990): "Discrete Cosine Transform – Algorithms, Advantages, Applications", Academic Press, San Diego USA.
[25]. Riggs, T., Ijenstein, B., and Thomas, C. (1979):"Spectral Analysis of the Normal Electrocardiogram in Children and Adults". Journal of Electro-cardiology, Vol. 12, No. 4, pp. 377-379.
[26]. Rituraj, J. (2015): "12 Lead ECG Data Compression Using Principal Component Analysis," International Journal of Emerging Trends and Technology in Computer Science, Vol. 4, No. 1, pp.34-39.
[27]. Sabarimalai, M., and Danpat, S. (2006): "Wavelet Threshold based ECG Compression using USZZQ and Huffman Coding of DSM", In Science Direct Biomedical Signal Processing and Control. pp. 261-270.
[28]. Sangjoon, L., Jungkuk, K., and Jong, L. (2011): "A Real-Time ECG Data Compression and Transmission Algorithm for an e-Health Device," IEE Transaction on Biomedical Engineering, Vol. 58, No. 9, pp. 2448-2455.
[29]. Tais, S., and Yan, W. (2005): "A 2-D ECG Compression Method based on Wavelet Transform and Modified SPIHT," IEEE Transaction on Biomedical Engineering, Vol. 56, No. 4, pp. 1261-1263.
[30]. Tarik, K., Abo-Zahhad, M., and Abdelfatah, M. (2014): "Compression of ECG Signals based on DWT and Exploitation the Correlation between ECG Signal Samples," International Journal Communications, Network and System Sciences, Vol. 7, No. 2, pp.101-118.
[31]. Zywietz, C., Van, J.H., and Kors, J.A (1998): "Signal Analysis for ECG interpretation," Methods Information Medicine, Vol. 29, pp. 317-329.

Adeleke, A. A, et. al. "Development of Hybrid Lossless ECG Signal Compression Technique by Concatenation of Discrete Cosine with Fast Fourier Transforms." *IOSR Journal of Electrical and Electronics Engineering (IOSR-JEEE)*, 15(4), (2020): pp. 46-56.