A Novel Approach Electrocardiograph Signal Compression based on Discrete Cosine Transform

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Abstract - *Storage COMPRESSED sensing (CS) or compressive sampling is an emerging technique for acquiring and reconstructing a digital signal with potential benefits in many applications. The method of CS takes advantage of a signal's sparseness in a particular domain to significantly reduce the number of samples needed to reconstruct the signal. and transmission limitations have made biomedical signal data compression an important feature for most biomedical computerized systems. In this paper A Hybrid Approach presenting Based on DCT for Biomedical Signal (ECG) Compression using MATLAB software. The advantage that MATLAB offers is that it is widely available, continuously updated and has wider reach. In addition, when compressed biomedical signals (ECG) or data are delivered over a public channel such as the Internet, TV etc their privacy and security would also be an important issue. Electrocardiogram (ECG) signal is a very important measure to know the Heart actual conditions so that easily found deceases. Various techniques have been proposed over the years for addressing the problem. We Show the fulfillment and feasibility of our system with respect to the comparison ratio efficiency*

***Key Words*: EC,.MIT-BIH, DCT, MATLAB, Signal Compression, Biomedical etc.**

1. 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. Scheme of ECG data compression are grouped into two categories: time domain (direct) methods and transform methods (see [4], [5], [6]). In direct methods, the compression is performed directly on the ECG samples but in transform methods signal is transformed to another domain in which signal is sparsely represented. In this article a strategy based on an enhanced sparse representation in transform domain (for both complete and Over complete dictionaries) for ECG denoising and compression is studied which is based on a recently proposed approach [7] for image denoising and also a recently proposed two dimensional sparse decomposition algorithm [8]. An enhanced sparse representation can be achieved by grouping similar 1D segments of the input signal into 2D data arrays. We have used this approach with a 2D separable complete and over complete dictionary (DCT+Wavelet or over complete (DCT) for ECG denoising and compression. Note that to use the approach proposed in [8], separability of dictionary is an essential assumption. Our procedure includes three steps: 2D transformation using the dictionary (completes or over complete) 1, shrinkage of the transform domain coefficients, and inverse 2D transformation.

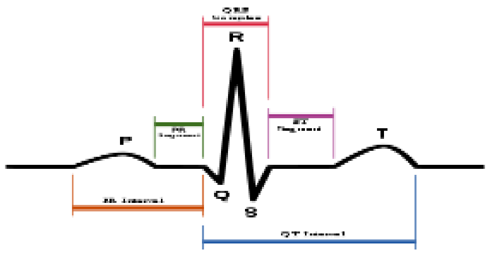

Fig-1: ECG signal specification

Due to the similarity between segments in a 2D array, the 2D transform can achieve a highly sparse representation. Experimental results demonstrate that its performance is highly better than Wavelet based denoising proposed in [2] and also better than extended Kalman other filtering proposed in [3](for higher input SNRs) but it does not achieve outstanding performance (compared to Wavelet) for ECG compression in terms of both SNR and sparsity.When constructing segments of the signals, we are immediately confronted with an important question on how such segments (time intervals) should be developed. Algorithmically, this boils down to the determination of the segmentation points of the signal. Fundamentally, we consider segments to be entities over which a signal exhibits a high level of homogeneity. More specifically, this notion may be quantified in terms of monotonicity of the signal reported within the bounds of the segments. Intuitively, we may envision that if a signal increases and then decreases within the same segment, its variability is high and we may suppose that the segmentation was not realized in an optimal manner and still could be improved. At this point, we have not specified the form of approximation done within each segment. In the simplest scenario, bearing in mind the monotonicity requirement satisfied within each segment, one can think of a linearization (linear approximation) of the signal occurring within the bounds of each segment. In other words, we envision that the segmentation results in a collection of local (as confined to the individual segments) linear models of signal compression. This is shown as a specific example; in general we can think of a series of polynomial approximation and in the same way we may refer to local quadratic approximations.This document is template. We ask that authors follow some simple guidelines. In essence, we ask you to make your paper look exactly like this document. The easiest way to do this is simply to download the template, and replace(copy-paste) the content with your own material. Number the reference items consecutively in square brackets (e.g. [1]). However the authors name can be used along with the reference number in the running text. The order of reference in the running text should match with the list of references at the end of the paper.

2. PROPOSED METHODOLGY

Flow chart of proposed Method is following.

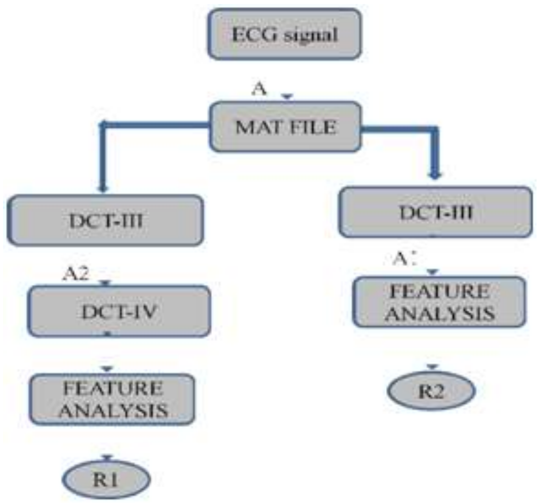

Fig- 2: Flow chart of proposed method

2.1. DCT-II

A discrete cosine transform (DCT) is finite sequence of 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 .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 for compression, since it turns out that fewer cosine functions are needed to approximate a typical signal.

DCT-II technique, which is very advance. When there is high correlation among the input samples, which is the case in many digital waveforms including speech, music, and biomedical signals. This transform is exactly equivalent to a DFT of 4n real inputs of even symmetry where the even-indexed elements are zero.

2.2 DCT-III

Because it is the inverse of DCT-II (up to a scale factor, see below), this form is sometimes simply referred to as "the inverse DCT" ("IDCT")[2].

Some authors further divide the x0 term by √2 (resulting in an overall $x_0/\sqrt{2}$ term) and multiply the resulting matrix by an overall scale factor of (see above for the corresponding change in DCT-II), so that the DCT-II and DCT- III are transposes of one another. This makes the DCT-III matrix orthogonal, but breaks the direct correspondence with a real-even DFT of half-shifted output. The DCT-III implies the boundary conditions: xn is even around n=0 and odd around n=N; X_k is even around k=-1/2 and even around k=N-1/2.

2.3 DCT- IV

The modified discrete cosine transform (MDCT) is a lapped transform based on the type-IV discrete cosine transform (DCT-IV), with the additional property of being lapped: it is designed to be performed on consecutive blocks of a larger dataset, where subsequent blocks are overlapped so that the last half of one block coincides with the first half of the next block. In DCT-IV, where the input is shifted by N/2 and two N-blocks of data are transformed at once.Irjet Template sample paragraph .Define abbreviations and acronyms the first time they are used in the text, even after they have been defined in the abstract. Abbreviations such as IEEE, SI, MKS, CGS, sc, dc, and rms do not have to be defined. Do not use abbreviations in the title or heads unless they are unavoidable.

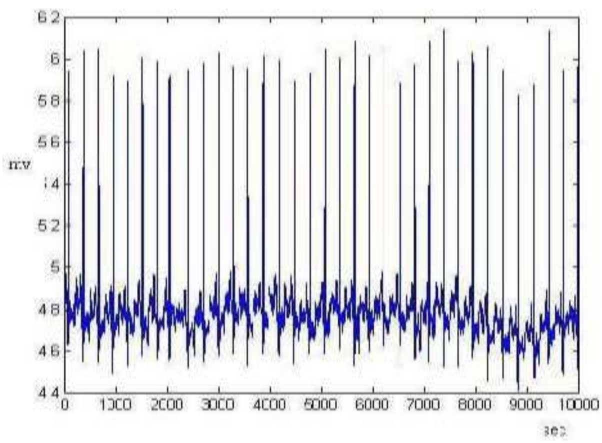

Fig- 3: ECG signal after DCT compression.

3. ECG SIMULATION AND FEATURES ANALYSIS

3.1 The Heartbeat Interval Features

Three heartbeat interval features for each single channel ECG recording relating to heartbeat intervals are calculated after heartbeat segmentation [12]. The time interval between the QRS onset and the QRS offset is known as QRS duration. The T-wave duration is defined as the time period between the QRS offset and the T-wave offset. The third feature is the presence or absence of a P-wave which is indicated by a Boolean variable that means the Boolean variable '1' implies the presence of P-wave and the variable '0' shows the absence of P-wave.

3.2 ECG Morphology Features

Two types of ECG morphology features are taken for each heart beat Ten features from QRS complex and nine features from T wave morphology are chosen from the selected heart beat after finding the fiducially point [12]. A fixed sample rate is used for extracting the morphology feature and the sampling windows are located by after detecting the heartbeat fiducially point (FP).Two sampling windows were formed based on R-peak. The window between FP-50 ms and 100 ms is considered which covers the contain of QRS-complex morphology as the portion of the ECG. A 60-Hz sampling rate is applied to the above window of the QRS-complex resulting in ten features. The second window approximately contains the T-wave morphology in between the time duration FP+150 ms and FP+500 ms. The ECG signal amplitude is sampled at 20 Hz in this window, resulting in nine features for T-wave morphology. Lower sampling rates is chosen for T-wave sampling windows as the frequency content of this wave is lower than the frequency content of the QRS- complex.

4. SIMULATION AND RESULTS

The experimental results are found out after MATLAB simulation. The visualization results of ten QRS morphology features and nine T-wave morphology feature features of the #tape 100 in the MIT-BIH database the tabulation result shows the visualization result which indicates the total number of arrhythmias present in the MIT-BIH arrhythmia database. The result implies the pictorial representation of each beat types, one cardiac feature and the corresponding twenty six feature waveform.

Simulation of ECG compression performed on MATLAB environment. Results show that DCT-III and DCT-IV domains are able to provide more SNR ratio.

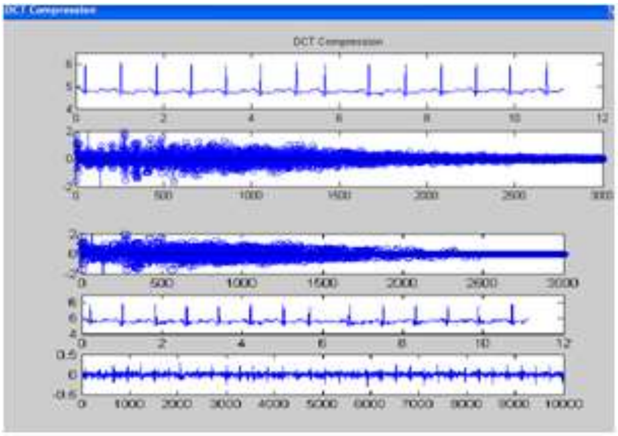

Fig-4 (a)DCT compression (b) Analysis

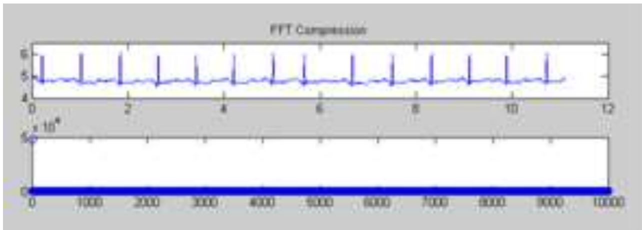

Fig-5 (a)FFT compression (b) Analysis

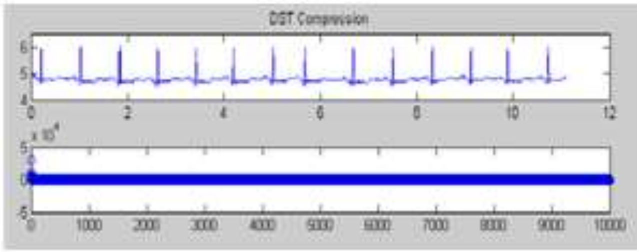

Fig-6 (a)DST compression (b) Analysis

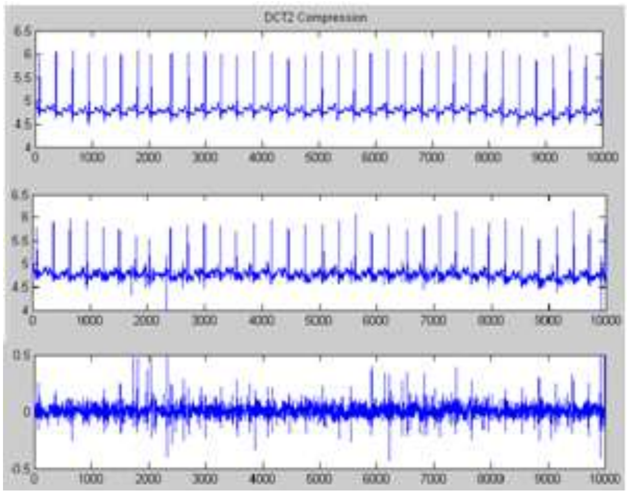

Fig-7 (a)DCT-III compression (b) DCT-IV compression (c) Proposed Method

5. CONCLUSION

Transform based techniques because of their high compression ability have gained popularity. In this paper the preprocessed signal is transformed to get the decorrelated coefficients. The thresholding or quantization of transformed coefficients gives the actual compression, which is lossy one. But it has good performance and low computational cost. 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 upto 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)- based method for electrocardiogram (ECG) compression is presented as DCT-III and DCT-IV The appropriate use of a block based Hybrid 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.

Table -1: Concluded Results

Method	Compression Ratio	PRD
DCT	91.68	0.8392
FFT	89.5723	1.0237
DST	70.4073	1.1967
DCT-II	94.28	1.5729
Proposed Method	96.34	1.785

6 FUTURE WORK

The Hybrid followed by DCT-II & DCT-III based approach being the superior among the techniques discussed in this thesis, can be developed as a practical solution by performing the following steps-

•Enhance the capability of the technique so that it can be also applied for the less common Power line Interference.

•Clinical evaluation of the method by collecting data from ECG machines in normal and stress test conditions. Such an evaluation can be used to study the effectiveness of the method for unpredictable real life ECG acquisition scenarios.

•Linear Predictive Coding (LPC) is a method of digitally encoding analog signals.

•A hardware implementation of the technique can be done for interfacing it with ECG acquisition environment for real time applications.

•A software implementation with GUI can be developed if an offline processing is planned. The system that has been developed to classify ECG signals is in software using MATLAB.

•Today, the importance of developing the large scale integrated chips is growing tremendously. Hence, we can implement the whole system in hardware using Verilog or VHDL

REFERENCES

[1] Brian Mcginley, Liam Kilmartin, Member, IEEE, Martin Glavin, Member, IEEE, And Edward Jones, Senior Member, IEEE IEEE JOURNAL OF BIOMEDICAL AND HEALTH INFORMATICS, VOL. 19, NO. 2, MARCH 2016 529 Compressed Sensing For Bioelectric Signals: A Review Darren Craven, Student Member, IEEE,

[2] Sucel Kocyigit, Mehmet Korurek And Bekir Karlik . IEEE TRANSACTIONS ON BIOMEDICAL ENGINEERING, VOL. 50, NO. 10, OCTOBER 2003 1203 Communications A Genetic Segmentation Of ECG Signal

[3] S. Jalaleddine, C. Hutchens, R. Stratan, And W. A. Coberly (1990): ECG Data Compression Techniques-A Unified Approach. IEEE Trans. Biomed. Eng., 37, 329-343.

[4] J. R. Cox, F. M. Nolle, H. A. Fozzard And G. C. Oliver (1968), AZTEC: A Preprocessing Scheme For Real Time ECG Rhythm Analysis. IEEE Tran. Biomed. Eng., Vol-BME-15, 128-129.

[5] M. Sabarimalai Manikandan And S. Danpat (2006): Wavelet Threshold Based ECG Compression Using USZZQ And Huffman Coding Of DSM. In Science Direct Biomedical Signal Processing And Control. 261-270.

[6] B. R. S. Reddy And I. S. N. Murthy (1986): ECG Data Compression Using Fourier Descriptors, IEEE Trans. Bio-Med. Eng., BME-33, 428-433.

[7] Mrs. S. O. Rajankar And Dr. S. N. Talbar (2010): An Optimized Transform For ECG Signal Compression. In Proc. Of Int .Conf. On Advances In Computer Science, 94-96.

[8] Shang-Gang Miaou, Heng-Lin Yen, Chih-Lung Lin (2002): Wavelet Based ECG Compression Using Dynamic Vector Quantization With Tree Code Vectors In Single Codebook. In IEEE Transaction On Biomedical Engineering, Vol. 49, No. 7, Pp. 671-680.

[9] R.Shanta Selva Kumari, V Sadasivam (2007): A Novel Algorithm For Wavelet Based ECG Signal Coding. Science Direct Computers And Electrical Engineering, 33, Pp. 186-194.

[10] J. Abenstein And W. Tompkins (1982): A New Data-Reduction Algorithm For Real Time ECG Analysis. IEEE Tran. On Biomed. Engg., 29(BME- 1):4, 3-8.

[11] N. Ahmed, T. Natarajan And K. R. Rao (1974): Discrete Cosine Transform. IEEE Trans. Trans. On Computers. C-23, 90-93.

[12] K. R. Rao And P. Yip (1990): Discrete Cosine Transform – Algorithms, Advantages, Applications, San Diego:Academic Press.