ECG SIGNAL COMPRESSION FOR TRANSMISSION IN MOBILE HEALTH MONITERING SYSTEM

A Dissertation submitted in partial fulfillment of the requirements for the award of the Degree of

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Submitted By

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DECLARATION

I, **Arshdeep kaur**, hereby declare that the work, which is being presented in the thesis entitled **"ECG signal compression for transmission in mobile health monitoring system"** by me in partial fulfillment of the requirements for the award of degree of Master of Engineering in Wireless Communications from Thapar University, Patiala, is an authentic record of my own work carried out under the supervision of **Dr. Hem Dutt Joshi**, Assistant Professor, Electronics and Communication Engineering Department.

The matter presented in this thesis has not been submitted in any other University/ Institute for the award of any other degree.

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ABSTRACT

The Electrocardiogram signal (ECG) is the most used biomedical signal giving most accurate analysis for heart/cardiovascular disease (CVD). CVD is the number one cause of deaths worldwide causing 17.5 million deaths in 2012 which amounts to 31% of total number of deaths. Heart failure is a huge leverage on society because of its high costs of treatment, lower quality of life and untimely death.

Statistics show that more than half of health agencies in US use telemonitoring services, where ECG signals are transmitted over mobile networks for continuous monitoring of patients from a distance. This is called mHealth i.e. use of mobile communication in medical industry. It is not only financially advantageous but also gives patient freedom to live a normal life. However this data is enormously huge and it is not economically feasible to transmit the data in raw form.

ECG records time varying electrical pulses generated in the heart and is primarily tool for evaluating and identifying cardiac disorders. It is sampled between 100 - 1000 Hz at 8–16 bit resolution. The data rate is 11–22 Mbits/h/lead approximately which is huge. So ECG data cannot be sent in raw format over wireless channels. Data needs to be compressed for transmission. This report discusses ECG compression using wavelet transforms out of all available techniques as they have shown to be promising contender for the proposed objective. As a part of this thesis report, an existing compression algorithm proposed by Bashar A. Rajoub has been implemented and its performance is compared with the new algorithm proposed in this report.

In this report a novel approach of empirical wavelet based ECG compression using set partitioning in hierarchical trees algorithm (SPIHT) for mobile device based application has been presented. The proposed algorithm implements empirical wavelet transform with SPIHT encoding. SPIHT is an embedded computationally simple coding algorithm suitable for wireless transmission. This algorithm was applied on different datasets of MIT-BIH database and the results show high accuracy and compression ratio when compared with existing ECG compression techniques. From the simulation it has been found that best performance of 35.9:1 CR with 1.15% PRD at 160bps for record 117 is achieved.

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LIST OF ABBREVIATIONS

Abbreviations	Description
AZTEC	Amplitude Zone Time Epoch Coding
AV	Atrioventricular
BPM	Beats per minute
CR	Compression Ratio
CVD	Cardiovascular disease
CORTES	Coordinate Reduction Time Encoding System
ECG	Electrocardiogram
EWT	Empirical Wavelet Transform
EMD	Empirical Mode Decomposition
FT	Fourier transform
FFT	Fast Fourier transform
MIT-BIH	Massachusetts Institute of Technology-Beth Israel Hospital
PRD	Percentage Ratio Distortion
SA	Sinoatrial
SAPA	Scan Along Polygonal Approximation
SPIHT	Set partitioning in hierarchical trees algorithm
WT	Wavelet transform

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CHAPTER I: INTRODUCTION

Heart disease or cardiovascular/heart disease (CVD) is the disease related to heart and blood vessels. The Electrocardiogram (ECG) signal is the vastly used biomedical signal, giving most accurate analysis for CVD. It records time varying electrical pulses generated in the heart by placing electrodes at different parts of body. ECG is recorded for a long duration of time to gather essential information for diagnosis of disease in a patient. ECG recording which measures potential across two points on body surface helps in prediction of many electrical and mechanical defects of the heart. ECG presents the graphical interpretation of the electrical activity of the heart.

In an ambulatory monitoring system these signals are transmitted over mobile networks for continuous monitoring of patients from a distance. This is called mHealth i.e. use of mobile communication in medical industry. However this data is unnecessarily huge (approx. 11–22 Mbits/h/lead) and it is not economical to transmit the data in raw form. Hence compression techniques for ECG are required for transmission. These techniques for ECG compression are broadly categorized as (a) direct methods; in which algorithm perform compression in time domain like the Turning Point (TP) method [1], Fan/SAPA [2], Amplitude Zone Time Epoch Coding (AZTEC) method [3], delta code algorithms [4], the Coordinate Reduction Time Encoding System (CORTES) [5] and SLOPE [6]. Some of these techniques are reviewed and presented in [7,8,9] (b) Transformational methods, in which signal is first transformed into frequency domain and then compression algorithms are applied e.g. Fourier Transformation (FT), Walsh transform [10], Fourier descriptors [11], Karhunen-Loeve Transformation (KLT) [4], and Wavelet transform. Various wavelet and wavelet packet based compression techniques are described in [12].

Hence, there is dire need of compression algorithms which compress ECG signals while retaining the clinically important information. The signal should be reproduced after decompression with minimum allowable reconstruction error. Existing compression algorithms have shown noticeable success in ECG compression. Still there is a need to propose efficient ECG compression algorithms which produce high compression ratio along with acceptable fidelity[13].

This work is primarily motivated by the desire to apply methods from the field of signal processing to the medical field for the compression of biomedical signal, such as ECG, in a way to develop some accurate and appropriate signal processing technique for ECG compression. The purpose of this thesis is to study the application of Wavelet Transform and Empirical wavelet transform (EWT) for ECG compression.

1.1 Electrocardiogram

Electrical activity of heart is recorded by electrocardiograph and the recording is known as electrocardiogram (ECG). Electrodes are placed on skin at selective places and they measure the electrical impulses originating in the heart. Many electrical and mechanical defects of the heart can be predicted by reading this graphical representation of ECG. ECG is simply voltage recording between a pair of electrodes. These are categorized as P, Q, R, S, and T [14]. The figure below shows the various sections of ECG wave

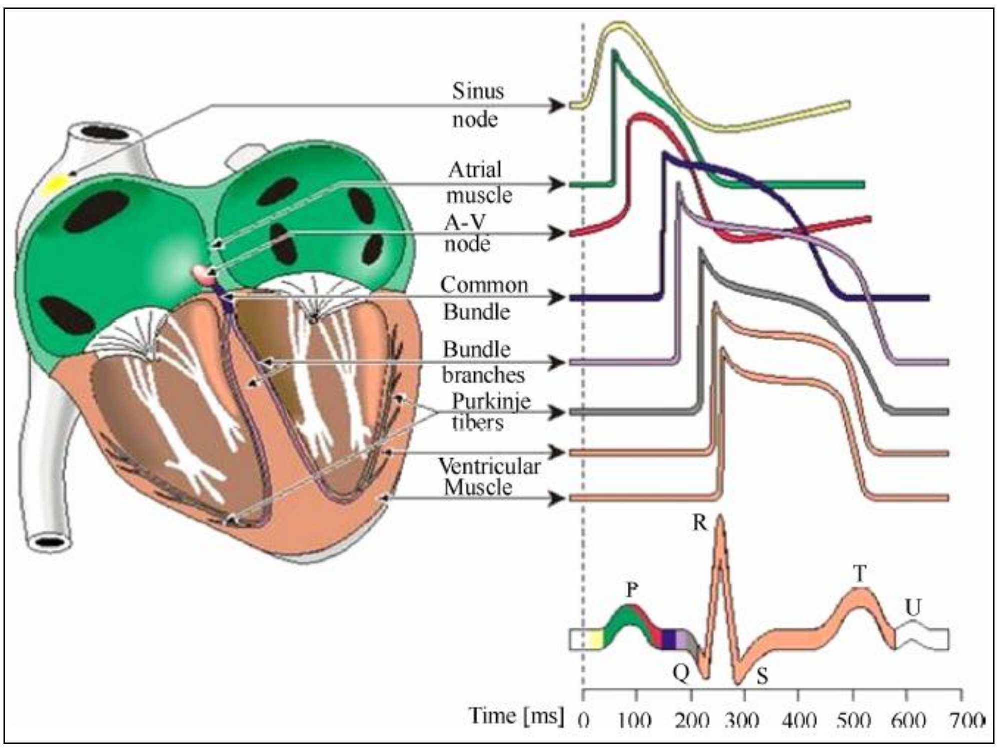

Figure 1 : ECG pulse [1]

The ECG is defined by waves, segments and intervals described below:

- P, QRS, T and U are names given to different waveforms. U wave is not always recorded in the ECG.
- Time interval between waves is termed as segments, e.g. PR segment is the time between the P and R waves.
- Intervals include both waves and segments, e.g. PR interval constitute the P wave and the PR segment.

Vertical length of the wave is measure of voltage while horizontal axis measure time. Frequency range of ECG varies from 0-100Hz while amplitude varies from .2mV to 5mV [14]. A normal ECG recording has defined range of PR, QRS and QT duration as follows:

- PR interval: 120-200ms
- QRS interval: 120ms
- QT interval: 440ms

1.2 ECG acquisition System

Patient's heart rate is monitored by ECG machines for diagnosis. Electrical activity between the electrodes or between one electrode and reference point is represented by a lead. The choice of location for the electrodes is determined by the type of clinical information required. Routine analysis of the ECG does not normally require data from all the leads. Even in an intensive therapy unit (ITU), when data from multiple leads is available, mainly one or two leads are monitored.

Leads II and VI represents best data for P waves. Normal Q waves are generally found in the leads I, II, aVL, V5, V6. Leads II and V5 are chosen as they provide most useful data in the case of medical diagnosis.

ECG machines are categorized based on the number of leads used on body to take the data. Hence, a 12-Lead ECG would capture 4 times data as done by a 3-Lead ECG [15].

3-Lead ECG

A 3-lead ECG machine, which is simplest of all ECG machines, uses 4 electrodes placed on each of the limbs of heart, which is used for regular heart rhythm monitoring.

5-Lead ECG

It uses five electrodes, four of which are placed on each of the four limbs of heart and 1 on the chest. It is most generally used ECG machine during a major surgical procedure.

12-Lead ECG

The 12-lead ECG uses ten electrodes, four of which are placed on each of the limbs and other six are placed on the chest. It is mainly used to diagnose heart attacks. Placement of electrodes is as shown in fig. (2)

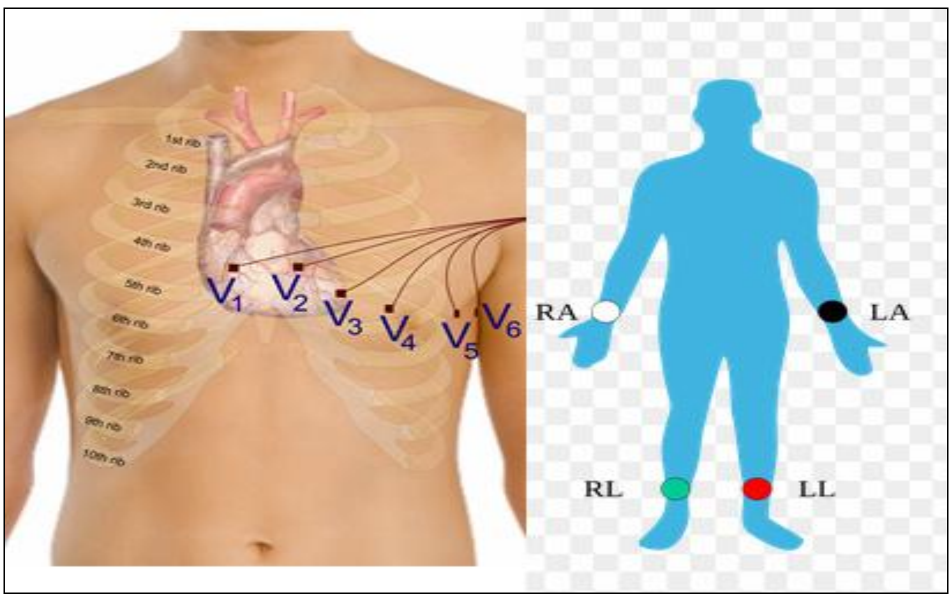

Figure 2 : Electrodes placement for ECG measurement [16]

1.3 *Proposed model of ECG compression and transmission System*

At Qualcomm Inc. in 2011, a project was launched with an aim to design a low power system which collects bio signals and is portable. Requirements of project for ECG acquisition and transmission were as follows (Refer fig. 3): [17]

1. A low power portable device with ECG sensor which can be placed on patient's body.
2. Amplification and noise removal performed by the portable ECG device.
3. The digitized signal is send from the low power ECG monitoring device to the patient's mobile.
4. The ECG signal to be compressed for real time transmission over the communication network via SMS/MMS.

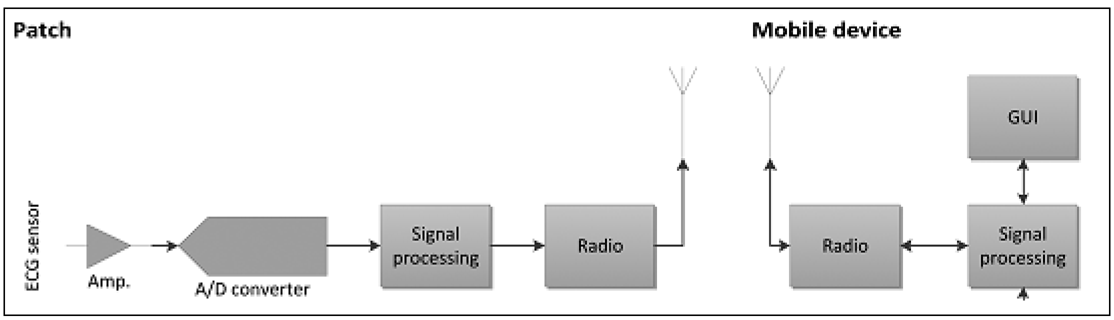

Figure 3 : Acquisition of ECG signals

1.4 ECG compression

CVD is the number one cause of deaths occurring globally accounting to approximately 30% of the total deaths. The reasons include lack of timely treatment in case of sudden cardiac arrest or unable to provide 24*7 monitoring to patients remotely. Hence there is a dire need to provide 24 hour monitoring to heart patients not only in hospitals but even remotely. Bio signals can be send over mobile networks to nearby hospitals to be monitored continuously. This is called mHealth that is use of mobile communication in medical industry. So it is helpful in providing timely treatment to patients when they go in critical state. This system provides freedom from long hospital bills and freedom for patient to stay at home [18].

But the data that is required to be transmitted over mobile networks is huge. Sampling range of ECG is 100-1000 Hz with 8–16 bit resolution. The data rate is 11–22 Mbits/h/lead approximately which is enormous. Hence over past few decades ECG compression techniques have been proposed to achieve the proposed objective.

1.5 Compression techniques

ECG compression techniques are broadly categorized as (a) direct methods; in which algorithm perform compression in time domain like differential pulse code modulation (DPCM), Amplitude Zone Time Epoch Coding (AZTEC), Analysis by Synthesis Coding (ASEC), Coordinate Reduction Time Encoding System (CORTES), FAN algorithm etc. Some of these techniques are reviewed and presented in [7,8,9] (b) Transformational methods, in which signal is first transformed into frequency domain and then compression algorithms are applied e.g. Fourier transform, discrete cosine transform (DCT), Walsh transform, Karhunen-Loeve transform (KLT), and wavelet transform. Various wavelet and wavelet packet based compression techniques are described in [12].

One of the very first popular ECG compression algorithms, Amplitude Zone Time Epoch Coding (AZTEC), was proposed by Cox et al. and was originally developed for preprocessing the real time ECG for rhythm analysis. A simple ECG compression algorithm that gave a fixed compression ratio of 2:1, without diminishing the large amplitudes of QS complexes, was turning point algorithm. However this algorithm has a major drawback which was the save points were not equally spaced in time proposed by Mueller in 1978. AZTEC and Turning Point algorithm combined, which retains the advantages of both was developed and named as Coordinate Reduction Time Encoding System (CORTES).

Number of data reduction techniques based on first order interpolation and two degrees of freedom were proposed, like fan algorithm and scan along polynomial approximation algorithm in three different varieties viz SAPA-1, 2 and 3.

An ECG wave sometimes needs to be pre-processed, before it could be compressed. Those techniques that exploit the cyclicity of the signal require QRS of the wave to be detected. This can be done in a number of ways, viz. by syntactic method

1.5.1 Time domain Techniques

The time domain techniques are also known as Direct Signal Compression methods. The signal is represented in form of discrete sample values. The compression techniques falling under this category involves selection of significant samples from all the discrete sample values of the signal. The general outline of the compression process involves deciding a threshold rule for the selection process. This extracts a set of significant sample values and as a result the same information can be represented with lesser number of samples and hence compression is achieved. Example of such techniques are turning point, amplitude zone time epoch coding, coordinate reduction time encoding system, analysis by synthesis coding, delta algorithm and fan algorithm etc [7].

1.5.2 Parameter Extraction Techniques

In Parameter extraction method, signal is modeled by features or parameters extracted from the signal. These features are then scalar quantized or vector quantized followed by entropy coding before transmission. It is an irreversible process. Parameter extraction compression techniques are divided into three categories: linear prediction based methods (LP), vector quantization based methods (VQ) and template matching methods. LP methods exploit correlation between adjacent samples and correlation between adjacent beats. In VQ signal is segmented into fixed length vectors and then quantized [12].

1.5.3 Transformation Based Techniques

Techniques in this category transform the signal into other domain which is the frequency domain for encoding the significant values for transmission. The signal samples are found to be statistically dependent. Signal is transformed into frequency domain so as that it could be compactly represented with a fewer number of coefficients. Further a threshold criteria is set for the transformed coefficients to get significant coefficients which when inverse transformed results in reconstructed signal with minimum distortion [12].

1.6 Wavelet Transform

In wavelet transform, a signal is expressed as coefficients of expansion of the signal with respect to basis function $\psi_{\omega,n}(t)$. Every member of $\psi_{\omega,n}(t)$ is dilated and translated element of a mother wavelet ψ according to relation in eq (1):

$$\psi_{\omega,n}(t) = \left(\frac{1}{\sqrt{|2^{\omega}|}}\right)\psi\left(\frac{t(t-2^{\omega}n)}{2^{w}}\right) \qquad \omega, n \in Z \qquad (1)$$

The coefficients of wavelet transform of the input signal are given by dot product of input signal x (t) and basis functions in eq (2) as:

$$W(\omega,n) = < x(t), \psi_{\omega,n}(t) > \qquad (2)$$

So the input signal in wavelet domain is expressed as coefficients $W(\omega,n)$.

In data compression, wavelets are used to take advantage of the redundancy already present in the signal. When signal is wavelet domain transformed, many coefficients become insignificant because of very small amplitude and hence reduced to zero without any major loss of information.

Wavelet transforms are made as tree-structured reconstruction filter banks as shown in fig (1). The signal is passed into analysis filter banks (Ho and H1) frame by frame generating low-pass and high-pass signals, which are further down sampled by a factor of 2. This filter pair is applied recursively to low pass down sampled signal to decompose the signal at different level frequency bands. The inverse transform is calculated by performing the reverse process. The signal is up sampled by factor of 2 and passed through synthesis filter banks (F0 and F1) [19].

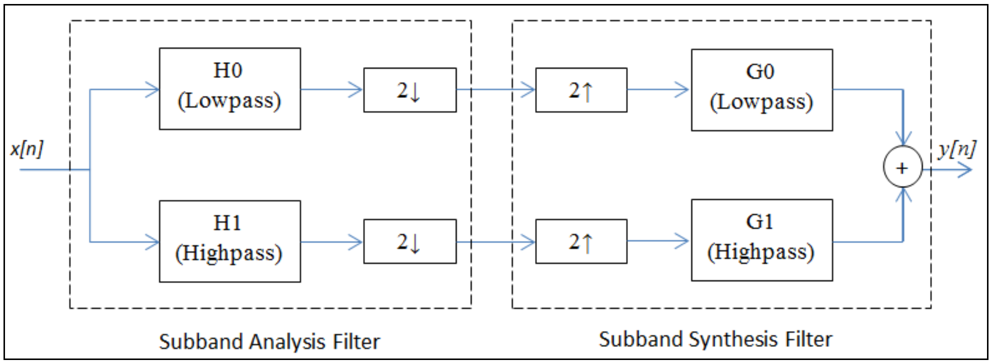

Figure 4 : Filter bank implementation [1]

The time domain signal is mapped to scaling and wavelet subspace in wavelet domain. Solution of equation (3) is the scaling function $\emptyset(t)$.

$$\emptyset(t) = 2\sum_{k} ho\,[k]\emptyset(2\mathrm{t}-\mathrm{k}) \qquad (3)$$

The scaling function determines the wavelet by high pass filer h1 as

$$\omega(t) = 2\sum_{k} h1\,[k]\emptyset(2\mathrm{t}-\mathrm{k}) \qquad (4)$$

There has been use of both Continuous Wavelet Transform (CWT) as well as Discrete Wavelet Transform (DWT). However CWT has some inbuilt advantages over DWT. Unlike DWT, there is no power of jump of frequency in CWT. Also in contrast to DWT, in time-frequency domain high resolution is achieved in CWT.

A number of time-frequency methods are available for high resolution signal decomposition. Out of these wavelets offer promising results because of the following properties [20, 21]

1. It is suitable for non-stationary signals.
2. Signals can be analyzed at different resolution using wavelet transform.
3. Localization property of wavelet transform and varying window length depending upon the frequency range for analysis.

4. It is appropriate for low power devices as it works as energy compactor with human visual system.

1.7 Emperical Wavelet Transform

Empirical wavelet transform detects the different modes of the signal adaptively and constructs a basis for filter supports based on the information obtained. In EWT, the segmentation of Fourier axis is done so as to separate different modes centered around a specific frequency [13]. Two steps involved in empirical wavelet transform are:

1) Segmentation of Fourier axis and selection of frame
2) Empirical wavelet transform

The detail coefficients $W_f^{\varepsilon}(n,t)$ for the EWT are given by the inner products with empirical wavelets, as show in equation (5).

$$w_f^{\delta}(n,t) =< f, \psi_n >= \int f(\tau)\overline{\psi(\tau - t)}d\tau \qquad (5)$$

The approximation coefficients $W_f^{\varepsilon}(0,t)$ are given by inner product with the scaling function as given by (6),

$$w_f^{\delta}(0,t) =< f, \emptyset_n >= \int f(\tau)\overline{\psi(\tau - t)}d\tau \qquad (6)$$

The original signal can be reconstructed from its decomposed wavelet and approximation coefficients using equation (7). The reconstructed signal $\overline{f(t)}$ is obtained by equation (3).

$$\overline{f(t)} = w_f^{\delta}(0,t) * \emptyset_1(t) + \sum w_f^{\delta}(n,t) * \psi_n(t) \qquad (7)$$

For the visual interpretation, EWT has been tested on two signals. Equation (8) shows the expression for the first signal. This signal and its corresponding EWT modes for N=3 and t=2 seconds are given in figure 5 and 6.

$$F(t) = 6t^2 + 2\sin(8\pi t) + 0.5\cos(40\pi t) \qquad (8)$$

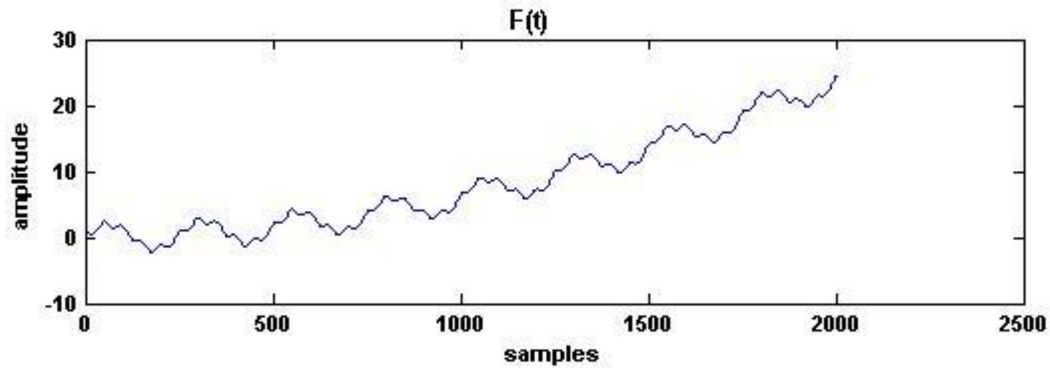

Figure 5 : Original signal F(t)

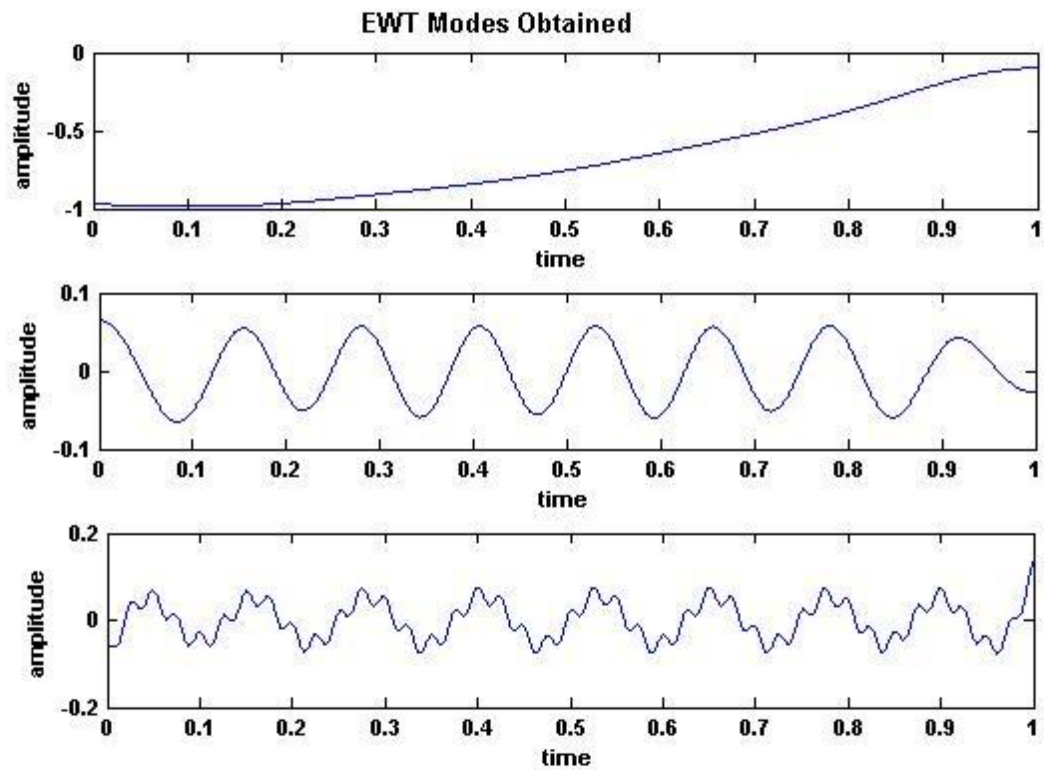

Figure 6 : EWT modes obtained for N=3

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Second signal on which EWT decomposition is tested is ECG signal 234m taken from MIT-BIH arrythemia database. First 10000 samples of ECG signal and the modes for N=4 are shown in figure 7 and 8.

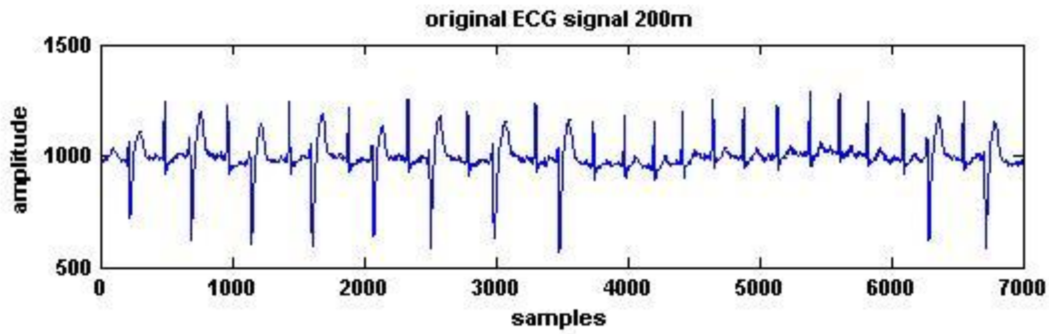

Figure 7 : First 7000 samples of standard ECG signal 200

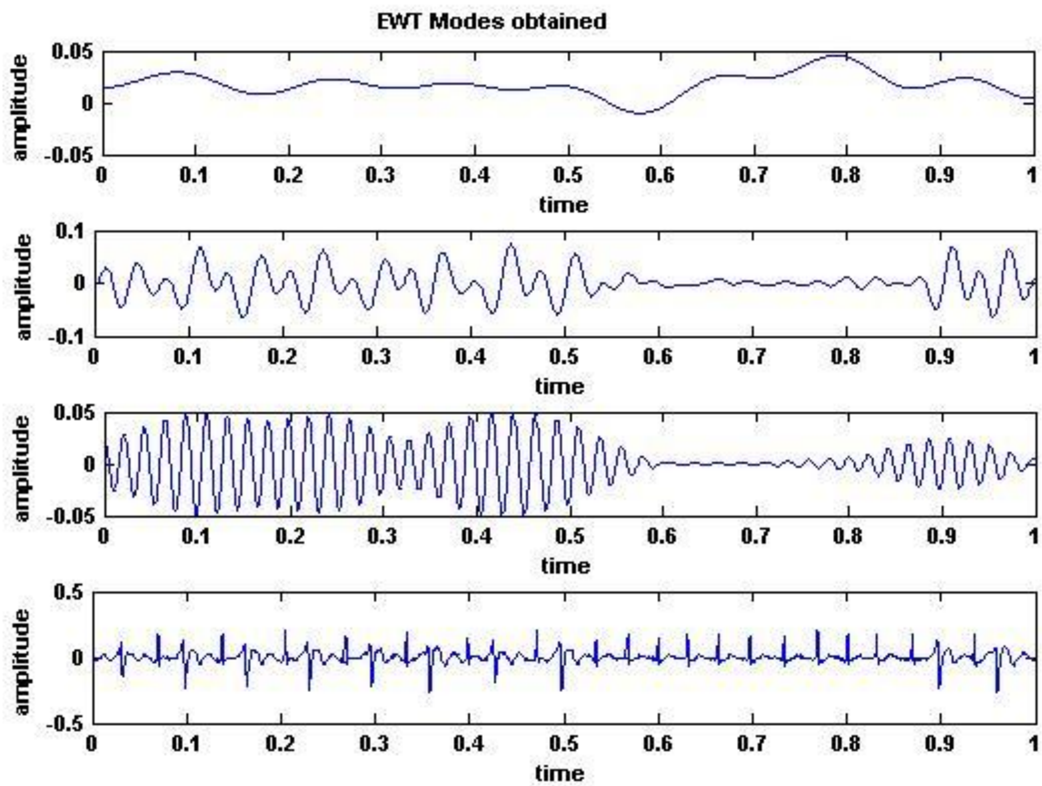

Figure 8 : EWT modes obtained for N = 4

1.8 Standard Database

MIT and Boston's Beth Israel Hospital provides MIT-BIH (Massachusetts Institute of Technology-Beth Israel Hospital) Arrhythmia database. It has 30 minute data of two leads namely one from limb lead II and one from either of data from V1, V2, V4 or V5.

This ECG data is selected from 47 patients studied by the BIH Arrhythmia Laboratory. The data is collected at 360 samples/sec/channel with 11-bit resolution. Out of 48 recordings 28 recordings are chosen from available 4000 ECG recordings of inpatients and out patients at hospital. The remaining 25 data are taken to include significant arrhythmias.

1.9 Compression Parameters

Compression of ECG signals is required: a) to store ECG; b) recording for ambulatory systems; and c) transmission of ECG data over tele-network or digital telecommunication network. Numerous techniques have been developed for compression. All the techniques are evaluated on the following compression parameters:

- ***Compression Ratio (CR):*** CR is defined as the ratio of the original data to compressed data without taking into account factors such as bandwidth, sampling frequency, precision of the original data, word length of compression parameters,

$$CR = \frac{Original\ signal\ length}{Compressed\ signal\ length} \tag{9}$$

- ***Percentage Mean Square Difference (PRD):*** PRD is a measure of error loss. This measure evaluates the distortion between the original and the reconstructed signal [16]. PRD calculation is as follows in equation (10):

$$PRD = \sqrt{\frac{\sum_{1}^{L}(x(i)-\overline{x(i)})^2}{\sum_{1}^{L}(x(i))^2}} \tag{10}$$

  Where x(i) is the original signal and $\overline{x(i)}$ is the reconstructed signal.

- ***QS***
  The quality-score (QS) is the ratio between the CR and PRD; a high QS value refers to a high quality of compression of a lossy compression method.

$$QS = \frac{CR}{PRD} \tag{11}$$

- ***Complexity***
  The algorithm for compressing data must have low complexity because of low processing of the pace maker.

- ***WDD***
  The weighted diagnostic distortion (WDD) measure is based on comparing the PQRST complex features of the two signals namely the original signal and the reconstructed ECG. This parameter measures relative information in the reconstructed signal with parameters like the location, amplitudes, duration and shapes of the waves and complexes that exist in every beat.

$$WDD(\beta, \beta') = \Delta\beta' * \frac{\Delta}{tr[\Delta]} * 100$$

$$\beta = [\Delta\beta_1\ \Delta\beta_2\ \ \Delta\beta_3 \dots \Delta\beta_p];\ original\ signal$$

$$\beta' = [\Delta\beta_1'\ \Delta\beta_2'\ \ \Delta\beta_3' \dots \Delta\beta_p'];\ reconstructed\ signal \tag{13}$$

1.10 Objective of Thesis:

In this thesis following objective is emphasized upon:

1. To develop a new coding framework based on Empirical Wavelet Transform.
2. Measurement of statistical parameters of compression on ECG signals recorded on 48 standard records.
3. To compare the results of proposed algorithm with the work done in literature.

1.11 Organization of Thesis

This thesis is organized as per the following format:

Chapter 1 includes definition of electrocardiogram signal, its parameters, its databases, ECG Lead Configuration, Need for ECG Compression and various techniques proposed in past.

Chapter 2 contains literature review on various ECG compression techniques namely compression using DCT, DWT, VPW-FRI, SPIHT etc.

Chapter 3 presents the implementation results of compression algorithm proposed by Bashar A. Rajoub in his paper "An efficient coding algorithm for the compression of ECG signals using wavelet transforms"

Chapter 4 presents the implementation results of compression algorithm proposed by R. Kumar and I. Saini in "Empirical Wavelet Transform Based ECG Signal Compression".

Chapter 5 presents the proposed EWT based ECG Signal Compression using SPHIT algorithm for transmission in mHealth telecardiography.

Chapter 6 presents the implementation results

Chapter 7 concludes the thesis with a discussion and future scope.

CHAPTER II: LITERATURE REVIEW

Previous section described the need for compression of ECG signals and reasons for wavelets being best suitable, along with various techniques and algorithms which use wavelet transformation for compression procedure. In this section, we review various techniques that have been proposed for compression of ECG signal till now as a part of literature review.

2.1 Turning Point

1. Mueller, C. W. *et al.* [1] says that to compress a signal choose only one point from a pair of successive points hence produces compression ratio of 2:1. It was developed to reduce the sampling frequency of the ECG signal from 200 Hz to 100Hz. However the shortcoming of this algorithm was the selected points did not produce equally spaced intervals.
2. Hargittai, S. *et al.* [22] says that compression ratio can be further increased by repeatedly applying the turning point algorithm. This algorithm chooses one point from N – points in each iteration. This algorithm is mainly employed in visualization and printing purpose.

2.2 ASEC

3. Zigel, Yaniv *et al.* [23] explores the redundancies in the ECG that exist in the form of correlation between adjacent beats (interbeat) and adjacent samples (intrabeat). Here a codebook is maintained per person of different types of pulses that are present in ECG of a particular person. It works on prediction scheme and encodes the error which is further transmitted over the channel.

2.3 DCT

4. Lai, S. C. *et al.* [24] proposes real time compression and transmission of ECG signal using DCT-IV spectrum. Preprocessing is performed followed by DCT-IV

transformation followed by encoding with non-uniform quantization. He demonstrated that it not only compresses the signal but also maintains the accuracy in the reconstructed signal.

5. Bendifallah, A. *et al.* [25] proposes an improved technique by improving the quantization and encoding scheme in DCT compression. It uses a uniform dead zone quantizer with larger dead zone for more compression. An efficient encoding scheme is also used which separates data into PLNZ, NZ_DCT vectors followed by encoding,
6. Lee, S. *et al.* [26] proposed ECG compression and transmission by first down sampling followed by calculating backward differences, peak detection and storing the classified result. DCT of stored data followed by filtering of the resultant data and then performing Huffman coding for transmission.

2.4 DWT

7. Rajoub, B. A. *et al.* [27] describes compression using DWT. First pre-processing is performed as an inevitable process following by wavelet transforming. Now insignificant coefficients (below a threshold) are set to zero. Threshold is decided based on desired EPE. Threshold is calculated from algorithm described in paper whose input is desired EPE. Wavelet coefficients are then encoded by coding significance map and significant coefficients separately.
8. Ktata, S. *et al.* [21] proposed implementation of SPIHT compression algorithm on wavelet transform of ECG signal. This scheme has been best described so far owing to incredible compression ratio and reconstruction signal quality. Enhanced version of Embedded Zero tree Wavelet algorithm is SPIHT. It employs bit plane encoding at acceptable level of complexity.
9. Ebrahimzadeh, A. *et al.* [20] presented wavelet transform using three level of quantization for thresholding. Quantization is a lossy process and hence results in reconstruction errors. Threshold is decided iteratively up to 3 iterations in this case. The samples are then encoded using EZW following by Huffman encoding. Target bit-rate is given and compression by EZW is performed to accomplish that target.

10. Mazomenos, Evangelos B. *et al.* [28] proposes a Low-Complexity ECG Feature Extraction Algorithm for Mobile Healthcare Applications. It has been shown that use of Haar wavelet as mother wavelet gives significant reduction in computation complexity. HFEA algorithm implemented in this paper is suitable for ultra low power systems and hence is suitable for ambulatory monitoring systems.
11. Zhitao, L. *et al.* [29] was first to modify the SPIHT algorithm for one dimensional signal as this algorithm showed significant results in image coding. Best feature about this proposed algorithm is that encoding and decoding process can stop at any quality requirement i.e. bit rate. Computation complexity is very low and hence is suitable for mobile health care applications.
12. Gupta, Anubha *et al.* [3] proposes a new method of estimating a wavelet from a given signal. The projection of the signal is maximized on the successive scaling subspace. Hence energy in wavelet subspace is minimized. This was used for estimation of analysis wavelet filter.
13. Sharma, L. N. *et al.* [30] describes multiscale PCA in wavelet domain for dimension reduction of multichannel ECG signals without distorting the clinical information. A new PC selection. The selection of principal components (PCs) is based on average fractional energy contribution of eigenvalue in a data matrix.

2.5 VPW-FRI

14. Vetterli, M. *et al.* [31] proposes a new sampling scheme based on degrees of freedom and called as rate of innovation. Using this scheme signals can be sampled at frequencies well below the nyquist frequency. This sampling scheme can also be applied for non band limited signals. This scheme can be successfully applied further in VPW-FRI for sampling of ECG signals and attain very low sampling frequencies and higher compression.

2.6 Real Time ECG Compression and Transmission

15. Mitra, M. *et al.* [32] attempts for real time ECG transmission from rural clinic to remote cardiologist. At rural clinic a desktop PC is connected with an ECG

machine and GSM modem. The ECG signal is compressed and formatted into SMS's. Message is then transmitted to cardiologist using GSM modem. At the remote end ECG is reconstructed using a mobile and a desktop for visual diagnosis by cardiologist. However this implementation is not suitable for prolonged ECG recording.

2.7 ECG Compression Survey Papers

16. Jalaleddine, S. M. S. *et al.* [7] presents a unified view on ECG compression schemes. Techniques mainly described are DPCM, AZTEC, CORTES, FAN/SAPA, and peak – picking and cycle to cycle compression methods. Various schemes proposed earlier were dependent on interpolators and predictors.
17. Priyanka *et al.* [9] presents a consolidated data on performance obtained of various ECG compression methods viz direct, transform and parameter extraction based methods.
18. Singh, V. *et al.* [8] proposes a new compression scheme which is actually sum total vector quantization and DPCM compression scheme. Compression is achieved by the implementation of vector quantization and low PRD because of used of DPCM in QRS region as we don't want to lose any data from this region.
19. Manikandan, M. S. *et al.* [12] reviews wavelet based ECG compression methods and their performances listing pros and cons of different wavelet-based compression methods. This paper briefly describes different kinds of compression techniques used in the one-dimensional wavelet-based ECG compression methods.

CHAPTER III: METHODOLOGY

One way to compress ECG signals is by using wavelet transforms. As discussed wavelet transforms breaks down the signal information into two sub categories viz.

a) coarse information and

b) detail information.

Coarse information is the low frequency information while detail information is the high frequency information. EPE (energy packing efficiency) of a band tells about the % of energy possessed by the sub-band. For electrocardiogram signal, it is observed that most of the energy is retained by approximation band in contrast to wavelet subband. Hence, the idea of compression lies in retaining maximum coarse information and least possible detail information. EPE given by the formula:

$$EPE_{D_i} = \frac{E'_{CD_i}}{E_{CD_i}} X\ 100\%$$

EPE of approximation band (coarse information) is around 99%. Hence most the information in detail bands (detail information) is reduced to zero giving high compression while maintaining tolerable PRD [27].

The algorithm for the compression is explained as below:

1) ECG signal is first preprocessed. Signal is first normalized followed by mean removal which reduces all the coefficients to less than one. After that resulting signal is zero padded at both the ends as it reduces the reconstruction errors.
2) Signal is now wavelet transformed up to decomposition level 5 using bior4.4 mother wavelet. The coefficients are divided into three sets. Approximation coefficients (A5) and detail coefficients (D5) are retained maximum possible. Third set (D4-D1) are reduced maximum possible based on EPE.
3) Based on EPE the three set of coefficients are thresholded. All the coefficients below the threshold are reduced to zero. Threshold is calculated according the following algorithm:

i) Compute the total sum energy in the coefficients.

$$E = \sum X^2$$

ii) Desired retained energy Enew is given as (eg: consider only 98% energy is desired to be retained)

$$Enew = .98 * E$$

iii) Sort the coefficients(X) in descending order (X_s).

iv) Use the algorithm given below to find the threshold value

a. Set egy=0
b. Set k=0
c. While egy <Enew
d. k=k+1
e. egy = egy + $(X_s[k])^2$
f. End
g. ThresholdValue= $X_s[k]$

4) Now based on the threshold, zero out the coefficients in each set and pass the rest to the coding stage.
5) Coding is done in two phases: coding of significant map and significant coefficients. If a coefficient is significant a one is appended to the significant map else zero is appended. Now the resulting set is encoded using variable length encoding scheme.
6) Lastly header information is also transmitted which is of 64 bits. Wavelet coefficients are stored in first 20 bits, index of last significant coefficient is stored in next 20 bits, next 20 bits store the maximum value of ECG signal and last 12 bits store mean of normalized signal.

Now decompression is exactly the reverse process of compression which implies following the above steps in reverse order.

The following tables describe the results of compression procedure discussed above on various signals from MIT-BIH arrhythmia database.

Table 1 : EPE D5=85%,EPE-D1-D4=98%

Signal	CR	PRD
104	17.55502878	0.842702
107	18.75271307	7.434941
111	19.58591507	0.689074
112	19.9845798	0.946919
115	25.24839275	1.920303
116	21.91595502	3.329988
117	23.89600811	1.001929
118	21.41971738	1.90545
119	23.29678231	6.163403
201	21.83104523	0.841821
207	21.80349933	1.37763
208	18.74728772	2.740931
209	19.20142233	1.460996
212	17.96008869	1.46658
214	22.92993631	1.297587
228	20.61068702	3.199048
231	22.76279968	1.464018
232	16.32653061	0.591503
100	22.88539643	1.096521
101	21.56226603	1.082353
102	17.35404392	0.673415
103	22.78481013	1.775829
107	18.75271307	7.434941
109	21.49610217	1.112396
111	19.58591507	0.689074
115	25.24839275	1.920303
117	23.89600811	1.001929
118	21.41971738	1.90545
119	23.29678231	6.163403

Table 2 : EPE D5=96%,EPE-D1-D4=98%

Signal	CR	PRD
104	12.65563	0.574808

107	13.14735	7.364375
111	12.73773	0.483294
112	16.43627	0.591617
115	21.90484	1.098769
116	18.77717	2.062439
117	20.55349	0.607978
118	15.10401	1.362452
119	18.70535	6.001183
201	17.82178	0.555747
207	8.291481	1.337247
208	13.77405	2.5073
209	16.11239	0.819324
212	13.8617	0.945828
214	18.97094	0.94224
228	8.577953	3.161729
231	19.64529	0.950189
232	7.159232	0.397525
100	18.93906	0.627525
101	16.29779	0.665795
102	12.81455	0.447583
103	20.0977	1.052695
107	13.14735	7.364375
109	13.27869	0.923832
111	12.73773	0.483294
115	21.90484	1.098769
117	20.55349	0.607978
118	15.10401	1.362452
119	18.70535	6.001183

Table 3 : EPE D5=97%,EPE-D1-D4=98%

Signal	CR	PRD
104	11.5436	0.550379
107	12.2617	7.358178
111	9.537827	0.470925
112	14.76082	0.551295
115	21.28428	1.001874
116	17.92903	1.92487
117	17.32157	0.563219
118	13.48806	1.303541

119	17.29037	5.98729
201	16.58137	0.528338
207	5.904463	1.337247
208	12.35639	2.486672
209	15.28662	0.737232
212	12.73835	0.880201
214	17.32273	0.906307
228	6.772398	3.161729
231	18.33357	0.883792
232	6.339578	0.378944
100	17.82546	0.563023
101	14.70722	0.618459
102	11.32026	0.423626
103	19.32021	0.963785
107	12.2617	7.358178
109	12.04237	0.906409
111	9.537827	0.470925
115	21.28428	1.001874
117	17.32157	0.563219
118	13.48806	1.303541
119	17.29037	5.98729

Table 4 : EPE D5=99%,EPE-D1-D4=98%

Signal	CR	PRD
104	5.773471	0.521974
107	8.190091	7.346586
111	3.528211	0.470925
112	7.259894	0.484308
115	17.42053	0.764317
116	13.91753	1.624369
117	7.01109	0.48284
118	8.569162	1.186405
119	12.37172	5.959138
201	8.591885	0.482422
207	2.943247	1.337247
208	7.108576	2.448233
209	11.50466	0.555935
212	8.55954	0.744005

214	7.846224	0.846627
228	3.583972	3.161729
231	14.35216	0.73901
232	4.096728	0.378944
100	13.565	0.433144
101	8.623615	0.524051
102	5.053124	0.404594
103	16.0814	0.772846
107	8.190091	7.346586
109	6.113784	0.885115
111	3.528211	0.470925
115	17.42053	0.764317
117	7.01109	0.48284
118	8.569162	1.186405
119	12.37172	5.959138

Note: The approximation coefficients of level five are thresholded using threshold T_{A5} selected at EPE_{A5} 99.9%. The detail coefficients of level five are thresholded T_{D5} using threshold selected at EPE_{D5} 97%. The wavelet coefficients of levels four to one are thresholded T_{D4-1} using a threshold that is allowed to vary according to EPE_{D4-1}, were the later takes on vales from 85% to 99%. The significant coefficients are stored using 7 bits signed representation.

Table 5 : CR and PRD for various EPE and ECGs

Signal	D4-D1	CR	PRD
104	85	14.8777	0.6190
104	96	9.1490	0.4304
104	97	7.9803	0.4135
104	99	3.7694	0.4135
107	85	23.490	0.9769
107	96	20.0557	0.5933
107	97	16.5001	0.5503
107	99	6.7370	0.4778

Note: Best performance with compression ratio of 23.49 was achieved for MIT-BIH record 117 with a PRD of .9769

The paper discusses the results of the compression procedure by applying the algorithm on DataSets collectively. A dataset is a collection of various ECG signals from MIT-BIH arrhythmia database.. DataSet2 consists of 1min records of 104, 107, 111, 112, 115, 116, 117, 118, 119,201, 207, 208, 209, 212, 214, 228, 231,232 signals from MIT-BIH database. Results for the dataset were reproduced and the findings are listed in Table 2.

Table 6 : CR and PRD of Dataset 2 for various ECGs

Signal	D4-D1	CR	PRD
DataSet2	85	20.50	2.02
DataSet2	96	15.02	1.64
DataSet2	97	13.55	1.50
DataSet2	99	08.41	1.50

Also as part of simulation effect of algorithm on each signal has also been studied. The paper primarily shows the orginal and reconstructed waveforms for the signals : 117, 210 and 232. Hence reproduction of results is shown for the forementioned signals only. Shown below are the original and reconstructed ECG signals with the error that occurred.

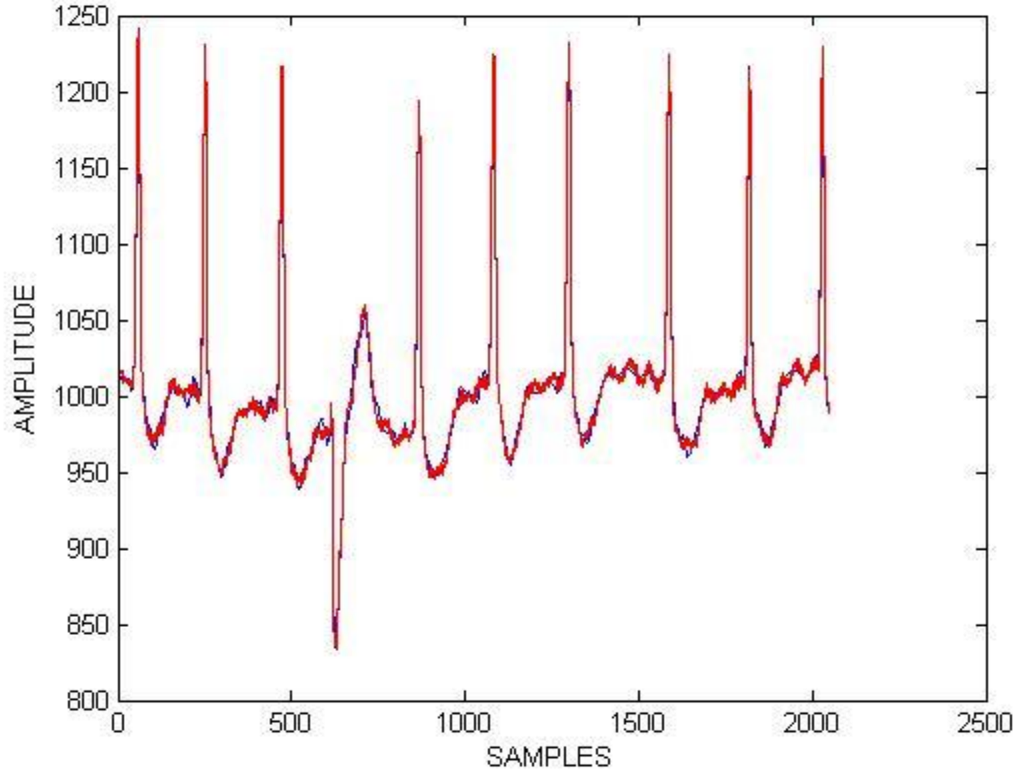

Figure 9 : Original and Reconstructed signal 210

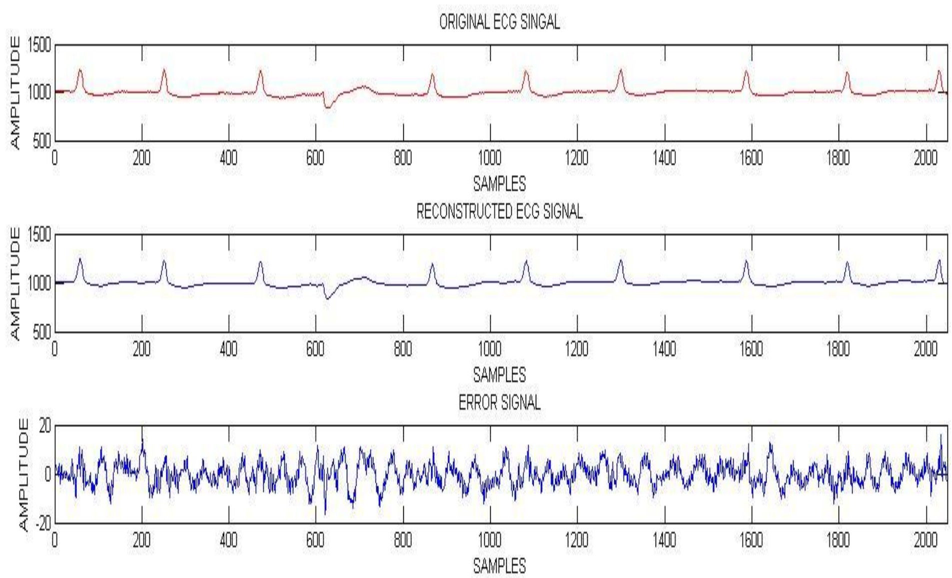

Figure 10 : The first 2048 sample of MIT-BIH record 210. CR=11.562:1, PRD=0.4611%,EPE D5=98%,EPE-D1-D4=98%.

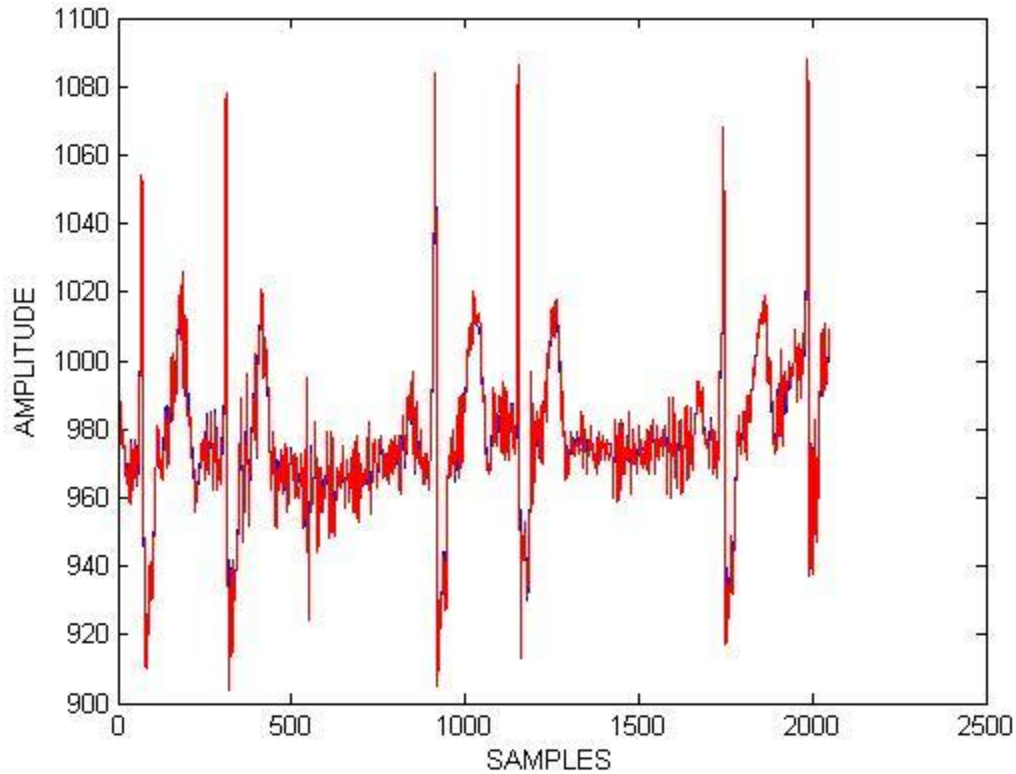

Figure 11 : Original and Reconstructed signal 232

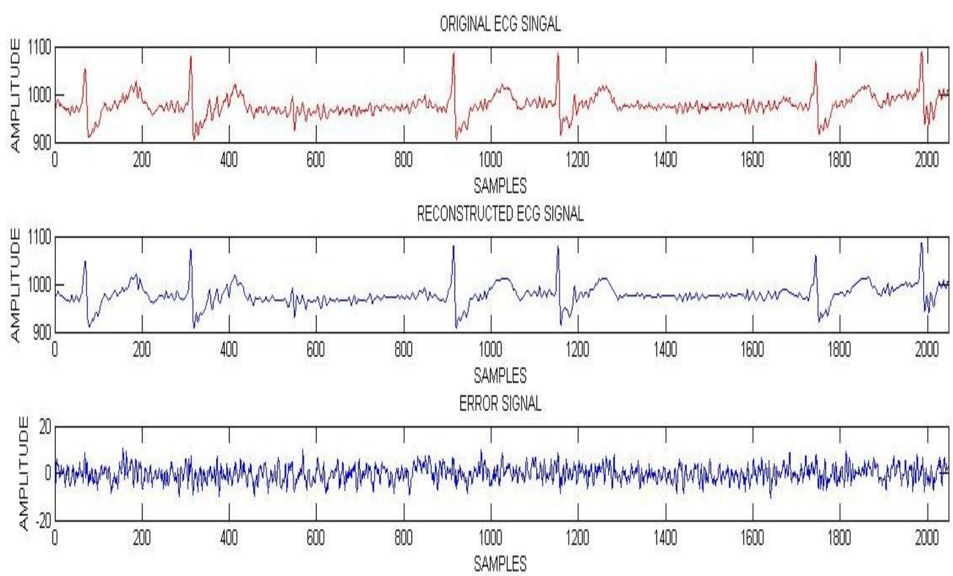

Figure 12 : The first 2048 sample of MIT-BIH record 232. CR=4.4814:1, PRD=0.3399%, EPE-D5=98%,EPE-D1-D4=98%.

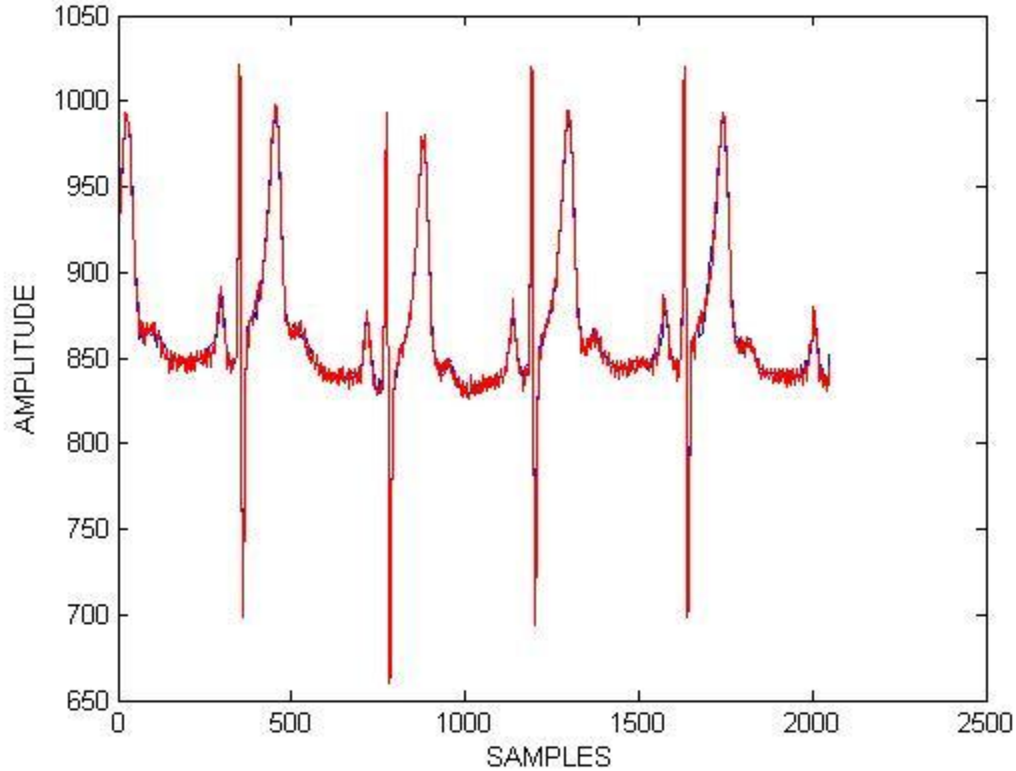

Figure 13 : Original and Reconstructed signal 117

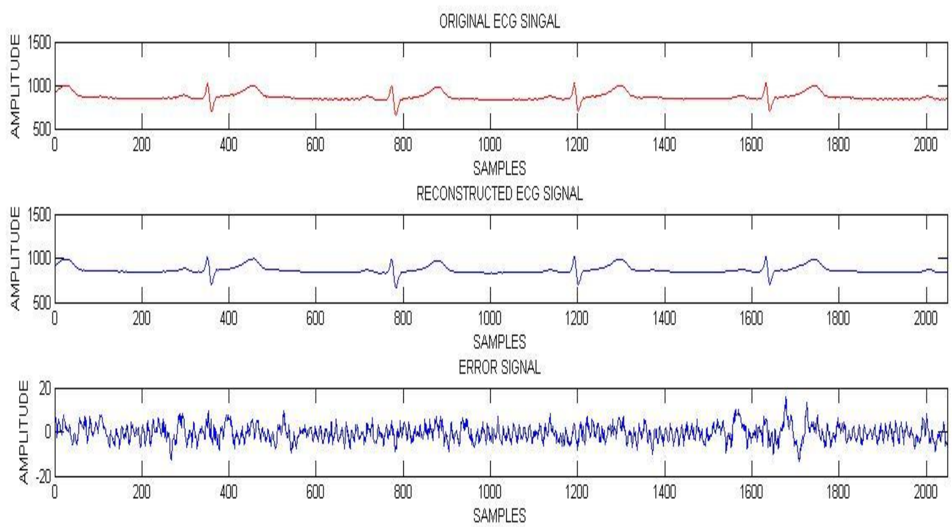

Figure 14 : The first 2048 sample of MIT-BIH record 117. CR=9.0320:1, PRD=0.4229%,EPE-D5=98%,EPE-D1-D4=98%.

METHODOLOGY 2

ECG signals provide valuable information in diagnosing heart diseases. Transmission of these signals over telephone lines or other communication channels is currently an important issue for the telemedicine applications.

R. Kumar and I. Saini implemented the algorithm proposed by Bashar A. Rajoub using recently evolved Empirical Wavelet Transforms. This algorithm has been implemented as a part of thesis work and results were successfully reproduced. The algorithm is as follows [33]:

- ***Pre-processing:*** Initially the ECG signal has been taken as input. Before applyingthe EWT, the ECG signal is pre-processed to reduce the DC content of the ECG signal and also to decrease the number of significant coefficients in the thresholding process. If *x(i)* be the input ECG signal then processed signal *y(i)* is given in equation 3.1.

  $$Y(i)=[(x(i)/Ax)-mx]$$

- ***EWT:*** EWT decomposes the signals into empirical modes. Modes can be thought of as the principal components (referred to as AM-FM components[4]) of the signal which represent the signal completely. In proposed algorithm each ECG signal is decomposed into three empirical modes. Flow diagram for the EWT is given in Figure 3.1.
- Signal is now wavelet transformed up to decomposition level 5 using bior4.4 mother wavelet. The coefficients are divided into three sets. Approximation coefficients (A5) and detail coefficients (D5) are retained maximum possible. Third set (D4-D1) are reduced maximum possible based on EPE.
- Based on EPE the three set of coefficients are thresholded. All the coefficients below the threshold are reduced to zero.
- Now based on the threshold, zero out the coefficients in each set and pass the rest to the coding stage.
- Coding is done in two phases: coding of significant map and significant coefficients. If a coefficient is significant a one is appended to the significant map else zero is appended. Now the resulting set is encoded using variable length encoding scheme.

- Lastly header information is also transmitted which is of 64 bits. Wavelet coefficients are stored in first 20 bits, index of last significant coefficient is stored in next 20 bits, next 20 bits store the maximum value of ECG signal and last 12 bits store mean of normalized signal.

The ECG compression algorithm has been tested on all 48 sets of ECG signal record files from MIT-BIH Arrhythmia database. Each record from this database is of 30 minutes duration and 650,000 samples with sampling rate 360 Hz. Threshold value for the detailed coefficients of mode second has been decided by taking p = 14 and that for mode third has been decided by taking q = 17. These threshold values are selected based on information content of each mode. Mode second contains lower amplitude content of the ECG signal and mode third contains higher frequency content with higher amplitudes so threshold values for mode second is kept lower than that for the mode third.

The result in tabular form after applying proposed algorithm are given in Table 4.4. Maximum value of CR obtained is 36.20 at a PRD of 2.4 % for the record 108 and minimum value CR obtained is 27 at a PRD of 3.7 % for the record 132.

First 10000 samples of record number 234 of MIT BIH database have been shown in figure 15. Preprocessing of the signal has been done to reduce the number of significant coefficients and is done by dividing each sample by maximum sample value and then mean removal. Preprocessed signal is shown in figure 16. After preprocessing, EWT is applied. In this algorithm we have proposed to decompose the preprocessed signal into three modes which are selected on the experimental basis to optimize the compression parameters. These three modes obtained have been shown in figure 17. Reconstructed signal is shown in figure 18. Reconstruction is at a CR of 28 and PRD 2.5 %.

Table 7 : Statistical parameters for records of MIT-BIH Arrhythmia database

S No.	**Record**	**CR**	**PRD (%)**
1	100	34	2.1

2	101	31	2.9
3	102	35	2.4
4	103	28	3.5
5	104	34	3
6	105	35	6
7	106	34	4.4
8	107	33	4.2
9	108	36	2.4
10	109	33	4.7
11	111	35	2.5
12	112	32	2.7
13	113	28	3.1
14	114	35	2.2
15	115	34	1.9
16	116	32	4.3
17	117	31	2.1
18	118	32	5
19	119	33	5
20	121	33	2.6
21	122	27	3.7
22	123	33	2
23	124	34	2.4
24	200	35	4.4

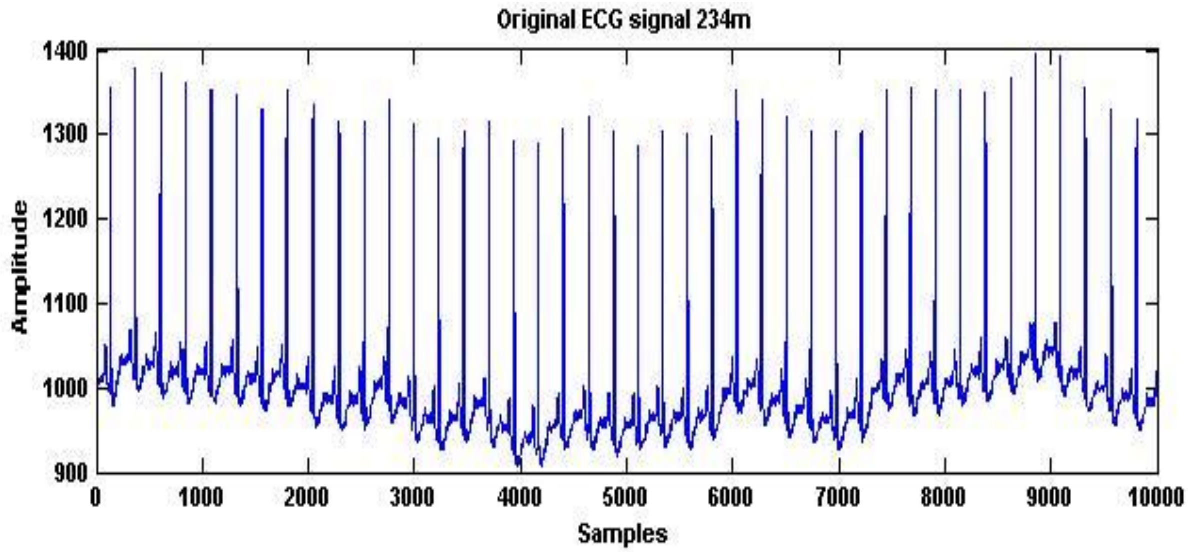

Figure 15 : Original signal of record no.234 of MIT-BIH Arrhythmia database

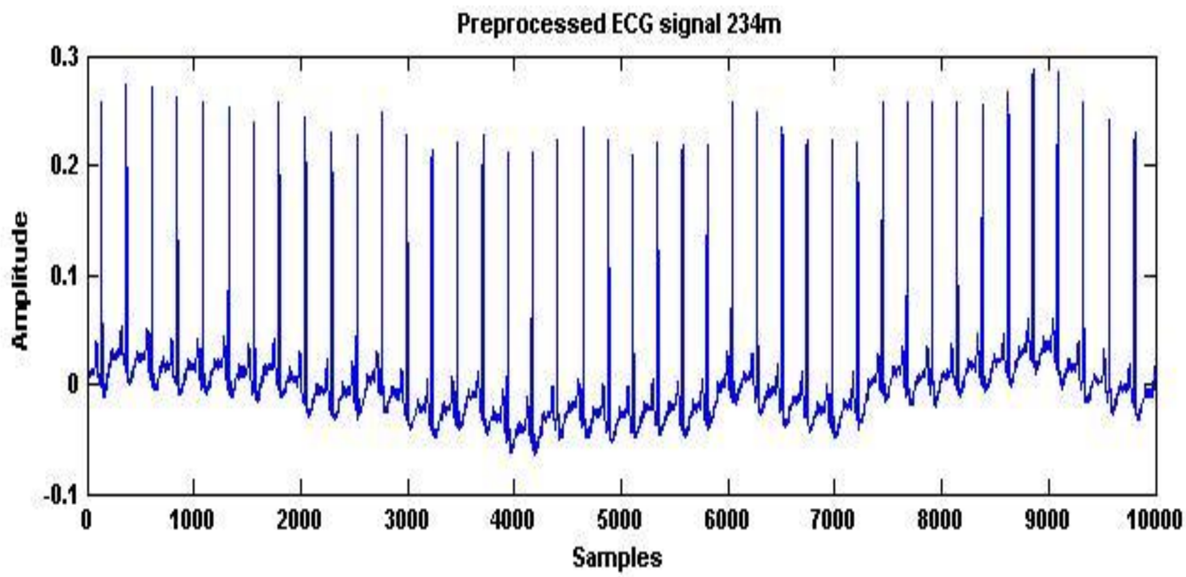

Figure 16 : Pre-processed signal of record no.234 of MIT-BIH Arrhythmia database

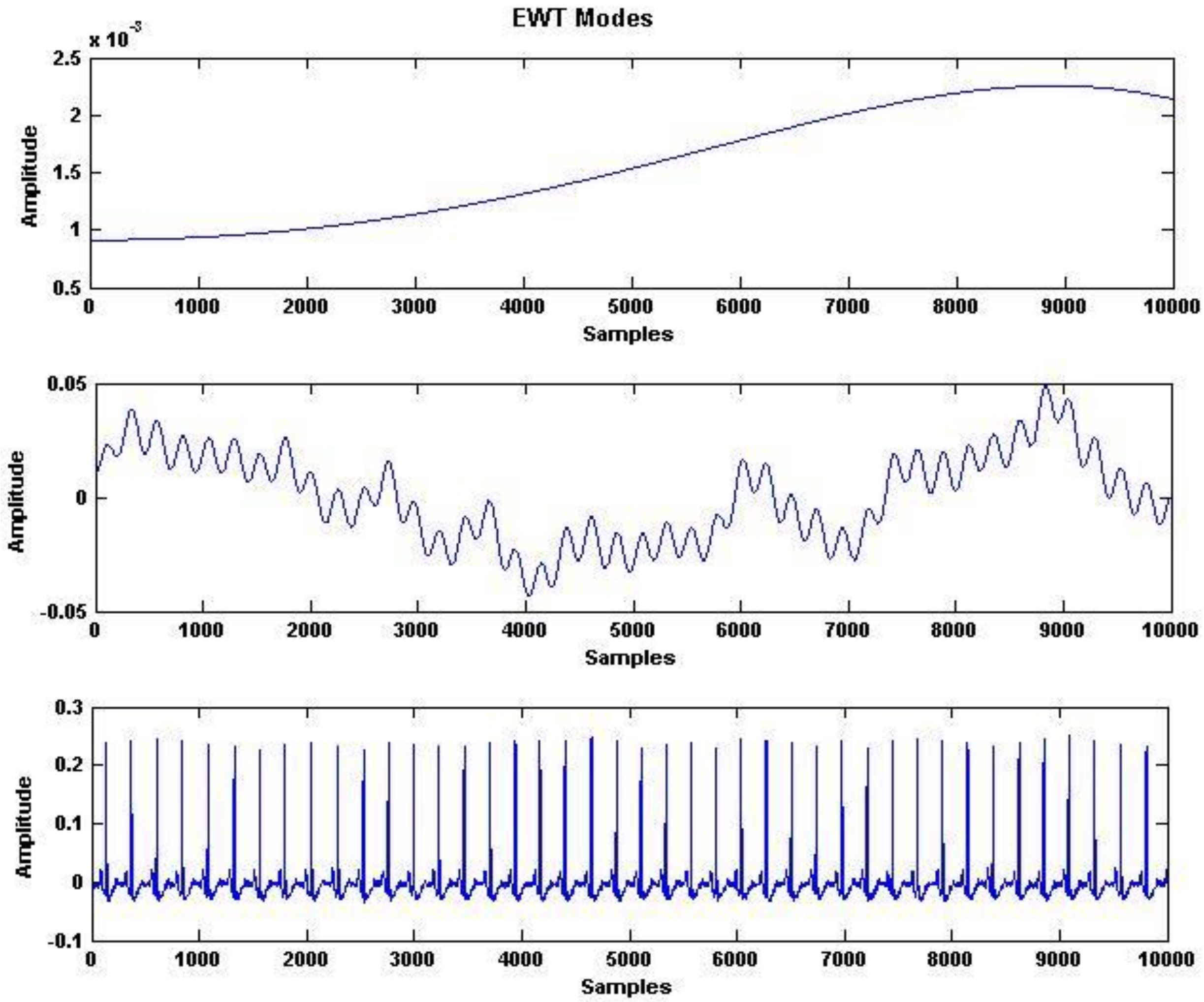

Figure 17 : EWT modes obtained of record no. 234 of MIT-BIH Arrhythmia database

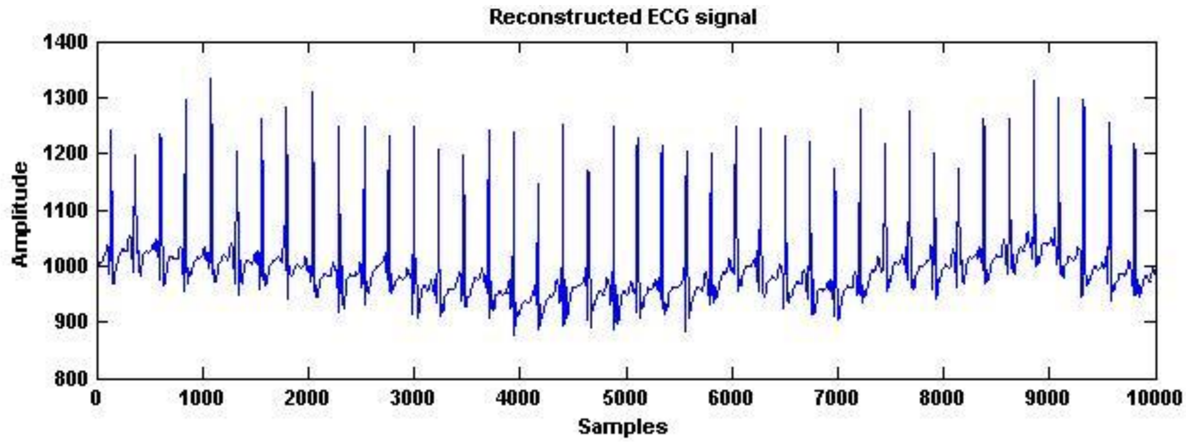

Figure 18 : Reconstructed signal of record no. 234 of MIT-BIH Arrhythmia database

CHAPTER V: PROPOSED ALGORITHIM OF ECG COMPRESSION

This chapter describes the EWT and SPIHT based compression algorithm suitable for transmission of ECG in wireless networks. The signal is first pre-processed by normalization and mean removal followed by empirical wavelet transform of the preprocessed signal. Empirical wavelets decompose the signal into different modes. Mode 2 and mode 3 decomposition of ECG record 117 is shown in figure (1a) and (1b). It can be seen that for mode 2 decomposition in figure (1a) that the variation in level 1 is minimal. So decomposition level 1 is discarded for further processing without significant loss of information. Similarly, in mode 3 decomposition as seen in figure (3) variation in level 1 and level 2 is negligible. So mode-3 coefficients are passed to next step for further processing. Alternatively, both mode 2 and mode 3 coefficients can be passed to next stage but it results in slight improvement in PRD with greater loss in CR. Hence in this proposed method, only mode-2 decomposition is considered for best matched results. After this discrete wavelet transform of the significant mode is performed and the obtained approximation and detail coefficients are SPIHT encoded for compression. Table (1) shows the implemented algorithm.

The algorithm is subdivided into 4 steps: Pre-processing, EWT, DWT and SPIHT encoding described as follows:

(i) Preprocessing: ECG signal is first normalized and then mean of the resulting signal is removed from the normalized signal. Normalization and mean removal reduce the number the significant coefficients on further processing [5].

(ii) EWT: The preprocessed signal is now empirical wavelet transformed with mode 2 decomposition. Since the variation in level-1 is very low (generally from -.01 to +.01) so coefficients of this level are discarded. Alternatively, mode-3 decomposition can also be performed. Since level 1 contain relatively insignificant information because of very low amplitude variation, either level-2 and level-3 or only level-3 coefficients can be passed to next stage for compression. The results shown in this paper are based on mode-2 decomposition.

(iii) DWT: The discrete wavelet transform (DWT) is then performed on coefficients obtained in step 2. The signal is broken down into approximation and detail coefficients using QMF filters with bior4.4 wavelet and decomposition level 5. Approximation and detail coefficients are SPIHT encoded for compression.

(iv) SPIHT encoding: It is applied to the coefficients obtained in step 3 in same manner as described by Zhitao Lu in [2].

ENCODER SIDE:

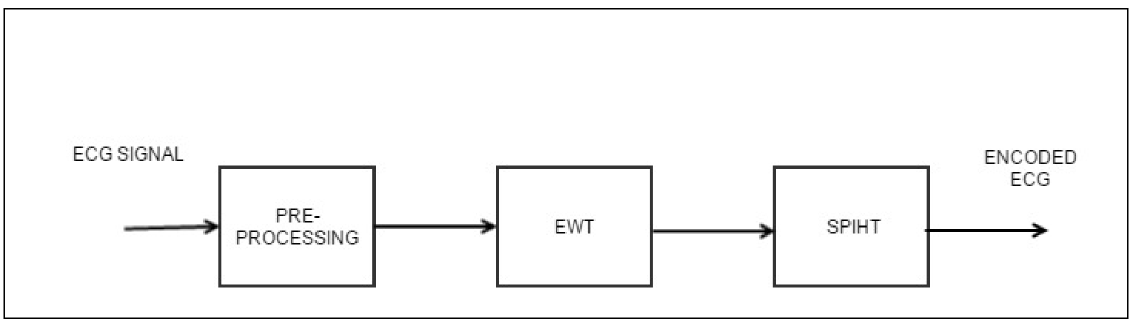

Figure 19 : ENCODER

DECODER SIDE:

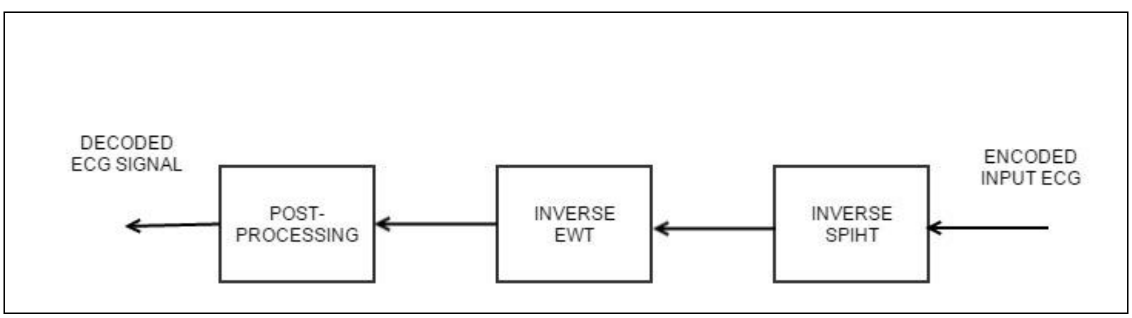

Figure 20 : DECODER

CHAPTER V: RESULTS

The algorithm is tested for all 48 recordings of MIT-BIH arrhythmia database. All records are sampled at 360 Hz with 11-bit resolution. These recordings are divided into two datasets: dataset1 and dataset2.

The dataset 1 consists of 30-min of data with record numbers: 109, 111,115,117, 118, 100, 101, 102, 103, 107 and 119. Table (2) shows the average compression ratio, PRD and total time (time taken by the algorithm for compression and decompression process) obtained to process dataset1by the proposed algorithm. CR is calculated by dividing the actual by compressed .mat size of the file. PRD is calculated by decompressing the compressed file and reconstructing the original transmitted signal.

To show the effect of loss of data by EWT and SPIHT during compression on the reconstructed signal, 3000 samples the record 117 is reconstructed at different bit rates (1000 bps, 400 bps, 200bps and 160bps) only for mode-2 EWT decomposition. As amplitude variation in mode 1 is very low, so the information content in mode 1 is very less and thus discarded. At 200bps, it is evident that the low level background noise is smoothed but the clinical features are faithfully preserved.

Table 8 : average test results for the first dataset

CR	40.15	31.9	26.9	23.01	20.07	17.8	15.99	14.62	13.38	12.33	11.44	10.66
PRD	2.08	1.82	1.70	1.63	1.59	1.57	1.55	1.54	1.53	1.52	1.52	1.51
Time	5.14	5.13	5.15	5.16	5.17	5.17	5.2	5.27	5.24	5.22	5.23	5.26

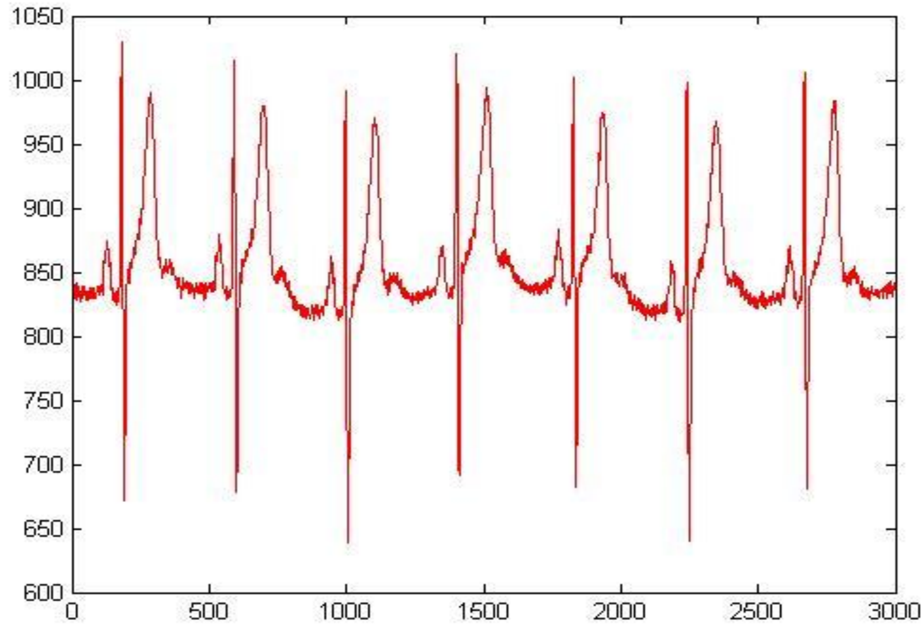

Figure 21 : Original Signal (117 from MIT-BIH)

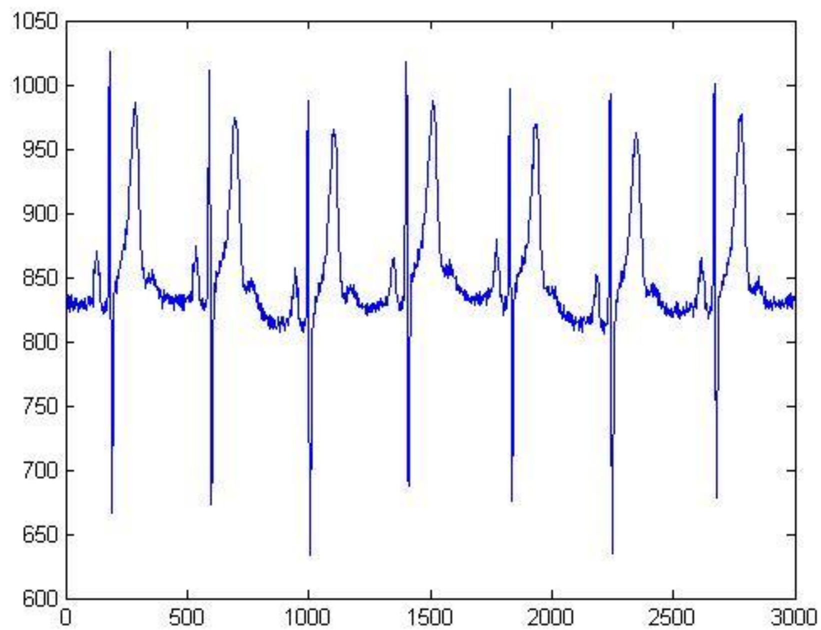

Figure 22 : Reconstructed at CR=5.93, PRD=.95%

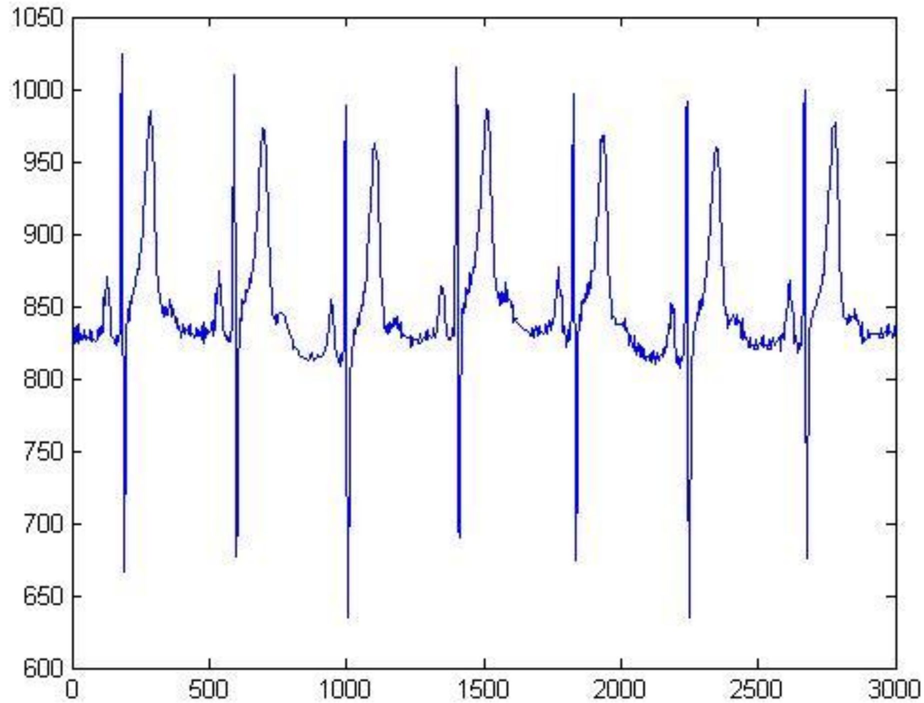

Figure 23 : Reconstructed at CR=14.62, PRD=.98%

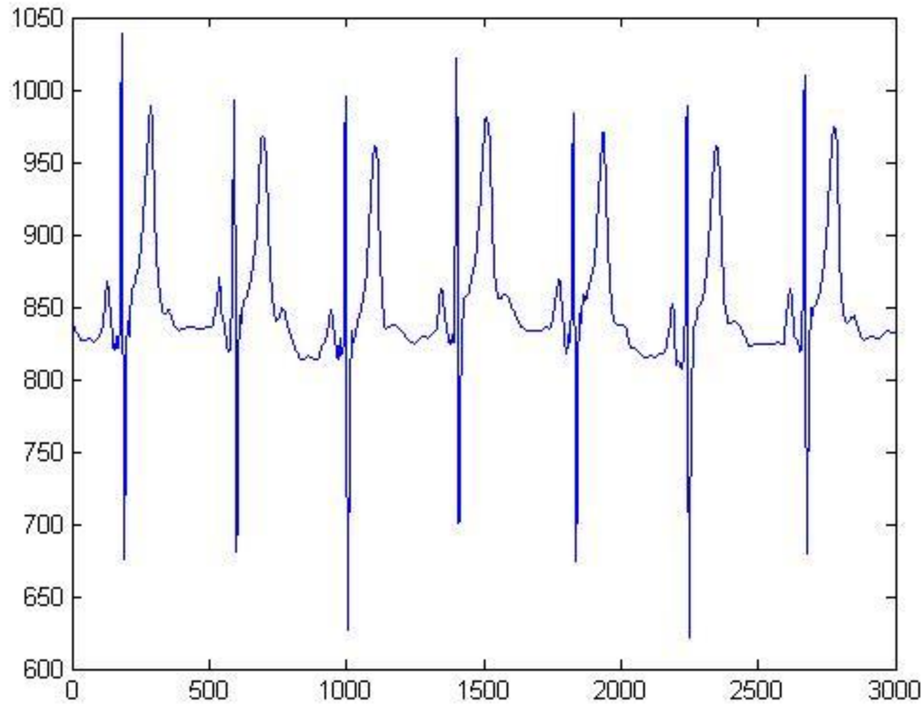

Figure 24 : Reconstructed at CR=29.2, PRD=1.07%

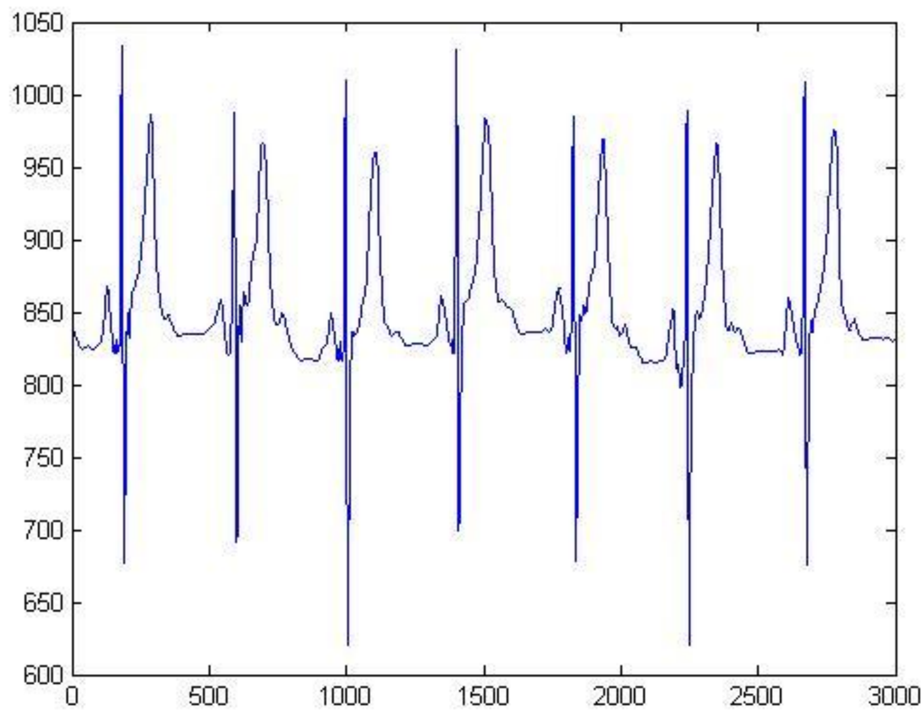

Figure 25 : Reconstructed signal at CR=35.9, PRD=1.15%

The Dataset 2 set consists of record numbers with 1-min of data: 104, 107, 111, 112,115, 116, 117, 118, 119, 201, 207, 208, 209, 212, 214, 228,231, and 232. Average results of CR, PRD and time obtained are shown in table 3.

Table 9 : Average test results for the second dataset

CR	23.01	21.33	20.07	18.9	17.8	16.9	15.9	15.2	14.62	13.93	13.38	12.79
PRD	1.36	1.33	1.31	1.29	1.28	1.27	1.26	1.25	1.24	1.23	1.23	1.22
Time	5.13	5.06	5.13	5.13	5.13	5.11	5.16	5.14	5.2	5.23	5.23	5.15

The figure (10) shows the CR v/s PRD for the proposed algorithm using various recording from MIT-BIH arrhythmia database. However it must be noted that this curve has been obtained by varying bitrates at decompression side. From the simulation it has been found that best performance of 35.9:1 CR with 1.15% PRD is achieved at 160bps for record 117.

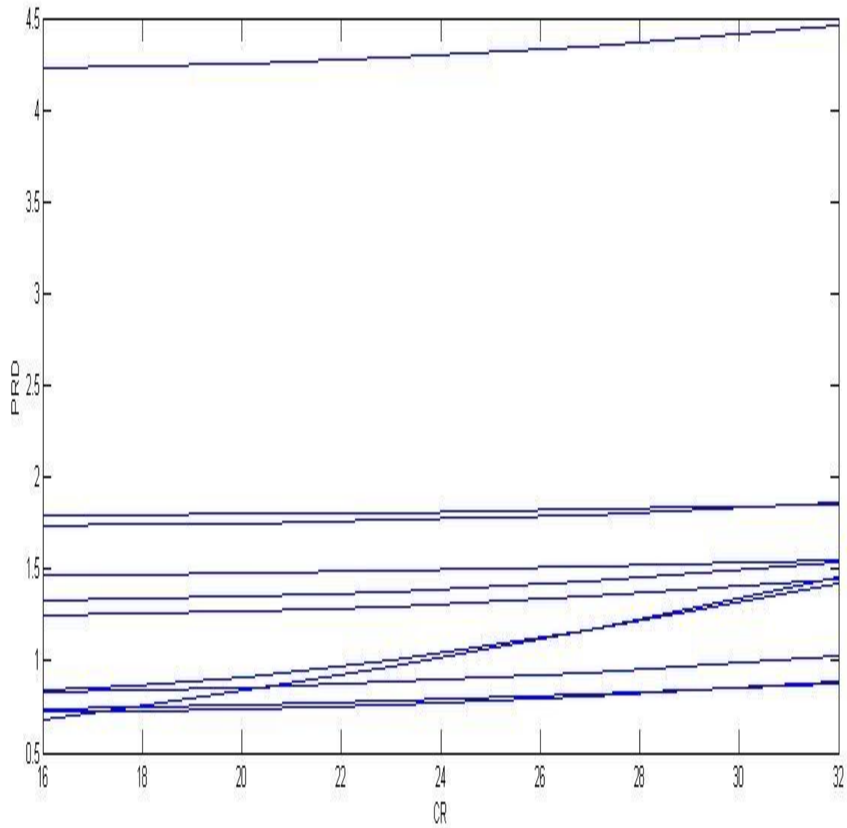

Figure 26 : CR v/s PRD for the proposed algorithm for various records of MIT-BIH

CHAPTER V: CONCLUSION

The performance of the proposed algorithm is compared with three algorithms proposed in literature namely SPIHT [7], wavelet based compression [8] and EWT-DWT based compression [9]. Each algorithm is tested for 1min data of 117 record. Table (4) shows CR and PRD results of the various algorithms. In [10], for same data, Hilton method reported a CR of 8:1 for PRD of 2.6% while in [11] for the same data, CR of 8:1 with 3.9% PRD was reported by Diohn. It can be seen that the algorithm proposed in this paper outperforms the existing algorithms in terms of both CR and PRD.

Table 10 : Comparison of different coding algorithms

Algorithm	CR	PRD	Time
Wavelet based [8]	23.4761	.9708	7.112
SPIHT [7]	21.5	2.88	.013
EWT [9]	34.2758	3.3004	2.2566
Proposed algorithm	**35:1**	**1.1**	**.6**

Data compression algorithm based on empirical wavelet transform has been proposed in this paper. The 1-D SPIHT coding algorithm proposed in [7] has shown superior results when applied with EWT in comparison to EWT based compression of ECG signals described in [9]. As seen in figure (10) the performance of this algorithm is consistent for a variety of ECG signal of MIT-BIH arrhythmia database. SPIHT is a low complexity algorithm and provides exact bit rate control according to desired CR and quality [7]. The characteristics like high efficiency, high quality and low complexity make this algorithm a very suitable candidate for compression of ECG signals in mHealth cardiograph systems.

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LIST OF PUBLICATIONS

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