

A Survey of ECG Signal Compression Techniques based on Discrete Wavelet Transform

Anand Kumar Patwari¹, Asst. Prof. Durgesh Pansari², Prof. Vijay Prakash Singh³

¹PG student, Dept. of Electronics and Communication, RKDF college of Engineering, Bhopal, India

²Asst. Professor, Dept. of Electronics and Communication, RKDF college of Engineering, Bhopal, India

³H.O.D., Dept. of Electronics and Communication, RKDF college of Engineering, Bhopal, India

Abstract-This paper presents the review of the different ECG compression techniques using wavelet transform. We have performed the study of so many ECG compression techniques and the resultant conclusions have been published with in this paper. There are so many techniques are popular for ECG compression. The wavelet based techniques are most popular and conveniently implementable. Here in this paper, we tried to give the brief description of most of them and to elaborate the techniques, which are the base of our future works.

I. INTRODUCTION

The “Electrocardiogram” (ECG) is an invaluable tool for diagnosis of heart diseases [1]. The volume of ECG data produced by monitoring systems can be quite large over a long period of time and ECG data compression is often needed for efficient storage of such data[2]. In a similar sense, when ECG data need to be transmitted for telemedicine applications, data compression needs to be utilized for efficient transmission[3]. While ECG systems are found primarily in hospitals, they find use in many other locales also. ECG systems are used by paramedics responding to accident scenes in emergency vehicles. They are also used by clinicians at remote sites. Certain military and/or space missions also employ ECG. A growing area of use for ECG is the 24-hour holters that are leased by consumers. These portable ECG devices record and store the data for subsequent interpretation by a doctor.

To record ECG signal waveform, a large amount of data should be saved[1-5]. To reduce the space for data storage, some compression must be used, but only if the difference between decompressed - reconstructed signal and the original one is minimal, i.e. if reconstructed signal is not distorted and if cardiologist can obtain the same diagnosis from reconstructed signal as if he would obtain it from original signal[5-7].

There are several ways to obtain compression of non - stationary signals and almost all of them use transform coding. In the given techniques in this paper the compression of the signal is obtained by Discrete Wavelet Transform (DWT)[7,8].

The main objective associated with the ECG compression is to obtain the Good compression ratio with the less error after reconstruction and the clear visibility of the ECG component, subjected for the further observation[6-10].

II. ELECTROCARDIOGRAM (ECG)

An electrocardiogram is simply a measure of voltage changes in the body. Any large electrical event can be detected. The electrically-active tissues in the body are the muscles and nerves. Small brief changes in voltage can be detected as these tissues ‘fire’ electrically[1,5].

The heart is a muscle with well-coordinated electrical activity, so the electrical activity within the heart can be easily detected from the outside of the body with the help of ECG. A normal heartbeat or cardiac cycle has P wave, a QRS complex and a T wave. A small U wave is sometimes visible in 50 to 75% of ECGs.

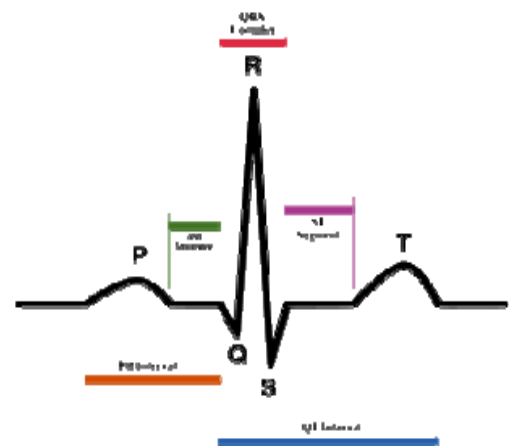


Fig.1 Diagram of a ECG cycle

III. ECG SIGNAL COMPRESSION

The Data compression can be lossy or lossless. Data reduction of ECG signal is achieved by discarding digitized samples that

are not important for subsequent pattern analysis and rhythm interpretation. An example is shown below:

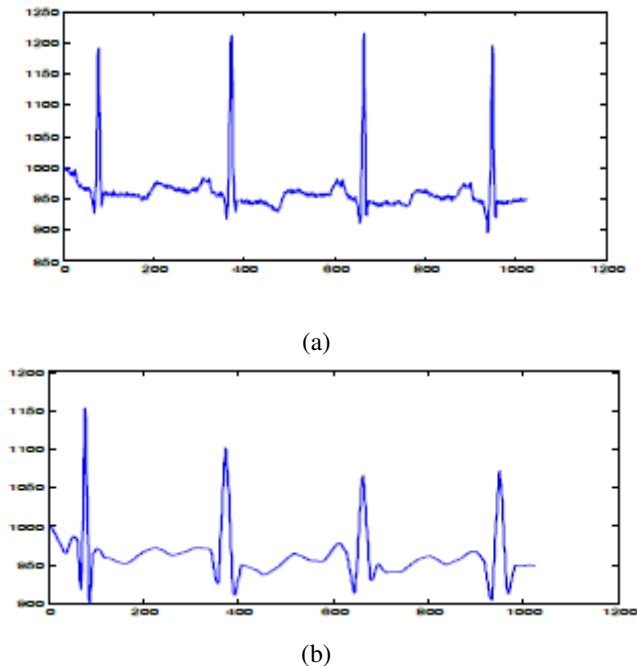


Fig.2 ECG signal : (a) Original (b) Reconstructed after compression

The data reduction algorithms are empirically designed to achieve good reduction without causing significant distortion error. ECG compression techniques can be categorized into: direct time-domain techniques; transformed frequency-domain techniques and parameters optimization techniques[1,9].

A. Direct Signal Compression Techniques: Direct methods involve the compression performed directly on the ECG signal. These are also known as time domain techniques dedicated to compression of ECG signal through the extraction of a subset of significant samples from the original sample set. Which signal samples are significant, depends on the underlying criterion for the sample selection process. To get a high performance time domain compression algorithm, much effort should be put in designing intelligent sample selection criteria. The original signal is reconstructed by an inverse process, most often by drawing straight lines between the extracted samples. Many of the time domain techniques for ECG signal compression are based on the idea of extracting a subset of significant signal samples to represent the original signal. The key to a successful algorithm is the development of a good rule for determining the most significant samples. Decoding is based on interpolating this subset of samples. The traditional ECG time domain

compression algorithms all have in common that they are based on heuristics in the sample selection process. This generally makes them fast, but they all suffer from sub-optimality. This category includes the FAN (Dipersio & Barr, 1985), CORTES (Abenstein & Tompkins, 1982), AZTEC (Cox et al., 1968), Turning Point (Mueller W., 1978) and TRIM (Moody et al., 1989) algorithms. The more recent cardinality constrained shortest path technique (Haugland et al., 1997) also fits into this category.

B. Transformed ECG Compression Methods: Transform domain methods, as their name implies, operate by first transforming the ECG signal into another domain. These methods mainly utilize the spectral and energy distributions of the signal by means of some transform, and properly encoding the transformed output. Signal reconstruction is achieved by an inverse transformation process.

This category includes traditional transform coding techniques applied to ECG signals such as the Karhunen–Loève transform (Olmos et al., 1996), Fourier transform (Reddy & Murthy, 1986), Cosine transform (Ahmed et al., 1975), subband-techniques (Husøy & Gjerde, (1996), vector quantization (VQ) (Mammen & Ramamurthi, 1990), and more recently the wavelet transform (WT) (Chen et al., 1993; (Miaou et al., 2002).

Due to the Transforms are used to obtain a suitable signal representation for efficient source Coding. We have so many transforms are available for the transformation of the ECG signal in another domain as given above. Other than this we also have the Wavelet Packet Transform (WPT), Cosine Packet Transform (CPT), Wave Atom Transform (WAT), options which are the fast and strategically transformation and decomposition of the signal in the another domain. [7, 8]

Wavelet technique is the obvious choice for ECG signal compression because of its localized and non-stationary property and the well-proven ability of wavelets to see through signals at different resolutions. The wavelet decomposition splits the analyzing signal into average and detail coefficients, using finite impulse response digital filters. The main task in wavelet analysis (decomposition and reconstruction) is to find a good analyzing function (mother wavelet) to perform an optimal decomposition. Wavelet-based ECG compression methods have been proved to perform well.

The ability of DWT to separate out pertinent signal components has led to a number of wavelet-based techniques which supersede those based on traditional Fourier methods. The discrete wavelet transform has interesting mathematics and fits in with standard signal filtering and encoding methodologies. It produces few coefficients, and the user does not have to worry about losing energy during the transform process or its inverse. While the DWT is faster and maps quickly to the sub-band coding of signals, the Continuous

Wavelet Transform (CWT) allows the user to analyze the signal at various scales and translations according to the problem.

C. Optimization Methods For ECG Compression: More recently, many interesting optimization based ECG compression methods, the third category, have been developed. The goal of most of these methods is to minimize the reconstruction error given a bound on the number of samples to be extracted or the quality of the reconstructed signal to be achieved. In (Haugland et al., 1997), the goal is to minimize the reconstruction error given a bound on the number of samples to be extracted. The ECG signal is compressed by extracting the signal samples that, after interpolation, will best represent the original signal given an upper bound on their number. After the samples are extracted they are Huffman encoded. This leads to the best possible representation in terms of the number of extracted signal samples, but not necessarily in terms of bits used to encode such samples. In (Nygaard et al., 1999), the bit rate has been taken into consideration in the optimization process. The ECG signal can be in time domain or in any other domain.

D. ECG Compression using Hybrid Transform: It is the combination of DCT & WAVELET Transform for better compression ratio. In this method we first apply DCT on ECG image which apply converts image into frequency components. Then we apply wavelet transform on frequency components which helps to obtain precise mathematical coefficient in matrix form. Now we apply compression by eliminating high frequency components.[7]

IV. COMPRESSION REQUIREMENTS

The strategy for compressing data must fulfill the following requirements[9]:-

A. Information preservation: Due to diagnostic restriction, it is imperative that the information found in the original data is preserved after compression.

B. Control of compression degree: Another preference is the ability to control the amount of data compression. Recent information is preferably stored in a data exact form with low degree of compression. However, with older data a more aggressive compression strategy is accepted.

C. Complexity Issue: Due to limited processing capacity of the pacemaker, an algorithm for compressing data has to have low complexity. This fact rules out many compression techniques involving extensive calculation, which could be potential candidates in other circumstances.

V. PERFORMANCE PARAMETERS

A. Compression Ratio: The compression ratio (CR) is defined as the ratio of the number of bits representing the original signal to the number required for representing the compressed signal. So, it can be calculated from:

$$CR = \frac{N b_c}{(N_s + M)(b_s + 1)}$$

Where, b_c is the number of bits representing each original ECG sample.[1,2,4-6,9]

B. Root Mean Square Error: The root mean square error (RMS) is used as an error estimate. The RMS is given as

$$RMS = \sqrt{\frac{\sum_{n=1}^N (x(n) - \hat{x}(n))^2}{N}}$$

where $x(n)$ is the original signal, $\hat{x}(n)$ is the reconstructed signal and N is the length of the window over which the RMS is calculated.[1,2,4-6,9,10]

C. Root-mean-square Difference: The distortion resulting from the ECG processing is frequently measured by the percent root-mean-square difference (PRD), which is given by:

$$PRD = \sqrt{\frac{\sum_{n=1}^N (x(n) - \hat{x}(n))^2}{\sum_{n=1}^N x^2(n)}}$$

As the PRD is heavily dependent on the mean value, it is more appropriate to use the modified criteria:

$$PRD_1 = \sqrt{\frac{\sum_{n=1}^N (x(n) - \hat{x}(n))^2}{\sum_{n=1}^N (x(n) - \bar{x})^2}}$$

where \bar{x} is the mean value of the signal.[1,2,4-6,8,9]

VI. THE DISCRETE WAVELET TRANSFORM

There is a number of time–frequency methods are currently available for the high resolution signal decomposition. But there is many of complexities and drawbacks are associated

with them which are minimized in the DWT.[1-4,5-7,9] The DWT is the appropriate tool for the analysis of ECG signals as it removes the main shortcomings of the other transforms; namely it uses a single analysis window which is of fixed length in both time and frequency domains. This is a major drawback of the other transform, since what are really needed are a window of short length (in time domain) for the high frequency content of a signal and a window of longer length for the low frequency content of the signal. The WT improves upon the STFT by varying the window length depending on the frequency range of analysis. This effect is obtained by scaling (contractions and dilations) as well as shifting the basis wavelet. The continuous wavelet transform (CWT) transforms a continuous signal into highly redundant signal of two continuous variables — translation and scale. The resulting transformed signal is easy to interpret and valuable for time-frequency analysis. The continuous wavelet transform of continuous function, $f(x)$ relative to real-valued wavelet, $\psi(x)$ is described by:

$$W_{\psi}(s, \tau) = \int_{-\infty}^{\infty} f(x) \psi_{s, \tau}(x) dx \quad (1)$$

where

$$\psi_{s, \tau}(x) = \frac{1}{\sqrt{s}} \psi\left(\frac{x - \tau}{s}\right) \quad (2)$$

s and τ are called scale and translation parameters, respectively. $W_{\psi}(s, \tau)$ denotes the wavelet transform coefficients and ψ is the fundamental mother wavelet. If $W_{\psi}(s, \tau)$ is given, $f(x)$ can be obtained using the inverse continuous wavelet transform (ICWT) that is described by:

$$f(x) = \frac{1}{C_{\psi}} \int_0^{\infty} \int_{-\infty}^{\infty} W_{\psi}(s, \tau) \frac{\psi_{s, \tau}(x)}{s^2} d\tau ds \quad (3)$$

where, $\Psi(u)$ is the Fourier transform of $\psi(x)$ and

$$C_{\psi} = \int_{-\infty}^{\infty} \frac{|\Psi(u)|^2}{|u|} du \quad (4)$$

The discrete wavelet transform can be written on the same form as Equation (1), which emphasizes the close relationship between CWT and DWT. The most obvious difference is that the DWT uses scale and position values based on powers of two. The values of s and τ are: $S = 2^j$, $\tau = k * 2^j$ and $(j, k) \in \mathbb{Z}^2$ as shown in Equation (5).

$$\psi_{j, k}(x) = \frac{1}{\sqrt{s_o^j}} \psi\left(\frac{x - k\tau_o s_o^j}{s_o^j}\right) \quad (5)$$

The key issues in DWT and inverse DWT are signal decomposition and reconstruction, respectively. The basic idea behind decomposition and reconstruction is low-pass and high pass filtering with the use of down sampling and up sampling respectively. The result of wavelet decomposition is hierarchically organized decompositions. One can choose the level of decomposition j based on a desired cutoff frequency.

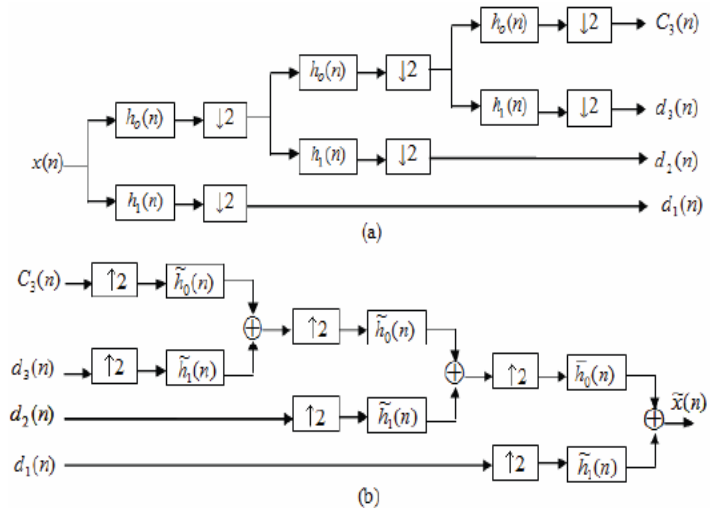


Fig.3 A three-level two-channel iterative filter bank (a) forward DWT (b) inverse DWT

VII. DWT BASED ECG COMPRESSION ALGORITHMS

As described above, the process of decomposing a signal x into approximation and detail parts can be realized as a filter bank followed by down-sampling (by a factor of 2).[1,9] The impulse responses $h[n]$ (low-pass filter) are derived from the scaling function and the mother wavelet. This gives a new interpretation of the wavelet decomposition as splitting the signal x into frequency bands. In hierarchical decomposition, the output from the low-pass filter h constitutes the input to a new pair of filters. This results in a multilevel decomposition. The maximum number of such decomposition levels depends on the signal length. For a signal of size N , the maximum decomposition level is $\log_2(N)$.

The process of decomposing the signal x can be reversed, that is given the approximation and detail information it is possible to reconstruct x . This process can be realized as up sampling (by a factor of 2) followed by filtering the resulting signals and adding the result of the filters. The

impulse responses h' and g' can be derived from h and g . If more than two bands are used in the decomposition we need to cascade the structure.

In (Chen et al., 1993), the wavelet transform as a method for compressing both ECG and heart rate variability data sets has been developed. In (Thakor et al., 1993), two methods of data reduction on a dyadic scale for normal and abnormal cardiac rhythms, detailing the errors associated with increasing data reduction ratios have been compared. Using discrete orthonormal wavelet transforms and Daubechies D10 wavelets, Chen et al., compressed ECG data sets resulting in high compression ratios while retaining clinically acceptable signal quality (Chen & Itoh, 1998).

In (Miaou & Lin, 2000), D10 wavelets have been used, with the incorporating of adaptive quantization strategy which allows a predetermined desired signal quality to be achieved. Another quality driven compression methodology based on Daubechies wavelets and later on biorthogonal wavelets has been proposed (Miaou & Lin, 2002). The latter algorithm adopts the set partitioning of hierarchical tree (SPIHT) coding strategy. In (Bradie, 1996), the use of a wavelet-packet-based algorithm for the compression of the ECG signal has been suggested.

By first normalizing beat periods using multi rate processing and normalizing beat amplitudes the ECG signal is converted into a near cyclostationary sequence (Ramakrishnan & Saha, 1997). Then Ramakrishnan and Saha employed a uniform choice of significant Daubechies D4 wavelet transform coefficients within each beat thus reducing the data storage required. Their method encodes the QRS complexes with an error equal to that obtained in the other regions of the cardiac cycle. More recent DWT data compression schemes for the ECG include the method using non orthogonal wavelet transforms (Ahmed et al., 2000), and SPIHT algorithm (Lu et al., 2000).

VIII. GENERALIZED METHODOLOGY

The proposed technique is implemented in two steps: (i) the transformed coefficients are thresholded using bisection algorithm and (ii) the thresholded coefficients are quantized. The pseudo code for the algorithm is explained as follows.

Step 0: Initialization

Get the user-specified PRD (UPRD);

Select the threshold TH in the range [THmin, THmax] where the range may be initialized by [0, TCmax]. (TCmax - maximum value of Transformed coefficients)

Get the convergence precision ϵ is 1%; Transform the ECG signal using different transforms.

Step 1: Take a copy of Transformed coefficients (TC) and threshold it by

$TH = (TH_{min} + TH_{max})/2$

Step 2: Inverse TC

Step 3: Compute the PRD

Step 4: if $(PRD < UPRD)$

Then $TH_{min} = TH$;

Else $TH_{max} = TH$;

Step 5: if $|PRD - UPRD| / UPRD > \epsilon$

Then go to Step 1

Step 6: Construct the binary lookup table to represent the zero and non-zero coefficients obtained after thresholding in Step1. This binary lookup table is encoded using Huffman coding.

Step 7: The non-zero coefficients are quantized using Max-Lloyd algorithm followed by arithmetic coding.

Step 8: End.

IX. CONCLUSION AND FUTURE WORKS

In our study we have seen the different methods of ECG compression. First of all we have seen the direct methods which corresponds compression of the signal in the time domain. This method requires the significant coefficient which is difficult to recognize in the time domain. So we found it's much better to use some transformation and to discard the signal coefficient in some other domain. We have seen multiple options for the Transforms. DCT, DFT and DWT are main of them, but the DWT is much better and convenient to use for the ECG signal decomposition. We also have the Hybrid transformation as an option for ECG compression, but it seems complicated. We also seen so many techniques based on DWT. We found the generalized technique appropriate as it also provides the optimization in terms of PRD and CR.

In the future we may work in improvisation for the same technique by using the different mother wavelets or by changing the decomposition levels.

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