ECG Signal Compression Using Standard Techniques

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Abstract: The electrical signal is generated by the heart and it is record by the electrocardiogram, for electrocardiogram (ECG) data compression has been purposed the last three decades. Such techniques have been vital in reducing the digital ECG data volume for storage and transmission. Continuous recording by ECG, So in It record is so voluminous, so it is practically do not to handle it without compression, for transmission purpose, in rural area such excellent cardiologist is not available so the data is send to other cardiologist a large data size takes many time to send, so by compression data size is reduced and take minimum time. The ECG data is compress by some technique DWT, DCT, Wavelet denoising and compression and Huffman coding the data base is taking from MIT-BIH record 104, and tested these technique on MATLAB. The DWT based algorithm gives better result to DCT based algorithm.

Keywords: MIT-BIH record 104, DWT, DCT, Wavelet denoising and compression, Huffman coding.

I. INTRODUCTION

The ECG is a bioelectric signal, which records the electrical activity of human heart. It gives the information to cardiologist about the human rhythm and function of the heart. We knows the information of heart by placing electrode across the chest of human body. ECG signal being used in a wide variety of biomedical applications requires accurate results, less power requirements, faster results and low cost maintenance. Therefore compression plays a very important role in acquiring these purposes without losing the original information [1].

Modern electrocardiogram (ECG) monitoring devices generate vast amounts of data and require huge storage capacity, many ECG compression methods were proposed to process, transmit, and store the data efficiently. They could be classified into the following four categories. 1) Parameter extraction techniques (e.g., linear prediction and neural network methods). 2) Transform-domain techniques (e.g., two dimensional (2-D) discrete cosine transform (DCT), and wavelet transforms). 3) Direct time-domain techniques (e.g., amplitude zone epoch take record data from the MIT-BIH arrhythmia database. To compress the signal are applied technique like DCT, DWT, Quantization and Huffman coding. Transform method converts the time domain signal to the frequency or other domains and analyses the energy distribution. Transformation methods involve processing of the input signal by a linear orthogonal transformation and encoding of the output using an appropriate error criterion. For signal coding (AZTEC), coordinate reduction time encoding system (CORTES), [2].

We reconstruction an inverse transformation is carried out and the signal is recovered with some error. Some other examples of transform techniques are Fourier transform (FT), Fourier descriptor, Karhunen-Loeve transform (KLT), The Walsh transform. The main features of this compression algorithm are the high efficiency and high speed. Compression techniques have been around for many years. However, there is still a continual need for the advancement of algorithms adapted for ECG data compression. The necessity of better ECG data compression methods is even greater today than just a few years ago for several reasons. The quantity of ECG records is increasing by the millions each year, and previous records cannot be deleted since one of the most important uses of ECG data is in the comparison of records obtained over a long range period of time.

II. ECG SIGNAL PROCESSING

The block diagram in Figure 1 presents this set of signal processing algorithms. Although these algorithms are frequently implemented to operate in sequential order, information on the occurrence time of a heartbeat, as produced by the QRS detector, is sometimes incorporated into the other algorithms to improve performance. The complexity of each algorithm varies from application to application so that, for example, noise filtering performed in ambulatory monitoring is much more sophisticated than that required in resting ECG analysis.

Once the information produced by the basic set of algorithms is available, a wide range of ECG applications exist where it is of interest to use signal processing for quantifying heart rhythm and beat morphology properties. The signal processing associated with two such applications—high-resolution ECG and
T wave alternates are briefly described at the end of this article. The timing information produced by the QRS detector may be fed to the blocks for noise filtering and data compression (indicated by gray arrows) to improve their respective performance. The output of the upper branch is the conditioned ECG signal and related temporal information, including the occurrence time of each heartbeat and the onset and end of each wave.

**Figure 1: Algorithm for Basic ECG Signal Processing**

The algorithm for real-time ECG signal compression and reconstruction is summarized in Figure 2. As shown in this figure, it is composed of five compressing procedures and four reconstruction procedures. For compression, the first procedure is to obtain backward differences after 1/2 down-sampling of the ECG signal.

**Figure 2: Block Diagram of Compression and Decompression Procedures**

The second procedure is to detect the peak of the differenced signal and classify it from the current peak to the previous peak and store the result. The third procedure is to obtain the DCT of the stored data. The fourth procedure is to filter the transformed data obtained in the previous procedure using a window filter, and the final procedure is to apply the Huffman coding algorithm.

The data transmitted to a server or a base station from e-health devices are the data block coming out of the last compression procedure. The channel number can be added to the protocol header if e-health devices need to transmit multiple bio-signals.

Figure 2 also shows the reconstruction procedure, which is the reverse order of the compression procedure. The first reconstruction procedure applies the inverse Huffman coding algorithm to the compressed and transmitted data. The second procedure obtains the inverse discrete cosine transform. The third interpolates the recovered time signal during the previous procedure using Spline interpolation, and the final procedure is to reconstruct the original signal after calculating the inverse difference[18].

ECG, which is an analog signal, is usually sampled at 200 Hz to 1 kHz depending on the purpose of applications. Usually, the sampled data are represented as a 2-byte data. In the proposed data compression algorithm, the acquired ECG signal is first downsampled by 1/2 and represented as 1-byte data after calculating the backward difference, decreasing its data size by 75%. The signed 1-byte data can be represented from −128 to +127 in decimal.
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CR = \frac{\text{Data size before Compression}}{\text{Data size after Compression}} \quad (1)

Higher the CR, smaller is the size of the compressed file. For good signal data size after compression should be minimum, so compression ratio of the signal is increase. The error is measured as the percent mean square difference (PRD) between original and reconstructed signal.

\[
\text{PRD} = \left( \frac{\sum_{i=1}^{N}(S(t_i) - \hat{s}(t_i))^2}{\sum_{i=1}^{N}(S(t_i))^2} \right) \times 100 \quad (2)
\]

Where N is the number of data samples, s(t) is the original signal and \( \hat{s}(t) \) is the reconstructed signal. For signal to be better, PRD should be minimum (means error should be minimum). For good signal error should be minimum, if error is minimum, then PRD should be minimum. It is increased speed of the signal.

IV. COMPRESSION METHOD

The record data becomes so large size & voluminous that it becomes practically impossible to handle it without compression, so for it we have to compress the ECG data by different techniques [8]. This technique reduce the redundancy between adjacent samples. These techniques are used for ECG data compression. There are following methods which are used for ECG data compression:

a) \textbf{Quantization}

Quantization is the procedure of confine something from a continuous set of values (such as the real numbers) to a relatively small discrete set (such as the integers). Quantization in mathematics and processing. It is the process of mapping a large set of input values to a (countable) smaller set – such as rounding values to some unit of precision. A device or algorithmic function that performs quantization is called a quantizer. The round-off error introduced by quantization is referred to as quantization error. In analog-to-digital conversion, the difference between the actual analog value and quantized digital value is called quantization error or quantization distortion. This error is either due to rounding or truncation. The error signal is sometimes modeled as an additional random signal called quantization noise. Quantization is involved to some degree in nearly all digital signal processing, as the process of representing a signal in digital form ordinarily involves rounding [9]. When the number of discrete symbols in a given signal is reduced, then the signal becomes more compressible. Quantization converts continuously valued measured irradiance at a sample to a member of a discrete set of gray levels or digital counts, e.g. the sample f \( [x, y] \) e.g., f \( [0, 0] = 1.234567890 \cdots \) w/mm\(^2\), is converted to an integer between 0 and some maximum value (e.g., 255) by an analog-to-digital conversion (A/D converter or ADC). The number of levels is determined by number of bits available for quantization in the ADC. A quantizer with m bits defines \( M = 2^m \) levels. The most common quantizers have \( m = 8 \) bits (one byte); such systems can specify 256 different gray levels (usually numbered from \( [0, 255] \), where 0 is usually assigned to “black” and 255 to “white”. Images digitized to 12 or even 16 bits are becoming more common, and have 4096 and 65536 levels, respectively.

After the sampling we have a sequence of numbers which can theoretically still take on any value on a continuous range of values.

Because this range in continuous, there are infinitely many possible values for each number, in fact even uncountable infinitely many. In order to be able to represent each number form such a continuous range, we would need an infinite number of digits- something we do not have. Instead, we must represent our numbers with a finite no of digits.

b) \textbf{Wavelet Denoising and Compression}

Wavelet denoising and compression is used for both purpose compression and denoising, but in our paper we are using for Compression the ECG data, we use the wavelet transform. The wavelet transform (WT) is a powerful tool of signal processing for its multiresolution possibilities. Rather than the Fourier transform, the Wavelet (WT) is suitable for application to non-stationary signals with transitory phenomena, whose frequency response varies in time. Wavelet denoising and compression is a one- or two-dimensional de-noising and compression-oriented function [10].
V. RESULTS

**Figure 5: Quantization**

Here in Fig. (5) we compress the signal by quantization technique, in this we make our original signal whose minimum value is 0.4 and maximum value is 0.7, then we make 53 levels of it, and apply quantization between two level from initial to last. Then finally we get the quantized signal that is compressed signal. The number of sample is reduced in compress signal and the bit size is also reducing the compress signal. Here we get CR=1.77 & PRD = 0.653.

**Figure 6: Wavelet Denoising and Compression**

Wavelet denoising and compression is used for both purpose denoising and compression but here we use only for compressing the signal. We take data from MIT-BIH record 104 and then apply this technique. Then we get compressed waveform as shown in Fig.(6). It shows the method on wavelet compression. In this we obtained CR = 1.97 and PRD = 1.69, threshold = 0.9999. For compression we are using hard thresholding and daubachie wavelet3, which resembles the ECG wave. It is of primary significance that the selection of the wavelet family should closely match the signal of interest. Daubechies wavelets have structural similarity with QRS complex and their energy spectrums are concentrated around low frequencies. Thus it is expected that some detail coefficients from multiresolution decomposition will show better resemblance with QRS complex of the ECG wave in time scale domain.

**Figure 7: Discrete Wavelet Transform**
In Fig. (7) compression is done by discrete wavelet transform. In this we compress the error signal (the difference between second RR interval and first RR interval) and the reference signal (that is signal is between first RR interval) by applying DWT, and to set threshold value $= 0.9999$ on the approximation coefficient and then apply IDWT to reconstruct the signal. The reconstruct signal is same as original signal, means not to disturb the original signal and then we get the CR $= 9$ & PRD $= 0.484$.

![Figure 8: Discrete cosine transform](image1)

In Fig. (8) compression is done by discrete cosine transform in this we compress the error signal and the reference signal, we get the CR $= 7.80$ & PRD $= 0.604$, and applied threshold value $= 0.9999$.

![Figure 9: Proposed algorithm](image2)

For data transmission we need some coding information so that data will be send in coding form (0&1), and that should be in reduced form. For this purpose we apply the Huffman coding that reduces the data size. This is used for lossless data compression, as compress signal is same to its original signal (no data is lost).

**Table 1: Compression of Various Techniques**

<table>
<thead>
<tr>
<th>Method</th>
<th>Compression ratio</th>
<th>Percentage Rms Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Wavelet Denoising and Compression</td>
<td>1.97</td>
<td>1.69</td>
</tr>
<tr>
<td>Quantization</td>
<td>1.77</td>
<td>0.653</td>
</tr>
<tr>
<td>DWT</td>
<td>9.00</td>
<td>0.484</td>
</tr>
<tr>
<td>DCT</td>
<td>7.80</td>
<td>0.604</td>
</tr>
</tbody>
</table>

**VI. CONCLUSION**

Electro cardiogram (ECG) is used for the measurement of electrical activity of the heart. In our research we study the compression method of ECG signal. ECG signal being used in a wide variety of biomedical applications requires accurate results, less power requirements, faster results and low maintenance cost. Therefore compression plays a very important role in acquiring these purposes without losing the original information. To evaluate the performance of these algorithms, several methods are available in ECG literature. Results indicate that by using the compression techniques, the use of online data communication schemes can be enabled with high compression without losing the quality of the transmitted signals.
According to our theoretical analysis, and according to what study we have done on the compression techniques, from above table (1), we conclude that DWT compression is highly efficient than DCT, Quantization, and Huffman coding. DWT gives a signal with the most accurate results after compression and still gives a for better compression ratio than other. Most of the biomedical data compression methods have been developed for ECG signals. From the results it can be concluded that as threshold value increases, the Compression Ratio (CR) increases and the error criterion Percentage RMS difference (PRD) value also increases which yields high data reduction and poor signal fidelity. Low threshold value gives low data reduction and high signal fidelity. So threshold value should be selected such that the quality of the ECG signal is not distorted on reconstruction and a good amount of data reduction is also achieved. The proposed method thus contains DWT as the transformation tool.

VII. REFERENCES