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ECG Signal Compression Validation by a New Transform Technique

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Abstract: Electrocardiogram signal compression algorithm is needed to reduce the amount of data to be transmitted, stored and analyzed, without losing the clinical information content. This work investigates a set of ECG signal compression schemes to compare their performances in compressing ECG signals. These schemes are based on transform methods such as discrete cosine transform (DCT), fast Fourier transform (FFT), discrete sine transform (DST), and their improvements. An improvement of a discrete cosine transform (DCT)-based method for electrocardiogram (ECG) compression is also presented as DCT-II. A comparative study of performance of different transforms is made in terms of Compression Ratio (CR) and Percent root mean square difference (PRD).The appropriate use of a block based DCT associated to a uniform scalar dead zone quantiser and arithmetic coding show very good results, confirming that the proposed strategy exhibits competitive performances compared with the most popular compressors used for ECG compression. Each specific transform is applied to a pre-selected data segment from the Physiobank ATM database, and then compression is performed.

Keywords- Compression Ratio, Compression factor, Compression time, ECG, PRD.

I. INTRODUCTION

An ECG signal is a graphical representation produced by an electrocardiograph, which records the electrical activity of the heart over time. The ambulatory monitoring system usually requires continuous 12 or 24-hours ambulatory recording for good diagnostic quality. For example, with the sampling rate of 360 Hz, 11 bit/sample data resolution, a 24-h record requires about 43 MByte per channel. So, 12-channel system requires nearly 513.216 M-Byte of storage disks daily.

Normally, the frequency range of an ECG signal is of 0.05–100 Hz and its dynamic range of 1–10 mV. The ECG signal is characterized by five peaks and valleys labelled by the letters P, Q, R, S, T as shown in fig1. In some cases (especially in infants) we may also find another peak called U. The performance of ECG analyzing system depends mainly on the accurate and reliable detection of the QRS complex, as well as T and P waves. The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. Once the QRS complex has been identified a more detailed examination of ECG signal including the heart rate, the ST segment *etc.* can be performed. In the normal sinus rhythm (normal state of the heart) the P-Rinterval is in the range of 0.12 to 0.2 seconds as shown in fig 1.

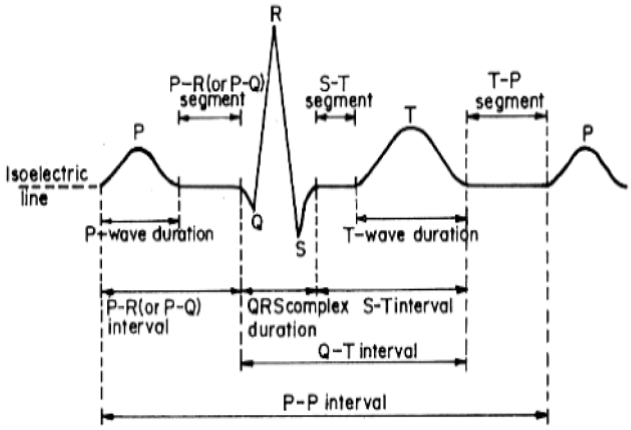

Figure 1.The normal ECG signal.

The QRS interval is from 0.04 to 0.12 seconds. The normal ECG signal. The Q-T interval is less than 0.42 seconds and the normal rate of the heart is from 60 to 100 beats per minute. So, from the recorded shape of the ECG, we can say whether the heart activity is normal or abnormal.

Because of the tremendous amount of ECG data generated each year, an effective data compression schemes for ECG signals are required in many practical applications including ECG data storage or transmission over telephone line or digital telecommunication network. ECG data compression techniques are typically classified into three major categories; namely direct data compression [3]-[4], transform coding [5]-[8], and parameter extraction methods [9]-[11]. The direct data compression methods attempt to reduce redundancy in the data sequence by examining a successive number of neighboring samples. These techniques generally eliminate samples that can be implied by examining preceding and succeeding samples.

Even though many compression algorithms have been reported so far in the literature, not so many are currently used in monitoring systems and telemedicine.

In this paper a new compression technique asked on transform coding-II and QRS complex estimation is proposed. There are two motivations in this work. The first motivation is the QRS complex estimation using the extraction of significant features of ECG waveform. The second motivation is the selection of the threshold levels in each sub band such that high CR and low PRD are obtained. The significant features of ECG waveform are extracted to estimate the QRS complex.

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Then, the estimated QRS-complex is subtracted from the original ECG signal. After that, the resulting error signal is discrete cosine transformed and the coefficients are threshold based on the energy packing efficiency. Finally the significant coefficients are coded and stored or transmitted.

II. COMPRESSION UTILITY

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. The ECG data compression techniques are limited to the amount of time required for compression and reconstruction, the noise embedded in the raw ECG signal, and the need for accurate reconstruction of the P, Q, R, S, and T waves. [20-22].

III. FEATURE EXTRACTION OF ECG SIGNAL

It has now gone beyond the capacity of the expert cardiologist to take care of large numbers of cardiac patients efficiently & effectively. Therefore, computer- aided feature extraction and analysis of ECG signal for disease diagnosis has become the necessity. The first step in computer aided diagnosis is the identification & extraction of the features of the ECG signal. The QRS complex is the most prominent feature and its accurate detection forms the basis of extraction of other features and parameters from the ECG signal. There are a number of methods, some of which deal with detection of ECG wave segments, namely P, QRS and T, while others deals with detection of QRS complexes. A good amount of research work has been carried out during the last five decades for the accurate and reliable detection of QRS segment in the ECG signal. The QRS detection algorithms developed so far can be broadly placed into four categories: (i) Syntactic approach (ii) Non-Syntactic approach (iii) Hybrid approach and (iv) Transformative approach.

[A] Syntactic Approach:

The syntactic approach is basically pattern recognition based QRS detection techniques. The ECG signal is first reduced into a set of elementary patterns like peaks, durations, slopes, inter-wave segments and thereafter use rule based grammar. The signal is represented as a composite entity of peaks, duration, slopes and inter-wave segments. These patterns are then used to detect the QRS complexes in the ECG signal. These methods are time consuming and require inference grammar in each step of execution for QRS detection. Even then the motivation for using a syntactic approach resides in the fact that human inspection of ECG waveform is firstly an extraction of structural and qualitative information. Once this information is obtained and some typical forms (like a QRS complex) are recognized then the numerical values of the durations and amplitudes are measured for use in diagnosis.

[B] Non-syntactic Approach:

Non-syntactic type is the most widely used class of ECG feature extraction techniques. In this class, we find the use of amplitude, slope and threshold limit as well as the use of different filters, mathematical functions and models. Okada reported a five step digital filter, which removes components other than those of QRS complex from the recorded ECG [24]. The final step of the filter produces a square wave and its on-intervals correspond to the segments with QRS complex in the original signal. A band pass filter was used to maximize the signal (QRS complex) to noise (T-waves, 60 Hz, EMG etc.) ratio to detect the QRS complex. Due to the inherent variability of ECG from different persons, as well as variability due to noise and artifacts, the filter design was suboptimal in specific situations. Pan and Tompkins developed a real-time algorithm for detection of the QRS complexes of ECG signals. It reliably recognizes QRS complexes based upon digital analysis of slope, amplitude and width [26].

[C] Hybrid Approach:

In hybrid approach, the syntactic and non-syntactic approaches are combined to detect the QRS complex. These are not in common use, as in syntactic approach, the trace is being made on actual morphology of the ECG signal and in non-syntactic approach; there is no consideration to maintain the morphology of the ECG signal.

[D] Transformative Approach:

Transformative Techniques, namely Fourier Transform, Cosine Transform, Pole –zero Transform, Differentiator Transform, Hilbert Transform and Wavelet Transform are being used for the QRS detection. The use of these transforms on ECG signal helps to characterize the signal into energy, slope, or spike spectra, and thereafter, the temporal locations are detected with the help of decision rules like thresholds of amplitude, slope or duration. Murthy and Prasad proposed a solution to the fundamental problem of ECG analysis, viz., delineation of the signal into its component waves [25].

IV. COMPRESSION TECHNIQUES

Lossless compression algorithms: the Run Length Encoding Algorithm, Huffman Encoding Algorithm, Shannon Fano Algorithm, Lempel Zev Welch Algorithm, Discrete Cosine Transform, Fast Fourier Transform, Discrete Sine Transform and Discrete Cosine Transform-II are implemented and tested with a set of ECG signal. Performances of the compression methods are also evaluated at the end of the paper.

[A] Run Length Encoding

Run Length Encoding or simply RLE is the simplest of the data compression algorithms. The consecutive sequences of symbols are identified as runs and the others are identified as non runs in this algorithm. This Algorithm deals with some sort of redundancy [4]. It checks whether there are any repeating symbols or not, and is based on those redundancies and their lengths.

[B] Huffman fano Approach

Huffman fano Algorithms calculate the frequencies first and then generate a common tree for both the compression and decompression processes [5]. Huffman Encoding and Shannon Fano approaches are implemented and executed independently.

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[C] Discrete Cosine Transform (DCT)

A discrete cosine transform (DCT) [19] expresses a sequence of finitely many data points in terms of a sum of cosine functions oscillating at different frequencies [9]. Discrete Cosine Transform is a basis for many signal and image compression algorithms due to its high de-correlation and energy compaction property [10]. In particular, a DCT is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using only real numbers. DCTs are equivalent to DFTs of roughly twice the length, operating on real data with even symmetry (since the Fourier transform of a real and even function is real and even), where in some variants the input and/or output data are shifted by half a sample.

[D] Fast Fourier Transform (FFT)

A fast Fourier transform (FFT) [11] is an efficient algorithm to compute the discrete Fourier transforms (DFT) and it's inverse [12]. An FFT is a way to compute the same result more quickly. Computing a DFT of N points in the naive way, using the definition, takes $O(N^2)$ arithmetical operations [13], while an FFT can compute the same result in only O(N log N) operations. The difference in speed can be substantial, especially for long data sets where *N* may be in the thousands or millions—in practice, the computation time can be reduced by several orders of magnitude in such cases, and the improvement is roughly proportional to *N* / log(*N*). This huge improvement made many DFT-based algorithms practical; FFTs are of great importance to a wide variety of applications, from digital signal processing and solving partial differential equations to algorithms for quick multiplication of large integers. The most well known FFT algorithms depend upon the factorization of *N*, but there are FFTs with O (*N* log *N*) complexity for all *N*, even for prime *N*. Many FFT algorithms only depend on the fact that is an *N*th primitive root of unity, and thus can be applied to analogous transforms over any finite field, such as number-theoretic transforms. Fast Fourier Transform is a fundamental transform in digital signal processing with applications in frequency analysis, signal processing etc [10]. The periodicity and symmetry properties of DFT are useful for compression.

[E] Discrete Sine Transform (DST)

Discrete sine transform (DST) [14] is a Fourier-related transform similar to the discrete Fourier transform (DFT), but using a purely real matrix. Like the discrete Fourier transforms (DFT), a DST operates on a function at a finite number of discrete data points. The obvious distinction between a DST and a DFT is that the former uses only sine functions, while the latter uses both cosines and sine (in the form of complex exponentials). However, this visible difference is merely a consequence of a deeper distinction: DST implies different boundary conditions than the DFT or other related transforms [15].

[F] Proposed Method (DCT-II)

The most common variant of discrete cosine transform is the type-II DCT [16]. The DCT-II is typically defined as a real, orthogonal (unitary), linear transformation. DCT-II can be viewed as special case of the discrete Fourier transform (DFT) with real inputs of certain symmetry [17]. This viewpoint is fruitful because it means that any FFT algorithm for the DFT leads immediately to a corresponding fast algorithm for the DCT-II simply by discarding the redundant operations. Increasing the block size increases the CR and the DCT computing time. Various results show that increasing the block size above a certain point results in a very modest CR gain, while the processing time increases. The type II DCT is commonly used for data compression due to its greater capacity to concentrate the signal energy in few transform coefficients.

V. PERFORMANCE EVALUATION

Depending on the nature of the application there are various criteria to measure the performance of a compression algorithm [18]. Following are some measurements used to evaluate the performances of lossless algorithms.

[A] Compression Ratio (CR)

Compression ratio is the ratio between the size of the compressed file and the size of the source file [23].

$$\text{Compression Ratio} = \frac{\text{size after compression}}{\text{size before compression}} \quad (1)$$

[B] Compression factor (CF)

It is the inverse of the compression ratio. That is the ratio between the size of the source file and the size of the compressed file.

$$\text{Compression Factor} = \frac{\text{size before compression}}{\text{size after compression}} \quad (2)$$

[C] Percent root mean square difference

PRD is the most prominently used distortion measure is the Percent Root mean square Difference (PRD) [18] that is given by

$$PRD = \left[\frac{\sum_{n=1}^{L_b}[x(n)-x'(n)]^2}{\sum_{n=1}^{L_b}[x(n)]^2}\right]^{(1/2)} \quad (3)$$

where x(n) is the original signal, x'(n) is the reconstructed signal and Lb is the length of the block or sequence over which PRD is calculated. PRD provides a numerical measure of the residual root mean square (rms) error.

[D] Compression Time (CT)

It is defined as the total time elapsed during the compression of original ECG signal. If the compression and decompression times of an algorithm are less or in an acceptable level it implies that the algorithm is acceptable with respective to the time factor. With the development of high speed computer accessories this factor may give very small values and those may depend on the performance of computers. All the above methods evaluate the effectiveness of compression algorithms using file sizes. There are some other methods to evaluate the performance of compression algorithms. Compression time, computational complexity and probability distribution are also used to measure the effectiveness.

VI. RESULTS AND DISCUSSION

Physiobank ATM database has been used to test the performance of the compression techniques.

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The ECG data is sampled at 333 Hz. The amount of compression is measured by CR and the distortion between the original and reconstructed signal is measured by PRD. The comparison table shown in Table 1, details the resultant compression techniques. This gives the choice to select the best suitable compression method. A data compression algorithm must represent the data with acceptable fidelity while achieving high CR. As the PRD indicates reconstruction fidelity; the increase in its value is actually undesirable. Although proposed method provides maximum CR, but distortion is more. So a compromise is made between CR and PRD.

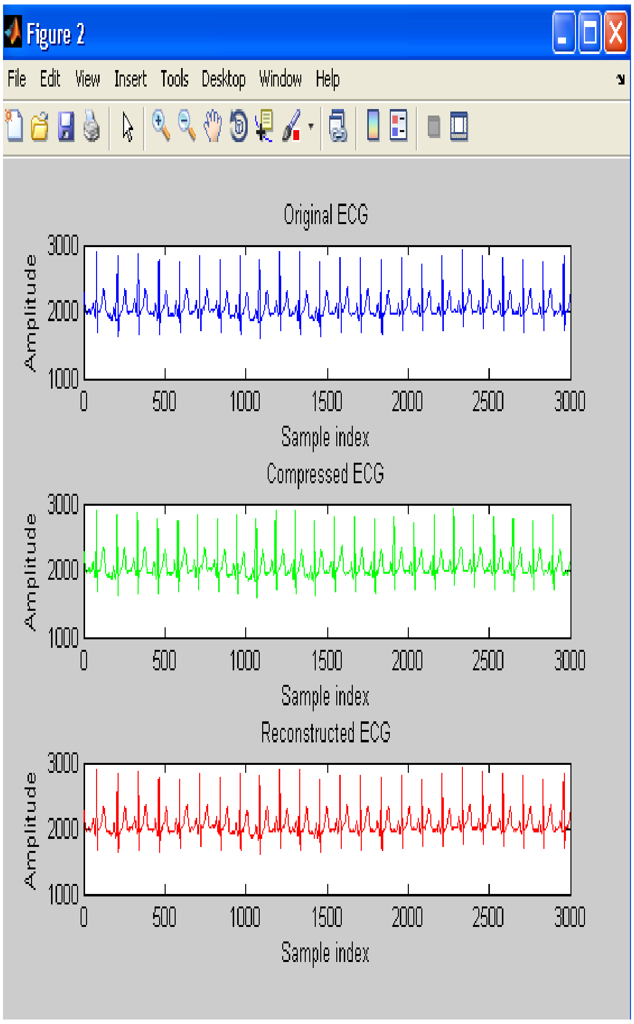

Figure 1. Result of the Sinus rhythm patient's ECG signal compressed by RLE Algorithm

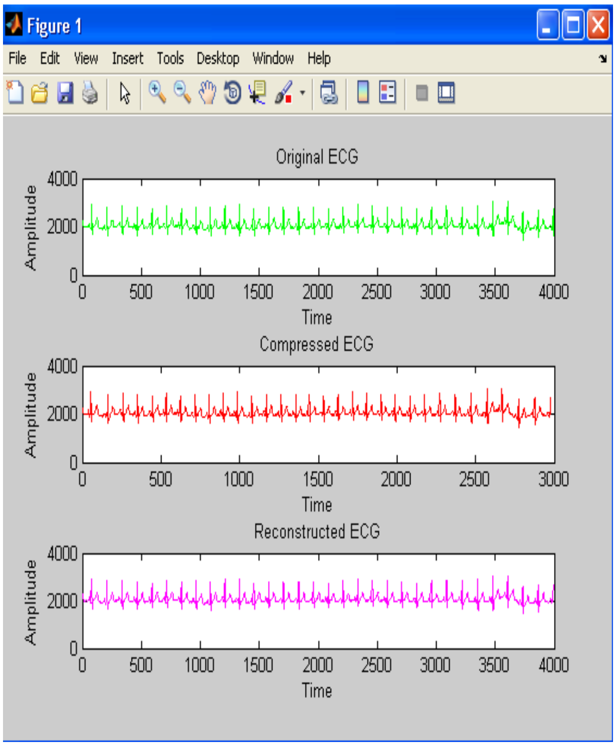

Figure 2. Result of the Sinus rhythm patient's ECG signal compressed by FAN Algorithm

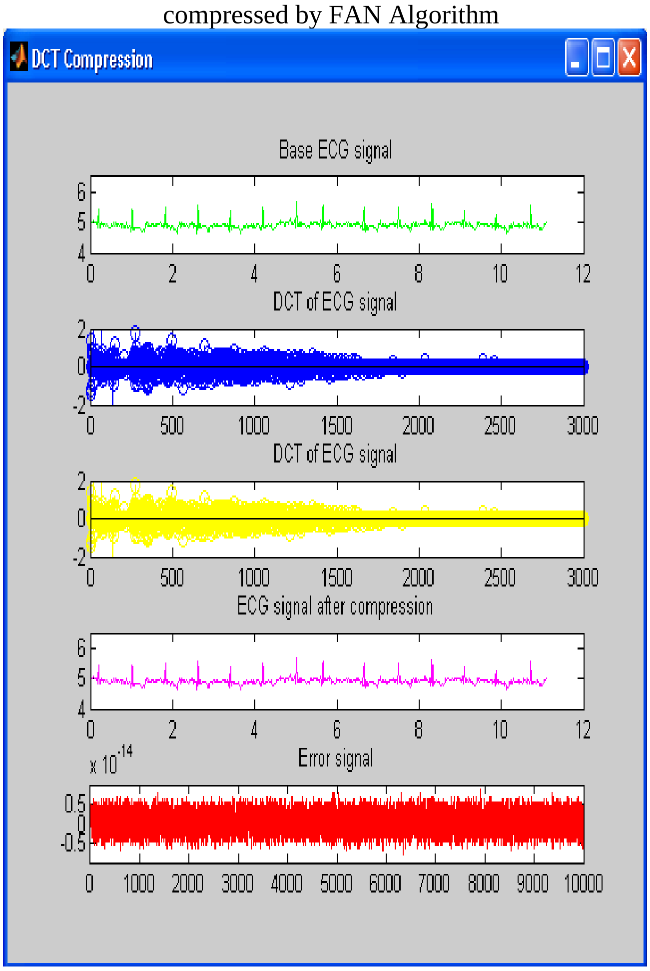

Figure 3. Result of the Sinus rhythm patient's ECG signal compressed by DCT Algorithm

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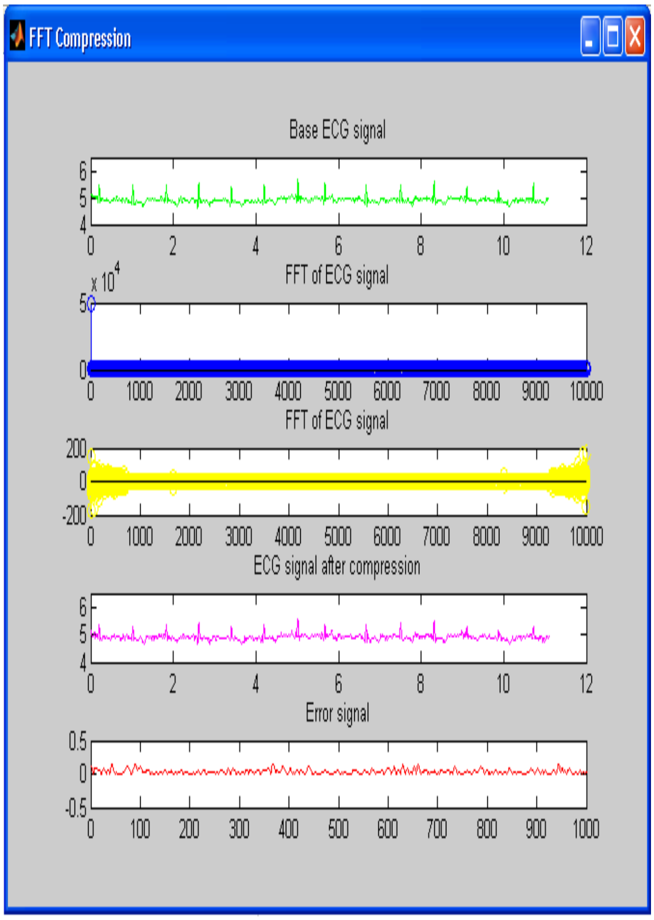

Figure 4. Result of the Sinus rhythm patient's ECG signal compressed by FFT Algorithm

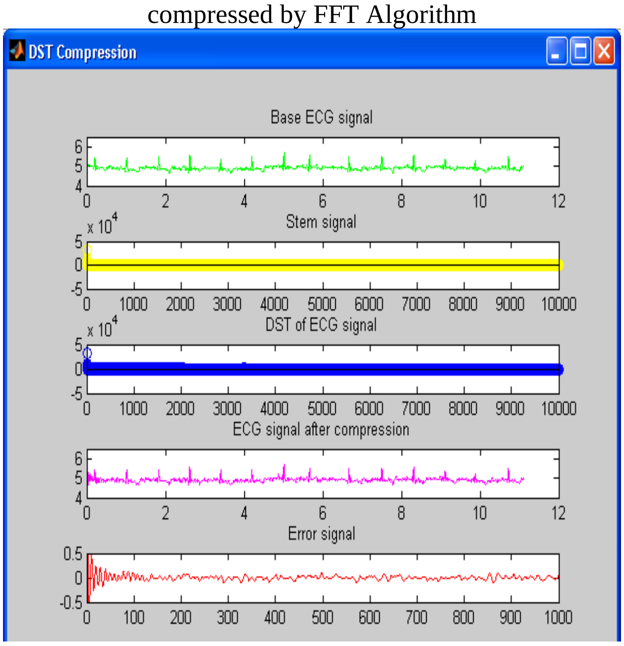

Figure 5. Result of the Sinus rhythm patient's ECG signal compressed by DST Algorithm

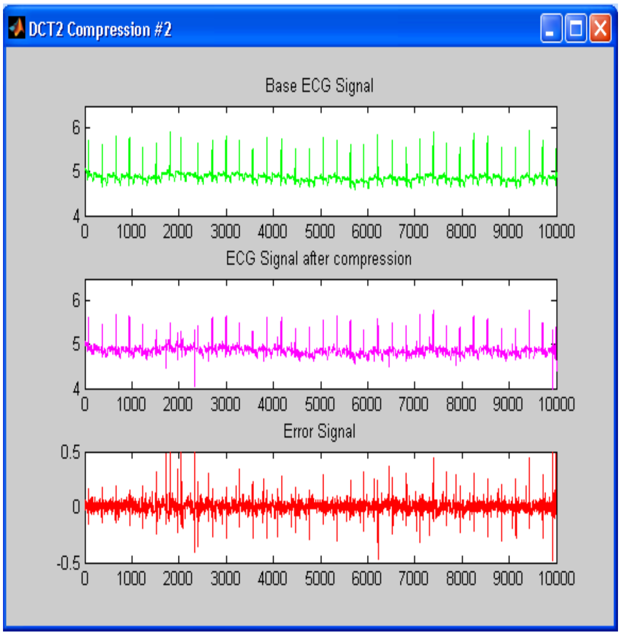

Figure 6. Result of the Sinus rhythm patient's ECG signal compressed by Proposed Method.

Table.1 Comparison table for the Performance of Compression Techniques:

Method	CR	CF	PRD	CT
RLE	97.80	0.01022	1.2134	0.421580
FANO	74.48	0.01342	1.0949	0.151020
DCT	93.97	0.01064	1.1200	6.193842
FFT	94.75	0.01055	0.9230	5.466393
DST	87.90	0.01137	1.2468	5.479781
Proposed	**98.57**	**0.01014**	**1.0164**	**0.508601**

VII. CONCLUSION

Among the six techniques presented, Fano provides lowest CR but distortion is low. Next is DST which gives higher CR 87.90 with PRD as 1.2468. FFT gives higher CR as 94.75 but PRD is high as 0.9230 But proposed method provides an improvement in terms of CR of 98.57 and PRD is also low as 1.0164. Thus an improvement of a discrete cosine transform (DCT)-based method for electrocardiogram (ECG) compression is presented as DCT-II in terms of amount of compression. The appropriate use of a block based DCT-II associated to a uniform scalar dead zone quantiser and arithmetic coding show very good results, confirming that the proposed strategy exhibits competitive performances compared with the most popular compressors used for ECG compression.

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