# ONLINE ECG SIGNAL COMPRESSION USING MODIFIED DISCRETE COSINE AND DISCRETE WAVELET TRANSFORMS

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**Abstract-The use of electronic instrument to monitor and diagnose problems of the human body has lately become essential. Electrical activity associated with the function of heart is known as Electrocardiogram (ECG). The ECG machine used to monitor electrical activity of the heart uses the electrochemical changes in the heart tissue to give out performance of the heart. The waveform is then used to measure the rate and regularity of heartbeats, as well as the size and position of the chambers, the presence of any damage to the heart. These ECG waveforms are used for diagnostic or research purpose. The designed system capture ECG signal from human body using electrodes. After performing signal conditioning on ECG it is then processed by ARM processor and the resultant signal is feed to the computer using serial cable. A new hybrid two stage electrocardiogram (ECG) signal compression method based on the modified discrete cosine transform (MDCT) and discrete wavelet transform (DWT) is used to process captured ECG signal on computer using MATLAB tools. The ECG signal is partitioned into blocks and the MDCT is applied to each block to de correlate the spectral information. Then, the DWT is applied to the resulting MDCT coefficients. Removing spectral redundancy is achieved by compressing the subordinate components more than the dominant components. The resulting wavelet coefficients are then threshold and compressed using energy packing and binary-significant map coding technique for storage space saving.**

**Keywords- Data compression; Electrocardiogram; Wavelet transform; Discrete cosine transform; Energy packing; Binary-significant map coding.**

## I. INTRODUCTION

The ECG signal obtained using electrodes is very weak. The frequency this 0.05 to 500Hz and approximate voltage is 1mV. Instrumentation amplifier is used to amplify it at initial level so that ECG signal will not get loaded. This intended for low level signal amplification where low noise, low thermal and time drifts, high input impedance an accurate close loop gain are required. Besides, high CMRR and high slew rate are desirable for superior performance.

The amplified ECG signal obtained is required to digitalized for further analysing and processing. For this purpose 32 bit ARM7 processor has been used. The LPC2138 microcontrollers are based on a 32-bit ARM7TDMI-S CPU with real-time emulation and embedded trace support, that combines the microcontroller with 512 kB of embedded high-speed flash memory. A 128-bit wide memory interface and a unique accelerator architecture enable 32-bit code execution at maximum clock rate. For critical code size applications, the alternative 16-bit Thumb mode reduces code by more than 30 % with minimal performance penalty.

To obtain significant signal compression, lossy compression is preferable to a lossless compression. Lossless compression is nothing but exact reconstruction of original signal and is based on the idea of breaking a file into a smaller form for transmission or storage and then putting it back together on the other end so it can be used again. Where as lossy compression simply eliminate "unnecessary" bits of information, that is why compressing an ECG signal lossy is proffered. In this case, compression is accomplished by applying an invertible orthogonal transform to the signal, and one tries to reduce the redundancy present in the new representation. Due to its decorrelation and energy compaction properties and to the existence of efficient algorithms to compute it, discrete cosine transform and modified discrete cosine transform have been widely investigated for ECG signal compression and DWT has been proven very efficient for ECG signal coding.

## II. SYSTEM DESCRIPTION

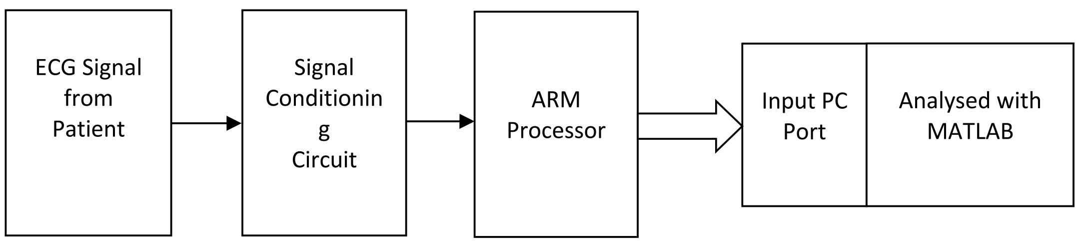



Fig 1. Generalize Block Diagram.

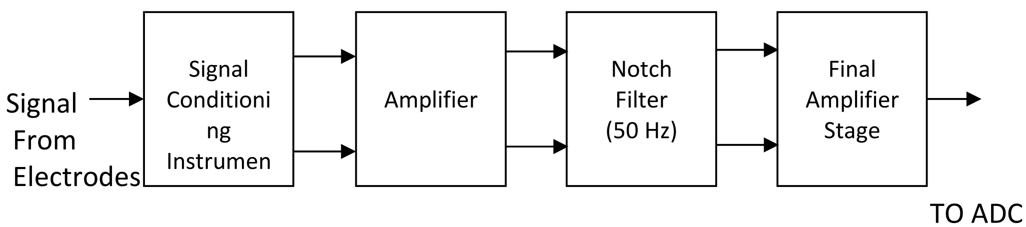
### A. ELECTRODE

The silver electrodes are used to pick up low level ECG signals, as they are mostly noise free and are acceptable from the point of long-term drift. The electrodes are connected to the limbs by an electrolytic gel. The bioelectric events before they can be put into amplifier for subsequent record or display have to be picked up from surface of the body. This is done by using electrodes. Electrodes make a transfer from the ionic conduction in the tissue to the electronic conduction, which is necessary for making measurements. Electrodes are also required when physiological parameters are measured by the impedance method and when irritable tissues are to be stimulated in electrotherapy. Two types of electrodes are encountered in practice – surface electrodes and deep-seated electrodes. The surface electrodes pick up the potential difference from the tissue surface when placed over it without damaging the live tissue, whereas the deep-seated electrodes indicate the electric potential difference arising inside the live tissue or cell. The same classification can be applied to electrodes used for stimulation of muscles. Following fig 2 shows the image of silver electrodes used designed system.

Fig 2. Silver electrodes.

Electrodes play an important part in making satisfactory records bioelectric signal and there choice requires careful consideration. They should be comfortable for patients to wear over long periods and should not produce any aftereffects. Another desirable factor is the convenience of application of the electrodes.

### *B. SIGNAL CONDITIONING CIRCUIT*




A Fig 3. Block Diagram Of Signal Conditioning Circuit.

*Instrumentation amplifier*

This intended for low level signal amplification where low noise, low thermal and time drifts, high input impedance an accurate close loop gain are required. Besides, high CMRR and high slew rate are desirable for superior performance. As ECG signal is of very low level, instrumentation amplifier is used to amplify it at initial level so that ECG signal will not get loaded.

Here we use OP07, which is high input impedance FET op-amp. Referring to fig. the instrumentation amplifier has a gain of 66. The inverting amplifier has a gain of 30 and the final stage has a gain of 4 , which gives us total gain

$$A=66\times30\times4 =7980 \approx 8000$$

Hence the total circuit gives us amplification of $8000\times1mV=8V$.

*DESIGN*

$$A = \left(1+\frac{R4}{R5}\right)x\frac{Rf}{R1}$$

Assume R5=1kΩ, Rf=100kΩ, R1=10kΩ

A=66 for instrumentation amplifier

Putting values in above we get

R4 = 5.6kΩ(choose 6kΩ)

### *A. Amplifier*

One more amplifier stage is used for further amplification of the signal obtained from the instrumentation amplifier. Here we are usingop-amps because it has high input, high CMRR, high open loop gain etc.

For inverting amplifier

$$A = -\frac{Rf}{R1}$$

A=30

Assume Rf =1MΩ

Putting values we get

R1=33kΩ(choose 32kΩ)

For the final stage A=4, $A = \left(1+\frac{Rf}{R1}\right)$

Assume Rf=10kΩ

R1=3kΩ

### *B. Notch filter*

The human body has a 50 Hz. Noise signal, which is filtered by this network.

$$Fn = \frac{1}{(2\pi RC)}$$

*DESIGN*

Assume C=0.1µF and 2C =parallel combination of two C.

Fn =50Hz

Substituting in the above formula we have

R=31.83 kΩ = (27+4.7+0.1) kΩ And

$\frac{R}{2}$ =15.9 kΩ = (12+3.9) kΩ

*C. Final amplifier stage:*

This stage amplifies the signal to a level required by the ADC card.

### *III. CIRCUIT DESIGN FOR SIGNAL CONDITIONING BLOCK*

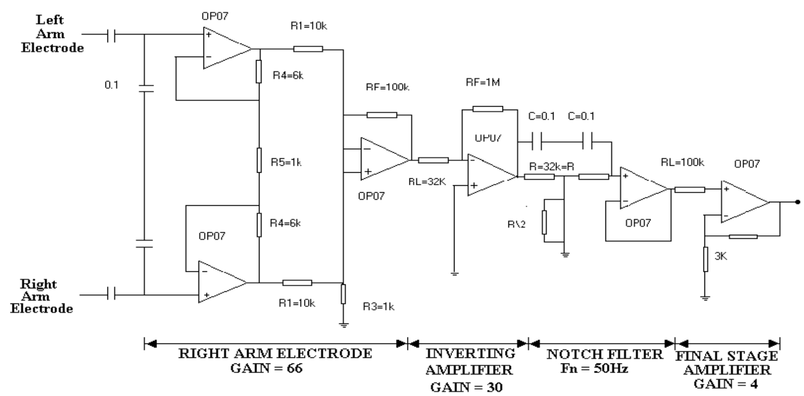



Fig 4. Circuit Diagram Of Signal Conditioning Circuit

### IV. ARM PROCESSOR

The LPC2138 microcontrollers are based on a 32-bit ARM7TDMI-S CPU with real-time emulation and embedded trace support, that combines the microcontroller with 512 kB of embedded high-speed flash memory. A 128-bit wide memory interface and a unique accelerator architecture enable 32-bit code execution at maximum clock rate. For critical code size applications, the alternative 16-bit Thumb mode reduces code by more than 30 % with minimal performance penalty.

**Features-**

- 16-bit/32-bit ARM7TDMI-S microcontroller in a tiny LQFP64 package.
- 8 kB to 40 kB of on-chip static RAM and 32 kB to 512 kB of on-chip flash memory. 128-bit wide interface/accelerator enables high-speed 60 MHz operation.
- In-System Programming/In-Application Programming (ISP/IAP) via on-chip boot loader software. Single flash sector or full chip erase in 400 ms and programming of 256 B in 1 ms.
- Embedded ICE RT and Embedded Trace interfaces offer real-time debugging with the on-chip Real Monitor software and high-speed tracing of instruction execution.
- USB 2.0 Full-speed compliant device controller with 2 kB of endpoint RAM.
- One or 10-bit ADCs provide a total of 6/14 analog inputs.
- Single 10-bit DAC provides variable analog output.
- Two 32-bit timers/external event counters,

  PWM unit (six outputs) and watchdog.

### V. WAVELET TRANSFORMATION

The basic idea of the wavelet transform (WT) is to represent any arbitrary function x(t) as a superposition of a set of basis functions (wavelets) [8]. These basis functions are obtained from a single prototype mother wavelet, by dilations or contractions (scaling) and translations (shifts). So, a wavelet transform decomposes a signal into a series of smooth signals and associated detailed signals at different resolution levels [12]. At each level, the smooth signal and associated detailed signal have all of the information necessary to reconstruct the smooth signal at the next higher resolution level. A multi-resolution WT involves two functions: a mother wavelet c(t) and a scaling function f(t). Since 1989, techniques based on the filter bank concept have been proposed by various researchers under the name of wavelet coding (WC) using filters specifically designed for this purpose [8 – 10]. In [8], Daubechies was the first to discover that quadrature mirror filter (QMF) banks can be iterated and under certain regularity conditions will lead to continuous-time wavelets. This is a very practical and extremely useful wavelet decomposition scheme, since FIR discrete-time filters can be used to implement them. It follows that the orthonormal bases in [8] correspond to a subband-coding scheme with exact reconstruction property, using the same FIR filters for reconstruction as for decomposition. Later a systematic way of constructing a family of compactly supported biorthogonal wavelets was developed by Cohen, Daubechies and Feauveau (CDF) [12].

## VI. MODIFIED DISCRETE COSINE TRANSFORM

MDCT is a linear orthogonal lapped transform, based on the idea of time domain aliasing cancellation (TDAC). It is designed to be performed on consecutive blocks of a larger dataset, where subsequent blocks are overlapped so that the last half of one block coincides with the first half of the next block. This overlapping, in addition to the energy compaction qualities of the DCT, makes MDCT especially attractive for signal compression applications. Thus, it helps to avoid artefacts stemming from the block boundaries [5,6]. MDCT is critically sampled, which means that though it is 50% overlapped, a sequence data after MDCT has the same number of coefficients as samples before the transform (after overlap-and-add). This means that a single block of IMDCT data does not correspond to the original block on which the MDCT was performed. When subsequent blocks

of inverse transformed data are added, the errors introduced by the transform cancel out TDAC. MDCT is defined as [6]:

$$X_c(k) = \sum_{n=0}^{N-1} x(n)\cos\left[\left(n+\frac{M+1}{2}\right)\left(k+\frac{1}{2}\right)\frac{\pi}{2}\right]$$

k = 0,1, ... M-l

(1)

where, *x(n), n* = 0, 1, 2, ... , *N*- 1 is the sequence to be transformed, *N= 2M* is the window length and *M* is the number of transform coefficients. The computation burden can be reduced if the transform coefficients given by equation (1) are rewritten in the following recursive form:

$$X_c = X(0)\cos\left[(M+1)\frac{\theta_k}{2}\right] + V_1\cos\left[(M+1)\frac{\theta_k}{2}\right] - V_2\cos\left[(M+1)\frac{\theta_k}{2}\right]$$

(2)

Where,

$V_m = x(m) + 2\cos\theta_k V_{m+1} - V_{m+2}$

(3)

m = N - 1,N - 2, ....1,0,

and

$$\theta_k = \left(k+\frac{1}{2}\right)\frac{\pi}{2} \qquad (4)$$

The DCT-IV computation algorithm of a data sequence *x (n)* can be summarized by the following:

1. Partition the data sequence in N, consecutive blocks, each one with N = 64 samples.

2. Recursively generate the *Vm* from the input sequence *x(n)* according to equations (3) and (4).

3. Calculate the DCT-IV coefficients for each block by evaluating the $k^{th}$ DCT-IV coefficient using equation (2) at the $N^{th}$ step.

In the decompression stage, inverse DCT-IV, termed IDCT -IV, is adopted. Because there are different numbers of inputs and outputs, at first glance it might seem that DCT should' not be invertible. However, perfect invertability is achieved by adding the overlapped IDCT-IV s of subsequent overlapping blocks, causing the errors to cancel and the original data to be retrieved. IDCT-IV transforms the *M* real coefficients, *Xc(0), Xc(1), ... , Xc(M-* 1), into *N = 2M* real numbers, *x(0), x(1), ... ,x(N-* 1), according to the Formula:

$$x(n) = \sum_{k=0}^{M-1} X_c(k)\cos\left[\left(n+\frac{M+1}{2}\right)\left(k+\frac{1}{2}\right)\frac{\pi}{M}\right]$$

(5)

n = 0,1,....N-1

Again, the computation burden of *x(n)* can be reduced considerably if equation (5) is rewritten in the following recursive form:

$$x(n) = X_c(0)\cos\left[\frac{\theta_n}{2}\right] + V_1\cos\left[\frac{3\theta_n}{2}\right] - V_2\cos\left[\frac{\theta_n}{2}\right]$$

(6)

Where, $V_m = X_c(m) + \cos\theta_n - V_{m+2}$

$$\theta_n = \left(n+\frac{M+1}{2}\right)\frac{\pi}{M} \qquad (7)$$

## VII. COMPRESSION AND DISTORTION MEASURES

All data compression algorithms seek to minimize data storage by eliminating redundancy where possible by increasing the compression ratio. The latter is defined as the ratio of the number of bits representing the original signal to the number of bits required to store the compressed signal. A high compression ratio is typically desired, but using this alone to compare data compression algorithms is not acceptable. Moreover, the bandwidth, sampling frequency, and precision of the original data very much affect the compression ratio. A data compression algorithm must also represent the data with acceptable fidelity.

In ECG signal compression, the clinical acceptability of the reconstructed signal has to be determined through visual inspection by cardiologists. The error signal resulting from the difference between the reconstructed signal and the original one may also be measured numerically. A lossless data compression algorithm produces zero residual, and the reconstructed signal exactly replicates the original signal. However, clinically acceptable quality is neither guaranteed by a low nonzero residual nor ruled out by a high numerical residual. The criteria for testing compression algorithms performance include three components: compression measure, reconstruction error and computational complexity. The compression measure and the reconstruction error are usually dependent on each other and are used to create the rate-distortion function of the algorithm. The computational complexity component is part of the practical implementation consideration.

### *A. Distortion measures*

One of the most difficult problems in ECG compression and reconstruction is defining the error criterion that measures the ability of the reconstructed signal to preserve the relevant information. As yet, there is no mathematical structure to this criterion, and all accepted error measures are still variations of the mean square error or absolute error, which are easy to compute mathematically, but are not always diagnostically relevant. In technical literature, the distortion resulting from the ECG processing is frequently measured by the percentage rms difference (PRD) [1 – 4]. It is most commonly defined as:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-\hat{x}(n))^2}{\sum_{n=1}^{N}x^2(n)}} X100 \qquad (8)$$

Where x(n) and x(n) are the values of the original and reconstructed samples, respectively, and N is the length of the window over which the PRD is calculated. Another definition, called here PRD1, subtracts from the signal its average value x, in the denominator of the above equation.

$$PRD_1 = \sqrt{\frac{\sum_{n=1}^{N}(x(n)-\hat{x}(n))^2}{\sum_{n=1}^{N}(x(n)-\bar{x})^2}} X100 \qquad (9)$$

This definition is independent in the DC level of the original signal. Despite their wide use, PRD and PRD1 do not indicate precisely the quality of signal's reconstruction [9] and the decompressed signal has to be evaluated by visual inspection.

*B. Compression measures*

The size of compression is often measured by CR, which is defined as the ratio between the bit rate of the original signal ($b_{original}$) and the bit rate of the compressed one ($c_{ompressed}$)

$$CR = \frac{b_{original}}{b_{compressed}} \qquad (10)$$

The problem of using the above definition of CR is that every algorithm is fed with an ECG signal that has a different sampling frequency and a different number of quantization levels; thus, the bit rate of the original signal is not standard. Some attempts were made in the past to define standards for sampling frequency and quantization, but these standards were not implemented, and developers of the algorithms still use rates and quantizers that are convenient to them [2]. In [9], the number of bits transmitted per sample of the compressed signal has been used as a measure of information rate. This measure removes the dependency on the quantizer resolution, but the dependence on the sampling frequency remains. Another way is to use the number of bits transmitted per second as a compression measure [13]. This measure removes the dependence on the quantizer resolution as well as the dependence on the sampling frequency.

## VIII. QUANTIZATION AND CODING ALGORITHMS

A quantizer simply reduces the number of bits needed to store the transformed coefficients by reducing the precision of those values. A quantization scheme maps a large number of input values into a smaller set of output values. This implies that some information is lost during the quantization process. The original wavelet coefficients c(n) cannot be recovered exactly after quantization. An encoder further compresses the quantized values losslessly to give better overall compression. The most commonly used encoders are the Huffman encoder and the arithmetic encoder, although for applications requiring fast execution, simple run-length encoding (RLE) has proven very effective [10]. In the following, wavelet coefficients quantization and coding algorithms are described.

*A. Energy packing efficiency strategy*

In this section, the quantization strategy adopted is based on the energy packing efficiency (EPE). It guarantees the balance between the compression achievement and information loss. Here, quantization process is performed by

selecting an appropriate threshold level l to control the compression ratio. Due to careful representation by combining the MDCT and DWT, it is reasonable to assume that only a few coefficients contain information about the real signal while others appear as less important details. The goal is to extract these significant coefficients and to ignore others smaller than specified threshold level l. The optimal value of l is determined such that the reconstructed signal is as close to the original one as possible. Usually the selection of optimal threshold level is not an easy task, because some of the coefficients that represent the actual signal details may be also killed, and as a result, signal distortion is the side-effect [14,15]. As can be deduced from the above discussion, the approximation band is the smallest band in size and it includes high amplitude approximation coefficients. The wavelet coefficients other than these included in the approximation band, detail coefficients, have small magnitudes. Most of the energy is captured by these coefficients of the lowest resolution band. This can be seen from the decomposition of 4096-sample ECG signal up to the fifth level. The total energy of the signal is 94393.5. About 99.73% of this energy is concentrated in the 136 approximation coefficients and only 0.27% of the energy is concentrated in the remaining 3960 detail coefficients. Here, threshold levels are defined according to the energy packing efficiencies of the signal for all subbands. EPE for a set of coefficients in the $i^{th}$ subband is defined as the ratio of the energy captured by the subband coefficients and the energy captured by the whole number of coefficients.

$$EPE_i = \frac{\sum_{m=1}^{L_i} (c(m))^2}{\sum_{m=1}^{L} (c(m))^2} X100 \qquad (11)$$

where Li and L are the number of coefficients in the $i^{th}$ subband and the whole number of coefficients respectively. A large threshold could attain high data reduction but poor signal fidelity and a small threshold would produce low data reduction but high signal fidelity. To explore the effect of threshold level (l) selection and the coefficients representation on the compression ratio and PRD, the following thresholding rule is set:

Keep all the wavelet coefficients in the approximation subband without thresholding and calculate the threshold value for each details subband separately by preserving the higher amplitude wavelet coefficients in the ith details subband that contribute to ai% of the energy in that subband.

One important feature of this rule is that the integer part of the wavelet coefficients in each subband is represented by different number of bits.

*B. Binary significant map coding algorithm*

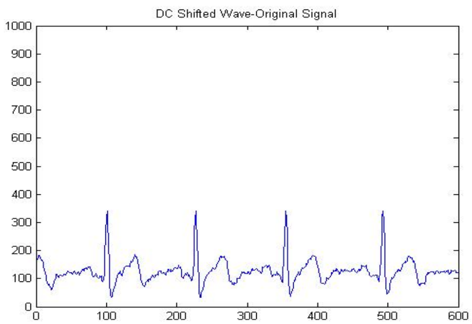
The coding algorithm adopted here is based on grouping the significant coefficients in one vector and the locations of the insignificant coefficients in another vector. The significant coefficients are arranged from high scale coefficients to low scale coefficients. Each significant coefficient is decomposed into the integer part and the fractional part, where M-bits are assigned to represent the integer part (signed representation) and N-bits represent the fractional part; i.e. each coefficient is represented by N+M bits. A binary significant map is used as flags to indicate if the coefficient is significant or not.

## IX. EXPERIMENTAL RESULTS

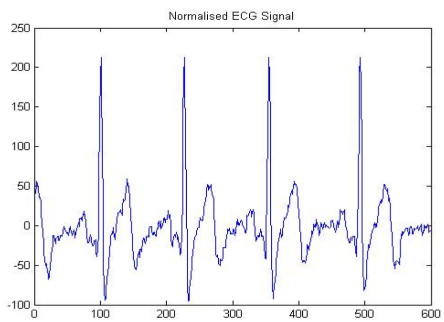
After performing signal conditioning on ECG it is then processed by ARM processor and the resultant signal is feed to the computer using serial cable. A new hybrid two stage electrocardiogram (ECG) signal compression method based on the modified discrete cosine transform (MDCT) and discrete wavelet transform (DWT) is used to process captured ECG signal on computer using MATLAB tools. The ECG signal is partitioned into blocks and the MDCT is applied to each block to de correlate the spectral information. Then, the DWT is applied to the resulting MDCT coefficients. Removing spectral redundancy is achieved by compressing the subordinate components more than the dominant components. The resulting wavelet coefficients are then threshold and compressed using energy packing and binary-significant map coding technique.

TABLE I. PERFORMANCE RESULT WITH DIFFERENT THRESHOLD VALUES ON HUMAN BODY

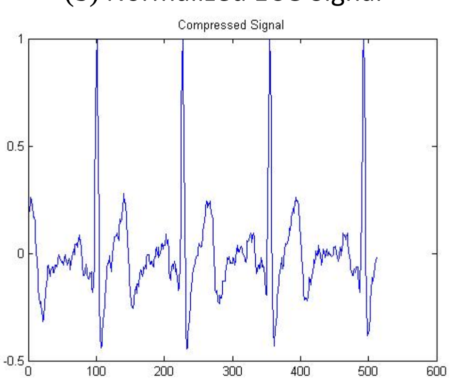
| ECG Signal | Threshold Value | Original Length | Compressed Length | Compression Ratio | PRD | PRD 1 | EPE |
|---|---|---|---|---|---|---|---|
| Person-1 | 0.1 | 512 | 268 | 47.6563 | 11.37 | 11.37 | 0.30 |
| | 0.3 | 512 | 169 | 66.9922 | 35.46 | 35.46 | 0.32 |
| | 0.5 | 512 | 143 | 72.0703 | 43.87 | 43.96 | 0.31 |
| | 0.7 | 512 | 73 | 85.7422 | 73.69 | 74.26 | 0.29 |



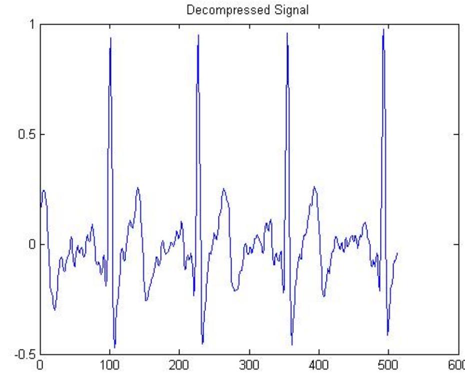

(a) DC Shifted-Wave Original Signal




(b) Normalized ECG Signal



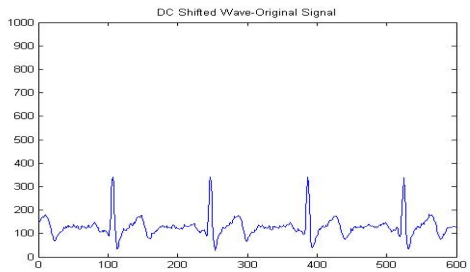

(c) Compressed Signal



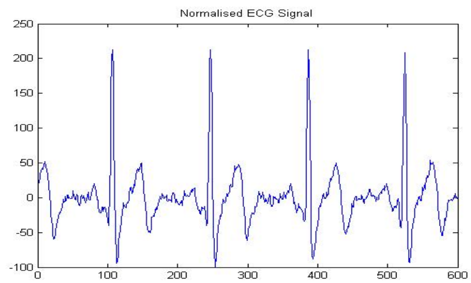

(d) Decompressed Signal

Fig. 5. ECG signal waveforms with threshold th=0.1 (a) DC Shifted-Wave Original Signal (b) Normalized ECG Signal (c) Compressed Signal (d) Decompressed Signal

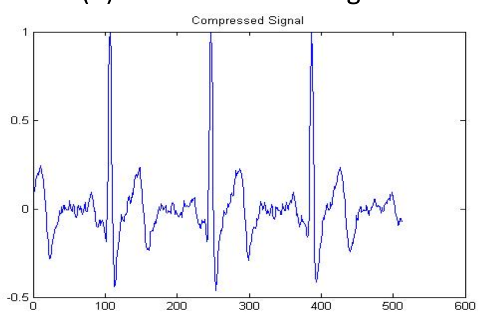

| ECG Signal | Threshold Value | Original Length | Compressed Length | Compression Ratio | PRD | PRD 1 | EPE |
|---|---|---|---|---|---|---|---|
| Person-1 | 0.1 | 512 | 268 | 47.6563 | 11.37 | 11.37 | 0.30 |
| | 0.3 | 512 | 169 | 66.9922 | 35.46 | 35.46 | 0.32 |
| | 0.5 | 512 | 143 | 72.0703 | 43.87 | 43.96 | 0.31 |
| | 0.7 | 512 | 73 | 85.7422 | 73.69 | 74.26 | 0.29 |
| ECG Signal | Threshold Value | Original Length | Compressed Length | Compression Ratio | PRD | PRD 1 | EPE |
| Person-1 | 0.1 | 512 | 268 | 47.6563 | 11.37 | 11.37 | 0.30 |
| | 0.3 | 512 | 169 | 66.9922 | 35.46 | 35.46 | 0.32 |
| | 0.5 | 512 | 143 | 72.0703 | 43.87 | 43.96 | 0.31 |
| | 0.7 | 512 | 73 | 85.7422 | 73.69 | 74.26 | 0.29 |



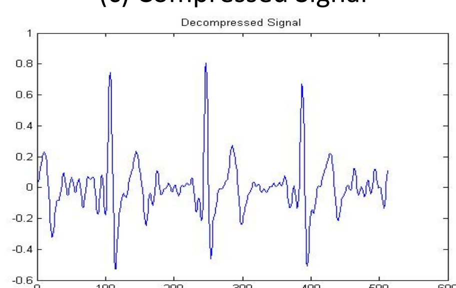

(a) DC Shifted-Wave Original Signal




(b) Normalized ECG Signal




(c) Compressed Signal




(d) Decompressed Signal

Fig. 6. ECG signal waveforms with threshold th=0.3 (a) DC Shifted-Wave Original Signal (b) Normalized ECG Signal (c) Compressed Signal (d) Decompressed Signal

## X. CONCLUSION

The ECG signal of patient obtained from electrodes is first conditioned and then processed through ARM7 processor. This processed signal is then fed to computer system for further analysis through MATLAB signal processing tools. A hybrid scheme combining discrete cosine transform and discrete wavelet transform for ECG signal compression has been presented & their combination removes the spectral redundancy by compressing the subordinate components more than the dominant components. The resulting transformed coefficients that represent the transformational signal are then thresholded and compressed using a new coding technique for storage space saving. Improvement in performance parameters is achieved with the interaction of DCT with DWT transformation method, followed by thresholding and encoding.

The method here described has the advantage of better performance ratios. Besides the good performance in quality versus compression ratio, the proposed compression algorithm has some other features which are very important in the real-time environment. First, the reconstructed signal quality and the bit stream can be controlled by removing the spectral redundancy in subordinate components and/or the dominant components. Secondly, the computational complexity of the proposed codec is low, as witnessed by the recurrence relation of the DCT coefficients.

Moreover, the proposed algorithm was also compared with some standards and already developed hybrid algorithms. It was observed that the proposed hybrid algorithm performs better than the existing algorithms.

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