Packet-size-Controlled ECG Compression Algorithm based on Discrete Wavelet Transform and Running Length Encoding

Asiya M. Al-Busaidi and Lazhar Khriji
Department of Electrical and Computer Engineering, College of Engineering, Sultan Qaboos University, Muscat, Oman

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Abstract: This paper presents a development of new size-controlled compression algorithm for Electrocardiogram signal (ECG). Discrete Wavelet Transform (DWT) method, Bit-Field Preserving (BFP) and Running Length Encoding (RLE) are selected as compression tools in this work. Even though DWT-BFP-RLE is a lossy compression method, it has shown a potential in preserving the critical (diagnostic) part of the signal. Knowing that the size of transmitted packets of the battery-powered mobile telecardiology systems is limited within few bytes, the current algorithm is aiming to ensure that the compressed packets fit into the limited payload size. A parametric study of different mother wavelets and decomposition levels of DWT is presented with an emphasize on compression ratio (CR), percentage mean-square difference (PRD) and quality score (QS). The mother wavelet giving the best CR and QS results is then adopted to perform the dynamic compression algorithm on ECG records from MIT-BIH arrhythmia database.

1 INTRODUCTION

The Electrocardiogram (ECG) signal is an important biomedical signal that is widely used in diagnostic procedures by cardiologists. The monitoring of ECG signal can be done inside the hospitals/clinics using sophisticated equipment or at home or outdoor by using wearable monitoring devices that transmit the signal via cellular network or other wireless technologies. With the increased need of high resolution, high sampling rate and long recording period of the monitored ECG, the data compression becomes more vital for storage and transmission.

Compression is the procedure of reducing the number of digitized ECG signal without significant loss of the diagnostic data. Many methods were proposed for ECG compression and they can be lossless or lossy but all of them can be grouped into two categories: direct methods and transform methods (Chen and Itoh, 1998). In direct methods, compression is applied directly on the time domain ECG signal, while in the transform methods the ECG signal is transformed into a different domain. In lossy methods; there is some kind of quantization of the input data which leads to higher compression ratio (CR) results at the expense of reversibility. But this may be acceptable as long as no significant clinical degradation is introduced to the encoded signal (Moody et al., 1988). The CR levels of 2 to 1 achieved by lossless methods are too low for most practical applications. Therefore, lossy coding methods that introduce small reconstruction errors are preferred in practice. In other words, the main important factors in ECG compression are: (1) the ability of reconstructing the important features from the compressed ECG data, (2) the compression ratio, (3) execution time, and (4) the amount of error between the original and reconstructed signal. Recently, there are some trials to combine the lossy and lossless compression techniques specifically for the ECG signal (Abo-Zahhad et al., 2014).

Discrete Wavelet Transform (DWT) is a powerful time-frequency signal analysis tool that was utilized for ECG filtering (de-noising), feature extraction and compression (Ballesteros et al., 2012; Ballesteros and Gaona, 2011; Chen and Itoh, 1998; Chouakri et. al, 2011). The DWT transforms the ECG signal into sub-bands that can be encoded using set partitioning in hierarchal tree (SPIHT) coding (Lu et al., 2000), vector quantization (VQ), energy package efficiency (EPE) and other encoding schemes. However, some of the encoding methods can be complex to implement on FPGA's or basic microcontrollers and require high computational costs, which make them unsuitable for wearable battery-powered health monitoring devices. Chan et

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al. (2008) proposed an encoding scheme to compress the DWT coefficients using bit-field preserving (BFP) and running length encoding (RLE) and it was tested on an FPGA system (Lee et al., 2011). The method was simple to implement and allows forward data processing compared to other methods that require sorting and heavy computations.

Most of the ECG compression methods are open loop methods that have fixed performance. On the other hand, there are new closed loop compression methods that were designed to check the quality of the compressed signal by evaluating the amount of error introduced to the reconstructed signal before transmitting the compressed packet (Benzid et al., 2006).

This paper introduces a dynamic compression method that was not addressed in published literature yet. The dynamic compression method handles the issue of the limited payload size when the compressed packet is exceeding the maximum payload available. In other words, it controls the size of the compressed packets dynamically by a closed loop. For example, in low power wireless technologies like Bluetooth, Bluetooth Low Energy, 6LoWPAN, and ZigBee, the payload size is not very large and thus sending a continuous raw data will not be efficient in terms of energy saving. Consequently, the data have to be compressed and the overheads have to be designed optimally to make sure that the packet holds much more data than headers. As a result the data rate is reduced without a significant loss in the clinical features. The proposed dynamic compression method was designed based on a modified DWT-BFP-RLE compression algorithm. The method was tested on ECG records from MIT-BIH Arrhythmia database after obtaining the proper compression parameters.

2 METHODS

2.1 Wavelet Decomposition and Reconstruction

The ECG signal is a non-stationary signal that has varying frequency components with time and the DWT showed its powerfulness in decomposing the different ECG waveforms. The wavelet-based techniques fit with the standard signal filtering methods and encoding schemes and thus produce good compression results (Addison, 2002). The discrete wavelet transform (DWT) method can be done using decimation and without decimation (redundant or shift-invariant). Here undecimated DWT has been chosen due its better results in de-noising (Raj and Venkateswarlu, 2011). The ECG signal can be decomposed into J decomposition levels as shown in Figure 1, using lowpass *g(n)* and highpass *h(n)* FIR filter banks and then down-sampling by a factor of 2. The decomposed signal in each level is divided into low frequency signal (a_n) and high frequency signal (d_n). The low frequency signal a_n is called the approximation signal and the high frequency signal d_n is called the detail signal. The low frequency signal is decomposed again into two signals and so on up to d_J and a_J. The filter banks are constructed from wavelet basis functions such as Haar, Daubechies, Biorthogonal, Coiflet, Symmlet, Morlet, and Mexican Hat. The selection of wavelet transform function mainly depends on the application. The decomposed signal can be reconstructed back again into the original signal using reconstruction filters, which are the inverse of the decomposition filters. In this work, Daubechies (Db4 and Db5) and Symmlet (Sym4 and Sym6) mother wavelets were adopted and the decomposition level (J) was varied from 3 to 7.

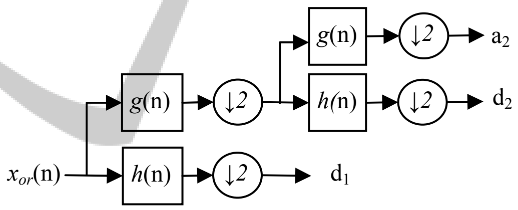

Figure 1: DWT with 2 level decomposition.

2.2 Thresholding and Bit-Field Preserving

After decomposing the signal into sub-bands using DWT, thresholds are applied to each sub-band. The thresholding process mainly contributes in filtering and used for decoding as well. One of the commonly used adaptive thresholds is provided in equation (1).

$$\lambda_n = \sigma\sqrt{2\log N} \tag{1}$$

where, σ is the standard deviation of the sub-band and N is the number of samples in the same sub-band. However, in this work the threshold ($Thres_{Sb}$) was calculated based on the bit-depth (B_{Sb}) of each sub-band and the desired preserved bit-length (I_{Sb}). The bit-depth B_{Sb} is the most significant bit of the maximum coefficient in the sub-band. While, the preserved-length I_{Sb} is controlled according to the desired compression performance where Sb stands for the sub-band coefficients d_1, d_2,.., d_J and a_J.

$$Thres_{sb} = 2^{B_{sb} - I_{sb} + 1} \quad (2)$$

A round-off mechanism is applied to the DWT coefficients before thresholding and encoding by adding 2^{Bn-Isb} to all coefficients to reduce the truncation error. Where, B_n is the bit depth before round-off mechanism and B_{Sb} after round-off.

2.3 Encoding

Before encoding the coefficients, the mean of the approximation coefficient a_J is subtracted and it will be added later on at the reconstruction stage. To encode the coefficients, first they are compared to the calculated sub-band threshold $Thres_{Sb}$. If the magnitude of the coefficient is greater than or equal to the sub-band threshold, it is considered as significant; otherwise it is considered as insignificant. The desired bits of interest of the significant coefficient will be sent to the bits-of-interest (BOI) packet and a one will be sent to the significant map (SM) stream. The SM stream indicates the sequence of significant and insignificant coefficients by ones and zeros, respectively. The BOI are the extracted bits from B_{sb}+1 to B_{sb}-I_{sb}+1, which represent BOI range, including the sign bit (B_{Sb}+1). In this works, each BOI is stored into one byte and the same for BOI range. Thus, I_{Sb} is no more than 6 (i.e. bits 0 to 6 hold the extracted bits and bit 7 for the sign bit).

To reduce the redundant zeros in SM stream and increase the compression ratio, it is divided into bytes and then running length encoding (RLE) is applied on the SM bytes. The RLE is well known method that replaces the consecutive bytes with their value followed by their number of copies (e.g. x=1 1 0 0 0 5 0 0 0 9 0 0 0 0 0 3 3 3, will be x_{enc}=1 2 0 3 5 1 0 3 9 1 0 5 3 3). The SM can be easily encoded (SMe) by encoding the consecutive zeroes. One byte is enough to represent the number of consecutive zeros up to 255 zeros. The last two sub-bands (a_J and d_J) have fewer samples and less consecutive zeros and thus RLE method was not applied to them. The overall compression scheme is illustrated in Figure 2.

2.4 Packetizing the Transmitted Data

To send the compressed BOI, BOI Range and SM packets, headers are required to indicate each segment of the compressed data. Table I shows the headers and the sizes of each packets. First, an indicator of the total number of samples of the ECG signal (Ns) taken for compression is placed at the beginning of the packet. Ns can have a value of 0, 1, 2, 3 and 4 which indicate that number of the compressed samples of 64, 128, 256, 512 and 1024, respectively. Then, for each transformed sub-band by DWT, headers were created to indicate the Bits-of-Interest Range (BOI Range), the number of bytes that holds the Bits-of-Interest (BOI Size), the number of bytes that holds the significant map (Size SM) or the encoded significant map (Size SMe). The BOI and SM follow the BOI Size and SM Size headers, respectively. Finally, the subtracted mean of the approximation sub-band (Mean of a_J) is divided into two bytes and placed at the end of the packet. At the receiver side, the packets are arrived in sequence and decompressed after decoding them using the information arrived.

Table 1: Format of the compressed packet.

Packet	*Description*	*Size*	*Details*
Ns	Number of Compressed Samples	1 Byte	2^n Samples
BOI Range (d_1)	The Range of Bits of Interest of the first detail sub-band d_1	1 Bytes	The 4 MSBs for the low bit range. The 4 LSBs for the high bit range.
BOI Size (d_1)	Number of BOI in the first detail sub-band d_1	2 Bytes	-
BOI (d_1)	Bits of Interest in the first detail sub-band d_1	Size BOI * 1Byte	Extracted using $Thres_{d1}$
SMe Size (d_1)	Number of encoded SM in the first detail sub-band d_1	1 Byte	-
SMe (d_1)	RLE Encoded Significant Map of BOI of the first detail sub-band d_1	Size SM * 1Byte	-
⋮			
BOI Range (a_J)	The Range of Bits of Interest of the approx. sub-band a_J	1 Bytes	-
BOI Size (a_J)	Number of BOI in the approx. sub-band a_J	2 Bytes	-
BOI (a_J)	Bits of Interest of the approx. sub-band a_J	Size BOI * 1Byte	Extracted using $Thres_{aJ}$
SM Size (a_J)	Number of SM in the approx. sub-band a_J	1 Byte	-
SM (a_J)	Significant Map of BOI of the approx. sub-band a_J	Size SM * 1Byte	-
Mean (a_J)	The mean of the approx. sub-band a_J	2 Bytes	The mean is subtracted from a_J and sent separately

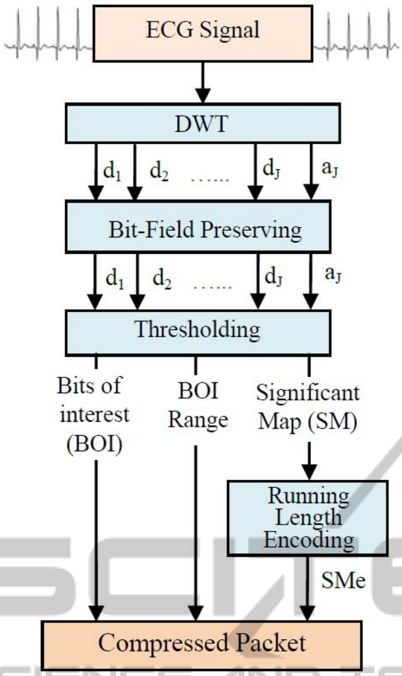

Figure 2: Compression scheme.

3 PROPOSED DYNAMIC COMPRESSION ALGORITHM

In this study, the ECG compression scheme based on DWT-BFP-RLE described in section 2 has been adopted and modified for telecardiology systems by considering the limit of the transmitted payload. The algorithm was designed to be a closed loop compression scheme that controls the size of the compressed packet. A schematic diagram of the algorithm is shown in Figure 3, which can be summarized into the following steps:

1. Store N (2^n) ECG samples into a buffer and compress them.
2. Check the size of the compressed packet. If the compressed packet size is less than or equal to the maximum allowable number of bytes (M), transmit the packet.
3. Otherwise, split the ECG data stored in the buffer into two new packets each with size N/2.
4. Apply the compression algorithm onto each packet separately, but in the correct sequence, where the first half of the data is to be compressed and transmitted first.
5. Go back to step 2 and repeat the process until all the data are transmitted.

The efficiency of this method is investigated and evaluated in the next section.

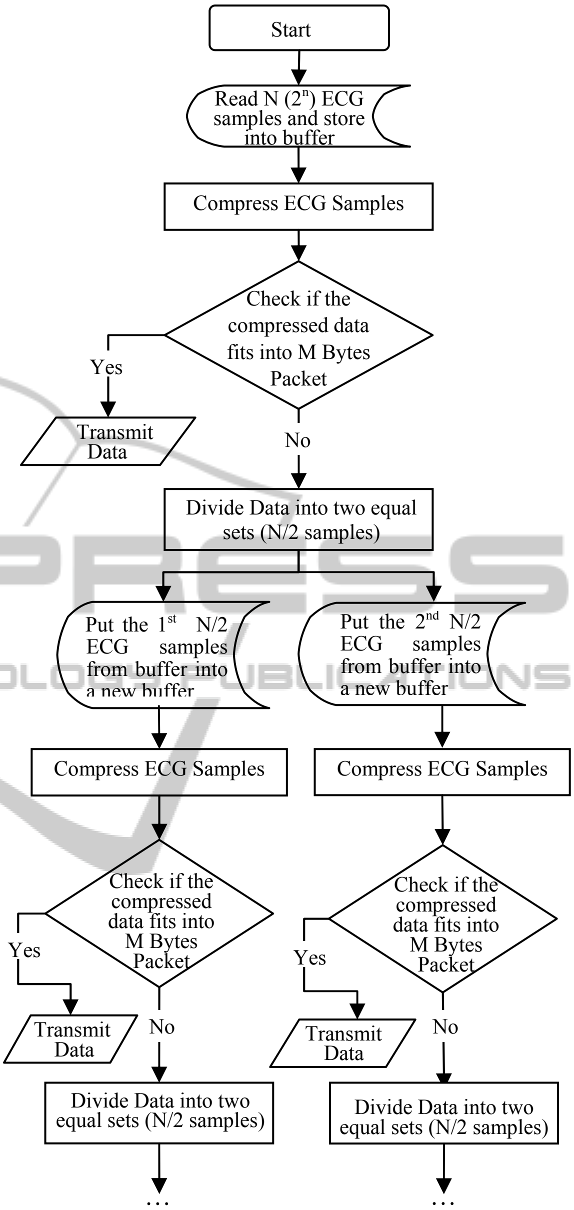

Figure 3: Dynamic Compression scheme.

4 SIMULATION RESULTS

To evaluate the proposed compression scheme, ECG records from MIT-BIH Arrhythmia (`mita`) database were used. The ECG signals in mita database were sampled at 360Hz and with 11-bit resolution. Ten different ECG records were used to evaluate the compression scheme; 100, 102, 107, 109, 117, 118, 119, 220 and 232. To test the proposed scheme, the first 10 minutes duration of each record was taken and divided into frames each contains 1024 samples (2.84 seconds). For each record, the mother wavelet filters Db4, Db5, Sym4 and Sym6 were applied with varying decomposition levels between 3 and 7. The results were evaluated using the compression measures provided in section 4.1.

4.1 Evaluation Scheme

First, the modified compression scheme was evaluated and then the dynamic compression scheme was studied based on the selected parameters. To evaluate the compression algorithm, the percentage root-mean square difference or PRD error between the original x_{or} and the reconstructed signal x_{re} was calculated by (3). Another measure to evaluate the compression algorithm is the compression ratio (CR) in equation (4). The CR calculates the ratio between the number of bits in the original signal (b_{or} = 11 bits ×1024= 11,264) and number of bits in the compressed packet (b_{comp} =8 bits × N_{comp}).

Fira and Goras (2008) saw that the CR and PRD are the most important compression measures in all literature, thus they suggested a new compression measure called "quality score" (QS) that represents the ratio between the CR and the PRD as shown in equation (5). The high quality score indicates a good compression performance.

$$PRD = \sqrt{\sum(x_{or} - x_{re})^2 \Big/ \sum(x_{or})^2} \times 100\% \tag{3}$$

$$CR = b_{or} / b_{comp} \tag{4}$$

$$QS = CR/PRD \tag{5}$$

4.2 Parametric Study

Figures 4 to 7 shows the original and reconstructed ECG signal of record 100 using different mother wavelets and decomposition levels. Surface plots of the average PRD and CR at different mother wavelets and decomposition levels of the same record are shown in Figures 8 and 9, respectively. According to Figure 8, Sym4 and Sym6 give better CR at the decomposition levels 4-7. However, the best CR results are obtained by Sym4 at levels 5-7. Figure 9 shows that levels 3 and 4 give the lowest PRD compared to other levels. However, it is interesting to note that Sym4 produces the lowest PRD at all decomposition levels. The QS of record 100 is shown in Figure 10. It is clear from the figure that Sym4 produces the best QS results at all decomposition levels.

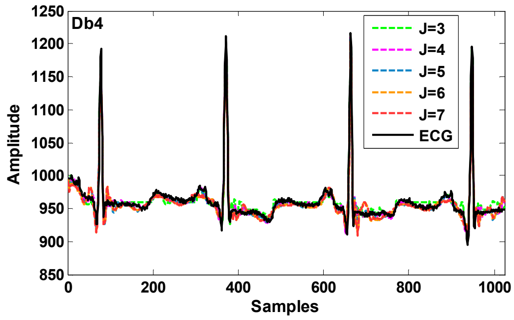

Figure 4: The original and reconstructed ECG of record 100 based on Db4 and J= 3 to 7.

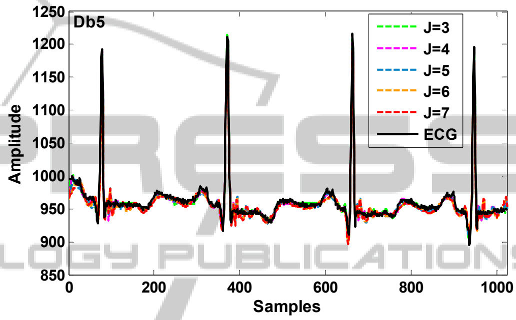

Figure 5: The original and reconstructed ECG of record 100 based on Db5 and J= 3 to 7.

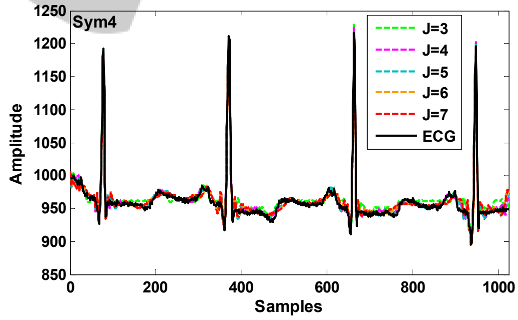

Figure 6: The original and reconstructed ECG of record 100 based on Sym4 and J= 3 to 7.

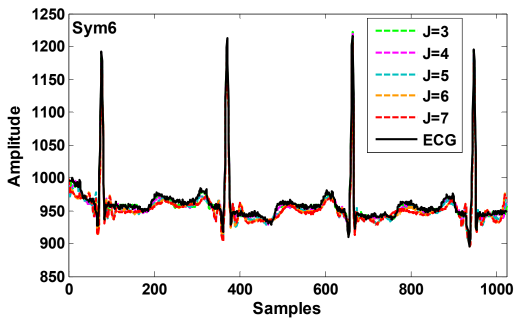

Figure 7: The original and reconstructed ECG of record 100 based on Sym6 and J= 3 to 7.

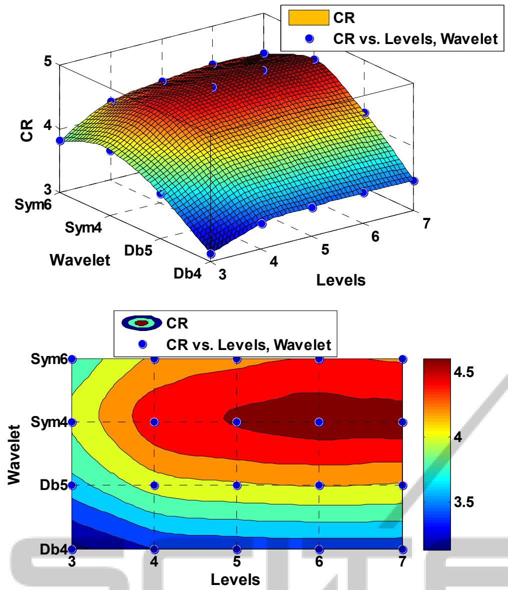

Figure 8: CR of ECG record 100 vs. decomposition level and wavelets.

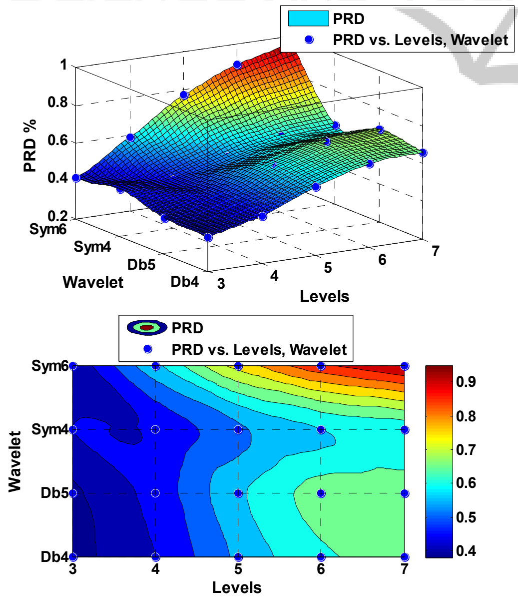

Figure 9: PRD of ECG record 100 vs. decomposition level and wavelets.

Figures 11 to 13 reflect the average CR, PRD and QS of the ten ECG records. Figure 11 reveals that the best CR value is of Sym4, which ranges between 3.99:1 and 4.84:1. The average PRD, shown in Figure 12, illustrates a gradual increase for almost all of the wavelets. But the increase is found to be a bit higher for Sym6 at higher decomposition levels with a value of 1.46% at level 7. In terms of the average QS, Sym4 shows the highest results among all the decomposition level. Hence, it is worthwhile to state that Sym4 reflects the best compression performance.

The modified DWT-BFP-RLE performed better compared to other well-known method as clearly shown in Table 3. Two preserved bit-lengths I_{Sb} values were tuned to get the preferred compression performance.

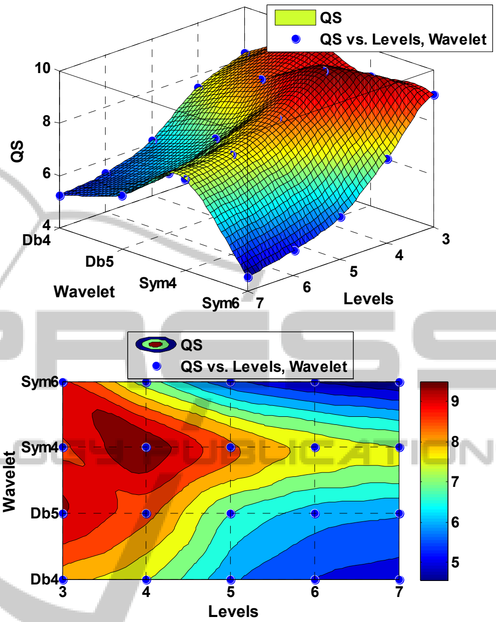

Figure 10: Quality score (QS) of ECG record 100 vs. decomposition level and wavelets. Note: surface plot axis is rotated to provide better projection.

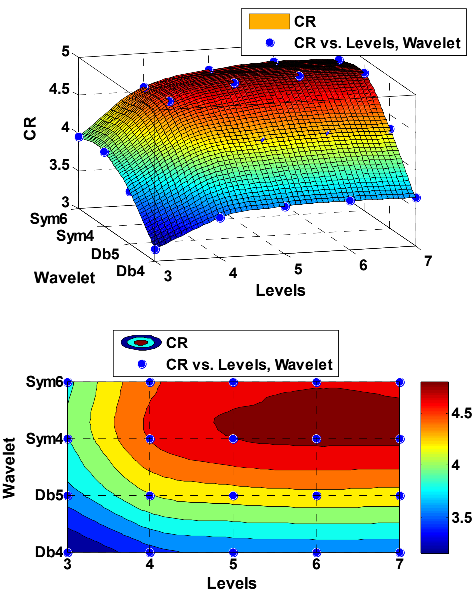

Figure 11: The average CR vs. decomposition level and wavelets.

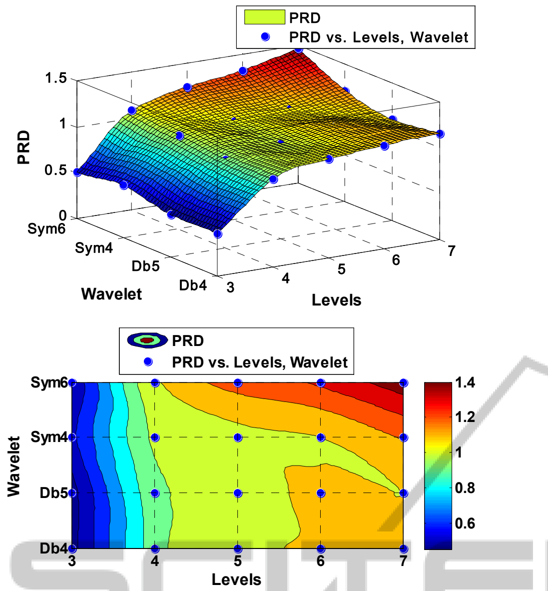

Figure 12: The average PRD vs. decomposition level and wavelets.

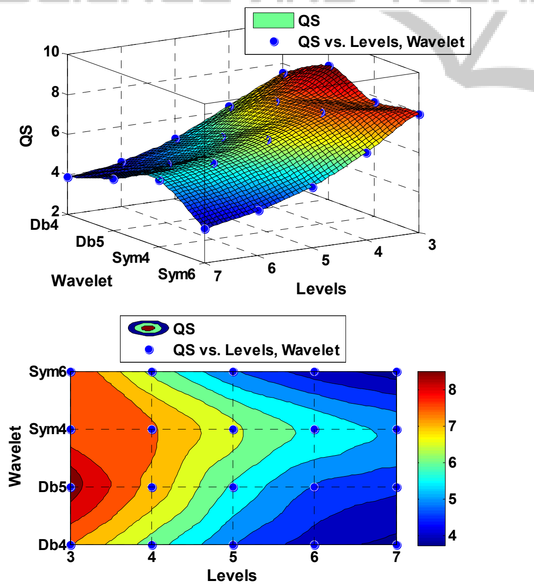

Figure 13: The average QS vs. decomposition level and wavelets. Note: surface plot axis is rotated to provide better projection.

4.3 Dynamic Compression

Sym4 mother wavelet and 4th level of decomposition were selected to demonstrate the dynamic compression scheme. From Figure 11, the average CR using Sym4 wavelet and at J=4 is 4.61:1, which corresponds to 305 of compressed samples. Accordingly, the number of samples to be

Table 3: Performance Comparsion with Other Methods for N=1024 and Duration of 10 Minutes (Sym4 and J=4).

Method	*Record*	*CR*	*PRD*	*QS*
SPIHT (Lu, 2000)	117	8.00:1	1.18%	6.78
Hilton (1997)		8.00:1	2.60%	3.08
Dojhon (1997)		8.00:1	3.90%	2.05
Proposed with I_{Sb}={1, 2, 2, 4, 6}		8.07:1	0.95%	8.51
Proposed with I_{Sb}={1, 2, 2, 3, 6}		8.30:1	1.14%	7.29

compressed was set to be Ns=256. The first 10 seconds of the ECG records 100, 117 and 119 were used to test the dynamic compression scheme. The available payload size (M) was assumed to be 70 bytes. Table 4 shows the number of compressed packets generated for each record, the average CR of these packets and the RPD between the original and reconstructed signal. The number of packets required to send 10 seconds of raw (un-compressed) data is 103 packets (3,600 samples× 2 Bytes /70 Bytes), since each ECG sample is represented by 2 bytes. The efficiency of the dynamic compression can be evaluated by calculating the percentage amount of the packet reduction (PR) shown in (6).

$$PR = \frac{N_{Raw} - N_{Compressed}}{N_{Raw}} \times 100\% \qquad (6)$$

where, N_{Raw} and $N_{Compressed}$ are the number of raw and compressed packets, respectively. It was found that record 100 was segmented into 27 packets to send 10 seconds of ECG data with an average CR of 3.02±1.65 and a high reduction of 73.79% in the number of transmitted packets. The records and their reconstructed signals are shown in Figure 14, where the grid lines indicate the generated packets. The visual results show acceptable results and confirm the efficiency of the proposed method.

Table 4: Obtained parameters of the dynamic compression scheme with Sym4 and J=4 (10 seconds for each record).

Record	*No. of Packets*	*Packet Reduction*	*Average CR ±σ*	*PRD*
100	27	73.79%	3.02±1.65	0.46%
117	35	66.02%	2.62±1.09	0.47%
119	26	74.76%	3.24±1.43	0.85%

4 CONCLUSIONS

This paper presents a closed loop ECG compression algorithm based on modified discrete wavelet transform (DWT), bit-field preserving (BFP) and running-length encoding (RLE) methods. The closed loop scheme is important for low-powered telecardiology systems that have limited payload. The proposed compression algorithm reveals a dynamic scheme to subdivide the ECG data into equal packets and apply compression on each packet again until they fit into the provided payload. Based on PRD, CR and QS, Sym4 and 4th level of decomposition were adopted to implement the dynamic compression scheme. The proposed dynamic scheme was tested on records 100, 117 and 119 using 10 seconds of data. The results showed that the method can divide the ECG records to 27, 35 and 26 packets with an average CR of 3.02±1.65, 2.62±1.09 and 3.24±1.43 and PR of 73.79%, 66.02% and 74.76% for records 100, 117 and 119, respectively. The optimal CR and PRD can be designed by controlling the preserved bit-length. Moreover, a packetizing scheme of the compressed data was proposed to have minimum headers and more space for the compressed data. Nevertheless, further improvement can be done on this method to have higher CR and QS. Our future prospect is to implement the method on ultra-low power hardware since the initial indication shows promising results.

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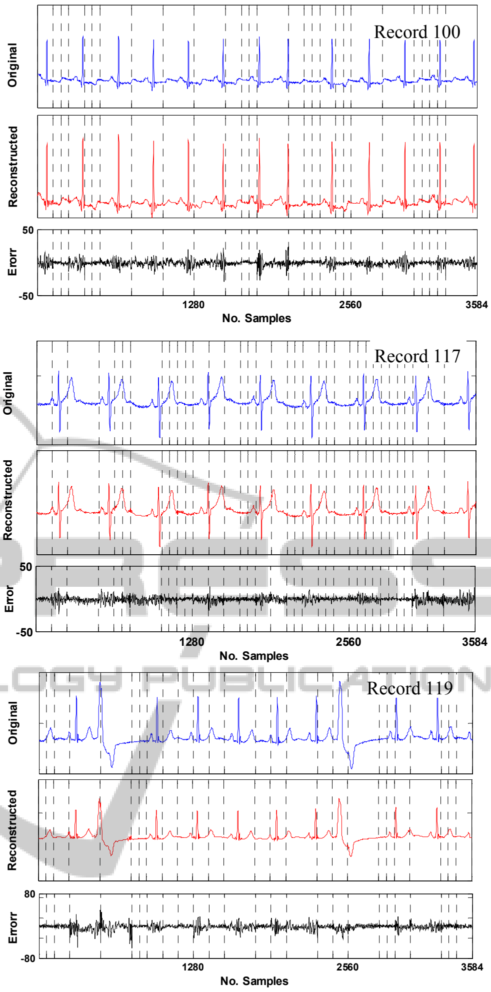

Figure 14: Visual results of ECG records 100, 117 and 119 subjected to dynamic compression scheme.

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