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# A Novel Approach of ECG Signal Compression using MRA Analysis based on WPD

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Abstract: In this paper, an electrocardiogram (ECG) signal compression is proposed based on the wavelet packet transform (WPT) that explore the multi-resolution analysis (MRA). An ECG signal is primary tool to examine the cardiac health; sometime, its need to store a long duration data for review the health condition that consumed storage space. This challenge overcome through the suitable compression technique to save the storage space. Here, several experiments are carried out with proposed method and signals. The WPT generate the large number of sparse data of ECG signal that help to achieve the compression as it computes the  $2^n$ sub-bands as compare to (n+1) sub-band of discrete wavelet transform (DWT). The performance of the proposed method is evaluated in term of compression ratio/rate with other fidelity assessment. As results shows, 42% average compression achieved at cost of good and acceptable quality of reconstruction, it also compared with original signal in terms of correlation and waveform comparison.

*Index Terms:* ECG Signal, Compression, Wavelet Packet Transform, Huffman, Run-length Coding

### I. INTRODUCTION

Electrocardiogram (ECG) Signal are widely utilized for monitoring and diagnostic of cardiac disease, and stored for review in future. As passing days, big number of the population has been suffering from cardiac disease. The National Vital Statics Reports by U.S. department of Health and Human services reported that cardiac disease lead in death causes in USA by 23% approximately of total 2,512,873 deaths in last decade. World Health Organization (WHO) working for establish telemedicine services related to cardiology and electrocardiography under the scheme for provide low cost health care services to all using information and communication Technology (ICT) in 28 countries. In the present time, especially for healthcare transformation in pandemic is ICT enabled tools used for consultancy, monitoring, diagnosis as well for record exchange. Here, so many challenging issues are involved with telemedicine services such as storage of medical record and sharing of records between the different medical practitioners using ordinary communication channel. Thus, the data compression provides the reliability in data saving management and its sharing in extra also effects on the energy consumption of devices. In this context, easy exchange of medical records such as diagnosis reports or data like electrocardiogram (ECG) or biomedical signals and image is possible with compressed form become popular for telemedicine facility and remote monitoringbased treatment [1,2]. Figure 1 illustrates the basic system for ECG signal analysis and its telemedicine application. It's contains basically recording and monitor unit, processing unit that perform the diagnosis analysis as heart rate variability [3]. Further, ECG records are kept save for future review using compression system. The compression system makes suitable compressed data packets of original to keep record save in storage device. Sometimes these records shared between cardiologist for further review and study through open network or using the telemedicine unit as shown in fig.1. In field of ECG signal compression, a remarkable progress reported in literature in the past two decades [4-6]. A number of methods and its review analysis presented by the many researchers for several methods. Here, transformation and coding techniques are attracted for the compress due to its compact signal representation ability [5-7]; especially, discrete wavelet

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transform (DWT) based methods. It is very efficient to represent signal or image with very few coefficients because of its high energy compaction property [8,9]; most of the signal energy is concentrated in a subset of the transform coefficients, allowing the remaining coefficient with very low energy. Further, and ECG signals are pre-processed as 2D-data or image with help of temporal periodicity or beat alignment. These techniques such as JPEG, SPIHT, JPEG2000, 2D-DWT with vector quantization, and many other shown the improvement in compression based on DCT, DWT, and hybrid approaches [4,10–15]. A detail review of these technique shown the improved compression performance with acceptable fidelity. However, these techniques applicable for the off-line processing and it requires preprocessing.

Throughout literature, performance of compression technique is evaluated using compression ratio (*CR*), percentage rootmean-square difference (*PRD*), signal-to-noise ratio (*SNR*), cross correlation (*CC*) and computation time. Where, x and y are original and reconstructed signal respectively, while  $\overline{x}$  and  $\overline{y}$  is mean value of respective signal. These are describing as followings:

• *Compression ratio* (CR):

 $CR = \frac{\text{Number of Encoded Sample}}{\text{Total number of Signal Sample}} \times 100$ 

• Percent root mean square difference (PRD):

$$PRD = \left(\frac{\text{Reconstructed noise energy}}{\text{Origional signal energy}}\right)^{1/2} \times 100$$
$$= \sqrt{\frac{\sum [x(n) - y(n)]^2}{\sum x(n)^2}} \times 100$$

• Signal-to-noise Ratio:

$$SNR = 10 \log_{10} \left( \frac{\text{Energy of input signal}}{\text{Energy of the reconstructed error}} \right)$$
$$= 10 \log_{10} \left\{ \frac{\sum x^{2}(n)}{\sum |x(n) - y(n)|^{2}} \right\}$$

• Correlation:

$$r_{xy} = \frac{\sum_{n=1}^{N} (x_n - \overline{x})(y_n - \overline{y})}{\sqrt{\sum_{n=1}^{N} (x_n - \overline{x})^2 (y_n - \overline{y})^2}}$$

In this manuscript, an effective compression technique is illustrated for *one*-dimensional ECG signal using discrete wavelet packet transform (WPT) analysis instead of traditionally *one*-dimensional DWT with variable length of coding techniques. An ECG signal compression based on transform techniques centered on wavelet techniques due to higher rate of compression as well quality control in signal reconstruction. Nowadays, its classified into two groups namely *one*-dimensional DWT and *two*-dimensional DWT. Currently, ECG signal compression attract great attention of *two*-dimensional DWT analysis due to high compression rate as well energy compaction of 2D array as well 1D array data. The related literature is listed in introduction of the manuscript, it organizes as section 2 as brief introduction of WPT; section 3 represents the propose technique and section 4 include all the results and its analysis of proposed technique and manuscript is conclude in section 5.



Fig. 1 Basic of ECG Signal Processing and Analysis System

## II. DISCRETE WAVELET PACKET TRANSFORM

In field of Signal and image processing, wavelet transform is very popular tool for data compression, denoising and many more application; JPEG2000 one of the most popular standard of image based on wavelet has been recognized by information and communication international societies[12,16].

In field of data compression, signal or image are decomposed into different sub-bands. It's possible due to multi-resolution property of wavelet transform, multi-resolution analysis (MRA) make possible to analyze a function at different frequency and resolutions. In case of  $L^1(\square)$  plane, it's decomposed a signal into  $2^1$  sub-bands and similarly a function belong  $L^2(\square)$  plane has decomposed into  $2^2$  sub-bands, it's illustrates that a function from  $L^n(\square)$  plane has been decomposed by MRA analysis into  $2^n$  sub-bands of different resolutions [9]. In MRA analysis, function having different resolutions at different level of wavelet packet transform (WPT) decomposition [17]; at each level of WPT decomposition, there are two solutions are arising such as dilation equation or scaling function  $\phi(n)$  and translation equation or wavelet function  $\Psi(n)$  [28, 63]. These are defined as

$$\phi(n) = \sqrt{2} \sum_{k} h[k] \phi(2n-k)$$
(1)

$$\psi(n) = \sqrt{2} \sum_{k} g[k] \phi(2n-k) \tag{2}$$

Here, g[k] and h[k] represent the low pass and high pass filters respectively in *fig.* 2 and *eq.* (1) and (2). The process of a multirate signal processing with quadrature mirror filter structure raises the wavelet decomposition [17–19].



Fig. 2 Schematic diagram of Discrete wavelet transform decomposition

In the MRA, DWT compute the coefficients as approximation and detail; where, approximation sub-band further decomposed up to n levels. However, WPT decomposes the signal and compute the sub-bands as approximation and detail coefficients at initial level, and iterate for each sub-band further like a full binary tree as illustrated in *fig.* 2. The WPT decomposition produces  $2^n$  different sub-bands at n level as opposed to (n+1) sub-bands of DWT. In the data compression prospective, the traditional DWT decomposition may not compute the sparse data of signals as produced by the WPT for the compression [17].

#### III. PROPOSED COMPRESSION TECHNIQUE

In this manuscript, discrete wavelet packet transform (WPT) analysis is exploited for ECG signal compression. The proposed technique analyzed on MIT-BIH Arrhythmia ECG records, traditionally one-dimensional time domain ECG signal compressed by using DWT and the recent analysis of field also contains the 2D DWT analysis of ECG as 2D transformation of ECG data [4,20,21]. Therefore, some information losses are introduced due to transformation of data form 1D to 2D. Here, the proposed technique utilizes for ECG data compression using its own originality as 1D signal, thus the significant information preserved. In *fig.*3 proposed technique is shown, it's gone through different signal and information process

techniques such as signal decomposition using WPT, thresholding, quantization and variable length coding technique.



Fig. 3 Proposed Compression System for ECG Signal

In signal decomposition, a signal vector is decomposed as linear combination of *n*. Let, *x* is the real-valued *n*-dimensional ECG signal which is decomposed with orthonormal wavelet transform basis  $\Psi = [\Psi_1 | \Psi_2 | \Psi_3 | ... | \Psi_n]$  as  $x = \Psi c$ , where, *c* represents the *n*-dimensional coefficient vector that contains the highly sparse nature data value of *x* in the wavelet domain. The coefficient vector *c* having most of zero amplitude or near zero amplitude value coefficients, it does not effect on the signal quality or significant information [6,22,23]. Therefore, to achieve desired compression ratio (CR), the threshold value is initialized to make sparse data sets. It computes the *c*<sub>s</sub> as s-sparse approximation of *c* coefficients vector, which contains all coefficients to threshold value of transform vector.

Here, two efficient ECG compression technique is presented based on the WPT and variable length of entropy coding techniques such as (a) ECG compression with DC drift and (b) ECG compression without DC drift; both the approaches utilized to compress the data point of signal as illustrate in *fig.* 3.

In first approach, original ECG signal is decomposed with WPT then the thresholding process eliminate the insignificant transform coefficient and consider as zero amplitude value. Therefore, new truncated transform coefficients are uniformly quantized and send to coder block, where actual compressed data are produced. In this work two different entropy coding techniques are used such as Huffman coding and Zero-run length coding. The performance efficiency of both coding techniques is different in terms of discussed fidelity parameters.

In second approach, ECG signal is preprocessed with DC drift removal and amplitude normalization

process. DC Drift is common error of ECG signal, due to DC drift features of ECG like as *P*, *QRS*, *T* waves are morphed. Therefore, elimination of DC drift is necessary, the origin of DC drift is associated with discharging of battery power of ECG recording apparatus [2,7]. Let the ECG signal f(m) of length *N* is associated with DC drifting, then the clean ECG is represented as in *eq*. (5),

$$X(m) = x(m) - \mu(x(m)), \quad \forall m = 1...N$$
(3)

Therefore, amplitude normalization is employed on the clean signal, its represented as,  $\overline{X}(m) = 1/pX(m)$ . Where,  $\overline{X}(m)$  is represented clean and normalized ECG signal and p is maximum peak amplitude [2]. Amplitude normalization process helps to preserve vector of ECG during in QRS or beat detection process, after the preprocessing step utilized remaining process of approach one is employed to compress the data as shown in *fig.* 3, where signal is decomposed using the discrete wavelet packet transform (WPT) and followed by thresholding, and quantization employed to produces more sparsity nature of data, due to sparsity nature of data is easy to compress as compare to original data. The proposed compression process is summarized and presented as *algorithm.* 1 and detail illustration of WPT presented in *fig.* 4.



Fig. 4 Proposed ECG Compression Schematic based on the WPD and Coding technique

Here, ECG signal is decomposed with wavelet packet transform (WPT) into sub-bands of approximation  $(c_{al})$  and detail  $(c_{dl})$  coefficients. Further, these sub-bands are represented as  $c_{al2}$ ,  $c_{dl2}$ ,  $c_{a22}$ , and  $c_{d22}$  at  $2^{nd}$ -level of decomposition. The computed sub-bands contain the sparse data of original signal and sent to the thresholding operation; the thresholding process compute more sparse data as per the global thresholding approach as define in eq. (4).

$$\overline{C}(i) = \begin{cases} 0 & \text{if } Thr \le |C(i)| \\ C(i) & \text{otherwise} \end{cases}$$
(4)

where, c and  $\bar{c}$  the wavelet coefficient before and after thresholding respectively. Afterwards, the sparse data process with uniform quantizer that produce the quantized data; and its results, sparse data magnitude represented with few amplitude levels. It helps to generate the code directory using the suitable coding technique as illustrated in *algorithm* -1 and *fig. 4*.

<u> </u>	1-1
Initial	
SIGNAL	x(m), Input ECG Signal
PRE-Proce	essing (PP)
Parameter	<b>DC Drift</b> , $X(m) = x(m) - \mu(x(m))$
	<b>Normalized Amplitude</b> , $\overline{X}(m) = \frac{1}{p}X(m)$
Return	<b>Preprocessed Signal</b> , $\overline{X}(m)$
WPT Anal	vsis
c = WPT (	Data, Wavelet, Level)
Parameter	<b>Data</b> , SIGNAL $\overline{X}(m)$ or $x(m)$
	Wavelet, wavelet packet or filter name (coiflet, debouches, etc.)
	Level, decomposition level 'l'
Return	<i>c</i> , wavelet coefficients $[c_{a12}, c_{d12}, c_{a22}, c_{d22}]$ at 2 <sup>nd</sup> Level
Threshold	ing
$\overline{c} = \text{THR} ($	Data, Value, Condition)
Parameter	Data, Wavelet coefficients (C)
	Value, Threshold Level
	Condition, Value $\leq c$
	IF, True
	Return $\bar{c} = c$
	ELSE
	Datum Z - 0
	$\mathbf{c} = 0$
Return <i>c</i> ,	Significant wavelet coefficients
Return $\overline{c}$ ,	Significant wavelet coefficients
Return $\bar{c}$ , <u>Quantizati</u>	Significant wavelet coefficients
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT$ (	Significant wavelet coefficients <u>on</u> Data, Level) Deta, Simificant wavelet coefficiente
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT$ ( Parameter	Significant wavelet coefficients <u>on</u> Data, Level) <b>Data</b> , Significant wavelet coefficients Level Ownigning level (1 + 1) in between May (a) and Min (a)
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT$ ( Parameter Paturn $\bar{c}$	Return $c = 0$ Significant wavelet coefficients On Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. ( $\bar{c}$ ) and Min. ( $\bar{c}$ ) Ourantize significant data (Spage data)
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT$ ( Parameter Return $\bar{c}$ ,	Significant wavelet coefficients on Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. ( $\overline{c}$ ) and Min. ( $\overline{c}$ ) Quantize significant data (Sparse data)
Return $\bar{c}$ , <u>Quantizatii</u> $\bar{c} = QNT$ ( Parameter Return $\bar{c}$ , <u>Coding</u>	Significant wavelet coefficients on Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. $(\bar{c})$ and Min. $(\bar{c})$ Quantize significant data (Sparse data)
Return $\overline{c}$ , <u>Quantizatii</u> $\overline{c} = QNT$ ( Parameter Return $\overline{c}$ , <u>Coding</u> Y = HUFF	Significant wavelet coefficients on Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. ( $\overline{c}$ ) and Min. ( $\overline{c}$ ) Quantize significant data (Sparse data) (Data) or Y=RLE(Data)
Return $\overline{c}$ , <u>Quantizatii</u> $\overline{c} = QNT$ ( Parameter Return $\overline{c}$ , <u>Coding</u> Y = HUFF Parameter	Significant wavelet coefficients on Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. ( $\overline{c}$ ) and Min. ( $\overline{c}$ ) Quantize significant data (Sparse data) <sup>1</sup> (Data) or Y=RLE(Data) Data, Quantize significant data
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT$ ( Parameter Return $\bar{c}$ , <u>Coding</u> Y = HUFF Parameter Return	Significant wavelet coefficients On Data, Level) Data, Significant wavelet coefficients Level, Quantization level (L+1) in between Max. ( $\overline{c}$ ) and Min. ( $\overline{c}$ ) Quantize significant data (Sparse data) <sup>1</sup> (Data) or Y=RLE(Data) Data, Quantize significant data Y, Compressed data code using Huffman/RLE coding
Return $\bar{c}$ , <u>Quantizati</u> $\bar{c} = QNT ($ Parameter Return $\bar{c}$ , <u>Cooling</u> Y = HUFF Parameter Return <u>Quantization</u>	Significant wavelet coefficients <u>on</u> Data, Level) <b>Data</b> , Significant wavelet coefficients <b>Level</b> , Quantization level (L+1) in between Max. ( $\bar{c}$ ) and Min. ( $\bar{c}$ ) Quantize significant data (Sparse data) <sup>1</sup> (Data) or Y=RLE(Data) <b>Data</b> , Quantize significant data <b>Y</b> , Compressed data code using Huffman/RLE coding

In this paper, Huffman and run-length coding (RLC) is utilized and evaluated separately for compression of computed in earlier stage as described above. These coding techniques consider as variable length codes (VLC) [4,14,23–26]; techniques are efficient for source coding with compression and decompression in loss-less mode; both coding algorithms are loss-less compression coding technique which are represents the original data into compressed bit-stream. Here, Huffman coding generate the binary code dictionary of compressed data, on the other hand RLC generate the data stream as a run length of quantize data. Further, two different approaches are utilized to compress ECG signal and performance evaluated using different parameters with pre-processing and without it. A detail analysis of performance of proposed technique is presented in the results and discussion section.

#### IV. RESULTS AND DISCUSSION

In this paper, an ECG signal compression method proposed based on the MRA analysis using WPT and its produce more compact sparse data set that processed further with coding and produce the compressed bit stream. The proposed algorithm is tested on 25 different records from the MIT-BIH arrhythmia database [27], which are acquired with 11 bit ADC resolution at 360 Hz of sampling rate, these test records are 100,101,102, 103, 104, 105, 106, 107, 108, 109, 111, 112, 113, 114, 115, 116, 117, 118, 119, 121, 122. 123,124,200 and 217. The proposed technique is utilized four different wavelets transform filters such as Coiflet (Coif5), Symlet (Sym6), Debauches (db12) and Haar on both compression approaches, these wavelet function decomposed on ECG signals and further process with thresholding, quantization and Huffman coding to obtain the compressed data stream. Here, proposed method evaluated using CR, PRD, SNR and correlation that describe the compression amount, reconstruction difference and similarity between original and reconstructed signal respectively. This analysis and performance are categorized in two approach based on two different coding techniques. In this section, results are represented with three different descriptive statistics method such as bar plot, box-plot and table for the interpreting the performance of algorithm and experiments.

#### A. Compression with DC Drift

In this work, ECG signal compressed in its original form as it recorded using the proposed method. The ECG signal is compressed using proposed methodology which consist two different data coding techniques. These coding techniques zero RLE and Huffman utilize individually, it's shown as *experimentone* and *experiment-two* respectively.



**Fig. 5** WPT and Zero RLE based algorithm Performance of Compression with Four Different wavelets using 25 ECG Records.

**Experiment-***One* is based on WPT analysis of ECG signal and Zero run-length coding technique. Here, four different wavelets are employed on ECG signal, these are having different energy compaction property due to performance of algorithm is different for each wavelet function. The method is tested on 25 different ECG signal as shown in fig. 5, thus the average performance in term of Compression ratio (*CR*) of each wavelet function is 28.20%, 25.40%, 25.35% and 23.61% for the Coiflet, Symlet, Debouches and Haar respectively. Here, maximum compression achieved is 50.16% and minimum compression achieved is 19.66% by using coiflet for two different records 122 and 101.

Here, quality measurement is also necessary of reconstruction signal and its evaluated using different fidelity parameters such as PRD, PRD1, SNR and correlation. Fig. 6 contains the boxplot representation which explores the four different fidelity parameters that evaluate the performance of Coiflet, Symlet, debouches and Haar wavelet function for 25 Different ECG signal.



Fig. 6 Reconstruction Performance in term of PRD, PRD1, SNR and Correlation of Coiflet, Symlet, Debouches and Haar wavelet for 25 different ECG records

The experiments are carried with 25 different ECG with different wavelet function, there is performance variation included due to energy compaction of wavelet function and signal characteristics. Here, Box-plot represents the graphically depicting groups of numerical data through their quartiles; it does easily determine the average data value, lower and upper quartiles and minimum-maximum data values. Therefore, the average performance of experiment-*one* as shown in fig. 6 in term of PRD is 4.00%, 3.06%, 3.25% and 6.57%; PRD1 is 2.61%, 1.89%, 2.22% and 4.48%; SNR is 28.01, 30.19, 29.61 and 23.59, and Correlation score is 0.9985, 0.9990, 0.9988 and 0.9931 for each wavelet function respectively. The performance of also evaluated using the human vision system (HVS) using fig. 7, which shows the original ECG signal, compressed

reconstructed signal and error signal. Fig. 7 represent the algorithm is efficient for compression without any loss of significant visual feature of ECG; it's also verified through correlation score.



Fig. 7 Visual representation of Original ECG Signal, Reconstructed Signal and error Signal Based on Experiment-*One* 

Experiment Two-An ECG signal compression based on WPT and Huffman coding technique is carried in experiment-two with 25 different ECG Records. Huffman coding create the binary code tree for transform coefficients on the basis of probability or occurrence of coefficients due to compression of ECG signal achieve higher than the zero run-length coding. The result analysis illustrated similar to experiment-on; where, Fig. 8 represents the compression rate of proposed method with Huffman on 25 ECG records. The performance of method in term of CR of each wavelet function is 41.17%, 33.24%, 36.04% and 32.98% for the coiflet, Symlet, debouches and Haar respectively. Here, maximum compression achieved is 67.13% using Coiflet and minimum compression achieved is 28.25% using Haar for two different records 102 and 112 respectively. Similarly experiment-one, reconstruction signal is evaluated using different fidelity parameters such as PRD, PRD1, SNR and correlation. Fig. 9 contains the box-plot representation which explores the four different fidelity parameters that evaluate the performance of Coiflet, Symlet, debouches and Haar wavelet function for selected dataset of ECG signal.

Here, reconstructed signal quality measured using PRD, PRD1, SNR and Correlation as similar to experiment-*one*. The average performance of experiment-*two* as shown in fig. 9 in term of PRD is 3.64%, 3.85%, 4.11% and 10.05%; PRD1 is 2.77%, 2.77%, 2.52% and 6.68%; SNR is 28.69, 28.26, 27.90 and 19.99, and Correlation score is 0.9994, 0.9981, 0.9982 and 0.9882 for each wavelet function respectively. The performance of also evaluated using the human vision system (HVS) using fig. 10, which shows the original ECG signal, compressed reconstructed signal and error signal.



**Fig. 8** WPT and Huffman coding-based algorithm Performance of Compression with Four Different wavelets using 25 ECG Records



Fig. 9 Reconstruction Performance in term of PRD, PRD1, SNR and Correlation of Coiflet, Symlet, Debouches and Haar wavelet for 25 different ECG records



Fig. 10 Visual representation of Original ECG Signal, Reconstructed Signal and error Signal based on Experiment-*Two* 



Fig. 11 WPT and Zero RLC coding-based algorithm Performance of Compression with Four Different wavelets using 25 ECG Records without DC Drift

#### B. Compression without DC Drift

This experiment is carried out with pre-processed data as discussed in earlier section. Here, WPT based compression technique is exploited with run length and Huffman coding technique.

#### **Experiment** Three

The proposed method is tested on 25 different ECG signal as shown in fig. 11, thus the average performance in term of Compression ratio (CR) of each wavelet function is 28.90%, 27.60%, 28.25% and 26.61% for the Coiflet, Symlet, Debouches and Haar respectively. Here, maximum compression achieved is 39.20% and minimum compression achieved is 19.66% by using debauches and coiflet for two different records 107 and 105, respectively. Here, reconstructed signal quality measured using PRD, PRD1, SNR and Correlation as similar to experiment-one. The average performance of experiment-two as shown in fig. 12 in term of PRD is 6.40%, 5.00%, 5.81% and 8.15%; PRD1 is 1.87%, 1.37%, 1.52% and 2.4%; SNR is 24.6, 26.25, 24.90 and 21.90, and Correlation score is 0.999, 0.9995, 0.9995 and 0.996 for each wavelet function, respectively. The performance of also evaluated using the human vision system (HVS) using fig. 13, which shows the original ECG signal, compressed reconstructed



Fig. 12 Reconstruction Performance in term of PRD, PRD1, SNR and Correlation of Coiflet, Symlet, Debouches and Haar wavelet for 25 different ECG records without DC Drift



Fig. 13 Visual representation of Original ECG Signal, Reconstructed Signal and error Signal based on Experiment-*Three* 





#### **Experiment** Four

The proposed method is tested on 25 different ECG signal as shown in fig. 14, thus the average performance in term of Compression ratio (CR) of each wavelet function is 42.60%, 40.80%, 41.25% and 36.64% for the Coiflet, Symlet, Debouches and Haar respectively. Here, maximum compression achieved is 59.20% and minimum compression achieved is 5.2% by using coiflet and symlet for two different records 116 and 119, respectively. Here, reconstructed signal quality measured using PRD, PRD1, SNR and Correlation as similar to experiment-one. The average performance of experiment-two in term of PRD is 5.60%, 6.00%, 5.90% and 10.5%; PRD1 is 1.8%, 1.9%, 1.72% and 3.4%; SNR is 24.8, 24.25, 24.95 and 19.75, and Correlation score is 0.999, 0.995, 0.998 and 0.993 for each wavelet function, respectively as illustrated in fig. 15. The performance of also evaluated using the human vision system (HVS) using fig. 13, which shows the original ECG signal, compressed reconstructed signal.



**Fig. 15** Reconstruction Performance in term of PRD, PRD1, SNR and Correlation of Coiflet, Symlet, Debouches and Haar wavelet for 25 different ECG records without DC Drift

Here, all four experiments illustrated that shown the efficiency of proposed compression technique based on sub-band coding of wavelet packet transform coefficients. These experiments shown the different efficiency of proposed method for different signals with several pre-processing operations; and found the efficiency of compression is higher with coiflet transform as compared to others in all experiments. The summary and comparison of proposed method and its evaluation is compared with existing contemporary techniques, and listed in Table. 1. As per the comparison of proposed method with other existing technique, it found that the WPT help to generate large sparse data as compare to DWT analysis-based technique; and its results comes in terms of higher compression rate with good and acceptable reconstruction quality as globally acceptable [28].



Fig. 16 Visual representation of Original ECG Signal, Reconstructed Signal and error Signal based on Experiment-*Four* 

 Table. 1 Comparison of proposed method with existing techniques

1				
Methods	Compression	PRD		
Proposed method with Coiflet &	28.20	4.00		
RLC for Original Signal	20.20	1.00		
Proposed method with Coiflet &	41 17	3 64		
Huffman for Original Signal				
Proposed method with Coiflet &	28.00	6.40		
RLC for Pre-processed Signal	28.90	0.40		
Proposed method with Coiflet &	42.60	5.6		
Huffman for Pre-processed Signal				
DCT & DWT Cascaded		2.33		
Approach (2019) [29]	28.02			
<b>Mother Wavelet (2019)</b> [30]	22.62	5.66		
<b>EP-based wavelet (2014)</b> [31]	14.6	4.00		

Overall, analysis shown the efficiency of proposed method with different signal variations is higher as compared to wavelet based contemporary techniques. Especially, coiflet and symlet transform are most suitable for ECG signal compression with proposed method as well as for the reconstruction.

#### V. CONCLUSION

The wavelet packet transform is suitable tool to generate sparse data with binary tree representation at each level of decomposition. It exploited for the compression of ECG signal in this paper with thresholding, quantization, and coding techniques. Here, ECG signal is pre-processed to remove the DC drift artifacts and compressed with four different approaches as discussed. As per the analysis, ECG signal can be compressed with or without DC drift using proposed method and achieve the comparable compression efficiency. However, the efficiency of proposed method with Huffman coding is better than the runlength coding for original signal as well as pre-processed signal. Here, original signal is compressed with proposed method are reconstructed more accurately as compare to pre-processed signals as observed. Further, different wavelet transforms are compared for 25 ECG signals, performance of transforms are varying due to different morphology of signals. Here, Coiflet transform achieve higher compression as low cost of reconstruction quality. Overall, the proposed method is suitable for the ECG signal compression; it preserves the signal quality even after the compression.

Compliance with Ethical Standards Conflict of interest: none. **Human and Animal Rights** Authors used the data available in [27] for their study and did not collect data from any human participant or animal.

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