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A secure ECG signal transmission for heart disease diagnosis

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Abstract

Due to the high sampling rate, the recorded Electrocardiograms (ECG) data are huge. For storing and transmitting ECG data, wide spaces and more bandwidth are therefore needed. The ECG data are also very important to preprocessing and compress so that it is distributed and processed with less bandwidth and less space effectively. This manuscript is aimed at creating an effective ECG compression method. The reported ECG data are processed first in the pre-processing unit (ProUnit) in this method. In this unit, ECG data have been standardized and segmented. The resulting ECG data would then be sent to the Compression Unit (CompUnit). The unit consists of an algorithm for lossy compression (LosyComp), with a lossless algorithm for compression (LossComp). The randomness ECG data is transformed into high randomness data by the failure compression algorithm. The data's high redundancy is then used with the LosyComp algorithm to reach a high compression ratio (CR) with no degradation. The LossComp algorithms recommended in this manuscript are the Discrete Cosine Transform (DCT) and Discrete Wavelet Transform (DWT). LossComp algorithms such as Arithmetic Encoding (Arithm) and Run Length Encoding (RLE) are also suggested. To evaluate the proposed method, we measure the Compression Time (CompTime), and Reconstruction Time (RecTime) (T), RMSE and CR. Simulation results suggest the highest output in compression ratio and in complexity by adding RLE after the DCT algorithm. The simulation findings indicate that the inclusion of RLE following the DCT algorithm increases performance in terms of CR and complexity. With CR = 55

Keywords: ECG (Electrocardiogram), Compression ratio (CR), Signal quality

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1. Introduction

ECG is a control system for Electrophysiological recording and measurement of the electrical performance in the heart. A sensors collection, called electrodes, is positioned on the chest or on the human body. These electrodes are collected and sent to an external station to inspect and record the effect of electric pulses in the heart. Due to the high sampling frequency of the collected ECG data, it is difficult to transmit these broad data because of the channel size and the power restrictions[15]. As a solution to the canal storage issue and power usage constraints, data compression is proposed. Compression techniques are commonly known as LosyComp and lossComp. The original data (OrgData) can be completely reconstituted without degradation in the initial data LossComp algorithms. The random scheme and the utilize compression methods just find it impossible to achieve a higher CR [39]. In this work, LosyComp algorithms are thus utilized with an appropriate distortion degree. First, in order to maintain the standard normal distribution and segmented within a ProUnit, the ECG OrgData were standardized. A losyComp algorithm is then applied to the pre-processed files, with a LossComp algorithm. DCT and DWT are utilized in this paper as a LosyComp algorithm for compression. The performance data of the DCT/DWT algorithm are strongly redundant. Therefore, it provides a high CR without additional loss of ECG data to incorporate a LossComp algorithm after the loss compressor Algorithm. RLE and Arithm are used in this work as a lossComp algorithm for compression [30].

A variety of works on the compression of ECG data have been studied. In [26], the authors used only the LosyComp technique, the DCT algorithm, to compress ECG data. In contrast to a lossy use case followed by a LossComp algorithm, the rapid response rate can be improved only by using LosyComp. A compression scheme composed of DCT and RLE followed by Hoffman coding was introduced in [34] by the authors. This compression system can provide high CR, but for compOperations and RecOperations, it is more complicated and time consuming. The authors present a comparative DWT, DCT, and hybrid (DWT + DCT) analysis in [24]. Usage of an algorithm for LosyComp (DCT) followed by a LosyComp algorithm that significantly distorted the ECG data (DWT). A LosyComp algorithm followed a LossComp algorithm in this manuscript to balance the loss of data, CR, and machine complexity. Different combinations of losyComp and LossComp algorithms were tested in order to discover the best output combination. The remaining components of his manuscript are arranged as follows: An overview of compression techniques is given in the second section. In this section, DWT, DCT, Arithm, and RLE are listed. The third section describes the pressure model and performance improvements that are proposed. In Section IV, simulation outcomes are discussed. Finally, the manuscript ends in section five.

2. Data compressing methods

In this section, a summary of the data compressing algorithms used in this manuscript was introduced. Data compression methods are commonly regarded to be techniques of LosyComp and LossComp. The following is a short overview of the algorithms of losyComp/ LossComp used in this work [38, 7]:

A. DCT

DCT is a time series signal transformation technique that converts a signals to the components of its frequency. DCT's key feature is its ability to concentrate the energy of the input signal on the first few coefficients of the output signal. This feature is heavily explored in the field of data compression. Suppose $f(x)$ is the DCT ECG input signal consisting of samples of N ECG data, and that $Y(u)$ is the DCT output signal consisting of N coefficients. The following equation [21, 23] gives the one-dimensional DCT [23]:

$$Y(u) = \sqrt{\frac{2}{N}}\alpha(u)\sum_{x=0}^{N-1} f(u)cos(\frac{\pi(2x+1)u}{2N}) \qquad (1)$$

Where

$$\alpha(u) = \left\{ \begin{array}{ccc} \frac{1}{\sqrt{2}} & , & u = 0 \\ 1 & , & u > 0 \end{array} \right\}$$

The element DC in $Y(0)$ is an average value of the OrdSignal $f(x)$, while the frequency $f(x)$ AC elements of the OrdSignal are different from the average. The opposite DCT action takes the input $Y(u)$ coefficients and transforms them into $f(x)$. The conversion to the reverse DCT is as follows:

$$f(x) = \sqrt{\frac{2}{N}}\alpha(u)\sum_{u=0}^{N-1} Y(u)cos(\frac{\pi(2x+1)u}{2N}) \qquad (2)$$

The majority of DCT coefficients have small values and are typically approximated to zero.

B. DWT

As Fig. 1 shows, the input signal is decayed by DWT into low frequency and high-frequency approximation elements. The decline of the input signal enables a resolution proportional to its scale to be studied on every frequency part [38, 7]. DWT is utilized for the Haar Base Function since it is less complex and performs well. The hair function coefficients are defined in DWT for every 2 consecutive samples $(S_{signal}(2m); S_{signal}(2m+1))$:

$$C_A(m) = \frac{1}{\sqrt{2}}[S_{signal}(2m); S_{signal}(2m+1)] \qquad (3)$$

$$C_D(m) = \frac{1}{\sqrt{2}}[S_{signal}(2m); S_{signal}(2m+1)] \qquad (4)$$

Calculating the $C_A(m)$ and $C_D(m)$ is equal to passing a signals via High Pass and Low Pass filters with a 2 sub-sample factor and standardization by $1/\sqrt{(2)}$, as shown in Equations 3 and 5.

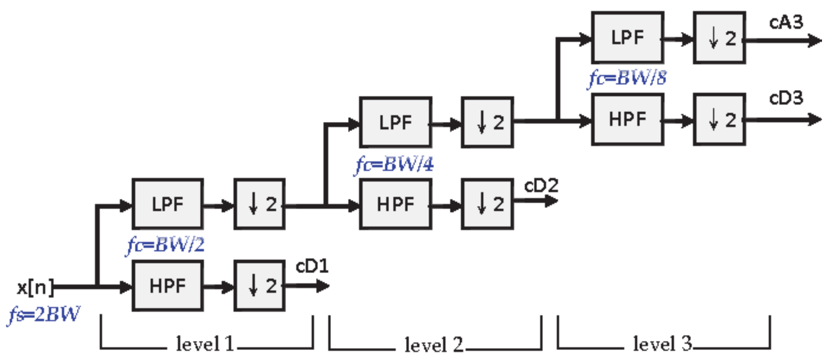

Figure 1: Tree of DWTs

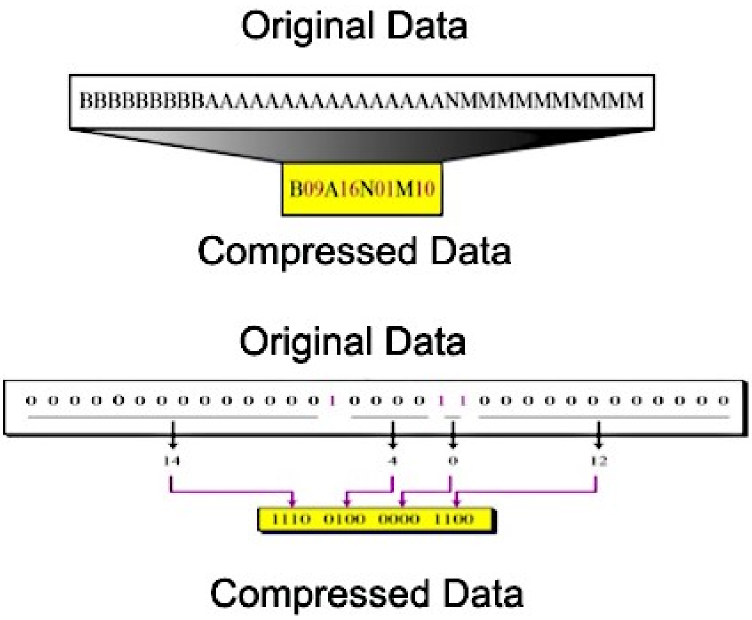

Figure 2: RLE Structure

C. RLE

RLE is the most basic LossComp algorithm for compression. The aim of RLE is for a single value to replace the sequences with the same data value with the series of events as seen in Fig. 2. RLE is effective when handling with data that contains multiple repeat values.

D. Arithm

Arithm is a LossComp data entropy encoding algorithm. Arithmetical codification utilizes a message consisting of input symbols and transforms it into a number less than one and larger than zero (a floating point). Next, the input symbol (data file) is read by the arithmetic algorithm and begins at an interval. The interval is then constrained depending on each symbol's possibility. A new interval needs more bits to start.

3. ECG data compression system proposed

As shown in Fig.3, the suggested compression system consists of a preprocessing unit(PrepUnit), CompUnit, RecUnit, and data combiner unit.

A. PrepUnit

This unit's responsibilities include reading, standardizing, and segmenting recorded ECG data. Standardization gives the ECG data a standard normal distribution property, which permits the ECG data to be given high CR on the same scale. Standardization transfers the mean of the ECG data to zero for the defaults seen in the algorithm. Let X be the ECG data vector; the structured ECG data Xs are given as follows:

$$X_s = \frac{X - \mu}{\sigma} \qquad (5)$$

where μ is the mean and standard deviation of X. In order to improve compression efficiency, the standard ECG data are then segmented with sampling time T_s. As shown in Fig. 3, every T_s second, a segment of the ECG data is produced by the preprocessing device. Consequently, the size of the ECG segment generated depends on T_s. Reducing T_s increases the average duration of compression. The value of T_s, however, can not be reduced below the threshold value to ensure that each inbound ECG segment comes in a new unit following completion of the previous segment:

$$T_s >= max(T_{losyComp}; T_{thrsh}; T_{LossComp}; T_{IlossComp}; T_{IlosyComp}) \tag{6}$$

where $T_{LosyComp}$ is the LosyComp algorithm's time, T_{thrsh} is the thresholding time, $T_{IlossComp}$ is the LossComp algorithm's time, $T_{IlossComp}$ is the inverse LossComp algorithm's time, and $T_{IlossComp}$ is the inverse LossComp algorithm's time. As a result, the following is the minimal sampling time (T_s):

$$T_{min} = max(T_{losyComp}; T_{thrsh}; T_{LossComp}; T_{IlossComp}; T_{IlossComp}) \tag{7}$$

The smallest CompTime and RecTime is achieved at $T_s = T_{min}$.

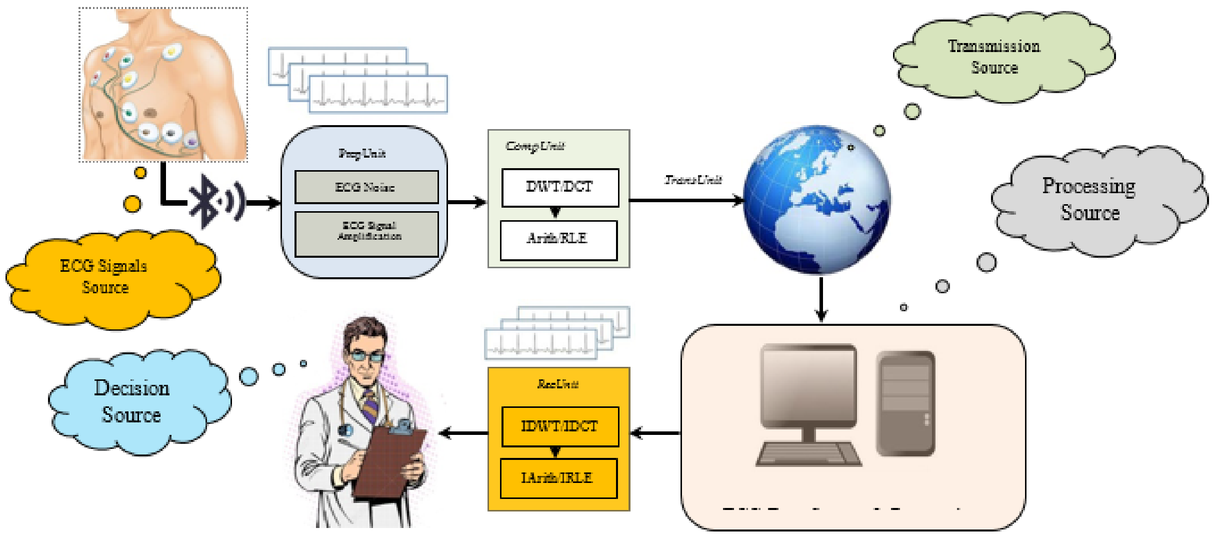

Figure 3: The proposed system infrastructure

B. CompUnit

The unit consists of an algorithm for LosyComp followed by an algorithm for LossComp. As a losyComp algorithm, each DWT and DCT algorithms are uilized. A threshold is then used to maximize the redundancy of the transformed data after the LosyComp algorithm. The transformed data values are set to zero below a threshold value. Consequently, the series of zero coefficients is increased/decreased based on changing of threshold values. The performance of the compression method can then be verified on the basis of the threshold value.

Algorithm 1 Pre-Processing

I/p: ECG_Data_Rec
O/p: Pre-Pro-cessed ECG_Data
▶ **ECG_Data Standarizing**
    Set ECG_data To x
    Set means of x To μ
    Set standard_deviation of x To σ
    x_s Equal to $(x - \mu)/\sigma$
▶ **Samplings**
    Set Number Of Required Samples To N
    Set Length Of ECG_Data To L
    Set floor(L equal to N) To sp
    Set 1 To k
Whilst k **Less than Or Equal to** N **do**
    if k Less then Or Equal to 1 then
    Set ECG Data (1 To sp) To Data
Otherwise
    (k -1) _ sp plus 1 To initially
    Set $(k * sp)$ To finally
    Set (ECG_Data (initial To final)) To Data
End_if
if k equale to N then
    Set ECG_Data($k{*}sp$ plus 1 To L) To vector
    Set [Data_Vector] To Data
End_if
    Set $k$plus sp To k
End_Whilst

To conclude, a LossComp algorithm for compressing is utilized. This method recommends both RLE and Arithmetic algorithms.

C. RecUnit

In order to reconstructing the OrgData of ECG files, the inverse process of the CompUnit is used. The RLE/Arithmetic algorithm is used in the first step, the IDCT/IDWT is applied.

D. Performance evaluation measures

Below are the performance evaluation measures utilized to assess the suggested compression method.

1) Root_Mean_Square_Error ($RMSE$): The difference between two signals' error is measured by the RMSE. The RMSE is then utilized to calculate the difference between the OrgData and RecData in this manuscript. The RMSE shall be:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n) - x'(n)]^2} \tag{8}$$

Where $x(n)$ is an OrgSig, and $x^{'}(n)$ is an an improving of ECG signal.

2) Compressing Ration (CR): The CR measured the varity between the OrgData and the RecData in terms of size as follows:

$$CR = \frac{OrgData\ Size - Compression\ Data\ Size}{OrgData\ Size} x100 \qquad (9)$$

3) CompTime and RecTime (T): The last CompTime and RecTime is the final performance factor used in this manuscript:

$$T = T_{comp.} + T_{re-const} \qquad (10)$$

where T_{comp} and $T_{reconst}$ are the CompTime and RecTime respectively and defined as the following:

$$T_{compr.} = T_{LosyComp} + T_{thrsh} + T_{LossComp} \qquad (11)$$

$$T_{re-const} = TI_{lossComp} + TI_{losyComp} \qquad (12)$$

Finally, the total time is given as follows:

$$T = T_{LosyComp} + T_{thrsh} + T_{LossComp} + TI_{losyComp} + TI_{lossComp} \qquad (13)$$

4) Percentage Root mean Difference (PRD): Accuracy is calculated by percent root mean difference by judicious comparison with the raw data. PRD does not display the exact quality of RecSignal, although it is commonly utilized, and evaluation should be carried out through visual inspection of the signals that have been decompressed. PRD is defined as:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x(n) - x^{'}(n))^2}{\sum_{n=1}^{N} x^2(n)}} x100 \qquad (14)$$

where $x(n)$ and $x^{'}(n)$ equates the OrgSampling and RecSampling values accordingly, and N is the length of window from which the PRD is computed. A lower PRD value, usually between the OrgSignal and the RecSignal, shows less error. A PRD calculation for ECG signal recording is shown in Table 4.3 below. 134 is occupied from the Dataset for “MIT-BIH Arrhythmia”.

5) Root_Mean_Square_Error (RMS): with respect to the OrgSignal, Root_Mean_Square provides the RecSignal error measurements. The RMS meaning is as follows:

$$RMS = 100x\sqrt{\frac{\sum_{n=1}^{N}(x_2(n) - x_1(n))^2}{N-1}} \qquad (15)$$

It is an RMS error between the ECG signal of the OrgSignal and RecSignal.

6) Signal_to_Noise_Ration (SNR): In decibels (dB), SNR is the ”peak signal-to-noise ratio” and can be expressed as follows:

$$SNR = 10x\log\left(\frac{\sum_{0}^{N-1}(X(n) - mean(X))^2}{\sum_{0}^{N-1}(X(n) - Y(n))^2}\right) \qquad (16)$$

The extensive utilization of SNR in ECG data compression literature can be seen in order to measure RecSignal quality in comparison to the OrgSignal.

7) Quality_Score (QS): QS is the CR and PRD ratio, which defines the compression technique's overall efficiency. With fewer errors, a higher Quality Score implies higher compression efficiency. QS is described as continuing:

$$QS = \frac{CR}{PRD} \tag{17}$$

8) Root_Mean_Square_Error ($RMSE$): may be well-defined in the equation that follows as the root_mean_square_error, and this equation is utilized to evaluate the signal:

$$RMSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[x(n) - x'(n)]^2} \tag{18}$$

Where $x(n)$ is an original signal, and $x^{'}(n)$ is an ECG signal improvement.

4. Performance evaluation measures

Python runs Intel (R) Core (TM) i7 3.9GHz CPU and 8 GB of RAM to assess the proposed compression method performance. The ECG data used is 1 MB in size. The CR with various $RMSE$ values is illustrated in Figure 4. As seen in this figure, the better CR in comparison with the Arithm/DCT and RLE/DWT is possible with DCT as a LosyComp algorithm and RLE as a LossComp. The RLE/DWT high CR is based on the DCT's ability to generate high-release results, rendering the use of RLE simpler. At high RMSE, both Arithm/DCT and DWT/RLE have around the same CR. The threshold value is changed to control the RMSE values. The threshold values are selected from 0:005 to 0:05 in these results. The segment-sized CR appears in figure 5. As in this figure, when the section size is raised, the CR increases slightly. The segment's size depends on the time (T_s) of the sample. This means that growing T_s gives large segments and vice versa. This calculation also indicates the highestCR of the RLE/DWT. Figure 6 indicates the CompTime and RecTime with RMSE of both tests. This figure shows that due to its simplicity, both RLE/DCT and RLE/DWT take a short time, while Arithm/DCT is more difficult and takes longer time. Fig. 7 indicates the size of the segment compression and RecTime. As this figure shows, increasing the segment size leads to a longer compression period. Therefore, the sampling time (T_s) controls the segment size is changed between CR and compression time. Fig. 8 provides a contrast of all the proposed CR and T compression algorithms. The RLE/DCT results in both CR and compression times as seen in this figure. Furthermore, RLE/DWT has perfect compression time and CR, while Arithm/DCT uses long period of time in comparison with RLE/DCT and RLE/DWT. Eventually, in the event of a DCT with RLE, Fig. 9 presents the ECG data OrgSinal and RecSignal with separate CR. In Fig. 9, the recovered ECG dates at CR are smallly distorted = 94%, i.e. $RMSE = 0 : 188$, while $CR = 55$. Both original and recovered ECG dates are less distorted, i.e., $RMSE = 0 : 065$ are approximately the same.

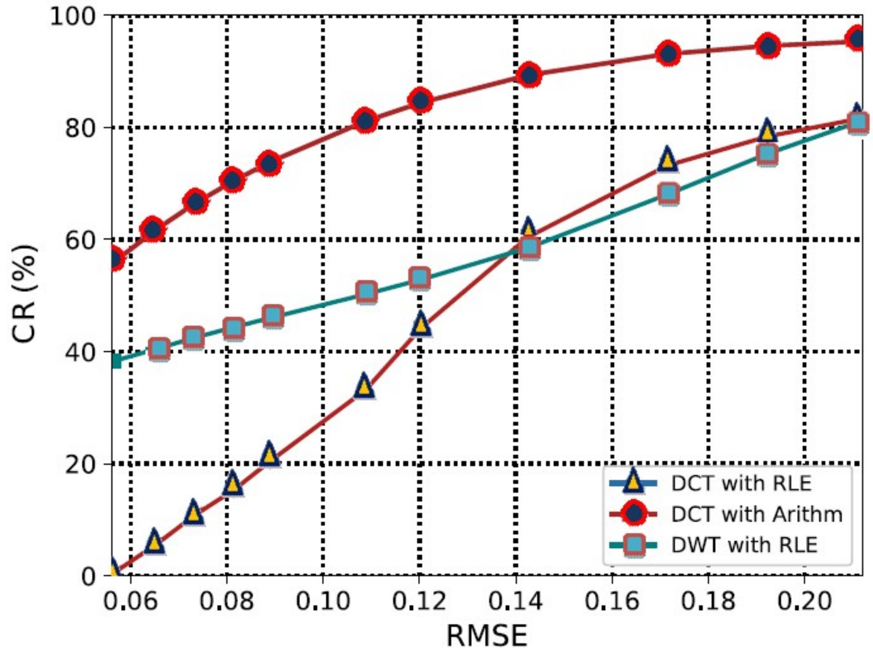

Figure 4: CR versus $RMSE$

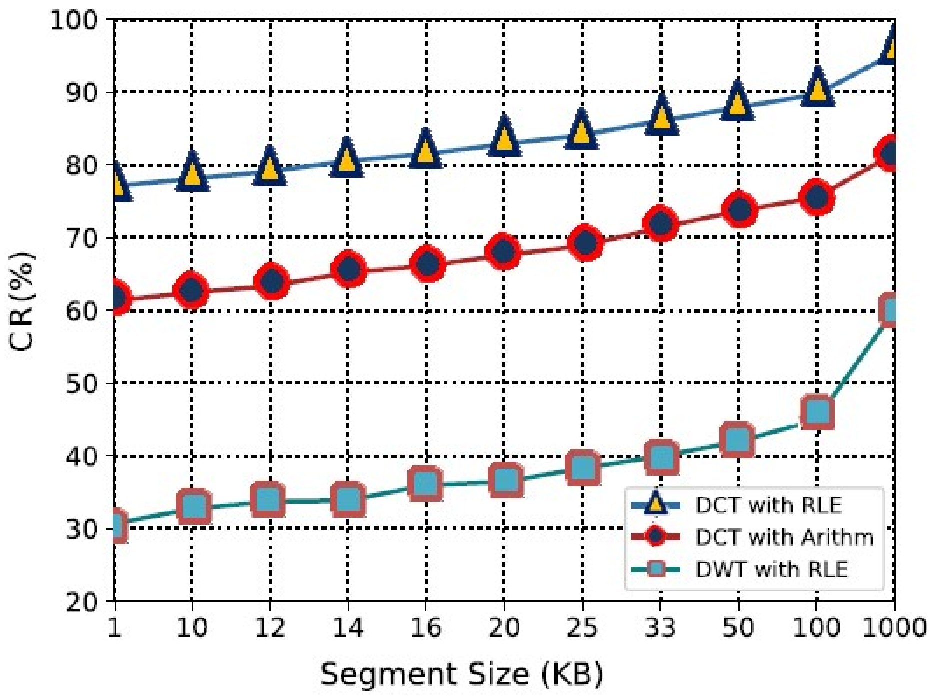

Figure 5: The Size of Segment with Compression ratio (CR)

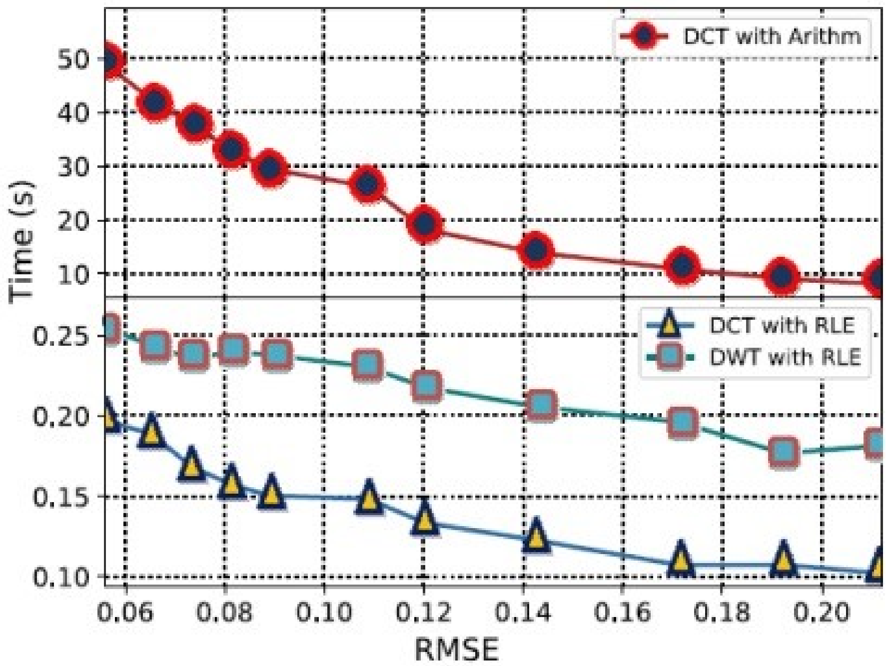

Figure 6: $RMSE$ with ComTime/RecTime of ECG Signal

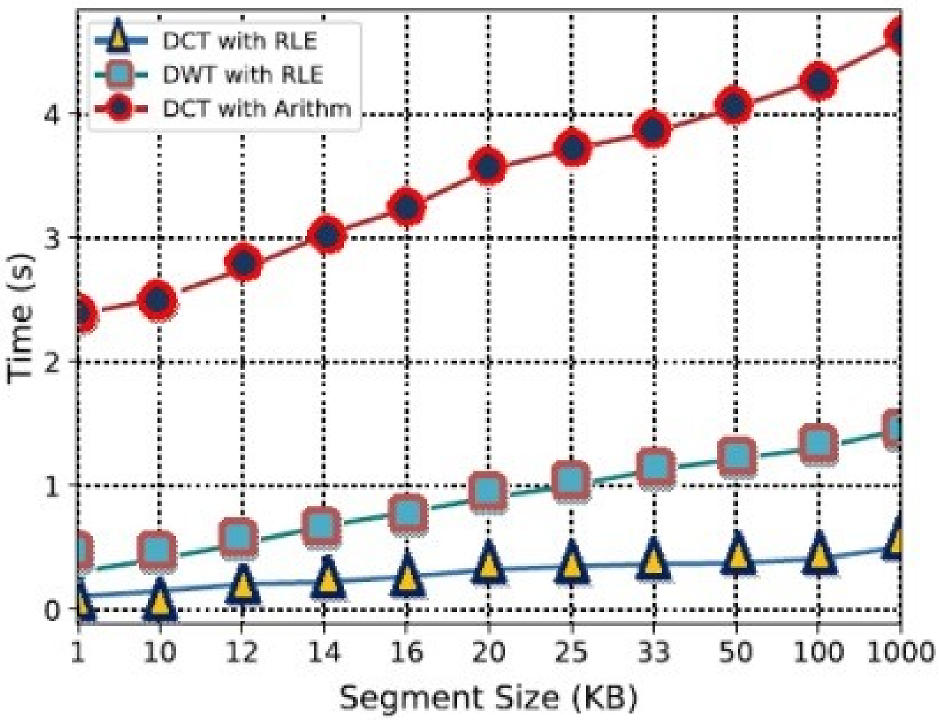

Figure 7: The Size of Segment with CompTime/RecTime of ECG Signal

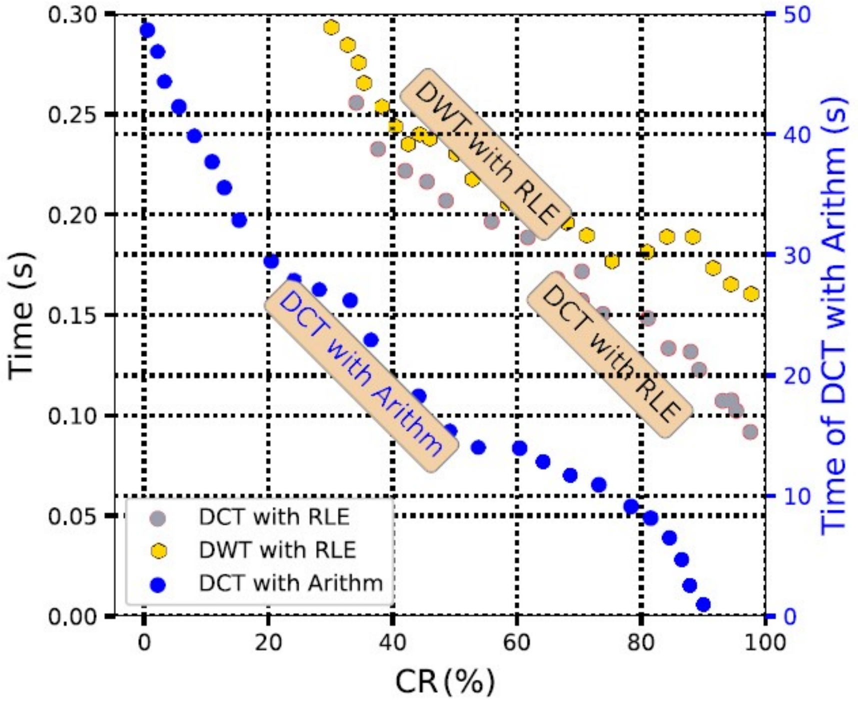

Figure 8: The Time of CompTime/RecTime of ECG Signals V_sCR with Various $RMSE$ Values

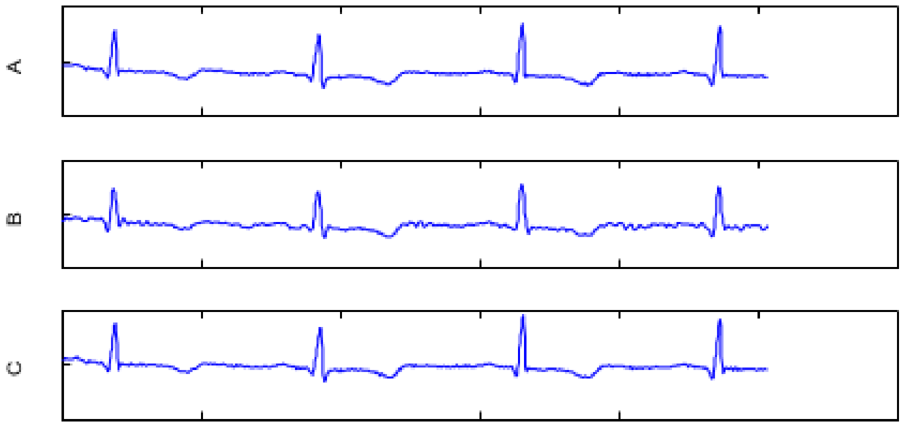

Figure 9: (A) ECG signal in its OrgSignal (B) DCT Utilization For RecSignal (C) DWT Utilization For RecSignal

Algorithm 2 Compressing and Reconstructing

I/p: Pre-pro-cessed_ECG_Data
O/p: Rec_ECG_Data
▶ **LosyComp**
    Then if DCT is chosen
    Set DCT(Preprocessed ECG_Data) To Transformed_Data
Otherwise
    Set DWT(Pre-pro-cessed ECG_Data) To Data_Processed(Transformed)
End_if
▶ **Thresholding**
Set Threshold_Value To Thrsh
Set Sort(jPre-pro-cessed_Dataj) To [Data Sorting, indexing]
    Set I equal to 1
    for Length of Data do
    if $jx(i) = x(1)j > T_{hr}$ then
    Set $i + 1$ To i
    continue
Otherwise
  Stop
End_if
End_for
    Set Transformed_Data(index($i + 1$:end)) Equal to Zero
▶ **LossComp**
    if RLE is Required then
    Set RLE(Transformed ECG_Data) To CompData
Otherwise
    Set Arithm(Transformed ECG_Data) To CompData
End_if
▶**RecUnit**
    if RLE is utilized then
    Set IRLE(ECG_CompData) To Decoded_Data
Otherwise
    Set IArithm(ECG_CompData) To Decoded_Data
End_if
    if DCT is utilized then
    Set IDCT(Decoded_ECG_Data) To RecData
Otherwise
    Set IDWT(Decoded_ECG_Data) To RecData
End_if
▶ Collection_of_Data
    Set [Final_O/p ECG_RecData] To Final_O/p

5. Expermintal findings

The MIT-BIH Arrhythmia Database provided the ECG records (Physionet Bank). DCT and DWT are applied to the same ECG signal (MIT BIH Rec 106 ECG) in this analysis, and the simulation results are described in Table 2. The global threshold is applied in all three cases. Various wavelet filters include Haar, db7, db10, bior3.5, coif3, coif4 and coif 5 are utilized to compress the ECG signal in the case of DWT. The original ECG signaling plot (MIT-BIH 100 record) and its RecSignal version are shown in Figure 10. Table 1 summarizes a comparative study of the various transformations.

Table 1: the results obtained from different transforms

Transform Class	CRs	PRDs	MSEs	MEs	SNRs
DCTs	5.01	9.02	$4.23x10^{-3}$	1.001	19.82
DCTs	7.022	9.88	$4.54x10^{-4}$	1.032	18.35
Haar Based on DWT	4.31	12.89	$2.12x10^{-4}$	1.25	19.68
dB7 based on DWT	4.32	10.43	$4.74x10^{-5}$	1.23	21.33
dB10 based on DWT	4.1	10.2	$6.95x10^{-5}$	1.11	19.13
Bior 3.5 based on DWT	4.3	12.1	$9.04x10^{-3}$	1.31	20.55
Coif3 based on DWT	4.22	7.99	$5.43x10^{-3}$	1.102	20.53
Coif4 based on DWT	4.16	9.01	$5.51x10^{-5}$	1.21	20.42
Coif5 based on DWT	4.42	8.9	$4.63x10^{-4}$	1.06	22.02

Table 2: Performance of the proposed technique based on Rec #106.

Performance Metrics	Realized Values
CR	25.74
QS	13.44
SNR	52.78
PRD	1.91
MSE	0.2

Table 3: Comparison of recommended algorithm performance with actual 50 training Records and The highest CR with the best residual results is obtained.

ECG Records Nos.	CRs %	PRDs %	QSs %	SNRs (dB)
100	19.85	3.28	6.05	52.77
101	17.95	3.60	4.99	55.70
102	21.35	4.18	5.11	51.65
103	19.33	4.09	4.72	59.75
104	21.16	5.30	3.99	53.58
105	20.02	4.57	4.38	57.78
106	18.66	4.92	3.79	57.48
107	21.94	5.58	3.93	56.99
108	23.18	4.71	4.92	49.96
109	22.36	5.01	4.47	56.16
111	21.17	5.58	3.79	52.58
112	22.91	2.07	11.08	47.31
113	20.81	4.53	4.60	60.23
114	22.48	4.17	5.39	51.09
115	22.25	3.13	7.11	55.33
116	19.47	2.89	6.75	57.75
117	25.74	1.91	13.44	52.78
118	23.83	3.31	7.19	48.85
119	26.01	4.41	5.89	51.00
121	32.47	2.36	13.73	53.14
122	21.71	2.39	9.10	54.93
123	24.38	2.69	9.06	50.92
124	27.12	2.20	12.34	57.97
200	22.64	7.64	2.96	50.04
201	16.04	3.71	4.33	60.18
202	24.73	4.72	5.24	58.11
203	19.37	7.14	2.71	51.88
205	19.68	3.04	6.48	53.05
207	28.23	6.15	4.59	54.75
208	21.36	7.83	2.73	50.64
209	15.38	4.61	3.33	56.70
210	21.87	5.92	3.70	53.28
212	16.77	5.52	3.04	55.51
213	15.61	4.04	3.86	60.41
214	24.15	5.74	4.21	55.14
215	20.18	8.65	2.33	46.92
217	22.48	4.95	4.54	59.55
219	23.35	4.80	4.86	49.33
220	20.80	3.20	6.49	53.22
221	22.14	5.36	4.13	54.94
222	21.66	5.49	3.95	51.70
223	21.00	2.73	7.70	61.04
228	27.12	8.41	3.22	47.73
230	18.52	5.28	3.51	56.13
231	19.61	4.89	4.01	56.48
232	17.09	5.24	3.26	44.62
233	19.74	6.68	2.95	53.37
234	19.10	4.51	4.24	59.62
Average	21.56	4.65	5.38	54.17

Table 4: finding simulation between the literature, methods and the recommended method for a dataset in record 117.

Record Number #	CRs %	PRDs %	MSEs %	PSNRs %
# 117- Based Literature 1	11.6	5.3	0.5	31.05
# 117- Based 2	14.9	5.83	0.36	29.98
# 117- Based Literature 3	14.3	2.43	0.4	33.91
# 117- Based Literature 4	15.1	2.5 0.52	33.44	
# 117- Based Literature 5	5.65	3.63	0.41	30.1
# 117- Based Literature 6	7.8	1.973	0.33	32.54
# 117- Based Literature 7	16	2.29	0.28	30.88
# 117- Based on Recommended Method	25.74	1.911	0.2	36.84

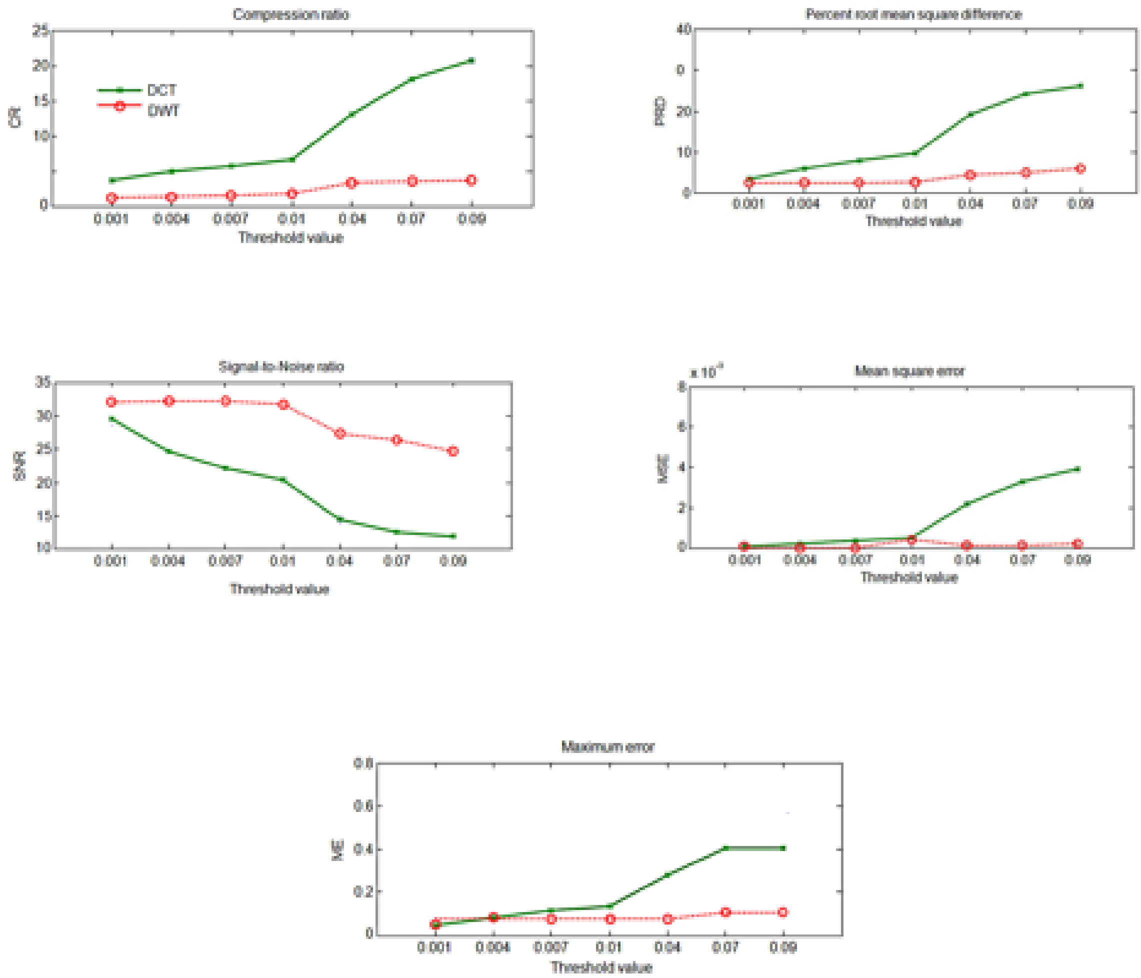

Figure 10: Varios Measurements Parameters with Threshold of ECG Signals CompSignal/RecSignal Based on Various Techniques

6. Conclusion

In this manuscript, a compression scheme consisting of losyComp and LossComp algorithms is developed. LosyComp techniques include DCT and DWT shift followed by threshold. As a

LossComp algorithm, we utilize RLE encryption and computation. The data generated by the missing compression portion has a high redundancy rate, which makes it easier to utilize non-LosyComp algorithms. CRs, RMSEs, and CompTime are computed to verify system efficiency. utilizing DCT as a LosyComp followed algorithm by RLE as a LossComp algorithm yields better findings than DWT and computational coding. The presented work can be developed as a future technology for purposes of ECGs signals compressing utilizing both DCT and RLE on HW devices and verifying their performance in various applications in real-time.

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