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Lossy ECG signal compression based on RR intervals detection with wavelet transform and optimized run-length encoding

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ABSTRACT

It is expensive to transmit or store significant amounts of electrocardiogram (ECG) records, particularly when using telecommunications channels that charge according to the volume of transferred data. The advancement of telemedicine renders compressing ECG signals even more necessary. Compression aims to reduce the size of data while maintaining the features of ECG signals. This paper presents a novel strategy for compressing ECG signals based on 3D format conversion. After identifying the RR intervals, we divide the signal into cardiac cycles and proceed with the cut and align process. A 3D discrete wavelet transform (DWT) is employed to minimize the correlation existing between two adjacent voxels. Moreover, an optimized run-length encoding (RLE), a novel lossless compression technique, has been proposed to increase the compression ratio (CR). The proposed strategy is applied to different types of ECG records of the Arryyhmia database. This algorithm demonstrates improved performance in terms of CR and percentage root-mean-square difference (PRD) compared to several recently published works.

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1. INTRODUCTION

Cardiac activity is reflected by the features of the electrocardiogram (ECG) signal. This last can be extracted by placing electrodes on the skin surface [1]. The storage and transmission of ECG signals has become a significant issue, especially because of the very fast development of telemedicine over the last decade [2]. In most ECG acquisition systems, the signal is recorded at a frequency of 1 kHz for high-resolution ECG [3]. For example, one recording per day at a resolution of 12 bits/sample requires, on average more than 1 gigabits of memory space. These figures far exceed the capacities of conventional storage and transmission systems. Compression of the ECG is therefore desirable if not necessary for archiving or transmission for later analysis [4]. ECG compression techniques are usually classified into three main categories: direct methods, methods using transforms, and methods based on the principle of extraction of characteristic parameters [5]. In direct methods, the signal samples are directly encoded without any transformation. The second category requires the transformation of the ECG in a domain other than the temporal domain. This can be for example, a discrete wavelet transform (DWT) type transformation. Finally, the third category uses the principle of parametric modeling of the ECG. These parameters are obviously reused in the reconstruction phase [6], [7].

ECG compression techniques can be classified as lossy or lossless. Lossless methods ensure that all diagnostic information is preserved, resulting in perfect fidelity to the original signal. However, these algorithms produce very low compression ratios (CR), leading to increased bandwidth and storage consumption. Losssless algorithms are usually based on statistical modes, integer transforms, dictionnary and prediction methods. In contrast, lossy compression methods remove a portion of the data while preserving the quality of the restored ECG signals, including essential features. Lossy ECG compression achieves high CRs. Using lossy and then lossless compression techniques, some approaches combine the two processes to further enhance the data and generate large reductions [8].

In the literature, many recent research studies have been developed in the field of ECG signal compression, in both cases lossless and lossy compression. In the lossless case, the authors of a recent paper by Fathi *et al.* [9] have minimized the remote healthcare monitoring system's energy consumption. The algorithm employs discrete Krawtchouk moments as a feature extractor to extract features from the ECG signal. In another work [10], the ECG compression system is based on a multichannel linear prediction and adaptive linear prediction algorithm.

In the lossy compression domain, Boukhennoufa *et al.* [11] have published an ECG data compression based on the set partitioning in hierarchical trees (SPIHT) technique combined with the vector k-tree partitioning (VKTP) encoder. This approach aims to increase the performance of compression method and reduce reconstruction errors. A deep-learning compression method has been presented by Shi *et al*. [12]. It is based on a binary convolutional auto-encoder equipped with a residual error complement. Kolekar *et al*. [13], have developed an electrocardiogram compression technique that uses modified run-length encoding (RLE) of wavelet coefficients. Mohebbian and Wahid [14], a semi-lossless strategy is proposed to compress the data, which can be used for monitoring and visualization. The model uses ant colony optimization combined with B-spline interpolation for compression. Luanloet *et al.* [15], developed an efficiency compression technique including RLE, scalar quantization, discrete cosine transform (DCT), Savitzky-Golay filtering, and Huffman coding. Chandra *et al.* [16], studies were performed on various combinations of wavelets and coding schemes to determine optimal parameters. Tun *et al.* [17] encodes an ECG by wavelet compressing with both local and global thresholds. Jha and Kolekar [18] ECG compression is performed using DCT and discrete orthogonal Stockwell transforms. Hamza *et al.* [19], have proposed a dual encoding scheme and an efficient ECG signal compression approach using DWT. The scanning description of ECG signals is the objective of the paper in [20]. The linear prediction and modified Huffman coding are implemented for analysis.

Compression based on the conversion of the 1D ECG signal into 2D allows for better performance in terms of compression efficiency for high-rate recording and transmission [21]. However, both 1D and 2D ECG data compression methods have advantages and disadvantages of their own [22]. Thus, in this work, we propose a new method for compressing biomedical ECG signals based on wavelet transforms and an efficient lossless encoder called optimized RLE. Our approach is applied to volumetric ECG signals to increase the CR and minimize the reconstruction error. To obtain 3D ECG signals, a detection of RR intervals is first needed. This last is based on QRS detection, which is of paramount importance in the automatic analysis and compression of ECG signals. Once the waves are identified and their positions located, it becomes easy to evaluate other parameters of the signal, such as the RR interval, the duration of the cardiac cycle in order to calculate heart rate, diagnosing arrhythmias, and assessing heart rate variability. Additionally, it helps in our proposed approach in cut and align process.

In this article, we propose three approaches for compressing ECG signals based on the transformation of the original one-dimensional ECG signals into a 2D format, followed by a new algorithm that converts the ECG signals into 3D. We will begin with the detection of the RR intervals according to many steps of the well-known Pan and Tompkins method [23], and then establish the evaluation criteria to assess the effectiveness of the compression algorithm by making comparisons with other ECG signal compression methods.

The remaining parts of this article are organized in the following sections: in section 2, the ECG characteristics and QRS detection and a short concept of wavelet transform are given. The description of the methodology is detailed in section 3. In the last section, a discussion of the obtained results is provided. Finally, in section 5, we summarize the synthesis of our work with a conclusion.

2. BACKGROUND

This section describes ECG characteristics and explains the main concepts used in our study, including QRS detection and DWT transform.

2.1. ECG signal characteristics

An ECG signal is constituted of P waves, QRS complexes, and T waves, as shown in Figure 1. By checking the variations of these waves, different cardiac diseases can be analyzed [24]. The frequency bands of a normal ECG are:

- ECG range: from 0 Hz to around 100 Hz.
- P wave: low frequency, low amplitude band of spectral components with frequencies of 0.5 Hz to 10 Hz.
- The T wave has a spectral band from 0.5 to 10 Hz analogous to the P wave. The frequency of the QRS complex is higher than the other ECG waves.
- The QRS complex has much higher frequency than the rest of the ECG waves. There are frequency components between 10 Hz and 15 Hz.
- The frequency of the baseline and any motion artifact is between 0.5 Hz and 7 Hz. High frequencies are between 15 Hz and 40 Hz.
- Very low frequencies are 5 Hz to 15 Hz, and extremely low frequencies are less than 4 Hz.

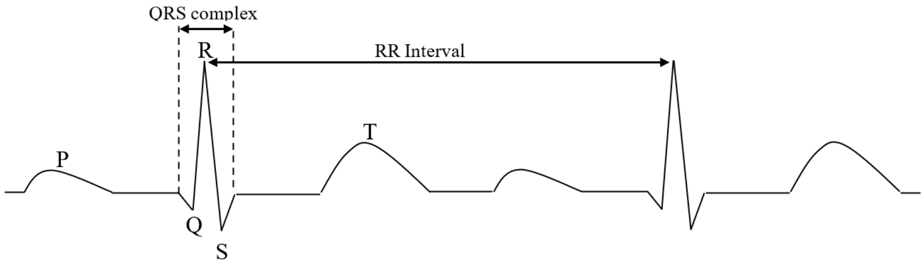


Figure 1. Morphology of an ECG signal

2.2. QRS detection

The morphology of QRS complexes varies from person to person and even from cycle to cycle within the same subject. Detecting these complexes is a difficult task. Furthermore, the QRS complexes' characteristics are shared by other waves in the signal, including the P and T waves, as well as disturbances from different sources.

Many strategies were developed in the field of R peak detection, for example in Giovanni *et al.* [25] presented an adaptive algorithm that enhances R-peak detection accuracy in ECG signals during strenuous physical activities. Also, an innovative approach based on intelligent signal processing (ISP) for R-peak detection is developed in [26]. The method comprises three main stages: decomposition of the ECG signal using fractional wavelet transform or fractional fourier transform. The limitations of the proposed algorithms are sensitivity to noise which can degrade R peak detection, computational complexity, calculating RR intervals accurately in real-time, which is crucial for telemedicine and wearable devices [25].

Pan and Tompkins [23] developed one of the most popular algorithms based on this principle. These techniques suffer from two major issues: the first is that the bandwidth of the QRS complex differs from one individual to another, and even within the same subject from cycle to cycle. The second difficulty is the choice of the decision threshold. The threshold is generally set empirically, and additional conditions must be taken into account before making the final decision.

2.3. Discete wavelet transform

Since the wavelet transform preserves significant signal properties, it is frequently used to compress ECG data. It offers multiresolution analysis by separating high-frequencies and low-frequency elements in different levels. Its improved time-frequency localization makes it possible to handle the non-stationary nature of ECG data better, in term of efficiency, than more traditional techniques like the DCT. This last is unsuitable for ECG compression due to its assumption of signal stationarity and poor time-frequency localization.

The 3D DWT is a great framework for volumetric data analysis by bringing traditional wavelet transforms into 3D. Figure 2 shows the decomposition of a 1D signal (Figure 2(a)), an image (Figure 2(b)), and a volume (Figure 2(c)) using the first level of DWT. The 3D DWT can be applied to 3D models and decomposed into multiple frequency components in different spatial dimensions. This multiscale analysis is useful for us since it allows us to extract both global and local information. By combining high-pass and low-pass filters, the 3D DWT allows a hierarchical decomposition that records different features at different resolutions.

In the first step, the information (1D, 2D, or 3D) is filtered along the x-direction and produces a low-pass image (L) and a high-pass image (H). Then L and H are filtered along the y-direction and produce 4 subbands: LL, LH, HL, and HH in 2D or 3D information. Finally, these 4 subbands are filtered along the z-direction and produce 3D 8 subbands: LLL, LLH, LHL, LHH, HLL, HLH, HHL, and HHH. Among these, LLL is the approximation component and represents the overall approximation of the volume [27].

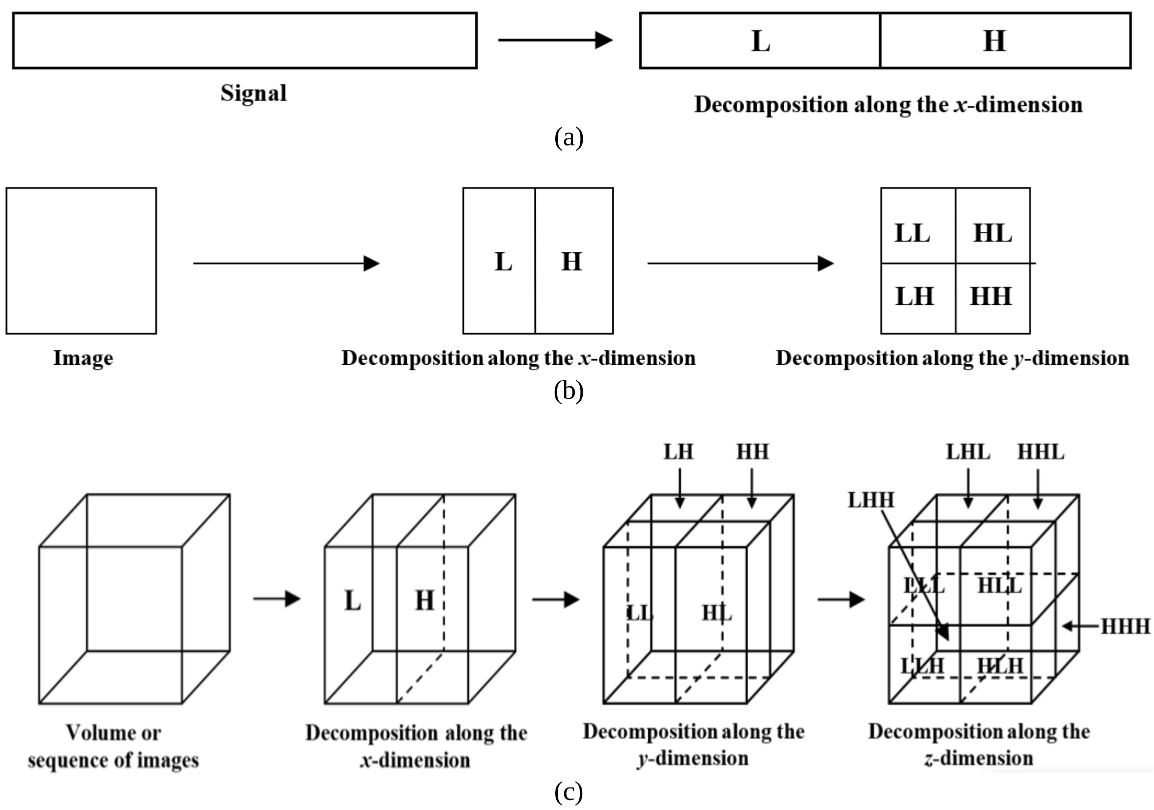


Figure 2. Discrete wavelet decomposition for one level of decomposition; (a) signal, (b) image, and (c) volume

3. METHOD

The MIT-BIH arrhythmia database [28] contains 48 sets of ECG data, which are sampled at 360 Hz. Every signal has two different leads of the ECG signal. All of the 48 recordings are 30 minutes long. The steps shown in Figure 3 have been proposed for compressing the one-dimensional ECG signal.

A three-level DWT was applied. The three-level decomposition was carried out using the biorthogonal wavelet bior4.4. Biorthogonal wavelets are excellent for compression of ECG signals compared to other wavelet families. An adaptive threshold is applied to wavelet coefficients for each ECG signal. The thresholding process removes insignificant coefficients, while preserving essential features.

In this section, we leverage the correlation between samples to enhance the efficiency of the compression. An adaptive threshold is applied to increase the number of repetitions of zeros. It can be said that the coefficients of low values are lost. The redundancy of the elements is significant in the coding stage. In the quantization step, we also lose information; we must lose it in a confirmed and clever manner since the quality of the restored signal depends on the threshold and the quantization step. Quantization is carried out by performing the Euclidean division of the coefficients.

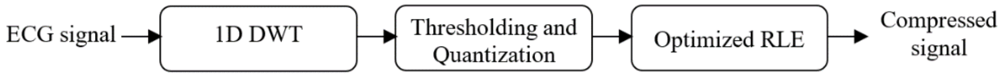


Figure 3. Compression scheme using 1D DWT

This article also proposes and refines an optimized RLE approach to overcome the issue of compressed signals exceeding the size of the original signal. It has a low computational complexity and is an effective compression method for wavelet coefficients. The elaborated steps include:

1. Determination of *n* binary digits for each of the appearances.
2. Determination of *b* binary digits for the average lengths of the sequences of repetitive values.
3. For all appearances in the sequence, the following applies:
   - If the occurrence is not repeated, then insert a ‘0’ followed by the index value *i* in binary on “*n*” bits.
   - If there is a sequence of repeated occurrences of the same value, then insert “1” followed by the number of repetitions in binary on “*b*” bits, then the representation of that value in binary on “*n*” bits.

The well-known standard RLE replaces sequences of repeated elements (runs) with a single value of 8 bits and a count of 8 bits. The performance of both the standard RLE and the optimized RLE improves as the length of the repeated sequences increases. An illustrated example of the optimized RLE algorithm is given in Figure 4. Note that the sequence in Figure 4(a) of a length of 72 bits is coded in 64 bits using the standard RLE and is compressed to only 42 bits (Figure 4(b)) by the optimized RLE.

The 2D ECG compression is an approach used to exploit the existing redundancies between two adjacent beats and between adjacent pixels. The block diagram of such an algorithm is presented in Figure 5. R peaks are used to accurately measure the time between heartbeats. This section describes an algorithm that can be used to find R peaks and the corresponding RR intervals. Pan and Tompkins [23] method is the foundation for our algorithm.

Figure 6 illustrates each step of the R peaks detection (RR interval). First, a band-pass filter is applied to the ECG signal and its derivative is calculated. A nonlinear transformation is then performed, called the squaring operation. Finally, thresholding is employed to identify R peaks [23].

(a)	65	65	66	66	66	67	67	67	68	
	8	8	8	8	8	8	8	8	8	= 72 bits

(b)	1	10	65	1	11	66	1	11	67	0	68	
	1	2	8	1	2	8	1	2	8	1	8	= 42 bits

Figure 4. Example of the optimized RLE (a) initial sequence and (b) coded sequence with the optimized RLE

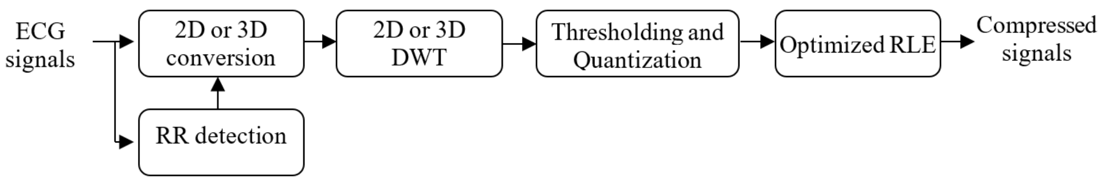


Figure 5. Compression scheme using RR detection with 2D or 3D DWT

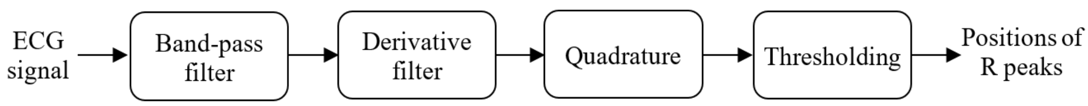


Figure 6. Steps of detection of R peaks

The ECG signals are filtered using a bandpass filter that focuses on frequencies between 5 and 15 Hz. This allows most of the energy from the R waves to pass through while reducing remaining noise. That is why a low-pass filter and a high-pass filter are applied. These two filters operate in series as a bandpass filter with a bandwidth of about [5, 15] Hz, which allows us to eliminate muscle noise at the main frequency (50 Hz). In (1) and (2) are the transfer functions of a second-order low-pass filter *L(z)* and a high-pass filter *H(z)*, respectively.

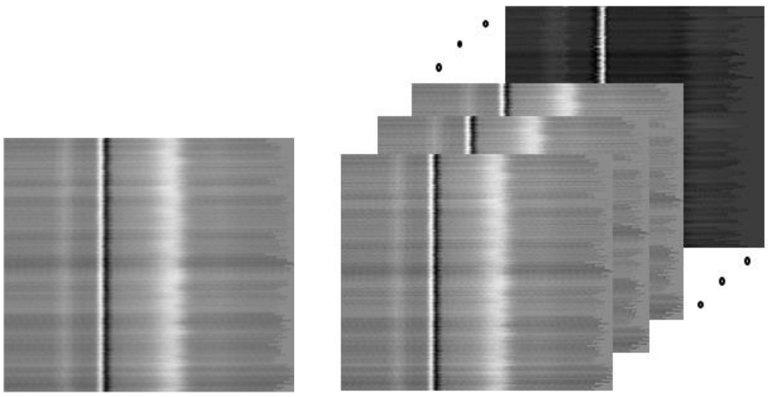
$$L(\mathrm{z}) = \frac{(1-\mathrm{z}^{-6})^2}{(1-\mathrm{z}^{-1})^2} \quad (1)$$

$$H(z) = \frac{(-1+32z^{-16}+z^{-32})}{(1+z^{-1})} \quad (2)$$

The derivative of the signal at this level shows high maximum values. We therefore continue the signal processing by applying a digital derivative filter (expressed by *D(z)* in (3)), where *T* is a constant. The obtained signal is then squared to eliminate the sign of the signal. The R peaks in the next stage have the highest amplitudes. To identify the locations of the R peaks, the signal can be thresholded by setting a threshold at 70% of the maximum value. Searching for R peaks involves detecting local maxima in the most recently obtained signal that exceed the specified threshold.

$$D(z) = \frac{1}{8T}(-z^{-2}-2z^{-1} + 2z^{1} + z^{2}) \quad (3)$$

Due to the pseudo-periodic nature of the signals, detecting R peaks is necessary to convert 1D ECG signals into a 3D format. The maximum RR interval determines the dimensions of the 2D structure, as shown in Figure 7. A “cut and align” process is employed to create a 2D grid filled with normalized ECG segments, scaling the amplitudes to a range of 0 to 255. To ensure uniform segment length, we pad shorter segments with a suitable value of 128, which will be ignored during the reconstruction phase (see Figure 7(a)). This systematic approach allows for effective organization and visualization of the ECG data. The transition from one plane to another in the 3D conversion is automatic each time a plane is filled (see Figure 7(b)).



(a) (b)

Figure 7. Format conversion (a) 1D/2D of 117.dat ECG signal and (b) 1D/3D of a set of ECG signals

The most common metrics in assessing any compression strategy are CR and percentage root-mean-square difference (PRD). CR is the ratio of the size of the original data to the size of the compressed data [23]. Its formula is given by (4). The reconstruction error is the relative difference between the original and reconstructed signal. The PRD is computed using the expression (5) [2]. Increasing CR leads to an increase in PRD, indicating a deterioration of quality as redundancy is reduced.

$$CR = \frac{Number\ of\ bits\ of\ the\ original\ signal}{Number\ of\ bits\ of\ compressed\ signal} \quad (4)$$

$$PRD = \sqrt{\frac{\sum_{i=0}^{N-1}(x_{org}-x_{rec})^2}{\sum_{i=0}^{N-1}x_{org}^2}} \times 100 \quad (5)$$

Where: x_{org} and x_{rec} represent the original signal and the reconstructed signal, respectively, with *N* samples.

4. RESULTS AND DISCUSSION

Table 1 presents the numerical values of CR and PRD for the standard RLE, arithmetic coding, and optimized RLE techniques. Compression of the ECG signal is performed in its original form (1D), minimizing distortion (PRD value = 1.89%) for eight recordings. The average CR is 7.57 for the optimized

RLE algorithm, compared to 4.60 for the standard RLE algorithm and 6.77 for arithmetic coding. The proposed lossless coder is the most efficient and is best suited for our application.

Table 1. Comparison of numerical results obtained from three lossless coders

Record	Optimized RLE (proposed) CR	Arithmetic coder CR	Standard RLE CR	PRD (%)
100	8.39	7.70	5.23	2.21
103	7.67	7.55	4.13	2.86
109	6.30	6.18	3.82	0.81
113	8.95	7.36	4.40	3.18
117	7.26	6.46	4.84	1.49
119	6.36	6.13	3.68	2.70
121	8.20	6.43	5.99	0.55
124	7.44	6.40	4.74	1.37
Mean value	7.57	6.77	4.60	1.89

The use of the bior4.4 mother wavelet is justified by the results obtained in Table 2. In this table, three mother wavelets have been used: bior4.4, bior3.7, and db6. The comparison is made based on the CR/PRD ratio of the different mother wavelets using our optimized RLE algorithm. The average value of the calculated ratios is 5.81 using bior4.4 compared to 5.03 for bior3.7 and 5.30 for db6. A good compromise between CR and PRD requires having the highest possible CR/PRD ratio.

The results of the 3D compression were compared with those of the 1D and 2D. Table 3 shows the good ratio compression efficiency achieved using the 3D format. The mean value of the ratio CR/PRD in 3D compression is 4.13 against 3.66 and 3.77 in 1D and 2D compression, respectively.

Table 2. Compression results for different mother wavelets

Record	Bior4.4			Bior3.7			Db6		
	CR	PRD (%)	CR/PRD	CR	PRD (%)	CR/PRD	CR	PRD (%)	CR/PRD
100	8.39	2.21	3.79	7.21	2.15	3.35	7.95	2.33	3.41
103	7.67	2.86	2.68	6.69	2.68	2.49	7.17	3.04	2.35
113	8.95	3.18	2.81	8.56	3.00	2.85	8.79	3.51	2.50
117	7.26	1.49	4.87	5.42	1.34	4.04	6.75	1.47	4.59
121	8.20	0.55	14.90	6.47	0.52	12.44	7.79	0.57	13.66
Mean value	8.09	2.05	5.81	6.87	1.93	5.03	7.69	2.18	5.30

Table 3. Comparative study between different formats

Record	1D compression		2D compression		3D compression	
	CR	PRD (%)	CR	PRD (%)	CR	PRD (%)
100	8.39	2.21	8.52	2.54	12.72	2.66
103	7.67	2.86	8.55	2.35	11.92	2.13
109	6.30	0.81	9.13	1.17	12.08	2.07
113	8.95	3.18	7.96	2.65	13.45	3.71
117	7.29	1.49	8.24	2.29	11.74	2.08
119	6.36	2.70	6.94	2.58	11.34	2.78
121	8.20	0.55	9.63	2.43	10.27	2.64
124	7.44	2.73	8.33	1.86	11.56	2.17
Mean values	7.57	2.06	8.41	2.23	11.88	2.87
Mean values of CR/PRD	3.66		3.77		4.13	

The original 100.dat ECG record, its reconstructed signal, and the reconstitution error resulting from the 3D compression/decompression method are shown in Figure 8. The original signal (Figure 8(a)) and the reconstructed one (Figure 8(b)) are almost identical. The visual reconstruction error is very low (Figure 8(c)). The visual results indicate that our method maintains a good quality of restored ECG signals.

A comparison of our method with some recently published algorithms for ECG signal compression is included in Table 4. Tun *et al.* algorithm's [17] CR values range between 9.17 and 10.79, which is an acceptable CR. The PRD values, which range from 0.18% to 0.42%, show very little distortion of the ECG signals and are all far below the permissible cutoff of 5%. For record 119.dat, the PRD of the Jha and Kolekar algorithm [18] is 10.83%, which is much higher than the maximum permitted value and less appropriate for correct ECG interpretation. With a comparatively high CR of 14.16 for record 119.dat, the algorithm of Hamza *et al.* [19] demonstrates its significant compression ability. Despite the increased CR, the

PRD of 6.00% shows that the allowable limit is exceeded, indicating significant distortion that may affect clinical reliability. For the signal 100.dat, the obtained CR in the Surekha and Patil approach [20] is 6.70, which is lower than the other techniques. Nevertheless, it shows an excellent distortion performance despite the lower compression, achieving an outstanding PRD of 0.03% for the record 109.dat. Strong compression performance is demonstrated by our suggested approach, which shows CR values ranging from 11.34 to 12.72 across a variety of records. Ranging from 2.07% to 2.78%, the PRD values are all below the 5% threshold. This demonstrates that the suggested algorithm achieves a good balance between minimal distortion and high CR.

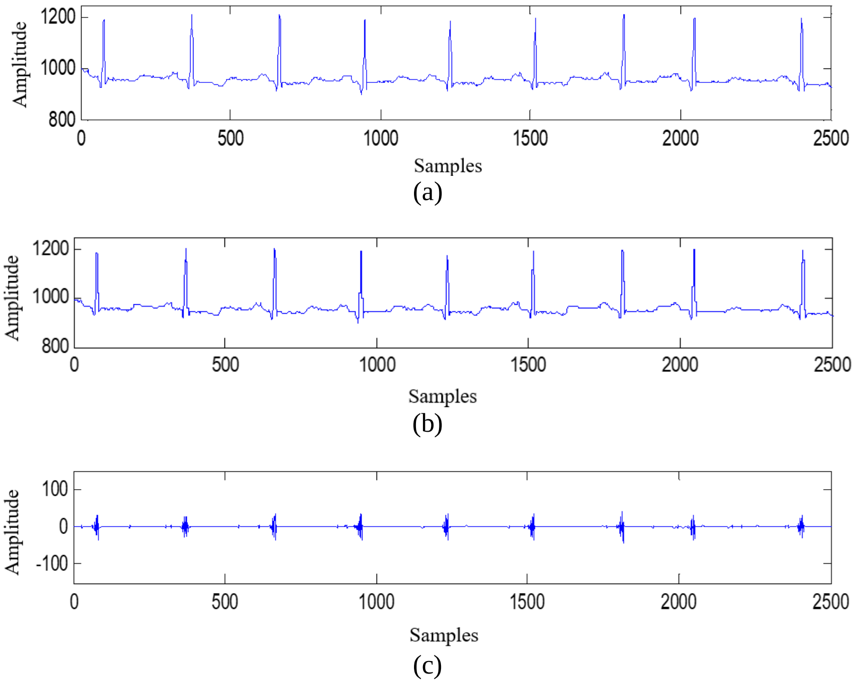


Figure 8. 3D compression/decompression of 100.dat ECG signal; (a) original ECG signal, (b) reconstructed ECG signal, and (c) error of reconstruction

Table 4. Comparative results of our approach with some existing techniques

Algorithm	Record	CR	PRD (%)
Tun *et al.* [17]	100	10.79	0.42
	103	9.32	0.22
	109	9.17	0.18
Jha and Kolekar [18]	119	8.15	10.83
Qasim Hamza *et al.* [19]	119	14.16	6.00
Surekha and Patil [20]	100	6.70	0.50
	109	11.06	0.03
Proposed algorithm	100	12.72	2.66
	103	11.92	2.13
	109	12.08	2.07
	119	11.34	2.78

5. CONCLUSION

Our compression technique is based on dimensional conversion (from 1D to 2D and 3D) formats and the 3D DWT transform. To improve the CR, we also proposed a new compression technique that we called optimized RLE. Our approach is applied to a set of ECG signals of the used dataset all at once. Its limitation involves being sensitive to noise, which may affect R peak identification. The obtained results have shown that the 3D approach is very effective and performs better than 1D and 2D domains in terms of CR and reconstruction fidelity. This is due to the strong correlation existing between two adjacent voxels in 3D. Compared with some recently published works, the proposed algorithm is the most effective approach in terms of achieving a high CR while minimizing PRD. The robust performance across different records makes our strategy a reliable choice for practical applications. For future research, a denoising step will be incorporated and applied to ECG signals contaminated by different noise sources.

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AUTHOR CONTRIBUTIONS STATEMENT

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C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are openly available in the MIT-BIH Arrhythmia Database, available at [https://physionet.org/content/mitdb/1.0.0/].

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