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PROPOSED ALOGORITHM FOR ECG DATA COMPRESSION BASED ON ADM

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ABSTRACT

Electrocardiographic (ECG) signals are biomedical signals commonly used to predict cardiovascular disease. When telemedicine-based healthcare systems are needed, ECG recordings must be stored and transmitted. This data is stored in a digital format with a higher number of bits per sample, which requires significant storage space. Therefore, data compression is very important to save storage space and bandwidth. Therefore, we propose a new compression technique based on the structure of the ECG signal. Our proposed technique consists of adaptive delta modulation (ADM) and arithmetic coding (AC). The proposed technique was tested on the MIT-BIH arrhythmia database. The average compression performance in terms of compression ratio (CR), percent root mean square difference (PRD), quality level and signal-to-noise ratio is 16.5, 2.5, 6.6 and 74.8 dB for 48 data sets for 1 min of data compression.

KEYWORDS: Electrocardiogram, Adaptive Delta Modulation, Arithmetic coding.

خوارزمية مقترحة لضغط بيانات تخطيط القلب الكهربائي استنادًا إلى تعديل دلتا التكيفي

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الملخص

الإشارات الكهربائية للقلب (ECG) هي إشارات طبية حيوية تُستخدم عادةً للتنبؤ بأمراض القلب والأوعية الدموية. وعند الحاجة إلى أنظمة الرعاية الصحية القائمة على الطب عن بُعد، يجب تخزين تسجيلات ECG ونقلها. يتم تخزين هذه البيانات بصيغة رقمية بعدد كبير من البتات لكل عينة، مما يتطلب مساحة تخزين كبيرة. لذلك، يُعد ضغط البيانات أمرًا مهمًا جدًا لتوفير مساحة التخزين وعرض النطاق الترددي. بناءً على ذلك، نقترح تقنية ضغط جديدة تعتمد على بنية إشارة ECG تتكون التقنية المقترحة من تعديل دلتا التكيفي (ADM) والترميز الحسابى (AC) تم اختبار التقنية المقترحة على قاعدة بيانات عدم انتظام ضربات القلب التابعة لمعهد MIT-BIH بلغ متوسط أداء الضغط من حيث نسبة الضغط(CR) ، والنسبة المئوية لجذر متوسط مربع الفرق(PRD) ، ومستوى الجودة، ونسبة الإشارة إلى الضوضاء ١٦,٥ و٢,٥ و٦,٦ و٧٤,٨ ديسيبل على التوالي، وذلك عبر ٤٨ مجموعة بيانات لمدة دقيقة واحدة من ضغط البيانات.

الكلمات المفتاحية : تخطيط القلب، تعديل دلتا التكيفي، الترميز الحسابي

1. INTRODUCTION

Electrocardiogram (ECG) signal is often used in conjunction with other tests to diagnose and monitor heart diseases such as chest pain, palpitations (sudden, noticeable heartbeat), dizziness, and weakness of the breath. **Fig. 1** shows one beat of ECG signal that consists of depolarization and repolarization of the atria and ventricles of the heart. ECG signal can be described by a series of waves called P, QRS, and T. P waves represent a depolarization of the atria. It appears as a ripple at the start of the ECG signal beat. The QRS complex expresses the ventricular depolarization. It appears as three closely related waves on the ECG signal (Q, R, and S waves). T-wave represents the repolarization of the ventricles. It appears as a ripple after the QRS complex Interval. ECG signal is a repeated heart beat [1].

In normal sinus rhythm (the heart's normal state), the P-R interval is between from 0.12 to 0.2 seconds, the QRS complex ranges from 0.04 to 0.12 seconds, the Q-T interval ranges from 0.35 to 0.44 seconds, and the heart rate is normal at 60 to 100 beats per minute. The frequency range of the ECG signal is from 0.05 to 100 Hz with a dynamic range of 1 to 10 mv [2].

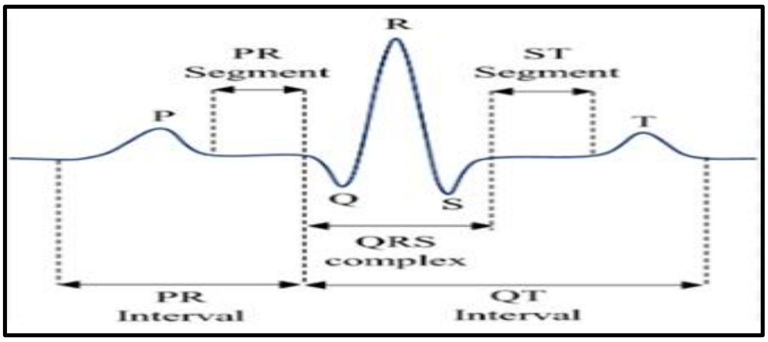

Fig. 1: ECG Signal

With health care revolution, telemedicine-based healthcare systems are emerged [3,4]. Patient does not need to go to the hospital to check his state. Simply, he attaches electrodes to his body and the ECG data are transmitted to the hospital. ECG data must be sent continuously in real time. Therefore, a very large amount of data must be sent immediately. With the increase of patients, there is a large need to dedicate a very large bandwidth to such ECG data transmissions. Thus, data compression is highly required to reduce the size of the data.

Many researches worked on ECG data compression using so many general compression methods that show a variety of compression ratio [5]. Most of them used general compression algorithms. However, if the data compression technique is dedicated to the data structure, the compression becomes more efficient such as video and audio compression standards. There are very few researches worked on the ECG signal data structure and use it as a base for choosing the suitable compression algorithm [6]. In this work, we focus on the ECG data structure to present a new efficient compression algorithm.

Compression algorithms can be divided into two basic groups; lossy and lossless. Lossy compression is characterized with higher CR than the lossless compression as it permits losing of some data to perform more compression effort. This leads to that the reconstructed data is different than the original data. This difference can be expressed by PRD. Lossless compression always has a low CR and a zero PRD. Most of the previous researches worked on lossy compression algorithms to achieve high CR. Some of them adds a lossy compression algorithm after the lossless one to improve the compression. There are few researches worked on lossless compression algorithms.

The wavelet transform has been utilized for ECG data compression in [7,8], and other researchers have integrated it with various lossless algorithms. Both wavelet transform and Huffman coding were applied [9]. The wavelet transform was paired with LZW [10]. H. S. Pal et al, employed the tunable-Q wavelet transform (TQWT) in [11], a method that facilitates a wavelet multiresolution analysis (MRA) with an adjustable Q-factor, aimed at optimizing performance. Furthermore, H. S. Pal and A. Kumar adopted TQWT [12] and refined its parameters using a collection of meta-heuristic optimization algorithms. These enhancements included multiple forms of Particle Swarm Optimization (PSO), the Artificial Bee Colony (ABC) algorithm and its hybrid with PSO, as well as the Grey Wolf Optimizer (GWO) in conjunction with PSO in [13,14].

Discrete Wavelet Transform (DWT) and Particle Swarm Optimization (PSO) are introduced in [15]. PSO is a computational method that optimizes a problem by iteratively attempting to improve the results with respect to a specific quality measure. Wavelet transform and run length encoding have been used in [16,17]. M. Ali et al compared many transforms to compress the ECG data. The compared transforms were discrete cosine, fast fourier, discrete wavelet, discrete wavelet packet, and discrete wave atom [18]. The wavelet transform (DWT) and various nature-inspired optimization techniques are utilized. The ECG compression method employs these optimization strategies to determine the optimal values for wavelet design parameters and threshold levels [19]. M. Feli and F. Abdali-Mohammadi utilize the discrete wavelet transform to smooth the ECG signal [20], followed by constructing its mathematical model with a genetic programming-based algorithm. This model is a piecewise mathematical function, where each sub-function models a different part of the signal. Subsequently, the LZW and arithmetic encoding methods are used.

DCT, 16-bit quantization, and run-length coding were used for compression, while a convolutional neural network was employed to evaluate the compressed and decompressed ECG databases, as demonstrated in recent work [21]. C.K. Jha and M.H. Kolekar investigated how the discrete cosine transform is used in compressing ECG data [22]. Shi et al. proposed an ECG compression method based on a binary convolutional autoencoder equipped with residual error compensation [23]. Their goal was to use deep learning to achieve efficient ECG compression while ensuring high signal quality. A. Lourenço and A. Ferreira combined linear predictive coding with the LZW algorithm for data compression of ECG [24].

Compressive Sensing has been utilized in a Block-Sparsity-based Joint approach as reported in [25]. Different algorithms in like Discrete Cosine Transform (DCT), Discrete Wavelet Length Encoding (RLE), Arithmetic Encoding (AE) as lossless compression techniques have been studied [26]. The simulation findings indicate that the inclusion of RLE following the DCT algorithm increases performance in terms of CR and complexity. The Golomb-Rice lossless compression codec types have been used in [27].

Differential Pulse Code Modulation (DPCM) has been used in various studies for signal preprocessing. It removes intrachannel data dependencies by subtracting each sample value from the previous one before modulation, thereby reducing data rate requirements and improving compression efficiency. T.-H. Tsai and F.-L. Tsai, for example, applied DPCM with adaptive linear prediction and Golomb-Rice coding [28]. DPCM/ADPCM (Differential Pulse Code Modulation/Adaptive Differential Pulse Code Modulation) techniques to enhance data compression performance has been employed. The compression methodology incorporates several distinctive techniques, including a combination of K-means clustering, arithmetic coding, and Huffman encoding. Specifically, it involves the application of K-means clustering in conjunction with Huffman encoding (DiKHE) and with arithmetic encoding (DiKAE) [29], The critical role of K-means clustering is to diminish interchannel dependencies, as detailed individually in [30].This strategy of integrating various compression techniques is systematically applied across different cluster sizes K (K = 2, 3, 4, 5, 6), showcasing their adaptability and efficiency in optimizing compression outcomes. S. Alam and R. Gupta employed a Differential Pulse Code Modulation (DPCM)-based approach for the real-time compression of Electrocardiogram (ECG) data, aimed at facilitating real-time tele-monitoring applications, as documented in [31].

This methodology demonstrated commendable performance in the compression of ECG data, indicating its potential for effective application in tele-monitoring contexts. Various algorithms, including Run Length Encoding (RLE), Huffman Encoding (HE), and Arithmetic Encoding (AE), (RLE) with Singular Value Decomposition (SVD) has been investigated as reported in [32]. SVD is utilized to decompose the signal into three smaller matrices that retain essential characteristics of the ECG. Subsequently, RLE is individually amalgamated with both Huffman Encoding (RLE-HE) and Arithmetic Encoding (RLE-AE).

B-spline interpolation and ant colony optimization are used in [33]. The B-spline coefficients of the signal are calculated as compressed data; the signal can be visualized without decompression.

In this paper we propose the compression technique tailored to the structure of the ECG signal, which integrates adaptive delta modulation (ADM) and arithmetic coding (AC). This approach has yielded perfect results in terms of (PRD) when compared with existing studies and has demonstrated good compression performance in all ECG data.

The rest of the paper is organized as follows; In Section 2, System model is presented. Section 3 presents the results and Discussion. Finally, Section 4concludes the paper.

2. SYSTEM MODEL

Adapting the compression technique with the data texture usually shows better compression such as using intra-prediction and inter prediction coding to compress videos in video compression standards like HEVC standard [34]. In this work we focus on the ECG data texture to choose the suitable compression technique to compress it.

It is clear that the ECG signal is an analog data in nature and most databases store ECG data sets in digital form. For Example, the most widely used MIT-BIH arrhythmia database stores the ECG signal at a sampling rate of 360 samples/sec with resolution of 11 bits/sample. Our proposed compression technique is based on representing data using Adaptive Delta Modulation (ADM) instead of Pulse Code Modulation (PCM) to make use of the data texture of ECG signal as an analog data. We will study the different algorithms of ADM to check the most suitable one to compress the ECG signals. Then we can use any lossless encoding technique to make more compression effort on the data.

ADM is based on DPCM which outputs 1 bit /sample. The output bit value of DPCM depends on the difference between the last two input consecutive samples. At the receiver, the decoder sets a step value that is added or subtracted from the last produced sample to generate the new sample based on the received code bit value. One of the major problems of DPCM is that the step value is constant.

Therefore, either slope overload or granular noise, as shown at **Fig. 2**, can be produced if the difference between the two consecutive samples at the transmitter is larger or smaller than the step size respectively.

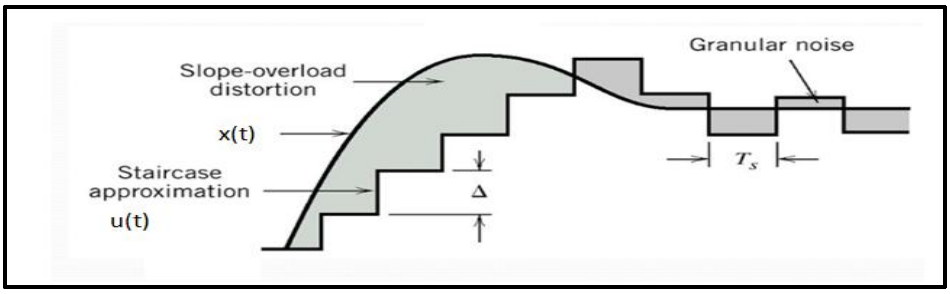

Fig. 2: Slope overload distortion & granular noise [35]

ADM tries to reduce slope overload distortion and the granular distortion in DPCM by making the step size flexible [35]. As shown in **Fig. 3**, this is done by increasing step size value if the previous encoded bits stream is consecutive ones or zeros and decreasing it if the previous encoded bits stream is an alternation between ones and zeros. ADM reduces the slope error associated with delta modulation, using a low-pass filter during demodulation to eliminate quantization noise [36]. The dynamic range of the adaptive delta modulation is large because the variable step size covers a large range of values.

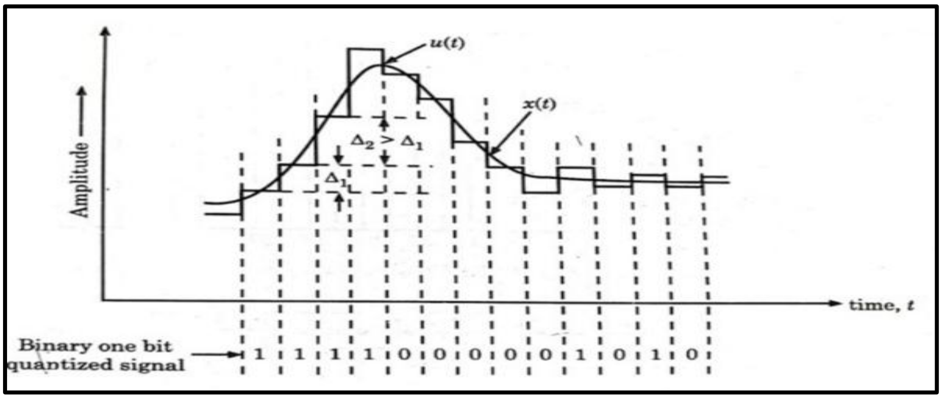

Fig. 3: ADM waveform [37]

Several step size adjustment algorithms are presented in the literature attempting to produce an acceptable reconstruction of the signal. In Jayant ADM, an increase in step size is achieved by multiplication with a constant and decreases it by dividing by the same constant as shown in **Eq. 1** [37].

$$|\mathrm{s}(\mathrm{k}+1)| = \begin{cases} 2 * \mathrm{s}(\mathrm{k}).\mathrm{e}(\mathrm{k}) & \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-1) = \mathrm{e}(\mathrm{k}-2) = \mathrm{e}(\mathrm{k}-3) \\ \dfrac{\mathrm{s}(\mathrm{k})}{2}.\mathrm{e}(\mathrm{k}) & \mathrm{e}(\mathrm{k}-1) = \mathrm{e}(\mathrm{k}-3) \text{ and } \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-2) \\ \mathrm{s}(\mathrm{k}).\mathrm{e}(\mathrm{k}) & \text{otherwise} \end{cases} \quad (1)$$

Song et al proposed a variable step size DM algorithm that adds or subtracts a fixed pitch bias to the previous step size value depending on the previous two outputs of the ADM as shown in Eq. (2) [38].

$$|s(k+1)| = \begin{cases} |s(k)| + \mathrm{s}_o & \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-1) \\ |\mathrm{s}(\mathrm{k})| - \mathrm{s}_o & e(k)! = e(k-1) \end{cases} \quad (2)$$

Where

k = 0, 1, 2, 3 . . . e (k) can be of positive or negative value.

S(k+1) = the magnitude of the new step-size.

S(k) = the magnitude of the old step-size.

Song algorithm is modified, in [39], so that the step-size adaptation is done by multiplying the previous step size value by a factor before adding or subtracting the fixed bitch size to or from it. The step size is limited to the minimum value of the fixed bitch size. The modified song equation is shown in Eq. (3)where α is the adaptation parameter which slightly greater than 1 and β=1/α.

$$|s(k+1)| = \begin{cases} (\alpha|\mathrm{s}(\mathrm{k})| + \mathrm{s}_o).\mathrm{e}(\mathrm{k}) & \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-1) \\ (\beta|s(k)| - \mathrm{s}_o)e(k) & e(k) \neq e(k-1) and \beta.s(k) > \mathrm{s}_o \\ \mathrm{s}_o\mathrm{e}(\mathrm{k}) & e(k) \neq e(k-1) and \beta.s(k) < \mathrm{s}_o \end{cases} \quad (3)$$

The modified ABATE algorithm [40] is another step-size adaptation algorithm and it is more susceptible to overcome the slope overload distortion than the SONG algorithm. The step size adaptation equation is shown in Eq. (4).

$$|s(k+1)| = \begin{cases} (|\mathrm{s}(\mathrm{k})| + \mathrm{s}_o).\mathrm{e}(\mathrm{k}) & \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-1) \text{and } \mathrm{s}(\mathrm{k}) < 8\mathrm{s}_o \\ \mathrm{s}(\mathrm{k})\mathrm{e}(\mathrm{k}) & \mathrm{e}(\mathrm{k}) = \mathrm{e}(\mathrm{k}-1) \text{and } \mathrm{s}(\mathrm{k}) = 8\mathrm{s}_o \\ \mathrm{s}_o\mathrm{e}(\mathrm{k}) & \text{oterwise} \end{cases} \quad (4)$$

Modified ABATE has less noise compared to all other ADM algorithm but gives error with decreasing values of the signal. SONG algorithm takes time to get adapted to the signal but gives better performance later. Modified SONG algorithm adapts fast and has equal performance like SONG algorithm.

It is expected that the bit stream after encoding ECG data by ADM will have repeated patterns of data due to the nature of ECG data which is repeated beats having approximately the same shape. Therefore, the ECG data encoded by ADM will be exposed to a lossless coding algorithm such as Huffman, Lempel-Zif-Welsh, or Arithmetic coding algorithms to improve the compression with no effect on the data quality. Next section shows the results of different compression solutions using ADM followed by a lossless compression algorithm.

3. RESULTS AND DISCUSSION

The proposed compression techniques are implemented on MATLAB 2021a using Massachusetts Institute of Technology (MIT-BIH). The MIT / BIH Arrhythmia database contains 2-channel ECG recordings from 48 arrhythmia patients aged between 23 and 89 years. Each record is represented as digital values sampled at 360 Hz in the two channels [41]. The experimental work has been performed on the first 10 sec of one channel of each signal.

It is very hard to report the results of all data sets for all the next experiments. Therefore, we will report the average results of a chosen set of data sets. We picked some different datasets that have different shapes as they are for different types of diseases.

3.1. PRD of different ADM algorithms

To judge on any compression technique, there are two important parameters that should be taken in consideration. The first parameter is compression ratio (CR) which represent how much data is compressed. It is calculated by dividing the required to represent original signal (NO) by the total number of bits required to represent compressed data of the signal (NR) as shown in Eq.(5)The second parameter is percent root mean square difference (PRD) which reflects the quality of compression by measuring the degree of distortion of signal between the reconstructed signal x_i^r and the original signal x_i as shown in Eq.(6). Because the two parameters work in two opposite directions that increasing the compression ration affects badly on the compression quality and vice versa, one can use a figure of merit called quality score (QS) that combines the two parameters into one value to fairly compare between different algorithms as shown in Eq. (7). Some researchers uses Signal to Noise Ratio (SNR) parameter to measure the quality of the reconstructed signal when comparing different algorithms. SNR can be calculated as shown in Eq. (8).

$$\mathbf{CR} = \frac{N_O}{N_R} \tag{5}$$

$$\mathbf{PRD} = \sqrt{\frac{\sum_{i=1}^{N}(x_i - x_i^r)^2}{\sum_{i=1}^{N} x_i^2}}\, x100 \tag{6}$$

$$\mathbf{QS} = \frac{CR}{PRD} \tag{7}$$

$$\mathbf{SNR} = 10log_{10}\frac{\sum_{i=1}^{N} x_i^2}{\sum_{i=1}^{N}(x_i - x_i^r)^2} \tag{8}$$

All ADM algorithms show a CR of 11 that every sample of data will be presented by only one bit. Therefore, the PRD is the parameter that will identify the best algorithm to compress the ECG data. **Table 1** shows the PRD results of compressing the chosen datasets. The results shows that Jayant algorithm is the best in terms PRD and modified Song algorithm is the second best one. **Fig. 4** shows the original signal of dataset number 100 and the reconstructed signal by each of ADM algorithms. As shown in **Fig. 4**, the reconstructed signal by Jayant is the most similar signal to the original one.

After many experiments on ADM algorithms, it was proven that the modified song algorithm gives good (cr) and good percentage root-mean squared difference (PRD). Jayant algorithm gives lower (cr) and lower (PRD) compared with all types of ADM algorithm.

Table 1: PRD of different ADM Algorithms

Dataset Algorithm	100	104	108	113	106	116	213	Avg
Jayant	1.43	1.6	0.78	2.1	3.1	2.2	3.2	2.1
Modified Song	2.2	2.1	1.3	5	5.5	4.6	4.3	3.6
Abate	3.6	3.8	3.6	4.1	4	3.7	3.5	3.8

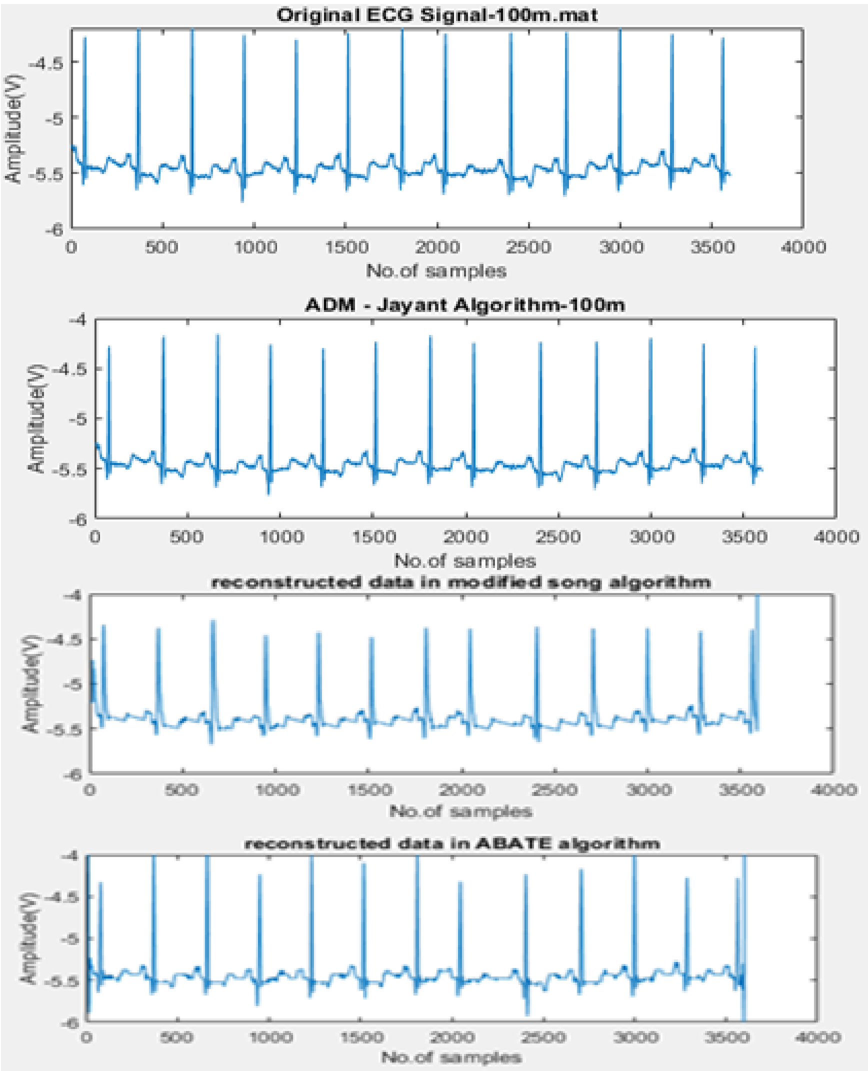

Fig. 4: The reconstructed signals by both Jayant, modified Song and ABATE algorithms

3.2. Modifying PRD by Up-sampling data sets

As the datasets are sampled at rate of 360 samples/sec and each sample is 11-bit resolution, we suppose that if we up sample the data to higher sampling rate, the PRD value will decrease. The decrement of PRD is very useful for high quality data transmission. However, increasing the samples increases the number of ADM output bits thus the CR decreases. Therefore, it is very important to check the effect of up-sampling on the quality of compression. **Table 2** shows the CR, average PRD, and QS results of compressing the chosen datasets at different sampling rates. The results prove our assumption that the up sampling improves the quality of the decompressed signal by decreasing the PRD. On the other hand, the impact of the up sampling on the quality of compression is bad that the QS value decreases. Therefore, we will keep the sampling rate as it is 360 samples/sec for the next experiments.

Table 2:CR, average PRD, and QS of different ADM Algorithms at different sampling rates

Sampling Rate (sample/sec) Algorithm	360 (CR=11)		720 (CR=5.5)		1080 (CR=3.66)	
	Avg PRD	**QS**	**Avg PRD**	**QS**	**Avg PRD**	**QS**
Jayant	2.1	5.23	1.12	4.91	0.94	3.90
Abate	3.8	2.8	2.7	2.04	2.25	1.63
Modified Song	3.6	3.05	2.26	2.43	1.8	2.04

3.3. Combining ADM algorithms with lossless compression algorithms

We can add any of lossless algorithms to improve the CR with no effect on the PRD. Therefore, we compress the output of different ADM algorithms by the three most popular lossless algorithms; Huffman, LZW, and Arithmetic coding algorithms. Any lossless algorithm needs the inputs data to be defined as code words while the output of data ADM coding is a stream of bits. Therefore, we divided that stream into code words with different sizes. **Table 3** shows the average CR results of the combination of ADM algorithms with different lossless algorithms. The results shows that the Arithmetic coding algorithm is the best choice to compress data after ADM algorithms. Further, the code word size of 8 bits shows the best results. Furthermore, the combination of modified Song algorithm with Arithmetic coding algorithm compresses data better than the combination of Jayant algorithm with Arithmetic coding algorithm. This is due to that Jayant follows the data better. Therefore, its result patterns of data varies more than that of modified song. With respect to the results, we choose to compress data by a combination of modified Song algorithm with Arithmetic coding algorithm using code word size of 8-bits if the target is higher CR. Otherwise, we choose to compress data by Jayant ADM algorithm if the target is lower PRD and higher QS.

Table 3: Average CR using a combination of different ADM Algorithms with different lossless algorithms a different code size.

Lossless algorithms	Huffman			LZW			Arithmetic Coding		
No. of bit	**4**	**8**	**16**	**4**	**8**	**16**	**4**	**8**	**16**
Jayant	10.7	7	5.3	4.8	6	6.5	11	9	7
Abate	12.3	10.6	7	7	7.6	7	13	13.4	12
Modified Song	13.4	13	12	12	12.3	13	14	14.3	12.4

3.4. Dataset lengths effect on compression results

It is important to state that if the ECG dataset length increases, the CR value will increase and the PRD value will decrease. This is because the dictionary of code words and their probabilities and data length are sent one time. Further, the probability of some repeated patterns increases. Furthermore, the average error in data will decrease. **Tables 4** and **5** show the results of compressing the first 10 sec. and 1 min. of all the MIT-BIH data base datasets using the chosen algorithms in terms of CR, PRD, QS, and SNR. The results show that the different compression parameters get better with increasing the dataset length.

Table 4: Compression results of the combined modified Song with Arithmetic coding algorithm at different dataset size.

	CR		PRD%		QS		SNR	
record no.	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***
100m	17.1	21.8	2.2	2	7.8	10.9	76.4	78.2
101m	13.7	16.2	2.7	2.4	5.1	6.8	72.3	74.2
102m	16	19	1.9	1.7	8.4	11.2	78.7	81.1
103m	14.5	17.4	3.8	4.3	3.8	4	65.2	62.7
104m	12.8	15.4	2.1	1.9	6.1	8.1	77.5	78.8
105m	12.8	15.4	2.0	2.0	6.4	7.7	78.3	78
106m	13.2	15.6	5.5	4.1	2.4	3.8	57.9	63.7
107m	12.1	14.1	3.8	3.8	3.2	3.6	65.4	65.4
108m	13.2	15.9	1.3	1.2	10.2	13.3	86.2	88.3
109m	11.9	14	2.5	2.4	4.8	5.8	69.4	74.5
111m	14.5	17.3	1.7	1.5	8.5	11.5	81.1	83.7
112m	13.5	16.4	1.8	1.5	7.5	10.9	80.7	84.3
113m	14.1	17.3	5	5.1	2.8	3.4	59.6	59.6
114m	15.5	18.3	1.5	1.3	10.3	14.1	84.3	86.9
115m	16.1	19.5	2.7	2.9	6	6.7	72.2	71.1
116m	13.2	15.1	4.6	4.2	2.9	3.6	61.7	63.4
117m	13.9	17	2	1.5	7	11.3	78	84.6
118m	11.6	13.5	2.8	2.6	4.1	5.2	71.8	72.8
119m	13	14.5	2.7	2.8	4.8	5.2	72.5	71.6
121m	17.3	21.8	1.9	1.4	9.1	15.6	79.8	85.8
122m	13.5	16.4	2.2	1.9	6.1	8.6	76	79.4
123m	15	19.2	2.4	2.3	6.3	8.3	74.7	75.5
124m	14	17.2	2.4	2.2	5.8	7.8	74.3	76.6
200m	13.7	15.4	2.3	2.3	6	6.7	75.2	75.4
201m	16.7	19.7	2	1.8	8.4	10.9	77.9	80.6
202m	15.5	18.8	1.8	1.7	8.6	11.1	80.4	81.5
203m	11	12.7	3.3	3	3.3	4.2	68.1	70.1
205m	16.8	20.9	2.1	1.9	8	11	77.7	79.7
207m	13	14.7	1.5	1.5	8.7	9.8	84.3	83.6
208m	11.8	13.6	2.8	3	4.2	4.5	71.8	70.2
209m	13.2	16	3.5	2.8	3.8	5.7	67.3	71.5
210m	14.5	17.7	1.8	1.7	8.1	10.4	80.5	81.7
212m	12.3	14.3	2.2	3	9.8	4.8	76.2	70.3
213m	12.3	14.2	4.3	4.5	2.9	3.1	62.7	62.3
214m	12.2	14.3	2.9	2.6	4.2	5.5	70.7	72.8
215m	13.3	14.7	2.7	2.2	4.9	6.7	72.1	76.6
217m	13	15.1	3.4	3.2	3.8	4.7	67.8	68.6
219m	12.1	14.7	3.3	2.8	3.7	5.3	67.9	71.5
220m	14.9	17.7	3.2	3.6	4.7	4.9	68.6	66.5
221m	13.4	16.6	2.5	2.6	6.4	6.4	74	73.3
222m	16.7	20.4	2.1	1.6	7.9	12.8	77.4	82.5
223m	12.6	14.9	2.8	2.8	4.5	5.3	71.7	71.6
228m	13.9	15.4	1.6	1.9	8.7	8.1	83	78.9
230m	13.6	15.8	3.5	3.2	3.9	4.9	67.3	68.6
231m	13.3	16	3.9	3.9	3.4	4.1	64.6	64.8
232m	14.1	16.6	1.5	1.3	9.4	12.8	83.3	86.9
233m	12.1	13.9	3.4	3.4	3.6	4.1	67.5	67.6
234m	15	17.8	2.6	2.5	5.8	7.1	73	73.8
Average	**13.8**	**16.5**	**2.7**	**2.5**	**5.1**	**6.6**	**73.4**	**74.8**

Table 5: Compression results of Jayant Algorithm at different dataset sizes.

	CR		PRD%		QS		SNR	
record no.	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***	**10 Sec.**	***1 min.***
100m	11	11	1.4	1.1	7.9	10	85	90
101m	11	11	2.1	1.9	5.2	5.8	77.5	79.1
102m	11	11	1.3	1.1	8.5	10	86.9	89.1
103m	11	11	2	1.9	5.5	5.8	78.1	75.7
104m	11	11	1.6	1.5	6.9	7.3	83.3	84.3
105m	11	11	2.2	2.1	5	5.2	76.4	76.4
106m	11	11	3.1	2.6	3.5	4.2	69.3	73
107m	11	11	2.6	2.4	4.2	4.6	73	72
108m	11	11	0.8	0.7	13.8	15.7	97	99.6
109m	11	11	1.6	1.4	6.9	7.9	83.2	80
111m	11	11	1.1	1	10	11	90.1	92.5
112m	11	11	0.9	0.8	12.2	13.8	94.5	94
113m	11	11	2.1	1.9	5.2	5.9	77.6	75
114m	11	11	0.8	0.6	13.8	18.3	96.7	102.2
115m	11	11	2.5	2.3	4.4	4.8	73.8	75.8
116m	11	11	2.2	2.1	5	5.2	76.4	71.6
117m	11	11	1.1	0.9	10	12.2	90.8	93.5
118m	11	11	1.9	1.8	5.8	6.1	79.7	80
119m	11	11	2.2	2.1	5	5.2	76.3	76.1
121m	11	11	0.8	0.7	13.8	15.7	96	98.6
122m	11	11	2.2	2.1	5	5.2	75.9	77.2
123m	11	11	2.1	1.6	5.2	6.9	77.4	82.3
124m	11	11	1.9	1.6	5.8	6.9	79	83
200m	11	11	2.4	2.1	4.6	5.2	75	77.6
201m	11	11	1.1	1	10	11	90.2	90.8
202m	11	11	1	0.9	11	12.2	93	94
203m	11	11	2.7	2.2	4.1	5	72.5	76.2
205m	11	11	1.2	1.1	9.2	10	88.9	87.6
207m	11	11	1.1	1	10	11	89.9	92.3
208m	11	11	2.3	2.2	4.8	5	75.9	73.6
209m	11	11	2	1.9	5.5	5.8	78.4	78.9
210m	11	11	1.3	1.2	8.5	9.2	86.8	88.6
212m	11	11	2.2	2.1	5	5.2	76.3	77.7
213m	11	11	3.2	3.1	3.4	3.5	68.9	67.2
214m	11	11	1.9	1.8	5.8	6.1	79.6	80.1
215m	11	11	1.9	1.8	5.8	6.1	79.5	80.1
217m	11	11	2.2	2.1	5	5.2	76.4	77.3
219m	11	11	2	1.9	5.5	5.8	77.9	74
220m	11	11	3.2	2.4	3.4	4.6	68.6	74.9
221m	11	11	1.9	1.6	5.8	6.9	79.3	82.5
222m	11	11	1.7	1.2	6.5	9.2	81.5	87.8
223m	11	11	2	1.9	5.5	5.8	78	77
228m	11	11	0.9	0.8	12.2	13.7	94	92
230m	11	11	2.6	2.1	4.2	5.2	73.4	77
231m	11	11	1.7	1.6	6.5	6.9	81	80.4
232m	11	11	0.9	0.7	12.2	15.7	95	98
233m	11	11	2.5	2.4	4.4	4.6	73.5	72
234m	11	11	2	1.9	5.5	5.8	78.5	79.1
Average	11	11	1.84	***1.65***	6	6.7	81.4	82.5

3.5. Comparing results with related work

It was very hard to make one comparison to the related work due to the different experiments' criterion. Some of the related work made the experiments on different data sets. Others made the experiments on different dataset duration. Therefore, we make many comparisons with the related work with each criterion. **Table 6** compares the results of the proposed algorithm with some of the related work that shows the results for records number 100 and number 205. The results show that our proposed algorithm shows the highest QS that it is higher than the nearest related work in terms of QS by about 40%.

Table 6: Compression results for different data sample

Ref	Algorithm	N0. of data	Duration	CR	PRD	QS
[11]	TQWT+DI-PSO	100	1 min	20.8	3.1	6.6
		205		20.5	2.6	7.8
[8]	Empirical mode decomposition (EMD) +discrete wavelet transform.	100	1min	19.8	3.2	6.05
		205		19.6	3.04	6.4
Proposed method	Modified song (Adaptive delta modulation) +Arithmetic code	100	1 min	21.8	2	10.9
		205		20.9	1.9	11

3.6. Comparing results with related work at 10 sec

We compared the results with other research over 10 seconds using a 48-database set. **Table 7** shows that our proposed algorithm outperforms the algorithm in [13], in terms of QS, by about 16% for the 48 records and outperforms the algorithm in [16], with the same comparison parameter QS, by 13% for the same 10 records that they showed their results for.

Table 7: Performance at 10 sec

Ref.	Algorithm	Test Database	CR	PRD (%)	QS
[16]	Wavelet transform +RL	48 records from MIT-BIH	10.16	3.92	2.58
	Wavelet transform +MRL		17.18	3.92	4.37
[33]	B-spline interpolation+ ant colony optimization	48 records from MIT-BIH	7.8	2.3	3.4
Proposed	Modified song (Adaptive delta modulation) +Arithmetic coding	48 records from MIT-BIH	13.8	2.7	5.1
[19]	Discrete wavelet transform (DWT)+ modified run-length encoding (MRLE) +CS	10 records from MIT-BIH	25.19	5.049	5.587
	Discrete wavelet transform (DWT)+ modified run-length encoding (MRLE) +FPA		21.25	4.88	4.78
	Discrete wavelet transform (DWT)+ modified run-length encoding (MRLE) +ABC		21.088	4.1	5.608
Proposed	Modified song (Adaptive delta modulation) +Arithmetic coding	10 records from MIT-BIH	**15.1**	**2.41**	**6.3**

3.7. Comparing results with other research in a 48-database set

Many of the related work showed their results for one minute. Therefore, we conducted an experiment lasting the same period. The results show that our proposed algorithm shows the best performance in terms of QS. Our QS is higher than the best of them [10] by about 10%. The results in **Tables 7** and **8** show that our algorithm with extending the period of data shows higher CR and lower PRD so higher QS which makes our algorithm suitable for compressing longer periods which may be an urgent need in future that enables monitoring the patient ECG remotely.

Table 8: Performance at 1 min

Ref.	Algorithm	Test Database	CR	PRD (%)	QS
[7]	Tunable *Q*-wavelet transform +RLE	48 records from MIT-BIH	20.61	4.43	5.88
[11]	TQWT+DI-PSO TQWT+ CWI-PSO TQWT+ LDI-PSO	48 records from MIT-BIH	21.0679 22.5929 23.182**0**	4.6105 4.6329 4.6678	5.5238 5.9227 5.9993
[8]	Empirical mode decomposition (EMD) +discrete wavelet transform.	48 records from MIT-BIH	21.56	4.65	5.38
[28]	Adaptive linear prediction + Golomb-Rice coding	-	2.89	-	-
[17]	discrete wavelet transform + run–length encoding	48 records from MIT-BIH	22.62	5.66	4.72
[23]	discrete wavelet transform and arithmetic encoding	48 records from MIT-BIH	5.52	2.94	1.90
Proposed Method	Modified song (Adaptive delta modulation) +Arithmetic coding	48 records from MIT-BIH	**16.5**	**2.5**	**6.6**

SUMMARY AND CONCLUSIONS

ECG compression is an important area of research and a growing technology use in healthcare because it enables convenient processing with reduced space and bandwidth requirements. Was even more popular. This article describes an intelligent compression technique that uses adaptive delta modulation and arithmetic coding to minimize PRD and maximize CR. The ECG data used to test this algorithm is from the MIT-BIH database. Proposed algorithms can significantly reduce storage and bandwidth requirements when data storage and transmission is required. A resampling is performed to improve PRD to Adaptive delta modulation. The proposed method achieved an average (CR) of 16.5 for a 1min ECG segment, with (QS) of 6.6 and (PRD) of 2.5, outperforming other existing approaches.

CONFLICT OF INTEREST

The authors have no financial interest to declare in relation to the content of this article.

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