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Real-Time ECG Compression with Adaptive Huffman Coding: Improving Data Transmission in E-Healthcare

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ABSTRACT

E-healthcare monitoring systems are becoming increasingly common due to their widespread use in everyday life. Among these systems, the electrocardiogram (ECG) signal is the most reliable method for diagnosing cardiovascular diseases (CVDs). Processing ECG signals is crucial for monitoring the heart's electrical activity and providing essential insights into CVDs. However, storing and transmitting sensitive ECG data presents a challenge, as traditional compression methods often cause issues in reconstructing the original data. Huffman coding processes input data as a stream and analyzes its frequency distribution. However, conventional Huffman coding requires prior knowledge of the data, which is not always available for all datasets. To address this limitation, this research proposes an adaptive, lossless ECG signal compression algorithm based on the Huffman coding technique for real-time e-health monitoring. The algorithm's performance is evaluated using both an evaluation and a validation dataset. When tested with the MIT-BIH database, the proposed algorithm achieves average compression ratios of 20.61, 24.41, and 30.96 for different dynamic and minimal window size variations, with corresponding percentage root mean square differences of 0.18 and 0.29.

Keywords: Adaptive Huffman Coding, Encoding, ECG Signal, Embedded platform, Lossless Compression.

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1. INTRODUCTION

The rising prevalence of medical health issues can be attributed to various factors, including poor lifestyle choices and genetic predispositions. These factors contribute to the increasing incidence of chronic conditions such as cancer, diabetes, Alzheimer's disease, and Cardiovascular Diseases (CVDs). According to a study by the World Health Organization (WHO), CVDs are the most prevalent chronic illnesses and the leading cause of mortality worldwide, with an estimated 23.6 million deaths projected by 2030 [1]. Consequently, the accurate diagnosis of CVDs has become a critical area of research in biomedical applications [2].

Electrocardiogram (ECG) signals serve as a reliable, non-invasive method for assessing cardiac activity and functionality. They provide essential structural insights into the heart, aiding in the detection and diagnosis of cardiovascular diseases. E-healthcare systems integrate technologies that facilitate the wireless transmission of patient data to intermediate devices such as personal computers (PCs), smartphones, or other smart technologies via Wi-Fi, Bluetooth, Near Field Communication (NFC), or Radio Frequency Identification (RFID). This data is subsequently relayed from the intermediate devices to hospital or cloud servers through a secure communication network.

Advancements in telemedicine have led to the widespread adoption of remote health monitoring systems, enabling patients to receive diagnoses and treatment remotely. However, transmitting ECG signals over wireless channels presents several challenges. Signal integrity can be compromised due to transmission interference, electrode movement, and muscle activity, which introduce noise into the signal. Furthermore, ECG data requires significant storage space and bandwidth for transmission over unsecured channels, raising concerns about data security. As a result, researchers have focused on developing efficient ECG signal processing methods, including compression techniques, to optimize data storage and transmission. A typical E-healthcare system is illustrated in Figure 1.

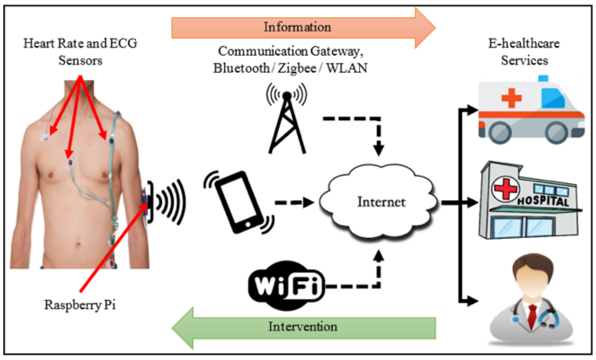

Figure 1. A typical E-healthcare system

ECG signal compression is a crucial aspect of biomedical signal processing, as continuous ECG monitoring over extended periods—such as through Holter monitoring—generates large volumes of data, necessitating efficient storage solutions. Additionally, the increasing mortality rate due to delayed treatment of sudden cardiac events highlights the need for remote monitoring systems that facilitate timely medical intervention. In this context,

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biomedical ECG signals are captured at the patient's location and transmitted to healthcare professionals, enabling remote diagnosis and treatment recommendations [3]. However, ECG signal sampling typically ranges from 100 to 1000 Hz with an 8- to 16-bit resolution, requiring a data transmission rate of 11–22 Mb/h per lead. Effective data compression and decompression techniques are essential for ensuring efficient and rapid data transmission [4].

A review of existing literature reveals varying levels of efficiency in signal compression and reconstruction. Consequently, there is a strong demand for a compression system that achieves high compression ratios while maintaining reconstruction accuracy. Huffman coding is widely utilized for data compression and encoding, replacing fixed-length code words with optimally selected variable-length code words based on data frequency distribution [5]. However, conventional Huffman coding requires prior statistical knowledge of the input data, which is not always available for all datasets. This limitation necessitates a two-pass encoding process to construct a statistical model before encoding the data, resulting in slower processing speeds [6]. Moreover, the variable-length nature of Huffman-coded binary strings complicates decoding, making it difficult to determine the endpoint of encoded data and detect errors such as missing or extraneous bits, leading to inaccurate signal reconstruction.

The proposed approach addresses these limitations by employing a one-pass adaptive Huffman coding technique that does not require prior statistical knowledge of the data. However, a potential drawback of this method is the risk of losing essential features of the ECG signal, which could negatively impact cardiovascular diagnosis and analysis. To mitigate this issue, the storage requirement has been optimized by grouping similar Huffman trees [7], [8], [9].

Various techniques have been proposed to reduce storage requirements and transmission costs in wireless networks, with a primary focus on data compression and decompression. These techniques are broadly classified into time-domain methods utilizing linear prediction [10], vector quantization-based methods, and frequency-domain techniques. The latter category includes wavelet transform-based methods incorporating Empirical Mode Decomposition (EMD) [11] and Set Partitioning In Hierarchical Trees (SPIHT) [12], both of which have been applied to ECG data compression. However, existing compression and encoding techniques often struggle to maintain high reconstruction quality, necessitating the development of alternative approaches to enhance the efficiency of ECG data compression and decompression.

Although lossy compression techniques offer higher compression ratios, they are generally not accepted in medical applications due to the risk of losing critical diagnostic information. In contrast, lossless compression techniques preserve the original ECG signal without any data loss, ensuring accurate heart disease diagnosis and compliance with medical regulatory standards. Thus, developing an effective lossless compression algorithm remains a key area of research in biomedical signal processing.

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2. MATERIAL AND METHOD

2.1. Experimental Setup

The proposed architecture is implemented using MATLAB R2020b on a Mac OS Sonoma computer with an Apple processor, an Apple M2 chip, an 8-core CPU with 4 performance cores and 4 efficiency cores, and 8 GB RAM. The hardware specifications used in this manuscript are raspberry-pi-3 B+, 1.4 GH quad-core,1GB of RAM, WiFi, and Bluetooth with AD8232 ECG sensor.

2.2 Proposed Methodology

Here, an adaptive method is employed for ECG data compression, following the proposed flow outlined in [13]. Huffman coding is a widely used technique for data compression and encoding, which replaces a fixed set of code words with an optimally selected set. The process begins by treating the input data as a continuous stream and analyzing its frequency distribution to facilitate efficient compression.

In the initial phase, a dynamic bit reduction technique is applied to compress the data. Subsequently, Huffman coding is utilized to further enhance compression, yielding the final compressed output. When text data is provided as input, the system first identifies the unique symbols within the input string and assigns numeric codes to each symbol. These numeric codes are then dynamically mapped to corresponding binary codes, generating a compressed binary output. The resulting binary data is then converted into ASCII codes, which serve as the input for the second phase of the system.

In this subsequent stage, Huffman coding is implemented to improve the efficiency of the dynamic bit reduction algorithm by further compressing the intermediate output. The Huffman coding approach follows a top-down methodology, structuring the binary tree to optimize compression efficiency from the root to the leaves. This scheme encodes characters in a file by assigning shorter binary codes to frequently occurring characters and longer codes to less common ones.

The decompression process operates in the reverse order, reconstructing the original data from the compressed format. The pseudocode for the adaptive lossless encoding function and its procedural steps are presented as follows:

Algorithm 1: **Encoding**
Input: ECG Signal (8 or 16-bit depth) **Output**: Compressed Signal
Step 1: Construct the Tree and Not Yet Transmitted (NYT) Initialize the output stream as $Huffstream \rightarrow uin8(\,)$ Identify the unique symbols from the stream and construct the NYT as $NYT \rightarrow unique(Inp\ ECG)$ Assign a location to each NYT as $NYTLocation \rightarrow \max(NYT) + 2$ Find the length of input ECG data n and the total number of nodes as $2 * n$ Construct the tree as:

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$tree \rightarrow (node\ number, node\ parent, left\ child, right\ child, node\ symbol, node\ weight, NYT\ location)$

Step 2: $Huffstream = [Huffstream\ uint8(\log_2 bitdepth))$

Step 3: $for\ i = 1: length(n)$

Step 4: $symbol \rightarrow Input\ ECG\ Singal(i)$ **// Read the current symbol**

// Update NYT tree and Huffstream of ECG signal

Step 5: $\boldsymbol{if}\ \sum(NYT == symbol)$

Step 6: $nodecode(NYTlocation - 1)$ // add the node code to the output stream

Step 7: update the huffstream as:

$huffstream(length(n) + 1: length(n) + bitdepth) = uint8(bitget(symbol, bitdepth: -1: 1));$ // Generate output symbols

Step 8: end

Step 9: Get the compressed signal and measure the compression ratio as

$$CR = (length(huffstream)/(length(Inp\ ECG\ Signal) * bitdepth)) * 100$$

After the lossless decoding stage, the dynamic Text Compression Decoder further processes the decompressed data, ensuring that it accurately reflects the original data structure. This two-step approach enhances the reliability and efficiency of the data restoration process. The pseudocode of the adaptive lossless decoding function process steps are presented as follows:

Algorithm 2: **Decoding**

Input: Compressed Signal

Output: Decoded ECG Signal (8 or 16-bit depth)

Step 1: Measure the bit depth of input data

Step 2: Construct the Tree and Not Yet Transmitted (NYT)

Initialize the output stream as $Huffstream \rightarrow num2str(bitdepth(uint8(\,))$

Identify the unique symbols from the stream and construct the NYT as $NYT \rightarrow 0: (2^{bit\ depth}) - 1$

Assign a location to each NYT as $NYTLocation \rightarrow \max(NYT) + 2$

Find the length of input ECG data n and the total number of nodes as $2 * n$

Construct the tree as:

$tree \rightarrow (node\ number, node\ parent, left\ child, right\ child, node\ symbol, node\ weight, NYT\ location)$

/ /Update NYT tree and Huff stream of compressed ECG signal to get the decoded output

Step 5: $while\ {\sim}isempty\ (stream)$

Step 6; go to the root node position as $position = 1$

// Update NYT tree and Huff stream of compressed ECG signal to get the decoded output

Step 5: $while\ {\sim}isempty\ (stream)$

Step 6: go to the root node position as $position = 1$

A unique numeric code is assigned to each specific group of symbols. In the subsequent stage, a corresponding binary codeword is generated for each initially assigned symbol, representing the compressed data. Huffman coding follows a top-down computational approach to construct a binary tree, optimizing data compression efficiency. Based on Huffman coding principles, the generated binary codes are analyzed, where the most frequently occurring characters in the input stream are assigned the shortest binary codes, while less common characters receive longer binary codes. The decompression process is performed by reversing the Huffman encoding procedure, restoring the original data from the compressed format.

2.3. Embedded Platform

The proposed methodology is validated through both MATLAB simulation and embedded system implementation. The validation process consists of two primary components: software-based implementation and hardware-based implementation.

In the first stage, ECG signal monitoring is designed and simulated using MATLAB, incorporating the proposed compression algorithms. MATLAB is utilized to analyze and evaluate the experimental performance, facilitating the development and testing of new filtering, compression, and cryptographic techniques for ECG signal processing. The mathematical evaluation of the proposed algorithms is conducted within the MATLAB environment to ensure their effectiveness and validate the experimental results.

For hardware implementation, the proposed algorithm is integrated into an embedded system platform to demonstrate its practical feasibility. The ECG signal is acquired using the AD8232 integrated circuit (IC), while the MCP3008 analog-to-digital converter (ADC) converts the analog signal into digital values. The Raspberry Pi 3 Model B+ is employed for processing the proposed algorithm, and a laptop is used for visualizing the complete end-to-end process. The developed system is further evaluated to assess the efficiency of the enhanced lossless ECG signal compression technique across both software and hardware platforms.

4. RESULT AND DISCUSSION

This section presents the experimental results and the proposed methodology for filtering, compressing, and encrypting ECG signals. The complete experimental analysis is conducted using MATLAB and validated with the publicly available MIT-BIH Arrhythmia dataset. This dataset comprises 48 ECG signals sampled at 360 Hz, each with a duration of 30 minutes, recorded from 47 individual patients.

The objective of ECG signal compression is to achieve a high compression ratio while preserving signal quality. To evaluate the consistency of the reconstructed signal, the compression performance is analyzed by testing the compression rate alongside other parameters. The selected compression parameters include those necessary for validating the dynamic compression process, as well as evaluating the compression ratio (CR) and percentage root mean square difference (PRD) output.

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The compression ratio (CR) quantifies the effectiveness of the encoding mechanism in reducing data size. While CR serves as an indicator of storage efficiency, it does not provide insight into the fidelity of the reconstructed signal. Therefore, additional evaluation metrics are necessary to assess both the compression efficiency and the accuracy of signal reconstruction.

$$CR = \frac{\sum_{n=1}^{N}(bit(\overline{\mathcal{S}[n]}))}{\sum_{n=1}^{N}(bit(\mathcal{S}[n]))} \tag{1}$$

Here, the encoded signal (S[n]) is first converted into bits. Then, the length of the encoded bits is divided by the length of the original signal to determine the Compression Ratio (CR). A lower CR indicates a higher output quality. Additionally, the Percentage Root-Mean-Square Difference (PRD) assesses the error or difference between the original signal (S[n]) and the reconstructed signal (Ŝ[n]), where N represents the length of the signal S. This process can be outlined as follows:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(\mathcal{S}[n]-\hat{\mathcal{S}}[n])^2}{\sum_{n=1}^{N}\mathcal{S}[n]^2}} \times 100 \tag{2}$$

Nonetheless, the previously mentioned method might not provide a precise performance measurement since PRD heavily depends on the original signal's mean value. Researchers in [12] indicated that additional efforts should be made to refine the baseline or decrease the DC level. To address this challenge, a refined and advanced version of the PRD equation has been proposed that operates independently of the mean value:

$$PRD\_New = \sqrt{\frac{\sum_{n=1}^{N}(\mathcal{S}[n]-\hat{\mathcal{S}}[n])^2}{\sum_{n=1}^{N}(\mathcal{S}[n]-\acute{\mathcal{S}}[n])^2}} \times 100 \tag{3}$$

The notation S'[n] represents the mean value of the original signal S[n]. When using the MIT-BIH dataset, it becomes necessary to remove the baseline, which is set at 1024 and added to every MIT-BIH dataset for storage purposes. As the compression ratio (CR) increases, the distortion also rises. Therefore, it is important to select a compression ratio that is appropriate for the specific type of service and the wireless channel environment. To compress and decompress the signal, we developed an adaptive Huffman coding approach to achieve a better compression ratio. Figure 2(a) displays the CR curves for various ECG records from the MIT-BIH arrhythmia database, including records 101, 102, 108, 202, 205, 209, 219, and 223. The PRD curves are shown in Figure 2(b). Additionally, Figure 2(c) presents the computational performance times for different MIT-BIH arrhythmia datasets. The performance of all illustrated curves is consistent (as CR rises, PRD also increases), confirming the effectiveness of the proposed method across various ECG records.

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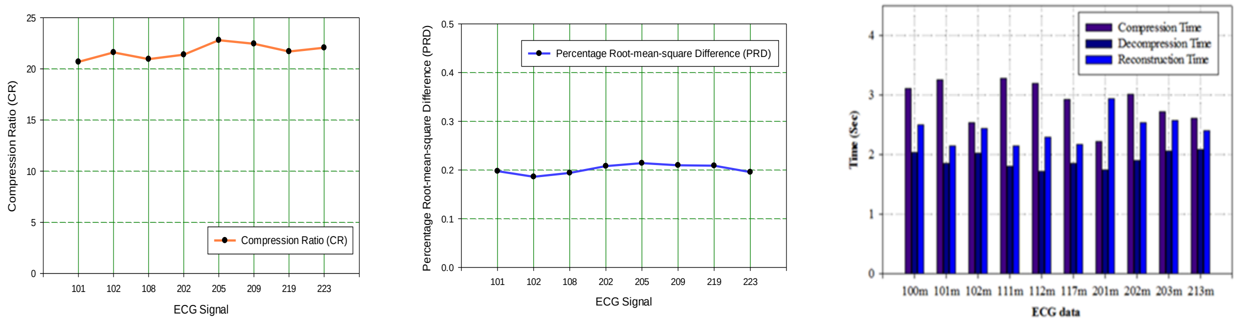

(a) (b) (c)

Figure 2. (a) CR curves. **(b)** PRD curves. **(c)** Computational times performance for different ECG records

Consequently, from comparing the compression methods, the proposed algorithm achieves almost higher CR and provides the best reconstruction quality by the smallest PRD. Moreover, the performance in terms of compression time, decompression time, decryption time, and reconstruction time are measured. The average compression time decompression time and reconstruction time are 3.7466, 0.8760, and 2.2295, respectively. Additionally, for each dataset (two databases, distinct ECG signals, and different CR), the calculation and execution times are specified in seconds. As shown in Table 1, the proposed method is slower than the other methods. Furthermore, it may be observed that as signal duration improves, the CR and PRD.

Table 1: Computational time comparison - proposed method vs. other compression methods

ECG Dataset	Methods References	Time (s)
100m.mat	Proposed Algorithm	3.82
	[14]	71.8
	[15]	5.57
101m.mat	Proposed Algorithm	3.74
	[14]	72.2
	[16]	5.32

Because of the number of iterations involved in the adaptive solution employed in the Huffman coding algorithm, trees are grouped. To estimate the performance of the adaptive Huffman coding algorithm, the performance of the proposed method has been compared with several proposed methods.

Table 2: Compression performance - software vs. hardware

	Compression Performance (Simulation)		Compression Performance (Embedded Platform)	
DS	CR	PRD	CR	PRD

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100	0.2061	0.1825	0.2934	0.1961
106	0.2441	0.1961	0.28486	0.2055
112	0.2370	0.1947	0.37875	0.2472
117	0.3281	0.2924	0.3522	0.3398
213	0.2404	0.2864	0.4188	0.2959

The performance results indicate that the proposed model achieves encouraging outcomes. The experimental analysis demonstrates that the proposed approach maintains signal quality while ensuring a reasonable compression ratio. Thus, this approach can used for real-time telemedicine applications. The experiment results after implementing both the simulation and embedded platform on the ECG de-noising mission demonstrated the feasibility of the proposed architecture. A new low-complexity lossless ECG compression algorithm based on adaptive Huffman code was developed for embedding the system on the Raspberry Pi 3 B+ micro-controller implementation and tested by the MIT-BIH database and real-time ECG signal record. Thus, the CR and PRD of simulation and embedded platform performance are shown in Table 3 above using the proposed lossless compression algorithm. The comparison performance results are given in detail in the above table. Since the proposed method improves compression performance across an unexplored area where lower PRD and greater CR are obtained on an embedded platform, it is evident that it pushes forward compression performance in an unexplored area. Finally, the agreement ratio between hardware and software implementations has been calculated and evaluated based on the experimental results of the compression performance for the average CR is 70.58% and the PRD is 90.4%.

4.1. Discussion

An adaptive lossless ECG signal compression algorithm based on the Huffman code algorithm is introduced in this research work. The evaluation set assesses the model's performance and ensures the ECG signal is reconstructed; the validation set is used to choose the optimal model. The proposed method has been validated using various normal and pathological cardiac signals from the MIT-BIH database. The algorithm achieves mean compression ratios of 20.61, 24.41, and 30.96 for its dynamic and minimal window size variants, with corresponding percentage root mean square differences (PRD) of 0.18 and 0.29. This method is suitable for real-time e-health monitoring. The PRD results indicate that the ECG signals can be effectively analyzed after reconstruction. The compression ratio (CR) results are also valuable for storing and transmitting ECG signals. A thorough analysis of the statistical results reveals the high performance of the proposed method in ECG signal compression, providing a straightforward solution to the storage challenges associated with ECG records. This research work presented the evaluation of the statistical results compared to other techniques recently published for CR, which are presented in Figure 3 and were analyzed using three different ECG datasets (a) 100.mat ECG signal, (b) 117.mat ECG signal, and (c) 118.mat ECG signal. The results of the proposed method applied to

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ECG signals have been analyzed, alongside various other techniques referenced as [17], [18], [19], [20], [21], [22], and [23]. At both the highest and lowest compression parameters, the proposed method demonstrates competitive performance compared to other techniques, achieving the best quality scores in Compression Ratio (CR) and Percentage Root-Mean-Square Difference (PRD). Specifically, the proposed algorithm improves the average CR by approximately 13% compared to [17], about 46% compared to [20], and around 21% compared to [23]. However, as the signal length increased, both CR and PRD also tended to rise. The Raspberry Pi (R-Pi) was utilized to facilitate the hardware implementation of the proposed work, including data collection, compression/decompression, and real-time data transmission, in order to assess the performance during runtime.

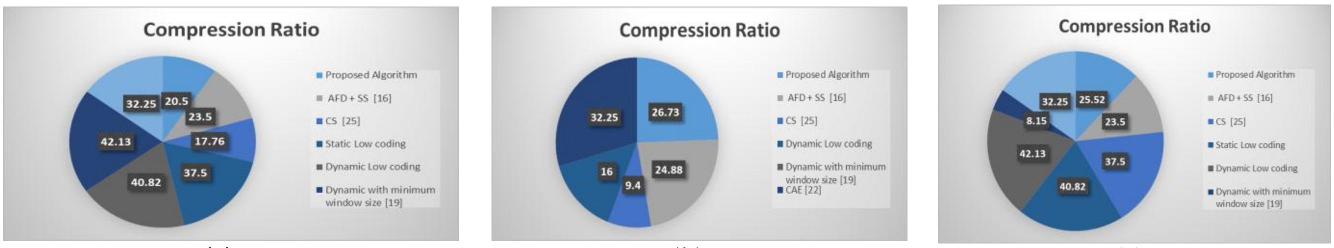

Figure 3. Compression results of the proposed method for various ECG signals: (a) 100.mat, (b) 117.mat (c) 118.mat

The result indicates the Percentage Reconstruction Distortion (PRD) for different datasets: approximately 68% for dataset [17], around 89% for [24], about 95% for [25], roughly 62% for [20], about 98% for [21], and approximately 93% for [23]. In e-healthcare applications, the requirements for ECG signals include low power consumption and efficient online data transmission, necessitating low complexity and reduced computational time. Despite these constraints, the reconstructed signals still yield significant results due to the high performance of the proposed method.

Furthermore, as is common in medical applications, data collected for clinical purposes often needs to be transmitted and/or stored with minimal reconstruction error for the information obtained from the sensors. To investigate this, a sample-to-sample error signal was computed between the original and reconstructed signals for each dataset. This research presented methods that ensure low computational time, low complexity, and lossless compression. The algorithm developed employs an adaptive approach to compress ECG signals, designed to simultaneously utilize potential redundancy across samples taken at different times. Three distinct ECG datasets were analyzed in this project to evaluate statistical outcomes, which were then compared to previously published PRD parameters. The evaluation results depicted in Figure 4 were analyzed using the following ECG datasets: (a) 100.mat ECG signal, (b) 117.mat ECG signal, and (c) 118.mat ECG signal.

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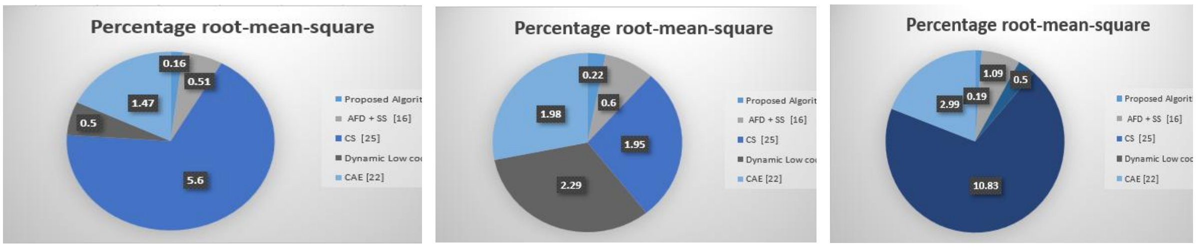

(a) (b) (c)

Figure 4. PRD results of the proposed method for various ECG signals: (a) 100.mat, (b) 117.mat (c) 118.mat

5. CONCLUSION

This study focuses on the development of an efficient compression mechanism for ECG signal processing, with primary tasks involving ECG coding and decoding. To achieve this objective, an adaptive compression technique based on the Huffman coding algorithm is proposed. The encoding and decoding processes of the proposed approach were evaluated using real ECG signals from the MIT-BIH Arrhythmia Database as well as real-time ECG recordings. The performance of the proposed method was assessed using Percentage Root Mean Square Difference (PRD) and Compression Ratio (CR) metrics. Comparative analysis with existing methods demonstrated superior performance in terms of both compression efficiency and signal reconstruction quality. The findings of this study validate the applicability of the proposed compression mechanism for ECG data. Additionally, the agreement ratio between hardware and software implementations was calculated and evaluated based on experimental results. The proposed method achieved an average compression ratio of 70.58% and a PRD of 90.4%, indicating its effectiveness in compressing ECG signals while preserving signal integrity. This approach offers a viable alternative for extracting high-resolution ECG signals from noisy measurements, ensuring a high compression ratio with minimal reconstruction error.

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CONFLICTS OF INTEREST:

The authors declare no conflict of interest.

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