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Electrocardiogram Compression Using Adaptive Decomposition Techniques for Smart Healthcare System

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Abstract

Purpose: Electrocardiogram (ECG) compression is a critical aspect of smart healthcare systems, to efficiently store, transmit, and process ECG data. The research aims to find an efficient compression technique that reduces storage and transmission requirements without compromising diagnostic information, especially in the context of remote monitoring, telemedicine, and the increasing use of wearable devices.

Method: The proposed approach integrates Adaptive Variational Mode Decomposition (AVMD) with Wavelet Packet Transform (WPT) for signal decomposition and transform coding. AVMD adaptively decomposes the signal into Intrinsic Mode Functions (IMFs), while WPT enhances time-frequency resolution and maintains a balanced representation of the signal. The framework is further optimized through arithmetic coding for efficient data compression. Experiments were conducted on ECG signals from the Physionet and Mendeley databases to validate the method's performance and reliability.

Results: The proposed method achieved a compression ratio of 41.19 and a Percentage Root Mean Square Difference of 0.29 for the Massachusetts Institute of Technology-Beth Israel Hospital Supraventricular Tachyarrhythmia database record no. 209, demonstrating superior compression efficiency and minimal signal distortion compared to existing techniques.

Conclusion: The integration of AVMD and WPT, combined with arithmetic coding, offers a highly effective solution for ECG data compression. The method ensures efficient storage and transmission of ECG data while preserving critical diagnostic information, making it a robust choice for smart healthcare.

Categories: Signal Processing and Image Analysis, Wireless Communication Systems
Keywords: smart healthcare, wavelet packet transform, ecg compression, avmd, diagnostic information preservation, imf, compression ratio, percent root mean square difference

Introduction

Signal compression is an important aspect in the area of storage and communication, regardless of the mode of transmission. The area of biomedical signal processing has witnessed a growing need for efficient compression techniques to manage the vast amount of data generated by electrocardiogram (ECG) signals. ECG waves are a representation of the heart's electrical activity and are crucial for identifying different cardiac diseases. These signals play a crucial role in diagnosing cardiovascular diseases, but their large data size poses challenges in storage and transmission. Traditional compression methods may result in the loss of important diagnostic information.

The signal decomposition using Empirical Mode Decomposition (EMD) and the Hilbert Transform (HT) yields finite Intrinsic Mode Functions (IMFs) with low indices that have a single extremum among their zero crossings and whose local maxima and minima envelopes are mirror images of one another. The authors argued that this decomposition approach is useful for non-stationary data analysis since it is orthogonal. Using a Discrete Wavelet Transform (DWT), before applying a cutoff, the components of low and high-frequency components are considered, and linear filters are used to predict a signal with low variance. Huffman Coding, Inverse linear predictive coding, and Inverse Discrete Wavelet Transform have been utilized to reconstruct the signal [1,2]. The study in [3] introduced a denoising method combining Wavelet Packet Transform (WPT) with soft thresholding for ECG signals corrupted by white Gaussian noise. The adaptive thresholding mechanism ensured efficient noise reduction without compromising the signal's vital features. However, their work was primarily focused on denoising rather than compression, along with leaving the potential for applying WPT for compression. Recent studies emphasize the effectiveness of Variational Mode Decomposition (VMD) as an adaptive technique for decomposing non-stationary signals such as ECGs into IMFs while maintaining signal integrity. For instance, the authors in [4] demonstrated the application of multirate processing combined with metaheuristic optimization and

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VMD for arrhythmia classification. Their approach optimized signal representation and achieved high diagnostic accuracy, underscoring the potential of VMD in medical signal processing. Authors in [5] developed a hybrid compression scheme using VMD and lifting wavelet transform with entropy encoding. Their approach optimized the decomposition parameters adaptively and provided minimal reconstruction error. While this method achieved good decomposition, it lacked fine resolution in time-frequency analysis provided by the WPT. Similarly, in the paper [6], the authors proposed a secure ECG compression method based on cryptographic techniques. They used the phase-encoded shift invert bus encoding approach. This made it suitable for monitoring systems, but they did not optimize for compression performance or real time applications. In a similar vein, in [7], the authors introduced a hybrid methodology that integrates VMD, Shannon energy envelopes, and deterministic learning for ECG arrhythmia classification, achieving significant improvements in diagnostic accuracy over traditional methods. The paper in [8] suggested a combination of WPT and Empirical Wavelet Transform (EWT) with ensemble classifiers for feature extraction. The author's reliance was entirely on the wavelet-based methods, which limited the systems performance in handling signals with highly non-linear or time-varying characteristics. The researchers in [9] segregated the QRS complex and plateau region and formed a QRS complex bank later used for Integer Cosine Transform for compression and arithmetic coding. In [10], the authors presented a method for compressing ECG signals by combining EMD with a transform method. The wavelet coefficients, once quantized, were encoded using a technique that involved creating a binary table and then performing Huffman coding.

To reconstruct the signal, the use of EMD in addition to wavelet analysis has been considered and further divided the signals and obtained a collection of Quadrature Mirror Decomposition, revealing the features of both the low as well as high features inherent in the wavelet. Also, the Dead Zone Quantization has been used that eliminate the coefficients that are close to zero and use just an IMF function and a combination of them [11,12].

A key challenge in signal compression is addressing noise and artifacts while preserving clinically relevant features. Authors in [13] evaluated five adaptive decomposition techniques, including VMD, highlighting their applicability for biomedical signals. Their results underscored the diagnostic advantages of adaptive decomposition in distinguishing signal components from noise. These insights are crucial for refining ECG compression algorithms, particularly in noisy environments typical of wearable health monitoring systems. The authors [14,15] have used VMD, a decomposition technique that non-recursively disassembles a signal into many IMFs concurrently. Each IMFs were represented like a mix of signal amplitude, instantaneous frequency, and time index, which enabled the extraction of band-limited modes. The authors in this paper have retrieved the signal with the help of Hilbert Transform; the signal facilitates the generation of a single-sideband analytical signal, which assists in assessing the bandwidth of each IMF. The original input signal was then picked up from the positive spectrum of frequencies by multiplying the harmonics of the signals with the analytical signal, which shifts the signal frequencies. Researchers have used bandwidth limitations, initialization parameters, and dual ascending for updating signals and estimating modes. Later the Least Mean Square (LMS) algorithm is selected to dynamically update the modes, guaranteeing seamless filtering and precise decomposition of the signal. They have chosen VMD over EMD because of its superior capability to efficiently handle signals and overcome the constraints of EMD, making it a preferable option for signal decomposition.

The research here addresses several gaps by introducing an integrated framework that combines AVMD and WPT. Previous studies have either employed traditional methods or static decomposition methods like DWT, WPT, EMD, and EWT, which focused on singular objectives like denoising, and multiresolution analysis for time-frequency representation. In contrast, this work utilizes AVMD's adaptive capability to decompose ECG signals to IMFs. This ensures optimal handling of signal variability, particularly the signal's non-linear and time-varying morphologies. The subsequent application of WPT enhances the time-frequency resolution. Additionally, the integration of arithmetic coding ensures a near-optimal compression ratio (CR) by effectively using the statistical properties of the ECG signal by minimizing the number of bits required to represent the data. The rest of the paper is structured as follows: Introduction section presents the Introduction along with a literature survey. Materials & Methods section provides a detailed explanation of the proposed compression technique, including the steps of VMD and WPT. The results are discussed in Results section, and the paper's work is concluded in Conclusion section.

Materials And Methods

VMD is a signal processing technique used for breaking down a signal into a collection of different oscillatory components. VMD can be applied for compression of input ECG signal by decomposing the ECG signal into its IMFs and then compressing these IMFs. ECG signals play a crucial role in diagnosing cardiovascular diseases, but their large data size poses challenges in storage and transmission. Traditional compression methods may result in the loss of important diagnostic information. This essay delves into the potential of VMD to address this challenge, offering an in-depth exploration of the mathematical expressions underpinning its application to ECG compression. Combining VMD with the WPT for ECG compression is an advanced technique that leverages the benefits of both methods. VMD is employed for adaptively decomposing the signal into modes, while WPT is used for further capturing frequency information in each mode. The procedure for ECG compression using this combined approach is outlined as follows, and a workflow diagram illustrating the complete methodology from input signal preprocessing to reconstructed output is given in Figure 1.

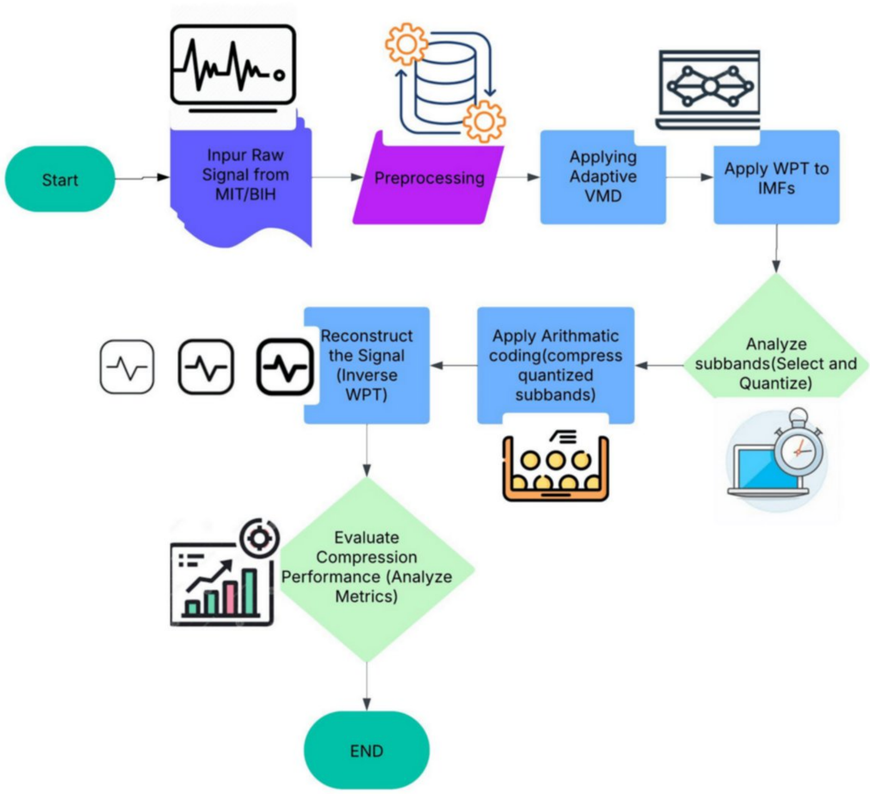

FIGURE 1: Workflow diagram illustrating the complete methodology

BIH/MIT, Beth Israel Hospital/Massachusetts Institute of Technology; VMD, Variational Mode Decomposition; WPT, Wavelet Packet Transform; IMFs, Intrinsic Mode Functions

Steps for ECG compression using VMD and WPT

1. Obtain the raw ECG signal data. Ensure that the signal is properly sampled and cleaned (remove noise, baseline wandering, etc.) for accurate decomposition.

2. Decompose the pre-processed ECG signal into adaptive modes using VMD. Obtain K IMFs representing different frequency components.

3. Apply WPT to each of the K IMFs obtained from the VMD. This involves decomposing each IMF into its wavelet packets.

4. The decomposed sub-bands are analyzed from each IMF and those that contain important information for ECG analysis.

5. The quantization process is considered for the selected sub-bands from each IMF to reduce the bit depth of each sample. The quantization parameters are adjusted based on the desired CR.

6. Entropy encoding techniques such as arithmetic coding are applied to further reduce the bit rate and enhance compression efficiency.

7. Reconstruction is made by applying inverse WPT on the selected and quantized sub-bands of each IMF and finally, the sum of the reconstructed IMFs is taken to obtain the final compressed ECG signal.

The mathematical representation of the above-combined process is as follows:

$$X(t) = \sum_{k=1}^{K} \left(\sum_{j=1}^{J} c_{k,j} \right)$$

X(t) is the original input ECG signal.

K represents the number of selected IMFs from VMD

J is the number of sub-bands obtained from the WPT for each IMF

$c_{k,j}$ represents the coefficients of the selected sub-bands

The mathematical expression for the WPT involves the breakdown of the signal *X(t)* into sub-bands by use of a set of scaling and wavelet functions. The decomposition can be represented as:

$$X(t) = \sum_{j=1}^{J} \sum_{k=0}^{2^{j-1}} d_{j,k} \, \Phi_{j,k}(t) + \sum_{k=0}^{2^{J-1}} \alpha_{J,k} \, \Phi_{J,k}(t)$$

where *X (t)* is the original signal, and *J* represents the decomposition level, here $d_{j,k}$ works as the detailed coefficients and $\alpha_{J,k}$ as the approximation coefficients. The basis functions $\Phi_{J,k}(t)$ are in time-frequency representation.

Adaptive VMD

Whenever the optimal Wiener filter is used for the reduction of noise, it is assumed that the signal is stationary [15]. Practically, it is not feasible. Therefore, it is extended to an adaptive LMS algorithm and its performance is evaluated. Adaptive Wiener filters are linear least-squared estimators for the stationary stochastic process. It does not provide information on how to estimate statistics. It is to be assumed that the cross-correlation vector and autocorrelation matrix are known. If there is not much change in noise or signal, a fixed filter will be less expensive computationally. In VMD, the modes are updated by the Wiener filter and are used for denoising. However, in this work, the Wiener filter is used for the same and further filtering is applied using the adaptive algorithm as LMS. The proposed algorithm is summarized below:

1. Initialize $\{(\hat{x}_{m_k})^1\}, \{\hat{f}_k^1\}, \hat{\lambda}^1, \quad m \leftarrow 0$, repeat $m \leftarrow m+1$

2. For $k = 1 : K$ do $\text{Update } (x_{m_k})^\wedge \text{ for all } f \geq 0$

$$\hat{x}_{m_k}^{(m+1)} \leftarrow \frac{\hat{x}(t) - \sum_{ik} \hat{x}_i^m(z) + \frac{\hat{\lambda}^m(z)}{2}}{1 + 2\hat{\lambda}(f - f_k^m)^2}$$

3. Update $f_k \quad \text{for all } f \geq 0 \text{ through Wiener filter}$

$$f_k^{(m+1)} \leftarrow \frac{\int_0^\infty f \left| \hat{f}_k^{(m+1)}(f) \right|^2 df}{\int_0^\infty \left| \hat{x}_{m_k}^{(m+1)}(f) \right|^2 df}$$

4. ($\text{Update } f_k \quad \text{for all } f \geq 0 \text{ through LMS algorithm} \backslash)$

$$f_k^{(m+1)} = f_k + \mu e_{m_k}(t) x_{m_k}(t)$$

where μ is the step size, $e_{m_k}(t)$ is the error signal, and $x_{m_k}(t)$ is the input signal for each mode m_k.

5. $\text{For all } f \geq 0, \text{ the dual ascent becomes}$

$$\hat{\lambda}^{(m+1)}(f) \leftarrow \hat{\lambda}^m(f) + \tau \left(\hat{x}(f) - \sum_k \hat{x}_{m_k}^{(m+1)}(f) \right)$$

6. Convergence until

$$\frac{\sum_k \|\hat{x}_{m_k}^{(m+1)} - s_{m_k}^m\|_2^2}{\|s_{m_k}^m\|_2^2} < \epsilon$$

The Wiener filter with a signal prior $\frac{1}{(f - f_k)^2}$ is used to identify the current residual. Adaptive Wiener filters are estimators that minimize the mean squared error for a stationary stochastic process linearly. It lacks information regarding the estimation of the data. It is necessary to assume the presence of cross-correlations and autocorrelations between the signal and noise. If both signal and noise are Gaussian and there is not much change in their characteristics, then the Wiener filter is optimal. Therefore, the LMS algorithm is chosen for better convergence and a more reasonable estimate of the gradient. The cost function of the steepest descent algorithm finds out the adaptive filter coefficients. These coefficients smooth the error due to the iterative and time-averaging nature of the LMS algorithm.

The combined adaptive VMD and WPT compression process involves adapting the expressions for VMD and WPT and integrating them. The mathematical expression for reconstructing the compressed ECG signal can be represented as:

$$X_{\text{compressed}}(t) = \sum_{k=1}^{K} \text{InverseWPT}\left(\text{Quantize}\left(\text{SelectSubbands}\left(\text{VMD}(X(t))\right)\right)\right)$$

Here, VMD *X(t)* represents the application of VMD on the ECG signal. Selecting sub-bands involves selecting significant sub-bands from each IMF. The quantization and compression steps are applied before the inverse WPT operation. The WPT algorithm is implemented by recursively decomposing the signal into sub-bands. Compression is achieved by discarding or quantizing coefficients in less relevant sub-bands. The adaptability of WPT to capture both transient and oscillatory components makes it suitable for ECG signals with varying characteristics.

Encoding

Entropy coding is a technique used to reduce the size of data by assigning shorter codes to patterns or values that occur more frequently, while less common patterns receive longer codes. This method helps compress information efficiently without losing critical details, making it ideal for applications like ECG data compression, where minimizing storage and transmission requirements is crucial. The idea is to exploit the statistical characteristics of the data to achieve higher compression ratios. There are several entropy coding methods, and two common ones are Huffman coding and arithmetic coding. In this study, arithmetic coding, a type of entropy coding, was chosen for its precision in representing data as a single compact value. Huffman coding is widely used in various applications, including image and text compression. However, arithmetic coding is a more sophisticated entropy coding technique that assigns a fractional value to the entire message. Instead of encoding symbols individually, arithmetic coding encodes the entire message as a single floating-point number between 0 and 1. The range (0, 1) is divided into subintervals, each corresponding to a symbol and proportional to its probability. The more probable symbols have larger subintervals.

Results

The ECG signal is taken from the Massachusetts Institute of Technology-Boston's Beth Israel Hospital (MIT-BIH) database, with a sampling frequency of 360 Hz and a resolution of 11 bits per sample. Further, the signal is used with a sampling frequency of 360 Hz from the Mendeley database for verification of the proposed method. The signals are derived from one lead, the Modified Limb Lead II (MLII). The frequency in adaptive VMD is determined by differentiation, which enables the circumvention of the constraints imposed by the uncertainty principle. VMD is both practical and sensitive to noise. The proposed method is evaluated using the performance metrics indicated below, which are widely employed in the academic literature.

Compression ratio

Although the CR is high, it leads to a decrease in the required number of bits for data transmission and storage. The primary objective is to achieve a high CR in ECG compression without compromising the quality of the reconstructed ECG signal. The expression is derived from.

$$CR = \frac{\text{Signal size before compression } B_0}{\text{Signal size after compression } B_1}$$

Percent root mean square difference (PRD)

The PRD quantifies the degree of distortion between the reconstructed and original pictures. The error criteria are defined as a metric to assess the reconstructed signal's capacity to retain pertinent information. It is represented by:

$$PRD = \sqrt{\frac{\sum_{n=1}^{N}(x(t)-x(r))^2}{\sum_{n=0}^{N-1}(x(t))^2}}$$

Where *x(t)* = Input ECG Signal (ECG Signal), *x(r)* = Reconstructed ECG Signal

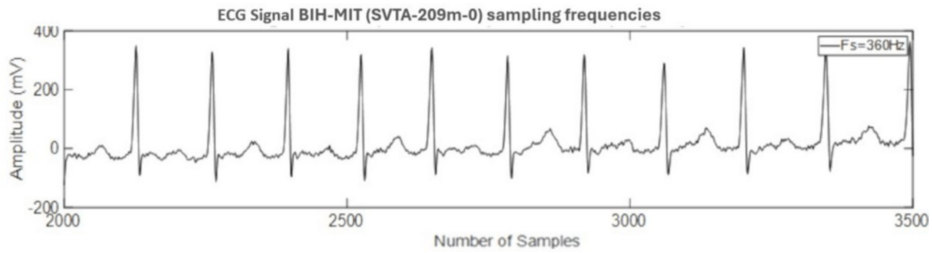

FIGURE 2: ECG signal considered for compression from the BIH-MIT database

ECG, electrocardiogram; BIH-MIT, Beth Israel Hospital-Massachusetts Institute of Technology; SVTA, Supraventricular Tachyarrhythmia

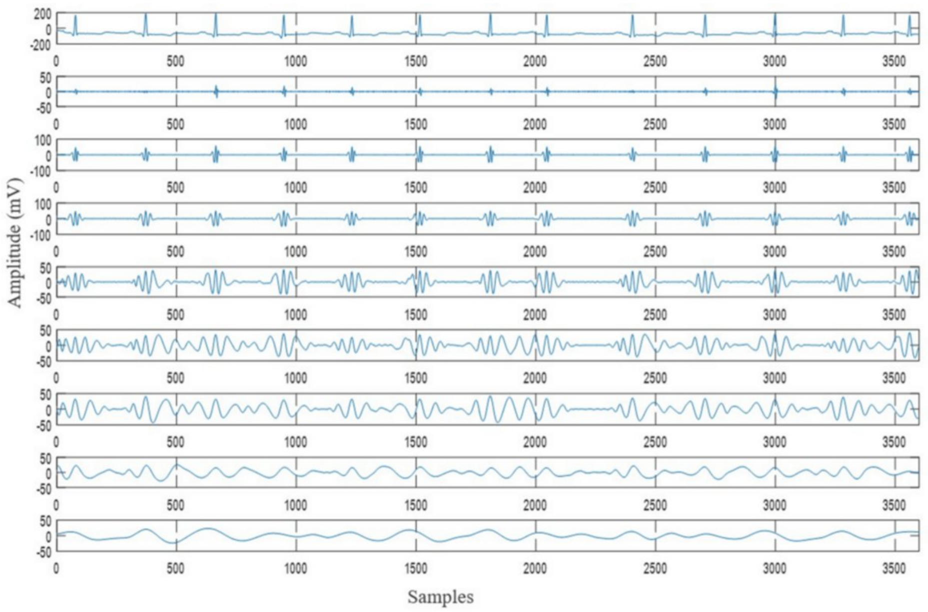

FIGURE 3: Decomposed ECG signal in terms of IMFs

ECG, electrocardiogram; IMFs, Intrinsic Mode Functions

Figure 2 shows the raw signal considered for compression from the MIT-BIH database, which presents the raw ECG signal extracted from the MIT-BIH dataset. This establishes the baseline for compression and highlights the quality of the input data. Figure 3 shows the decomposition of the raw signal into IMFs using AVMD. This step is crucial as it allows the adaptive extraction of signal components with different frequency characteristics, ensuring an accurate representation of the signal. Figure 4 illustrates the reconstructed ECG signal after applying the proposed method, along with the error plot. The overlap of the original and reconstructed signals, combined with the low error, visually confirms the method's high fidelity in signal reconstruction. The decomposition of the original signal was made using adaptive VMD techniques.

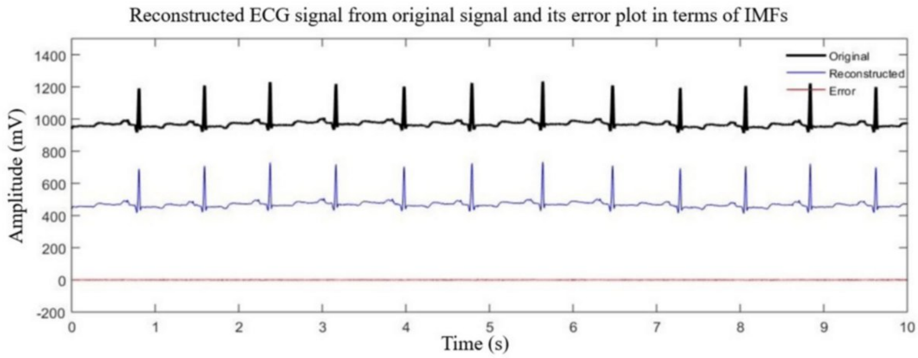

FIGURE 4: Reconstructed ECG signal from original signal and its error plot in terms of IMFs

ECG, electrocardiogram; IMFs, Intrinsic Mode Functions

Table 1 shows the compression performance according to the proposed method, compared to the existing techniques.

ECG Database	Methodology	CR	PRD
Fetal PCG [1]	DOCMs + HOM [1]	18.33	0.21
MIT-BIH arrhythmia database [9]	DCT [9]	31.51	0.84
MIT-BIH arrhythmia database [10]	EMD [10]	21.56	4.65
Mendeley [12]	Lempel-Ziv-Welch (LZW) + Huffman [11]	37.6	-
Mendeley [13]	EMD + Huffman [13]	35.57	4.38
MIT-BIH SVTA	Proposed Method (AVMD + WPT)	41.19	0.29

TABLE 1: Performance comparison

ECG, electrocardiogram; CR, compression ratio; PRD, Percentage Root Mean Square Difference; PCG, Phonocardiography; DOCM, Discrete Orthogonal Charlier Moment; HOM, Householder Orthonormalization Method; BIH-MIT, Beth Israel Hospital-Massachusetts Institute of Technology; DCT, Discrete Cosine Transform; EMD, Empirical Mode Decomposition; SVTA, Supraventricular Tachyarrhythmia; AVMD, Adaptive Variational Mode Decomposition; WPT, Wavelet Packet Transform

Discussion

The results indicate that the proposed method (AVMD + WPT) achieved the highest CR of 41.19% with a low PRD of 0.29, suggesting a strong balance between compression efficiency and signal fidelity.
It demonstrates significant advantages over traditional approaches in terms of compression efficiency, noise handling, and diagnostic fidelity. By use of AVMD for adaptive decomposition and WPT for enhanced time-frequency resolution, the framework effectively handles non-linear and time-varying ECG signals. The incorporation of LMS algorithms ensures dynamic mode adjustments, further reducing noise and improving accuracy. Comparative analysis with existing methods highlights the proposed method's ability to achieve a higher CR and lower PRD while maintaining signal integrity. However, the computational demands of AVMD and WPT, particularly for resource-constrained devices, remain a key limitation that needs to be addressed. By incorporating lightweight algorithmic designs and leveraging hardware acceleration, such as FPGA- or GPU-based implementations, the method can be adapted for real-time healthcare applications, including wearable and IoT-based systems.

Conclusions

The combined approach aims to exploit the advantages of both adaptive VMD and WPT to achieve effective ECG compression while preserving important diagnostic information. The decomposed signal is processed through adaptive modes using VMD, after which WPT is used, which again decomposes the IMFs into wavelet packets. Further quantization and arithmetic coding resulted in reducing bitrate and enhancing CR to 41.19 and 0.29 as PRD. The result was found excellent with this novelty. In terms of compression performance, record no. 202 from the Mendeley database has a CR and PRD of 38.26 and 0.37, whereas record no. 100 from the MIT-BIH Physionet database has a CR and PRD of 38.19 and 0.39. When comparing the results of various compression strategies, it is observed that the proposed approach achieves significantly superior compression performance to the other techniques. Adjustments and optimizations may be required based on the explicit quality of the ECG signals in future applications. Future work will focus on optimizing computational efficiency for real-time use, multi-lead ECG compression, and secure transmission through blockchain integration. These advancements will address storage, transmission, and security challenges, paving the way for scalable and reliable ECG compression solutions in modern healthcare systems.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

Concept and design: Sudeshna Baliarsingh, Mihir Narayan Mohanty

Drafting of the manuscript: Sudeshna Baliarsingh

Acquisition, analysis, or interpretation of data: Mihir Narayan Mohanty

Critical review of the manuscript for important intellectual content: Mihir Narayan Mohanty

Supervision: Mihir Narayan Mohanty

Disclosures

Human subjects: All authors have confirmed that this study did not involve human participants or tissue. **Animal subjects:** All authors have confirmed that this study did not involve animal subjects or tissue. **Conflicts of interest:** In compliance with the ICMJE uniform disclosure form, all authors declare the following: **Payment/services info:** All authors have declared that no financial support was received from any organization for the submitted work. **Financial relationships:** All authors have declared that they have no financial relationships at present or within the previous three years with any organizations that might have an interest in the submitted work. **Other relationships:** All authors have declared that there are no other relationships or activities that could appear to have influenced the submitted work.

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