

Efficient electrocardiogram signal coding for medical devices using linear prediction

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ABSTRACT

The growing adoption of wearable health monitoring and internet of things (IoT)-based medical devices has increased the demand for efficient electrocardiogram (ECG) compression techniques that reduce data size while preserving diagnostic fidelity. This paper proposes a compression method that combines linear predictive coding (LPC) with a residual thresholding mechanism. The ECG signal is modeled using a tenth-order LPC framework, and the residual is sparsified by retaining only the most significant components. The novelty of this work lies in applying threshold-based residual sparsification tailored to ECG signals, enabling high compression ratios (CR) while preserving clinically relevant waveform features. Experimental results using PhysioNet ECG data show that the proposed method achieves CRs of up to 38:1, while a moderate threshold (α is 0.005) provides a practical trade-off, achieving around 20:1 compression with preserved P wave, QRS complex, and T wave. The method offers a low-complexity solution suitable for wearable and IoT-based healthcare applications.

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1. INTRODUCTION

The growing need for compact data storage and efficient communication in biomedical systems, driven by real-time transmission demands, limited memory in wearable devices, and energy constraints, has prompted the advancement of reliable signal compression methods [1]–[5]. One widely used approach is source coding, which is commonly applied in speech [6], image [7], and video processing [8] to eliminate unnecessary data, enabling compact storage and fast transmission. Among various methods, linear predictive coding (LPC), initially developed for speech signals, has emerged as a viable model-based approach for biomedical data, including electrocardiogram (ECG), due to its ability to represent quasi-periodic signals compactly. LPC is used in codecs such as LPC-10 and code-excited linear prediction (CELP) [9]. In contrast, transform-based methods, such as joint photographic experts group (JPEG) and JPEG2000, are widely adopted in image processing [10]. Biomedical signals, particularly ECG recordings, also benefit significantly from compression techniques, which are crucial in remote health monitoring and mobile healthcare systems [11]–[16]. With the rise of internet of things (IoT)-enabled health systems, continuous ECG monitoring now produces large volumes of data, especially when using high sampling rates (e.g., 1000 Hz) and high-resolution formats (e.g., 16-bit) [5]. Among these signals, the ECG is one of the most essential tools for diagnosing heart conditions [11]–[16].

To manage this data more efficiently, compression techniques are necessary to reduce storage requirements and transmission load without compromising critical clinical details, such as the P-wave, QRS complex, and ST segment [17]–[22]. These techniques generally fall into two categories: waveform-based and model-based. Waveform-based methods work directly on the signal and aim to reduce redundancy. For example, wavelet transforms are used for localized frequency decomposition, while discrete cosine transforms are effective for energy compaction. Other approaches include compressed sensing, which exploits signal sparsity to reduce sampling requirements [23]–[25]. Model-based methods take a different approach by building mathematical models to represent the signal, often leading to more compact and structured compression [26]–[28]. Initially developed for speech compression [19]–[26], LPC models each sample as a linear combination of past values, producing a residual signal used for reconstruction. Due to their quasi-periodic nature, biomedical signals like ECG can also be effectively compressed using this technique.

In wearable ECG and IoT-based healthcare systems, practical constraints such as limited battery life, restricted bandwidth, and low computational resources make efficient signal compression essential. Continuous ECG monitoring generates large data volumes, increasing energy consumption and transmission load, especially in resource-limited settings. Therefore, compression methods must not only reduce data size but also preserve clinically important features such as the P wave, QRS complex, and T wave to ensure reliable diagnosis. These challenges highlight the need for solutions that balance high compression efficiency, low complexity, and diagnostic fidelity. This study proposes a computationally efficient ECG compression method intended for wearable and IoT healthcare systems, where limitations in storage capacity, transmission bandwidth, and processing resources are critical. The method integrates low-order LPC with a threshold-based selection of prediction residuals, so that only the most relevant signal components are transmitted. The use of a low-order LPC model, together with sparsified residuals, enables effective data reduction while preserving ECG waveform features that are important for clinical analysis. To ensure practical deployment, an appropriate threshold value is determined to balance compression ratio (CR) and reconstruction accuracy, supporting real-time operation in wearable devices. The proposed approach is evaluated using ECG recordings from the PhysioNet database and assessed through commonly used performance metrics [29]–[32]. Experimental results show that CRs of up to 38:1 can be achieved, indicating the potential of the method for telemedicine, remote monitoring, and wearable ECG applications. The remainder of this paper is organized as follows. Section 2 describes the proposed encoder–decoder architecture, including preprocessing, LPC/line spectral frequencies (LSF) estimation, residual sparsification, and quantization. Section 3 presents and discusses the experimental results and performance evaluation. Section 4 concludes the paper and outlines future work.

2. RESEARCH METHOD

The proposed ECG compression framework, as shown in Figure 1, follows an encoder–decoder architecture composed of four main stages: preprocessing and LPC analysis in the encoder, as shown in Figure 1(a), and frame and signal reconstruction in the decoder, as shown in Figure 1(b). The detailed processing stages are illustrated in Figures 2 and 3. This section also describes how LPC parameters and residual signals are quantized for efficient transmission.

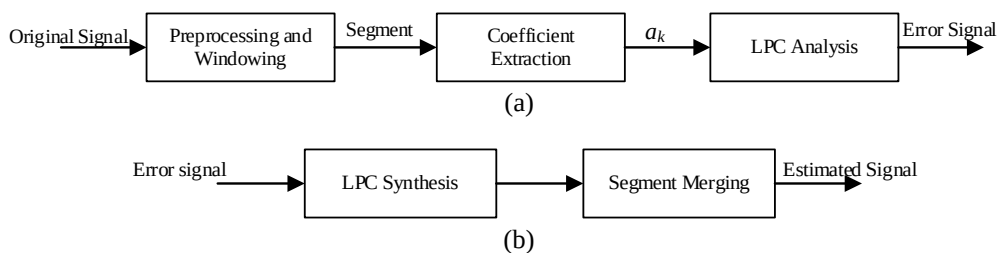


Figure 1. Classical source-filter model; (a) encoder and (b) decoder

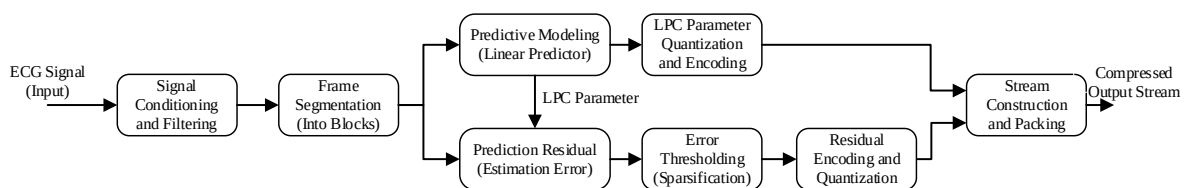


Figure 2. The suggested encoder

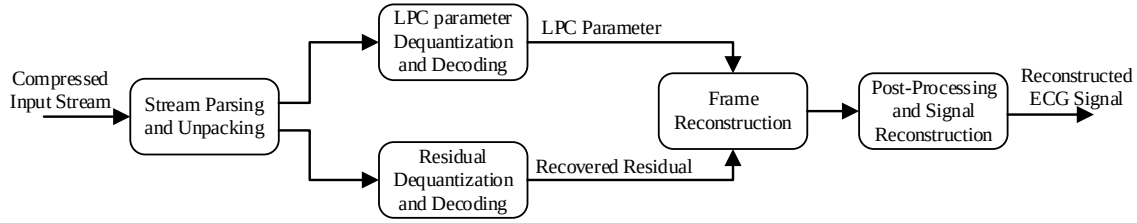


Figure 3. The suggested decoder

2.1. Signal conditioning

Prior to LPC analysis, the ECG signal undergoes preprocessing to improve quality and robustness. Synthetic Gaussian noise is added solely for simulation and testing, not in real-time applications, followed by normalization and low-pass filtering using a finite impulse response (FIR) filter with a 100 Hz cutoff frequency. The filtered signal is then segmented into frames for LPC analysis.

2.2. Modeling and coefficient estimation

Each ECG sample is modeled as a linear combination of previous values. The residual signal, defined as the difference between the original and predicted signal, is transmitted or stored in a compressed form. During synthesis, this residual signal is applied to a filter defined by $1/A(z)$, where $A(z)$ is the transfer function derived from the prediction coefficients a_k . Removing the residual or using an incorrect synthesis filter leads to reconstruction errors. The predicted sample $\hat{x}(n)$ and residual error e are expressed as (1) and (2) [33]–[36]:

$$\hat{x}(n) = a_1 x(n-1) + a_2 x(n-2) + \dots + a_p x(n-p) \quad (1)$$

$$e = x - \hat{x}, \quad x = [x(0), x(1), \dots, x(N-1)]^T, \quad \hat{x} = [\hat{x}(0), \hat{x}(1), \dots, \hat{x}(N-1)]^T \quad (2)$$

where x and $\hat{x}$ are the original and predicted signal vectors, respectively, $(\cdot)^T$ denotes the transpose operator, a_k are the prediction coefficients, p is the prediction order, and $e(n)$ represents the residual signal. For each frame, a set of prediction coefficients is derived by minimizing the mean squared error between the original and predicted signals.

The prediction error E is defined as [33]–[36]:

$$E = \|e\|_2^2 = \|x - \hat{x}\|_2^2 \quad (3)$$

where $\|\cdot\|_2$ represents the Euclidean norm, meaning the square root of the sum of the squared elements. Minimizing this error with respect to each coefficient yields a system of p linear equations with p unknowns, known as the normal equations. This system is typically derived using the autocorrelation method [33]–[36]:

$$\Gamma a = \gamma, \quad a = [a_1, \dots, a_p]^T \quad (4)$$

where Γ is the $p \times p$ autocorrelation matrix with elements $[\Gamma]_{lk} = \gamma_{xx}(l-k)$ and $[\gamma]_l = \gamma_{xx}(l)$, $l, k = 1, \dots, p$. Here, the autocorrelation function $\gamma_{xx}(l)$ is defined as (5) [36]:

$$\gamma_{xx}(l) = E\{x(n)x(n-l)\} \quad (5)$$

where $\gamma_{xx}(l)$ is the autocorrelation of $x(n)$, E denotes the average or expected-value operator, and l is the sample lag. The matrix has a Toeplitz structure because each diagonal contains the same autocorrelation value. This structure permits efficient numerical computation of the predictor coefficients. The zeroth-order coefficient is taken as $a_0 = 1$ when the predictor is written in normalized polynomial form. By making use of (4), the minimal error can be obtained without explicitly calculating every residual sample. It is given by [36]:

$$E_{\min} = \gamma_{xx}(0) - \gamma^T a \quad (6)$$

where $\gamma_{xx}(0)$ represents the average signal power, while $\gamma^T a$ represents the part of that power explained by the linear predictor. Consequently, minimizing (3) and solving (4) produces the coefficient set that gives the lowest mean-square prediction error.

2.3. Residual thresholding

A thresholding mechanism retains only the highest-amplitude components, exploiting the inherent sparsity of the residual signal. The threshold value θ is defined as a fraction of the peak residual amplitude in each frame. The thresholded (sparse) residual signal is defined as (7):

$$e_{\text{sparse}}(n) = \hat{e}(n) = \begin{cases} e(n), & \text{if } |e(n)| \geq \theta \\ 0, & \text{otherwise} \end{cases} \quad (7)$$

This selective retention preserves most of the residual energy using fewer samples, thereby improving compression efficiency without significantly affecting signal fidelity.

2.4. Linear predictive coding-based signal recovery

Once both the LPC parameters and the residuals are quantized and transmitted, the decoder reconstructs the ECG signal using these components. The predicted signal closely approximates the original and preserves key morphological features essential for clinical interpretation. This approach provides an effective balance between compression efficiency and signal fidelity, making it well-suited for applications with limited bandwidth and storage capacity.

2.5. Parameter representation and quantization

Even though linear prediction coefficients capture ECG shapes accurately, sending them directly causes problems because small quantization errors can make the synthesis filter unstable. To prevent this, the predictor coefficients are converted into LSFs through line spectral pair (LSP) analysis. This frequency-based format handles rounding errors much better while still keeping an exact match with the original filter. In vector form, this conversion splits the predictor vector into two parts: a symmetric vector p and an anti-symmetric vector q :

$$p = a + Ja \quad (8)$$

$$q = a - Ja \quad (9)$$

where $a = [1, a_1, a_2, \dots, a_p, 0]^T$ is the expanded coefficient vector of size $(p+2) \times 1$, p representing the predictor order, the matrix J is a $(p+2) \times (p+2)$ reversal matrix, Ja denotes standard matrix-vector multiplication, and the superscript T indicates vector transposition.

The original linear prediction coefficients are extracted via:

$$a_{[1:p]} = \frac{1}{2}(p_{[1:p]} + q_{[1:p]}) \quad (10)$$

where the subscript $[1:p]$ extracts the elements from index 1 to p . The vector p is symmetric because flipping it leaves it unchanged ($Jp = p$), while q is anti-symmetric because flipping it reverses its sign ($Jq = -q$). Because of these symmetry properties, all roots of their related polynomials lie directly on the unit circle in the complex plane, with fixed roots at 0 and π radians. Furthermore, their phase angles strictly alternate in an ascending order:

$$0 < \omega_1 < \omega_2 < \omega_3 < \dots < \pi \quad (11)$$

where each ω_i denotes an individual line spectral frequency in radians, ensuring synthesis filter stability as long as this order is preserved. In the LPC framework, the ECG signal is reconstructed using an all-pole synthesis filter $H(z) = 1/A(z)$, driven by a residual signal $e(n)$. The residual captures fine temporal variations, while the filter restores the spectral envelope. Accurate reconstruction of both is vital for preserving the clinical morphology of the ECG signal. To quantize LSFs efficiently, an order-preserving differential quantization scheme is employed. The original frequencies $\omega_i \in (0, \pi)$ are first normalized to the unit interval $[0,1]$ by dividing each by π , yielding $\bar{\omega}_i = \omega_i/\pi$ for $i=1, \dots, 10$. Differential pulse-code modulation (DPCM) is then applied across the ordered set to eliminate inter-coefficient correlation and enforce the stability condition. The first coefficient, $\bar{\omega}_1$, is quantized directly using a uniform 5-bit scalar quantizer over its operational dynamic range and converted to its binary index. For each subsequent coefficient i from 2 through 10, a difference value is formed by subtracting the quantized previous coefficient from the current unquantized value: $\Delta_i = \bar{\omega}_i - \widehat{\bar{\omega}_{i-1}}$. Subtracting the reconstructed value rather than the exact predecessor prevents error accumulation across indices. This differential increment Δ_i is rounded, bounded, and encoded using non-uniform bit allocations: 5 bits each for coefficients 2 to 4, 4 bits each for coefficients 5 to 7, and 3 bits each for

coefficients 8 to 10 (requiring a total budget of 41 bits per frame). This descending bit distribution allocates high resolution to the leading parameters that represent vital diagnostic morphology, such as the QRS complex and P-wave, while dedicating coarser resolution to trailing parameters where fine spectral details are less sensitive to quantization error. Finally, by constraining each quantized difference $\Delta_i > 0$, the strict ascending order $\widehat{\omega}_1 < \widehat{\omega}_2 < \dots < \widehat{\omega}_{10}$ is guaranteed upon synthesis, ensuring filter stability.

2.6. Proposed linear predictive coding compression scheme

The proposed ECG compression framework integrates residual thresholding and LSP-based parameter representation into a unified LPC-based system, designed to reduce the data rate while preserving the morphological fidelity of the ECG signal. For each frame, a tenth-order LPC model estimates the prediction coefficients, and the predicted signal is subtracted from the original to generate a residual signal. This residual is typically sparse, with most values being zero or near zero.

Figure 2 shows the suggested ECG compression encoder, where the input ECG signal is conditioned and divided into segments. Linear prediction is then applied to obtain the prediction model and residual signal. The prediction parameters are quantized, while the residual is thresholded to remove insignificant components and subsequently encoded. Instead of transmitting the full residual, a thresholding step retains only the most significant components, reducing data size while preserving essential waveform features. After thresholding, the remaining residual values and corresponding LSP coefficients are encoded to form a compact representation of the frame. As a result, the system achieves efficient compression while maintaining the essential morphology of the ECG signal. Finally, the resulting parameter and residual information are combined to form the encoded output.

Figure 3 presents the corresponding decoder. The compressed signal is parsed to separate the model parameters and residual information. The predictor parameters are recovered and used to reconstruct the predicted ECG signal, while the residual data are decoded separately. The recovered residual is then combined with the predicted signal, followed by post-processing and filtering to generate the reconstructed ECG signal.

2.7. Excitation signal representation

To reduce the data size, the retained residual samples are scaled into a compact dynamic range and represented using a 4-bit format (including the sign bit). Let $e_{max} \geq e_i \forall i \in 1, 2, 3, \dots, N$, where e_i denotes the residual amplitude. To reduce error and preserve faithful recovery, a scaling process is applied to map the residual amplitudes into a fixed period from 0 to 15, allowing 4-bit representation per sample (3 bits for magnitude and 1 bit for sign). For each residual frame, the maximum absolute amplitude is determined as $e_{max} = \max_{1 \leq i \leq N} |e_i|$. This value is subsequently represented on a logarithmic scale as $g_{max} = \log_2(e_{max})$, where g_{max} is used to select the corresponding scaling range. Depending on the value of g_{max} , the first two bits of each frame are used to indicate the scaling range as follows: [00] if $g_{max} > -6$, [01] if $-8 < g_{max} \leq -6$, [10] if $-10 < g_{max} \leq -8$, and [11] if $g_{max} \leq -10$. Each range corresponds to a specific scale factor that restores the residuals to a normalized range of approximately 1–16 after scaling. The scale factors are defined as: [00] maps to $\times 2^8$, [01] to $\times 2^{10}$, [10] to $\times 2^{12}$, and [11] to $\times 2^{14}$. After scaling, one is subtracted from each magnitude, and the result is rounded to fit within the [0, 15] range. Finally, each scaled value is converted to a 4-bit binary format that includes the sign, ensuring compact and accurate representation of the residual signal. This $\log_2$ -based quantization method efficiently compresses the LPC residual while maintaining high reconstruction accuracy. The system employs LSFs instead of raw LPC coefficients due to their improved robustness against quantization errors. Thresholded and scaled residuals are encoded using the described 4-bit scheme, achieving efficient data representation without sacrificing perceptual or diagnostic fidelity. Table 1 summarizes the scaling logic, range classifications, and output mapping.

Table 1. Residual signal scale codes, $\log_2$ ranges, and output mapping for 4-bit quantization

Scale code	Range before adjustment (Linear)	Range before adjustment (Log ₂)	Scale number	Range after adjustment
Rare	$\infty - 2^{-6}$	> -6	-	-
00	$2^{-6} - 2^{-8}$	[-06, -08]	2^6	1-16
01	$2^{-8} - 2^{-10}$	[-08, -10]	2^8	1-16
10	$2^{-10} - 2^{-12}$	[-10, -12]	2^{10}	1-16
11	$2^{-12} - 2^{-14}$	[-12, -14]	2^{12}	1-16
Rare	$0 - 2^{-14}$	< -14	-	-

2.8. Energy encoding and adaptive thresholding

This quantization approach preserves the spectral accuracy required for reliable ECG reconstruction. The signal is processed in short frames, with ten LPC coefficients and a sparse residual signal computed for

each. To reduce the bit rate, residual samples with the highest amplitudes are selectively retained, typically preserving 90% of the residual energy. The adaptive threshold is computed based on the signal's dynamic range:

$$\text{Threshold} = \alpha \times \max(|e[n]|) \quad (12)$$

where α is a scalar between 0 and 1 that controls the sparsity level. Larger values of α result in higher compression by retaining fewer residual samples, although this may reduce reconstruction quality. In addition to the 41 bits used for encoding LSP coefficients, five extra bits are allocated to represent the original frame's energy. This value is later used to rescale the reconstructed signal. The adaptive thresholding method is particularly effective in multi-pulse LPC frameworks, where minimizing the number of non-zero residuals is key to achieving high compression efficiency.

3. RESULTS AND DISCUSSION

The ECG signals were segmented into frames at a sampling rate of 1000 Hz. The original ECG data was collected from the databases in [29]–[32]. Two reconstruction approaches were evaluated: one using the full (exact) residual signal, and the other using a sparsified residual obtained by applying a threshold of $\alpha=0.005$. This value was selected as a moderate trade-off based on preliminary experimentation and its effectiveness in retaining key ECG features while significantly reducing data size. The entire system was implemented in MATLAB.

For each ECG frame, linear prediction analysis was performed to determine the associated LPC coefficient vector and prediction residual waveform. The resulting residual data were subsequently represented either without modification or in a sparse form by suppressing samples whose magnitudes fell below the specified threshold. The compressed data was organized into fixed-size packets for low-bitrate transmission. At the decoder, LPC coefficients and residuals were used to reconstruct waveforms that preserved clinically significant ECG features. Conventional ECG compression methods reported in previous studies can achieve substantial reductions in signal size; nevertheless, their resulting compressed representations commonly require data rates in the range of approximately 2–8 kbps, which can still be significant for continuous real-time telemetry over bandwidth-constrained communication channels. As an example, ECG telemedicine implementations designed for mobile and wireless environments have demonstrated compressed transmission rates of nearly 8 kbps, as reported in [37]. Similarly, standard ECG compression frameworks that rely on delta coding combined with entropy coding or transform coding often operate at several kbps under real-time constraints [38]. In comparison, the proposed compression and coding scheme reduces the required transmission rate to below one kbps for continuous ECG monitoring. This substantial reduction improves communication efficiency and makes the approach particularly appropriate for wearable healthcare devices and IoT-enabled medical systems. The CR is defined as (13) [36]:

$$\text{CR} = \frac{R_{\text{original}}}{R_{\text{compressed}}} \quad (13)$$

where R_{original} denotes the data rate of the uncompressed ECG signal and $R_{\text{compressed}}$ represents the corresponding rate after compression and coding. A larger value of CR signifies greater data-size reduction, thereby lowering the requirements for both data storage and wireless transmission. To quantify reconstruction accuracy, the signal's global SNR is computed as (14):

$$\text{SNR}_{\text{global}} = 10 \log_{10} \left(\frac{\mathbf{x}^T \mathbf{x}}{\mathbf{e}^T \mathbf{e} + \varepsilon} \right) \quad (14)$$

The residual reconstruction error vector is $\mathbf{e} = \mathbf{x} - \hat{\mathbf{x}}$, where $\mathbf{x}$ and $\hat{\mathbf{x}}$ are the input and recovered signal vectors, respectively, and ε is a small constant. For frame-based evaluation, the average frame-wise SNR is computed by calculating the SNR for each frame and then averaging over all M frames [36]:

$$\begin{aligned} \text{SNR}_i &= 10 \log_{10} \left(\frac{\|\mathbf{x}_i\|_2^2}{\|\mathbf{e}_i\|_2^2 + \varepsilon} \right) \\ \text{SNR}_{\text{avg}} &= \frac{1}{M} \sum_{i=1}^M \text{SNR}_i \end{aligned} \quad (15)$$

In this formulation, $\mathbf{x}_i$ is the clean signal vector, $\hat{\mathbf{x}}_i$ is the reconstructed signal vector, and $\mathbf{e}_i = \mathbf{x}_i - \hat{\mathbf{x}}_i$ is the residual error or noise vector for frame i . The notation $\|\mathbf{x}_i\|_2^2$ and $\|\mathbf{e}_i\|_2^2$ represents the energy of the clean signal and the error signal, respectively, such that $\|\mathbf{a}\|_2 = \sqrt{\sum_i |a[i]|^2}$, while ε is a strictly positive threshold

parameter introduced to prevent numerical singularities. Finally, SNR_i gives the local signal-to-noise ratio for frame i , M is the total frame count, and SNR_{avg} is the overall mean SNR in decibels across the full set of frames.

The percent root-mean-square difference (PRD) is a standard benchmark for evaluating the fidelity of reconstructed biomedical signals, such as ECG, following lossy compression. To account for temporal variations in cardiac morphology, PRD is computed on a frame-by-frame basis. The PRD for frame i is formulated using the Euclidean norm as (16) [36]:

$$\text{PRD}_i(\%) = \sqrt{\frac{\|e_i\|_2^2}{\|x_i\|_2^2}} \times 100 \quad (16)$$

Here, the squared norm ratio directly compares the energy of the residual error to the energy of the uncompressed signal block. Once each frame's PRD is obtained independently, the global reconstruction fidelity is assessed via the mean frame PRD [36]:

$$\text{PRD}_{\text{avg}} = \frac{1}{M} \sum_{i=1}^M \text{PRD}_i \quad (17)$$

where M denotes the total number of frames. This averaging smooths out transient noise or isolated segment variations, delivering a reliable, robust index for benchmarking compression algorithms. The performance of LPC-based ECG compression using sparse residual representation was evaluated on a short frame under two conditions: one using the full residual and the other applying thresholding with $\alpha=0.005$. As shown in Figure 4, both reconstructions closely match the original waveform. The thresholded residual preserved key morphological features while significantly reducing data size, demonstrating the method's ability to maintain ECG waveform fidelity. No inter-observer variability was assessed in this preliminary evaluation. This indicates that the method provides an effective trade-off between compression efficiency and signal fidelity, making it suitable for low-bitrate applications such as wearable monitors and remote diagnostics. To assess its scalability, the analysis was extended to the 200-second ECG signal as illustrated in Figure 5.

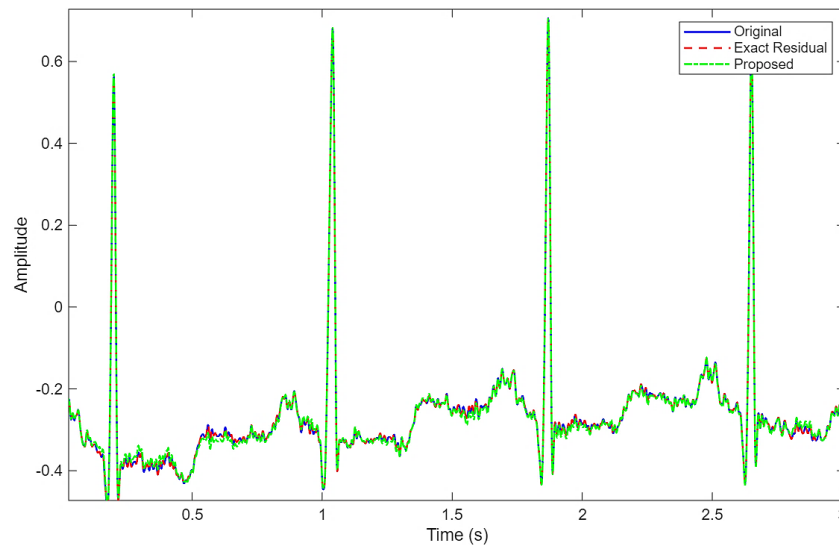


Figure 4. Reconstruction of a 3-second ECG segment using exact and sparsified residual signals, showing that the sparsified approach reduces data size without significant loss of morphology

Most of the residual energy is concentrated in a few dominant pulses, as shown in Figure 6. Despite the reduction in non-zero values, the thresholded residual maintains essential temporal and amplitude characteristics, resulting in a compact representation with minimal impact on reconstruction quality. These results demonstrate that the proposed compression framework preserves diagnostic ECG morphology across both short and long recordings, while offering a substantial reduction in data size through sparse residual representation.

Table 2 summarizes the quantitative performance of the proposed method across various threshold values, illustrating the trade-off between signal fidelity and compression efficiency. Using the exact residual ($\alpha=0$) results in near-lossless reconstruction with $\text{PRD}=0\%$ but yields only modest compression. As the

threshold increases, the CR improves, reaching a maximum of 38:1, although this comes at the expense of signal quality. A threshold of $\alpha=0.005$ offers a practical balance, achieving a 20:1 CR while preserving key diagnostic features, with a PRD of 5%. These results underscore the method's adaptability for scalable ECG data reduction, particularly in wearable healthcare and remote cardiac monitoring, where both efficiency and fidelity are critical.

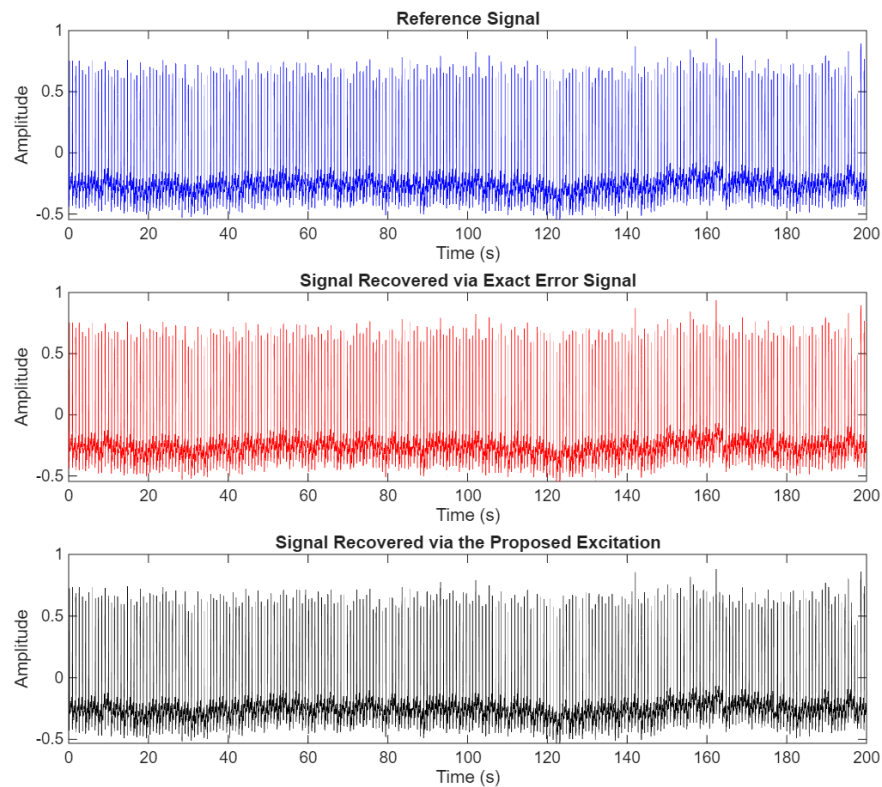


Figure 5. Comparison of a 200-second ECG signal with its reconstructions using exact and thresholded residuals, illustrating overall signal fidelity and compression effects

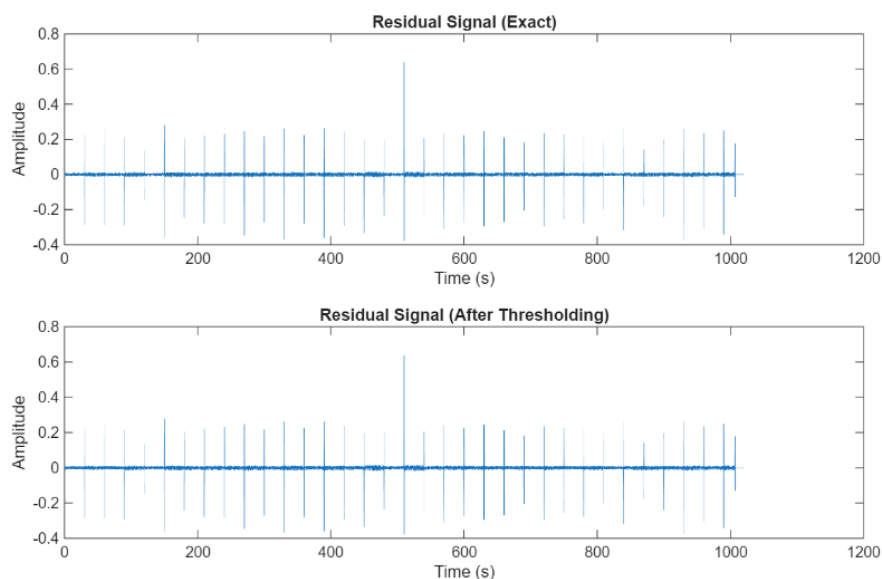


Figure 6. Exact residual versus sparsely thresholded residual ($\alpha=0.005$), illustrating the preservation of dominant residual components after thresholding

Table 2. Comparison of exact and sparse residuals for LPC-based ECG reconstruction under different (α) values

Scheme	α	PRD	SNR_{global} (dB)	SNR_{avg} (dB)	CR
Original residual	0	Close to zero	44.2	195.82	4:1
Sparsified residual	0.002	1.08%	38.53	60.22	6.4:1
Sparsified residual	0.005	5.03%	13.33	15.19	20.07:1
Sparsified residual	0.007	8%	6.2	7.99	38:1

4. CONCLUSION

This study presented an efficient ECG compression method that integrates LPC with adaptive residual thresholding and LSF-based parameter quantization. The system was evaluated on real ECG data and demonstrated strong performance across multiple compression levels. Using exact residuals enabled near-lossless reconstruction, while applying a threshold of $\alpha=0.005$ achieved a practical balance between data reduction and signal fidelity, resulting in a CR of 20.07:1. The use of LSFs and selective residual quantization further contributed to filter stability and diagnostic accuracy. These findings demonstrate the method's effectiveness for both real-time and long-term ECG monitoring in bandwidth- and storage-limited settings, including wearable technologies and telemedicine systems. The current evaluation was conducted on a limited dataset and primarily on ECG signals with small white Gaussian noise. Future work will therefore focus on validation using larger and more diverse datasets, including arrhythmic ECG signals, evaluation under various noise conditions such as motion artifacts and baseline wander, and real-time implementation on embedded hardware platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nvestigation

R : **R**esources

D : **D**ata Curation

O : Writing - **O**riginal Draft

E : Writing - Review & **E**ditng

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial, personal, or professional interests that could have appeared to influence the work reported in this paper.

DATA AVAILABILITY

The ECG datasets analyzed in this study are publicly available through PhysioNet, including the datasets cited in [29]–[32].

REFERENCES

- [1] B. Lal, V. Abolghasemi, R. Gravina, D. O'Keeffe, and D. Roshan, "Compressed Learning for Real-Time ECG Signals Classification," *IEEE Sensors Journal*, vol. 26, no. 7, pp. 10891-10904, Apr. 2026, doi: 10.1109/JSEN.2026.3660078.
- [2] B. S. Prabakaran, A. Akhtar, S. Rehman, O. Hasan, and M. Shafique, "BioNetExplorer: Architecture-Space Exploration of Biosignal

- Processing Deep Neural Networks for Wearables,” *IEEE Internet of Things Journal*, vol. 8, no. 17, pp. 13251–13265, Sept., 2021, doi: 10.1109/JIOT.2021.3065815.
- [3] I. S. Fathi, M. A. A. Makhoul, E. Osman, and M. A. Ahmed, “An Energy-Efficient Compression Algorithm of ECG Signals in Remote Healthcare Monitoring Systems,” *IEEE Access*, vol. 10, pp. 39129–39144, 2022, doi: 10.1109/ACCESS.2022.3166476.
 - [4] G. Hassan, K. M. Hosny, M. M. Fouda, and I. S. Fathi, “Efficient Compression of Fetal Phonocardiography Bio-Medical Signals for Internet of Healthcare Things,” *IEEE Access*, vol. 11, pp. 122991–123003, 2023, doi: 10.1109/ACCESS.2023.3329889.
 - [5] S. K. Jose and N. K. R. Gangireddy, “A Digital Compressed Sensing Framework With Optimized Measurement, Quantization, and Sparse Recovery for IoT-Enabled Wearable Edge ECG Health Monitoring Devices,” *IEEE Transactions on Instrumentation and Measurement*, vol. 75, pp. 1–10, 2026, doi: 10.1109/TIM.2026.3677996.
 - [6] L. R. Rabiner and R. W. Schafer, *Digital Processing of Speech Signals*, Englewood Cliffs, NJ: Prentice-Hall, 1979.
 - [7] R. C. Gonzales and R. E. Woods, *Digital Image Processing*, 4th ed. Pearson Education International, 2018.
 - [8] I. Dotsinsky, “Suppression of AC railway power-line interference in ECG signals recorded by public access defibrillators,” *BioMedical Engineering Online*, vol. 4, no. 65, 2005, doi: 10.1186/1475-925X-4-65.
 - [9] B. S. Atal and S. L. Hanauer, “Speech Analysis and Synthesis by Linear Prediction of the Speech Wave,” *The Journal of the Acoustical Society of America*, vol. 50, no. 2B, pp. 637–655, 1971, doi: 10.1121/1.1912679.
 - [10] L. V. Batista, E. U. K. Melcher, and L. C. Carvalho, “Compression of ECG signals by optimized quantization of discrete cosine transform coefficients,” *Medical Engineering and Physics*, vol. 23, no. 2, pp. 127–134, 2001, doi: 10.1016/S1350-4533(01)00030-3.
 - [11] G. Cosoli, S. Spinsante, F. Scardulla, L. D’Acquisto, and L. Scalise, “Wireless ECG and cardiac monitoring systems: State of the art, available commercial devices and useful electronic components,” *Measurement: Journal of the International Measurement Confederation*, vol. 177, 2021, doi: 10.1016/j.measurement.2021.109243.
 - [12] O. Sayadi and M. B. Shamsollahi, “ECG denoising and compression using a modified extended Kalman filter structure,” *IEEE Transactions on Biomedical Engineering*, vol. 55, no. 9, pp. 2240–2248, 2008, doi: 10.1109/TBME.2008.921150.
 - [13] J. Pan and W. J. Tompkins, “A Real-Time QRS Detection Algorithm,” *IEEE Transactions on Biomedical Engineering*, vol. 32, no. 3, pp. 230–236, Mar. 1985, doi: 10.1109/TBME.1985.325532.
 - [14] H. S. Malvar, “Lapped Transforms for Efficient Transform/Subband Coding,” *IEEE Transactions on Acoustics, Speech, and Signal Processing*, vol. 38, no. 6, pp. 969–978, 1990, doi: 10.1109/29.56057.
 - [15] M. M. Abo-Zahhad, A. I. Hussein, and A. M. Mohamed, “Compression of ECG Signal Based on Compressive Sensing and the Extraction of Significant Features,” *International Journal of Communications, Network and System Sciences*, vol. 08, no. 05, pp. 97–117, 2015, doi: 10.4236/ijcns.2015.85013.
 - [16] S. M. Szilagyi, L. Szilagyi, and L. David, “ECG signal compression using adaptive prediction,” in *Annual International Conference of the IEEE Engineering in Medicine and Biology - Proceedings*, 1997, pp. 101–104, doi: 10.1109/ieems.1997.754475.
 - [17] F. I. Abro, F. Rauf, M. Batool, B. S. C. Dhry, and S. Aslam, “An Efficient Speech Coding Technique for Secure Mobile Communications,” in *2018 IEEE 9th Annual Information Technology, Electronics and Mobile Communication Conference, IEMCON 2018*, 2018, pp. 940–944, doi: 10.1109/IEMCON.2018.8614855.
 - [18] B. Bessette, R. Salami, R. Lefebvre, and M. Jelinek, “Efficient methods for high quality low bit rate wideband speech coding,” in *2002 IEEE Speech Coding Workshop: A Paradigm Shift Toward New Coding Functions for the Broadband Age, SCW 2002 - Proceedings*, 2002, pp. 114–116, doi: 10.1109/SCW.2002.1215742.
 - [19] J. Hai and E. M. Joo, “Improved Linear Predictive Coding method for speech recognition,” in *ICICS-PCM 2003 - Proceedings of the 2003 Joint Conference of the 4th International Conference on Information, Communications and Signal Processing and 4th Pacific-Rim Conference on Multimedia*, 2003, pp. 1614–1618, doi: 10.1109/ICICS.2003.1292740.
 - [20] T. Moriya, Y. Kamamoto, and N. Harada, “Enhanced Lossless Coding Tools of LPC Residual for ITU-T G.711.0,” in *2010 Data Compression Conference, IEEE*, 2010, pp. 546–546, doi: 10.1109/DCC.2010.71.
 - [21] X. Yu, X. You, X. Liu, and C. Li, “An improved algorithm for residual signal excitation based on LPC 10,” in *Proceedings - 2022 7th International Conference on Communication, Image and Signal Processing, CCISP 2022*, 2022, pp. 318–323, doi: 10.1109/CCISP55629.2022.9974264.
 - [22] F. A. Muin, T. S. Gunawan, E. M. A. Elsheikh, and M. Kartiwi, “Performance analysis of IEEE 1857.2 lossless audio compression linear predictor algorithm,” 2017, doi: 10.1109/ICSIMA.2017.8312033.
 - [23] E. J. Candès and M. B. Wakin, “An Introduction To Compressive Sampling,” *IEEE Signal Processing Magazine*, vol. 25, no. 2, pp. 21–30, 2008.
 - [24] S. Hosny, M. W. El-Kharashi, and A. T. Abdel-Hamid, “Survey on compressed sensing over the past two decades,” *Memories - Materials, Devices, Circuits and Systems*, vol. 4, pp. 1–21, 2023, doi: 10.1016/j.memori.2023.100060.
 - [25] L. R. Chandran, I. Karuppasamy, M. G. Nair, H. Sun, and P. K. Krishnakumari, “Compressive Sensing in Power Engineering: A Comprehensive Survey of Theory and Applications, and a Case Study,” *Journal of Sensor and Actuator Networks*, vol. 14, no. 2, 2025, doi: 10.3390/jsan14020028.
 - [26] S. K. Jose and N. K. R. Gangireddy, “Energy-Efficient Atrial Fibrillation Detection From Compressive Sensing-Based ECG Using a Lightweight CNN-BiLSTM Model for Resource-Constrained Wearable Health Monitoring Systems,” *IEEE Sensors Journal*, vol. 26, no. 14, pp. 21098–21107, Jul. 2026, doi: 10.1109/JSEN.2026.3697094.
 - [27] B. Liu, M. Mohandes, H. Nuha, M. Deriche, F. Fekri, and J. H. McClellan, “A Multitone Model-Based Seismic Data Compression,” *IEEE Transactions on Systems, Man, and Cybernetics: Systems*, vol. 52, no. 2, pp. 1030–1040, Feb. 2022, doi: 10.1109/TSMC.2021.3077490.
 - [28] C. Tan, L. Chen, Y. Zhou, and Y. Su, “SOOCoder: A Universal ECG Compression Model Using a Self-Organized Operational Autoencoder,” in *ICASSP 2026 - 2026 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, Barcelona, Spain, 2026, pp. 7847–7851, doi: 10.1109/ICASSP55912.2026.11464783.
 - [29] A. L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals,” *Circulation*, vol. 101, no. 23, pp. e215–e220, Jun. 2000, doi: 10.1161/01.CIR.101.23.e215.
 - [30] G. B. Moody and R. G. Mark, “The impact of the MIT-BIH arrhythmia database,” *IEEE Engineering in Medicine and Biology Magazine*, vol. 20, no. 3, pp. 45–50, 2001, doi: 10.1109/51.932724.
 - [31] G. Moody, “MIT-BIH Normal Sinus Rhythm Database,” *PhysioNet*, 1997, doi: 10.13026/C2NK5R. [Online]. Available: <https://www.physionet.org/content/nsrdb/1.0.0/>. (Accessed: Aug. 1, 2025).
 - [32] G. B. Moody and R. G. Mark, “MIT-BIH Arrhythmia Database,” *PhysioNet*, 1997, doi: 10.13026/C2F305. [Online]. Available: <https://physionet.org/content/mitdb/1.0.0/>. (Accessed: Aug. 1, 2025).
 - [33] J. Makhoul, “Linear Prediction: A Tutorial Review,” in *Proceedings of the IEEE*, 1975, pp. 561–580.
 - [34] J. Proakis and D. Manolakis, *Digital Signal Processing: Principles, Algorithms, and Applications*, 3rd ed., vol. 1, Upper Saddle River, NJ: Prentice Hall International Inc., 2012.

- [35] A. S. Spanias, "Speech Coding: A Tutorial Review," in *Proceedings of the IEEE*, 1994, pp. 1541–1582, doi: 10.1109/5.326413.
- [36] S. Alabed, M. Al-Rabayah, O. M. Bwaleh, and S. A. Hasan, "Efficient ECG signal coding with interpolation-enhanced LPC for telehealth and wearable devices," *e-Prime - Nexus of Electrical, Electronic, and Intelligent Engineering*, vol. 17, 2026, doi: 10.1016/j.eprime.2026.201162.
- [37] F. Pineda-López, A. Martínez-Fernández, J. L. Rojo-Álvarez, A. García-Alberola, and M. Blanco-Velasco, "A flexible 12-lead/holter device with compression capabilities for low-bandwidth mobile-ECG telemedicine applications," *Sensors*, vol. 18, no. 11, 2018, doi: 10.3390/s18113773.
- [38] E. Merdjanovska, M. Mohorčič, M. Depolli, A. Rashkovska, and T. Javornik, "Data Compression for Wireless ECG Devices," in *Proceedings of the 15th International Joint Conference on Biomedical Engineering Systems and Technologies*, SCITEPRESS - Science and Technology Publications, 2022, pp. 15–21, doi: 10.5220/0010818100003123.

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