

Electrocardiogram signal modeling based on regular-pulse excitation

Samer Alabed¹, Mohammad Al-Rabayah², Omar M. Bwaliez³

¹Department of Biomedical Engineering, School of Applied Medical Sciences, German Jordanian University, Amman, Jordan

²College of Engineering and Technology, American University of the Middle East, Egaila, Kuwait

³Department of Management Sciences, Business School, German Jordanian University, Amman, Jordan

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ABSTRACT

The growing demand for modern wearable sensors and internet of things (IoT) telemedicine systems requires lightweight data compression methods aimed at reducing transmission bandwidth and wireless power consumption while maintaining high clinical diagnostic quality. Traditional methods usually demand complex processing or distort electrocardiogram (ECG) waveform characteristics, especially when high compression ratios (CRs) are targeted. This paper presents an efficient, lightweight ECG compression framework combining predictive coding with N -residual sparse sampling, which retains only one residual sample for every N data points. By integrating linear predictive coding (LPC), sparse residual sampling, and streamlined quantization and encoding, the proposed approach eliminates the need for computationally heavy transformations, prior model training, or predefined codebooks. Experimental evaluations demonstrate perfect reconstruction of the ECG signal at CRs up to 4. Optimal subsampling achieves CRs between 14.6 and 28.4, with signal-to-noise ratio (SNR) values ranging from 15.73 dB to 42.5 dB and percent root-mean-square difference (PRD) between 1.9% and 5.6%, while consistently keeping PRD below 9%. With its minimal computational overhead, low memory footprint, and preserved diagnostic integrity, this method is well-suited for energy-efficient, real-time implementation on resource-constrained wearable healthcare devices.

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Corresponding Author:

Samer Alabed

Department of Biomedical Engineering, School of Applied Medical Sciences

German Jordanian University

Amman, 11180 Jordan

Email: samer.alabed@gju.edu.jo

1. INTRODUCTION

The rapid growth of remote healthcare and wearable medical devices has created a strong need for smaller file sizes and faster data sharing [1]. However, continuous wearable electrocardiogram (ECG) monitoring creates huge amounts of data that quickly drain battery life, memory, and wireless bandwidth. Existing compression methods, such as time-domain techniques, transform algorithms, compressed sensing, and artificial intelligence (AI), have clear limitations: they either require too much processing power or damage important diagnostic details when compressing data too much. Therefore, finding a simple way to shrink ECG files while keeping signal quality clear and intact remains a key challenge for real-time patient monitoring. Successfully implemented across audio [2], image [3], and medical signal [4] processing, linear predictive coding (LPC) proves particularly effective for biomedical signals like ECGs due to its ability to handle periodic signal characteristics within a robust mathematical framework. Furthermore, the evolution of next-generation

wireless communication systems demands these compression techniques not only to save power but to ensure real-time diagnostic integrity [5]–[7]. Modern intelligent healthcare systems generate massive ECG datasets recorded at a 1,000 Hz sampling rate and a 16-bit resolution, causing rapid file size expansion [8]–[10]. As ECGs serve as essential diagnostic tools for cardiovascular health assessment [11]–[16]. The objective is minimizing storage and transmission requirements while preserving critical morphological features that clinicians depend on diagnostic interpretation. Any encoding approach must balance efficiency with clinical accuracy to maintain diagnostic value. Signal compression can be broadly classified into two primary methodologies [17], [18]. Waveform based methods process the signal to identify and eliminate repetitive patterns. Conversely, model-based methods construct a mathematical model to represent the signal [19]–[22], typically providing a more efficient and structured approach to data storage [23]–[25]. This research employs a model-based approach utilizing LPC [19]–[23]. The technique operates by predicting subsequent signal segments based on preceding data characteristics. Consequently, Only the prediction residual, representing the difference between the predicted and actual signal values, needs to be stored. Given the inherent predictability of biomedical signals, this approach yields exceptional compression efficiency.

Despite the significant amount of research on ECG compression techniques, most of the current methods rely primarily on transform-based approaches such as wavelet or discrete transforms that often require a lot of computation, making these techniques unsuitable for use in resource-constrained wearable and internet of things (IoT)-based health care devices. Furthermore, it is also difficult to achieve an adequate level of ECG compression while retaining the majority of the important diagnosable morphological features of the ECG waveform. In this study, we have proposed a simple and efficient ECG compression algorithm specifically for use in wearable and IoT-based health care applications where bandwidth, storage and processing are limited.

Real ECG data taken from the PhysioNet database [26]–[28] were used to validate this method and the evaluation used standard performance metrics as criteria for this validation. Results indicate that substantial compression ratio (CR) can be realized with a minimal loss in the quality of the signal and therefore make it suitable for telemedicine, remote monitoring, and wearable ECG applications. To overcome the fundamental trade-off between computational overhead and diagnostic accuracy in wearable healthcare devices, this paper introduces a novel, training-free ECG compression framework that synergistically merging LPC technique with a regular-pulse excitation (RPE) technique and an efficient parameter quantization and encoding schemes. Using this combined model for the ECG signal first allows it to be modelled with an LPC representation to account for its temporal correlation and then uses the RPE, which only keeps the significant excitation sample, provides a substantially reduced size representation of the transmitted data while still preserving most of the critical characteristics of the ECG waveform without requiring complex matrix transformations, codebook searches, or heavy offline model training. By pairing this sparse representation with tailored parameter quantization, the proposed technique delivers multi-rate adaptability: achieving near-lossless, high-fidelity reconstruction at lower sub-sampling factors ($N=1$ to $N=4$) and reaching high CRs up to 40.3 at $N=10$ while maintaining percent root-mean-square difference (PRD) values strictly below 9% and signal-to-noise ratio (SNR) values above 15 dB. Consequently, this lightweight framework significantly outperforms conventional time-domain and transform-based schemes in computational simplicity and energy efficiency, establishing an ideal, clinically reliable front-end for real-time deployment in resource-constrained wearable ECG sensors and low-power IoT telemedicine networks.

2. METHOD

Recently, several methods are proposed to compress ECG signals based on transformation schemes [29]–[32]. On the other hand, our ECG compression method works through four main steps within an encoder-decoder system that both compresses and reconstructs the data, as shown in Figure 1. First, we preprocess the signal by filtering and conditioning it for analysis. Next, we apply LPC analysis, as shown in Figure 1(a), to create a predictive model of the signal's behavior [20]–[23]. The core compression happens in the third step, where we compress the residual signal by removing redundant and unnecessary data. Finally, we reconstruct the original signal using the preserved information as shown in Figure 1(b). To ensure efficient transmission, we also quantize both the LPC parameters and the processed signal components.

2.1. Preprocessing

The ECG records are taken from the MIT-BIH Arrhythmia Database, which contains 48 annotated half-hour two-channel ambulatory ECG recordings sampled at 360 Hz [27], [28]. Prior to ECG signal compression, preparatory conditioning is essential to ensure signal integrity and reliability. This preprocessing phase encompasses several sequential operations. For experimental validation purposes, white noise is initially introduced to the signal, a procedure exclusively employed within controlled testing environments and excluded from practical implementations. Subsequently, signal normalization is performed, followed by low-

pass filtering to attenuate high-frequency noise components and enhance signal smoothness. The final preprocessing step involves signal segmentation into smaller, overlapping frames utilizing a Hanning window function. This windowing approach enables independent analysis and compression of discrete signal segments, thereby enhancing overall processing efficiency.

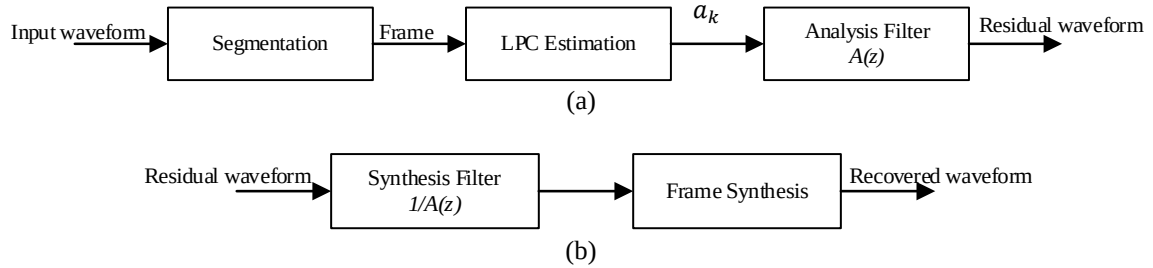


Figure 1. Conventional LPC architecture; (a) analysis stage and (b) synthesis stage

2.2. Linear prediction analysis

The fundamental principle of the LPC methodology involves modeling each ECG signal segment based on preceding samples [20]–[23]. This process generates a predicted signal representation. Subsequently, the residual signal is computed as the difference between the actual signal and the predicted values. Rather than storing or transmitting the complete ECG signal, only the significantly reduced residual signal requires processing. During reconstruction, a decoder utilizes the compressed residual signal in conjunction with a synthesis filter. This filter is constructed from the same parameters employed during the prediction phase. In cases where the residual signal experiences loss or the filter exhibits imperfections, the reconstructed signal will not achieve perfect fidelity to the original. ECG signal prediction can be formulated as a linear estimation problem where the current sample is approximated from a finite sequence of past samples [19]–[22]. Let $s(i)$ represent the ECG sample at discrete time index i , p denote the prediction order, and a_k denote the weighting coefficient assigned to the k -th past sample. The vector of past samples and the corresponding predictor coefficient vector are defined as (1):

$$s_i = [s(i-1) \quad s(i-2) \quad \cdots \quad s(i-p)]^T, \quad a = [a_1 \quad a_2 \quad \cdots \quad a_p]^T \quad (1)$$

Here, $(\cdot)^T$ denotes the transpose operator. Using these vectors, the estimated ECG sample is obtained from their inner product:

$$\hat{s}(i) = a^T s_i \quad (2)$$

The prediction error $e(i)$ is defined as the difference between the actual sample and its estimated value. The optimal coefficients are chosen to minimize this error over the analyzed frame via the quadratic cost function:

$$J(a) = \sum_i e^2(i) = \sum_i [s(i) - a^T s_i]^2 \quad (3)$$

In (3), $J(a)$ is the function used to evaluate the prediction quality. To determine the optimal coefficients efficiently, the signal autocorrelation sequence is defined as (4):

$$R_{ss}(k) = E\{s(i)s(i-k)\} \quad (4)$$

where $R_{ss}(k)$ is the autocorrelation at lag k and $E\{\cdot\}$ denotes the mathematical expectation operator. The resulting autocorrelation terms can be arranged into a matrix system. With p denoting the selected prediction order, the coefficients are obtained from:

$$\begin{bmatrix} R_{ss}(0) & R_{ss}(1) & \cdots & R_{ss}(p-1) \\ R_{ss}(1) & R_{ss}(0) & \cdots & R_{ss}(p-2) \\ \vdots & \vdots & \ddots & \vdots \\ R_{ss}(p-1) & R_{ss}(p-2) & \cdots & R_{ss}(0) \end{bmatrix} a = \begin{bmatrix} R_{ss}(1) \\ R_{ss}(2) \\ \vdots \\ R_{ss}(p) \end{bmatrix} \quad (5)$$

The coefficient a_0 is used as a fixed reference and is set to 1. The autocorrelation matrix is symmetric and Toeplitz, allowing efficient solution via the Levinson–Durbin algorithm. After solving (5) for the predictor weights, the minimum prediction error energy is given by (6):

$$J_{\min} = R_{ss}(0) + a^T r, \quad r = [R_{ss}(1) \ R_{ss}(2) \ \cdots \ R_{ss}(p)]^T \quad (6)$$

2.3. The proposed excitation

Rather than retaining all values within the residual signal, the system preserves only one value per N samples. The key principle of this approach is the periodic selection of retained samples. Specifically, when ($N = 4$), one sample is retained every four samples, resulting in a pulse being placed at every fourth sample position. The objective centers on capturing the most significant amplitude variations or pulses within the residual signal, representing components that the LPC model inadequately predicted [19]–[21]. Through selective retention of these critical pulses, substantial CRs are achieved. In contrast to maintaining a predetermined number of pulses, this methodology intelligently identifies the most significant residual signal components. The residual error is partitioned to N separate sub-bands, and the energy of every sub-band is computed to select the one containing the most significant information. The proposed method retains only the highest-energy sub-band while discarding the remaining ($N - 1$) sub-bands. This selective retention reduces the amount of transmitted data while preserving the dominant signal components required for accurate ECG reconstruction. This strategy assumes that the largest-energy band contains the most important features that the LPC model failed to predict accurately, such as the rapid amplitude changes in QRS complexes. By focusing on this critical information, we maintain diagnostic quality while achieving strong compression performance. The proposed strategy is executed through three sequential operations: polyphase decimation, localized energy quantification, and principal trajectory selection. First, the residual sequence $e[n]$ is decimated into N vectors $e_i = [e[i], e[i + N], \dots, e[i + (K - 1)N]]^T$ for phase offsets $i \in \{0, 1, \dots, N - 1\}$, where N is the decimation factor and K denotes the down-sampled vector length. To concentrate the transmission budget onto the most informative excitation features, each candidate branch is scored by its localized energy content, and only the single phase maximizing the quadratic Euclidean norm is retained while all non-dominant trajectories are discarded. This selection is formally expressed as (7):

$$i_{opt} = \arg \max_{i \in \{0, 1, \dots, N-1\}} (e_i^T e_i) = \arg \max_{i \in \{0, 1, \dots, N-1\}} (\|e_i\|_2^2) \quad (7)$$

where $\arg \max(\cdot)$ returns the index of the optimal phase i_{opt} , $(\cdot)^T$ indicates matrix transposition, and $\|\cdot\|_2$ represents the standard Euclidean vector norm. This selective approach captures most of the residual energy using fewer samples, which improves compression efficiency while keeping the signal quality nearly intact.

2.4. Signal reconstruction

After all the compressed data is transmitted, the decoder begins reconstructing the original signal. It uses the compressed parameters and residual components to accurately rebuild the ECG signal. The excitation sequence is recovered by reversing the subsampling operation. Because $N - 1$ samples are eliminated for every N samples, the omitted samples are initially reconstructed using a sample-and-hold strategy, where each retained sample is repeated across the subsequent $N - 1$ discarded sample locations. To counteract power distortion introduced by zero-order repetition, the reconstructed residual frame is energy-normalized: using the transmitted frame energy, the repeated excitation vector is scaled such that its total energy exactly matches that of the original residual frame. Finally, this reconstructed, energy-matched residual sequence is fed into the all-pole LPC synthesis filter to recover the estimated ECG waveform frame. The reconstructed signal closely matches the original, keeping all the important features that doctors need for diagnosis. This approach provides an effective balance between data reduction and signal quality preservation, making it highly suitable for applications with limited storage capacity or restricted transmission bandwidth.

2.5. Encoding and quantization of linear predictive coding coefficients

While LPC parameters are effective for signal modeling and prediction [19]–[21], they are not ideal for direct transmission because they become unstable and sensitive to quantization errors at low bit rates. Instead, they are transformed to line spectral pairs (LSPs), which are closely associated with line spectral frequency (LSF) representation. These spectral parameters provide a more stable and quantization-friendly representation while maintaining a one-to-one correspondence with the LPC coefficients. LSFs are derived by decomposing the p -th-order predictor sequence into symmetric and anti-symmetric auxiliary coefficient sequences:

$$p_k = a_k + a_{p+1-k} \quad (8)$$

$$q_k = a_k - a_{p+1-k} \quad (9)$$

for $k = 0, 1, \dots, p+1$, with the boundary conditions defined as $a_0 = 1$ and $a_{p+1} = 0$. The LPC parameters are exactly reconstructed from the arithmetic mean of these two sequences:

$$a_k = \frac{p_k + q_k}{2}, \quad k = 1, \dots, p \quad (10)$$

The sequence p_k exhibits symmetry ($p_k = p_{p+1-k}$), whereas q_k exhibits anti-symmetry ($q_k = -q_{p+1-k}$). For a stable LPC model, the roots of the corresponding polynomials $P(z) = \sum_{k=0}^{p+1} p_k z^{-k}$ and $Q(z) = \sum_{k=0}^{p+1} q_k z^{-k}$ lie on the unit circle in complex conjugate pairs, with fixed real roots at $z = -1$ and $z = +1$, respectively, and exhibit a monotonic interlacing property:

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

The angular positions of these roots define the LSFs. Preserving this interlacing property during quantization and transmission ensures the stability of the reconstructed LPC synthesis filter, thereby enabling accurate and stable ECG signal reconstruction. To achieve high compression while guaranteeing synthesis filter stability, line spectral frequencies are encoded via closed-loop predictive differential quantization (PDQ) over normalized coordinates $0 < f_1 < \dots < f_p < 1$. The fundamental parameter f_1 serves as an absolute anchor, whereas subsequent coefficients are encoded differentially relative to the reconstructed preceding value. Filter stability is strictly preserved by enforcing a minimum-separation threshold, $\hat{f}_i = \max(\hat{f}_{i-1} + \Delta f_i, \hat{f}_{i-1} + \delta_{\min})$, preventing root crossover on the unit circle and containing quantization drift through immediate feedback. Bit-depth allocation is nonuniform to mirror the physiological spectral distribution of the ECG. The low-order coefficients receive higher quantization resolution to preserve dominant depolarization and repolarization morphologies against phase distortion. Conversely, high-order coefficients describe rapidly attenuated out-of-band energy and are quantized coarsely. This selective bit allocation substantially lowers the per-frame bit budget without compromising clinical diagnostic integrity.

2.6. Suggested encoding method

A novel ECG data compression system has been developed that integrates multiple advanced techniques. The primary objective involves achieving substantial data size reduction for enhanced transmission efficiency while ensuring complete preservation of ECG signal morphological accuracy. The operational framework proceeds as follows: original ECG recordings taken at a rate of 1000 samples per second [26]–[28]. For each segment, the system employs a sophisticated predictive model to generate an anticipated signal representation. Subsequently, this prediction is compared against the original signal, with the minimal difference constituting the error signal. This error component proves instrumental for compression purposes, as it predominantly comprises negligible, near-zero values that facilitate efficient data reduction.

Figure 2 illustrates the encoding process of the proposed ECG compression system. The original ECG waveform is first subjected to a preprocessing stage to remove unwanted components and prepare the waveform for subsequent processing. The preprocessed waveform is then segmented into individual frames. Each frame is modeled using LPC to obtain a set of prediction coefficients, while the corresponding prediction residual waveform is generated from the difference between the original frame and its LPC-based prediction. The LPC parameters are subsequently quantized to reduce their representation cost, whereas the residual waveform is processed by the residual encoder to obtain a compact representation. Finally, the quantized coefficients and encoded residual signal are merged by the bitstream assembler to produce the compressed encoded stream. The critical component within this process involves regular pulse excitation. Rather than transmitting the complete residual signal, this stage selectively retains the most significant components, thereby achieving substantial data reduction while preserving essential ECG signal characteristics. The retained parameters undergo subsequent encoding, yielding a highly efficient representation that maintains the fundamental morphology of the cardiac signal.

Figure 3 illustrates the decoding and reconstruction process of the compressed ECG waveform. The encoded stream is first processed by the bitstream parser, which separates the compressed coefficient information from the encoded residual data. The quantized LPC coefficients are reconstructed through the coefficient decoder and supplied to the LPC reconstruction stage to generate the predicted waveform for each frame. In parallel, the encoded residual information is decoded to recover the corresponding residual waveform. The predicted waveform and reconstructed residual are then combined through the synthesis filter to recover the individual ECG frames. Finally, the reconstructed frames are integrated by the frame assembler to generate the complete ECG waveform.

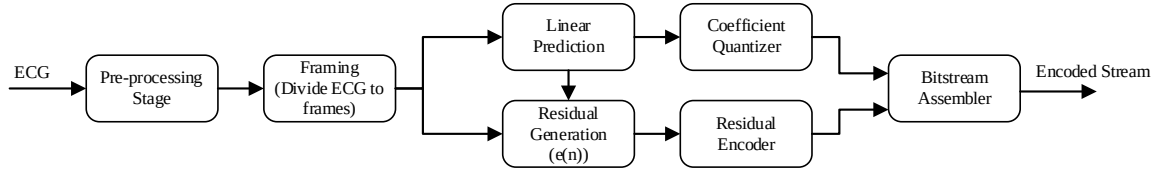


Figure 2. Block diagram of the proposed ECG signal encoder

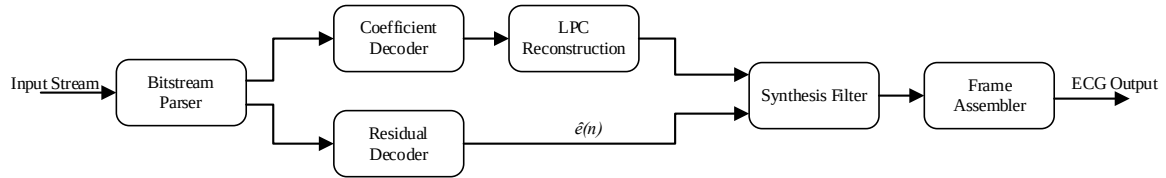


Figure 3. Block diagram of the proposed ECG signal decoder

2.7. Quantization of the residual signal

The proposed system targets efficient ECG signal compression contingent upon the selected parameters. High reconstruction fidelity is preserved through prioritized encoding of critical residual components that maintain diagnostic signal characteristics. To achieve further data reduction, retained residuals undergo scaling into a compact dynamic range and are encoded via four-bit formatting, incorporating the sign. To minimize quantization error and ensure precise reconstruction, a methodology maps residual values into a certain range of zero to 15, yielding a four-bit per-value resolution with one bit designated for sign indication. The scaling procedure initiates by computing the logarithmic gain factor $g_{\max} = \log_{10}(e_{\max})$. Based on the $g_{\max}$ amplitude, the initial two frame bits are allocated as follows: [00] when $g_{\max}$ is greater than -2, [01] when it is between -3 and -2, [10] when it is between -4 and -3, and [11] when it is less than -4. Every code represents a designated scaling value: [00] is associated with $\times 10^2$, [01] is associated with $\times 10^3$, [10] is associated with $\times 10^4$, and [11] is associated with $\times 10^5$. Then, we subtract one from each value and round it to ensure it falls within the range from zero to 15. We then represent these scaled values to four-bit binary number with built-in sign representation, resulting in an efficient way to encode the residual waveform.

This technique encoded the error signal while preserving the reconstruction quality. LSFs are utilized in place of direct linear prediction coefficients to guarantee filter stability and robust performance during quantization. Following amplitude normalization of the prediction residual, a four-bit per-sample quantization scheme is applied to compress the residual data stream. This dual representation achieves substantial bit-rate reduction while preserving key diagnostic morphology across the cardiac waveform. The detailed scaling parameters and mapping intervals are summarized in Table 1.

Table 1. Four-bit residual quantizer specifications: scaling prefixes, dynamic spans, and reconstruction values

Prefix	Unscaled input range	Input range (Log ₁₀ domain)	Exponent multiplier	Normalized dynamic range
Low-probability	$\infty - 10^{-1}$			
00	$10^{-1} - 10^{-2}$	[-1, -2]	10^2	1-10
01	$10^{-2} - 10^{-3}$	[-2, -3]	10^3	1-10
10	$10^{-3} - 10^{-4}$	[-3, -4]	10^4	1-10
11	$10^{-4} - 10^{-5}$	[-4, -5]	10^5	1-10
Low-probability	$0-10^{-5}$			

This packaging strategy effectively preserves the key characteristics of the ECG signal, ensuring accurate and reliable reconstruction. The original signal is processed in short intervals, with every segment producing ten LPC parameters along with an efficient representation of the error signal. To further reduce the required storage space, the error signal is processed to identify the sub-band containing the highest energy level. As defined in (7), the dominant high energy component is preserved, since it carries the most significant data required for accurate reconstruction.

$$e_{\text{selected}}[n] = e_{i_{\text{opt}}}[n] \quad (12)$$

When employing elevated N values, substantially higher CRs are achieved due to the retention of fewer samples from the original signal. However, this approach presents a trade-off whereby the reconstructed signal quality may experience degradation. To ensure reconstruction accuracy, additional data consisting of six supplementary bits is preserved. These bits store the original signal's energy information, which is subsequently utilized to modify the recovered signal to its correct magnitude characteristics.

3. RESULTS AND DISCUSSION

The proposed method was implemented using around seven minutes of real ECG recordings retrieved from the databases [26]–[28]. To assess the effectiveness of the proposed compression method, two reconstruction scenarios were investigated: the first based on the complete residual signal, and the second using the compressed residual waveform. This value was selected based on preliminary experiments, which indicated that it provides an effective compromise between preserving important ECG characteristics and achieving significant data reduction. The complete system was developed and implemented in MATLAB. For each ECG segment, the LPC parameters and error signal were generated. In the uncompressed case, the entire residual signal was preserved, whereas in the compressed approach, scarification was applied by eliminating residual samples with amplitudes below a predefined threshold. The resulting compressed data were then arranged into frames to transmit via a very low data rate channel. At the receiver side, the decoder utilized the received information to reconstruct the original ECG signal while maintaining the essential morphological and clinically relevant features of the original signal. This performance shows its potential for real-time use on resource-limited devices like wearable monitors and remote diagnostic tools. The data compaction efficiency of the coding scheme is evaluated via the CR, defined as (13):

$$CR = \frac{\mathcal{B}_{orig}}{\mathcal{B}_{rec}} \quad (13)$$

where $\mathcal{B}_{orig}$ denotes the total bit count of the uncompressed ECG signal and $\mathcal{B}_{rec}$ represents the aggregate bit volume required to reconstruct the waveform. A higher CR denotes high compression efficiency, which is beneficial for reducing storage needs and transmission bandwidth. The SNR measures how closely the reconstructed signal matches the original and serves as a key metric for evaluating signal compression quality. The overall SNR across the entire recording is determined via (14):

$$SNR_{global} = 10\log_{10} \left(\frac{\|s\|_2^2}{\|s-\hat{s}\|_2^2 + \varepsilon} \right) = 10\log_{10} \left(\frac{s^T s}{e^T e + \varepsilon} \right) \quad (14)$$

where s and $\hat{s}$ denote the original and synthesized ECG sequence vectors, respectively. The notation $\|\cdot\|_2$ denotes the Euclidean vector norm, defined as $\|x\|_2 = \sqrt{x^T x}$. The expression $\|\cdot\|_2^2$ represents the squared Euclidean norm, calculated via the vector inner product $x^T x$, while $(\cdot)^T$ designates the matrix/vector transpose operator and ε is a very small value. For frame-based assessment, the average SNR is determined by computing the SNR for each segment k and subsequently averaging across all F frames, such as (15) and (16):

$$SNR_k = 10\log_{10} \left(\frac{\|s_k\|_2^2}{\|s_k - \hat{s}_k\|_2^2 + \varepsilon} \right) \quad (15)$$

$$SNR_{avg} = \frac{1}{F} \sum SNR_k \quad (16)$$

Here, s_k represents the reference or clean signal vector in frame k , $\hat{s}_k$ is the estimated or reconstructed signal vector for the same frame, $\|\cdot\|_2$ denotes the standard Euclidean norm such that $\|x\|_2 = \sqrt{\sum_n |x[n]|^2}$ and F is the number of frames. On the other hand, the PRD is a standard metric for measuring the quality of the recovered ECG signals. To account for temporal variations across the recording, we compute the PRD for each individual frame. In block k , the corresponding metric is evaluated using (17):

$$PRD_k = 100 \times \frac{\|s_k - \hat{s}_k\|_2}{\|s_k\|_2} = 100 \times \sqrt{\frac{(s_k - \hat{s}_k)^T (s_k - \hat{s}_k)}{s_k^T s_k}} \quad (17)$$

Lower PRD values indicate higher reconstruction quality, as the metric computes the normalized error relative to the original frame's energy. The cumulative reconstruction distortion across the recording is summarized by (18):

$$PRD_{avg} = \frac{1}{F} \sum_{k=1}^F PRD_k \quad (18)$$

Generally, a PRD between 0% and 2% indicates near-perfect reconstruction with negligible visual difference from the original signal, whereas values between 2% and 9% ensure that key clinical features are fully preserved. Consequently, average PRD serves as a standard metric for reliably benchmarking ECG compression techniques.

As shown in Figure 4, the reconstructed ECG signals obtained using both the complete residual signal and the proposed sparse residual representation exhibit a high degree of similarity with the original ECG waveform over the selected 6-second interval. The reconstruction based on the complete error signal provides a near-lossless representation, as expected, since all prediction residual components are preserved. In comparison, the proposed approach retains only the most significant residual components while discarding less informative samples, resulting in a considerable reduction in the transmitted data. Despite this reduction, the reconstructed signal successfully preserves the main ECG morphological characteristics, including the P-wave, QRS complex, and T-wave regions. This demonstrates the effectiveness of the proposed residual selection strategy in maintaining diagnostic information while improving compression efficiency.

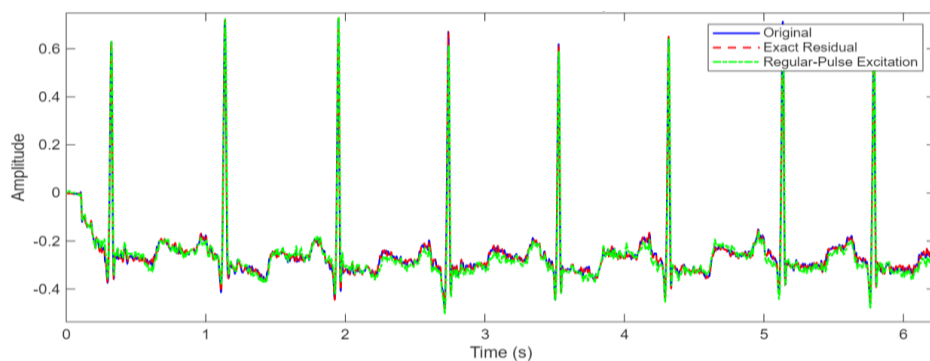


Figure 4. Comparison of the original and reconstructed ECG signals over a 6-second interval via; i) the complete error signal and ii) the proposed error signal

To further evaluate the robustness and scalability of the proposed method, a longer ECG recording with a duration of 100 seconds was analyzed, as presented in Figure 5. The reconstructed waveform obtained using the proposed approach closely follows the original ECG signal over the entire recording duration, with no significant distortion or loss of important waveform patterns. Compared with the reconstruction using the complete residual signal, the proposed method achieves a higher compression efficiency while maintaining comparable signal quality. These results confirm that the proposed framework with residual sparsification is capable of handling long-duration ECG monitoring scenarios, making it suitable for continuous wearable healthcare applications where bandwidth, storage capacity, and power consumption are limited.

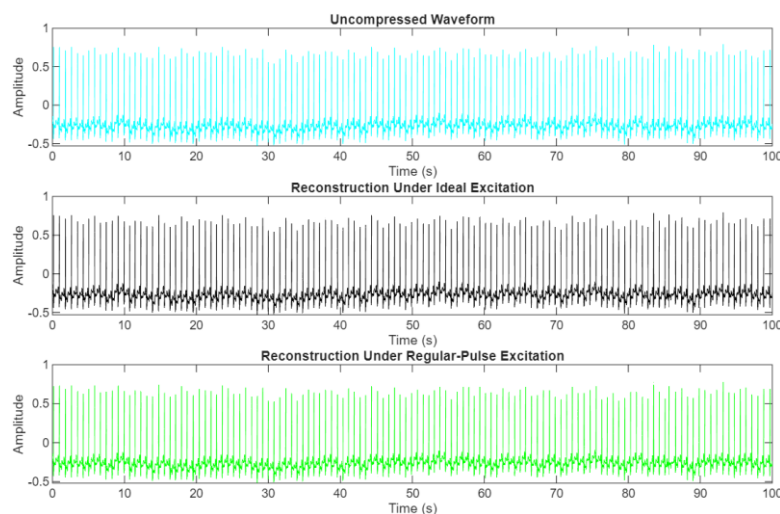


Figure 5. Comparison of the complete 100-second ECG signal with its reconstructed versions obtained using the original error signal and the proposed approach

Table 2 demonstrates the performance characteristics of the methodology across various parameter settings, illustrating the tradeoff between achieving high compression rates and maintaining signal quality. If the complete signal is retained, i.e., $N=1$, the reconstructed signal achieves near-lossless accuracy; however, the compression benefit remains limited. As N increases, CRs improve dramatically, reaching up to 40, but signal quality suffers accordingly. Experimental results indicate that $N=4$ or $N=6$ yields the optimal trade-off between compression performance and signal fidelity. Under these configurations, the proposed approach achieved a CR ranging from 14 to 28 while fully preserving critical diagnostic features. These findings demonstrate the adaptability of our method, making it particularly well-suited for resource-constrained wearable devices and remote health monitoring applications where low computational overhead and high signal accuracy are paramount. In the literature [29], [30], it has been shown that many traditional ECG compression methods will produce a compressed data stream of a few kbps for real-time telemetry applications, even when aggressive compression is employed. As an example, mobile telemedicine ECG systems have shown that the bitrates of compressed ECG data sent over low-bandwidth wireless links can be as high as 8 kbps [29]. Likewise, there are conventional ECG compression methods that are based upon delta coding and these methods also produce compressed ECG data that is transmitted in real-time exceed several kbps [30]. In contrast, the compression and coding approach suggested in this paper results in an effective data rate for continuous ECG transmission of less than 1 kbps with reasonable quality, resulting in significantly more efficient telemetry and making it very suitable for IoT applications.

Table 2. Performance comparison of original vs. suggested LPC residuals across varying N configurations

Method	N	SNR (dB)	PRD	CR
Exact residual	1	Very high	Very low	4
Sparse residual	4	42.5	1.9%	14.6
Sparse residual	6	15.73	5.6%	28.4
Sparse residual	10	10.52	7.9%	40.3

From a communications perspective, achieving a CR close to 42 while maintaining PRD below 8% and SNR above 15 dB makes the compressed ECG signal highly suitable for transmission over low-power wireless channels, including internet-of-things and cooperative relay-based healthcare networks. This is particularly important in smart and portable healthcare systems, where continuous monitoring must be supported under strict energy and bandwidth constraints. Therefore, the proposed method not only improves signal compression performance but also acts as an enabling front-end for efficient data transmission in modern telemedicine and IoT-based medical applications. Furthermore, the results demonstrate that the proposed method can operate at multiple quality levels. At lower bit rates, it achieves very high compression with acceptable distortion, while at higher-quality settings (lower N), it provides near-lossless reconstruction with significantly improved SNR and very low PRD. This flexibility allows the system to adapt to different application requirements, making it highly suitable for real-time ECG monitoring, wearable devices, and embedded healthcare systems where both efficiency and reliability are critical.

The suggested ECG compression method was tested on records from the MIT-BIH Arrhythmia [27], [28]. Table 3 shows a full comparison between the proposed method for compressing ECGs and some of the most important categories of existing methods, such as time-domain methods, orthogonal transform-based methods, compressed sensing, and AI-based methods. The comparison is based on the CR, the percent root difference, the SNR, and the overall methodological characteristics.

Differential pulse code modulation (DPCM), delta coding, amplitude zone time epoch coding (AZTEC), and turning point (TP) algorithms [33]–[38] are examples of time-domain methods that were used to compress ECGs. These methods are easy to use and don't require a lot of processing power, which makes them good for early embedded systems. But their performance is still limited, with CRs usually between 3 and 10 and PRD values between 4% and 8%. The primary constraint of these methodologies is their failure to accurately capture the frequency-domain attributes of ECG signals. Because of this, important diagnostic features, like the sharp changes in the QRS complex, may be distorted, making them less reliable in the clinic.

Methods based on orthogonal transforms, such as the discrete wavelet transform (DWT), the Karhunen-Loève transform (KLT), the discrete cosine transform (DCT), and other basis transforms [37], [38], work better because they take advantage of the fact that ECG signals are not stationary. These methods can compress data more (usually up to 20 times) and have lower PRD values (3%-6%) because they can pack energy very well. DWT has been the most effective of these because it can show things at different resolutions. But there is still a big problem: transform-based methods don't directly model how samples are related in time. So, there is still redundancy in the transformed coefficients, which stops any further improvement in compression efficiency.

Recent AI-based techniques [39], especially those utilizing deep learning and autoencoders, have shown considerable enhancements in reconstruction quality, attaining PRD values as low as 2%. These techniques can learn how to represent complex signals and change to fit different signal patterns. But they need a lot of training data and powerful computers to work well. Also, their ability to generalize is still an issue, especially when they are used on ECG patterns that haven't been seen before or on different groups of patients. Because of these limits, they can't be used in real-time or portable healthcare systems. Compressed sensing methods [40], [41] try to get around these problems by taking advantage of signal sparsity in a transformed domain. These methods can get CRs of 10 to 25, which is pretty high, while still keeping the quality of the reconstruction good. Still, the biggest problem with them is that the reconstruction process is very complicated and usually uses iterative optimization algorithms. Because of this, they aren't as good for real-time applications and places where power is limited. Reconstruction errors may also cause clinically important ECG features to be distorted.

The proposed method enjoys a superior balance between compression efficiency and reconstruction quality and achieves better compression and reconstruction results through its combination of LPC and regular-pulse linear prediction. The proposed method achieves CRs between 14 and 40 which exceed all other methods that were tested according to Table 3. The system maintains PRD values between 1.9% and 7.9% which remain within acceptable clinical limits. Unlike methods of compressed sensing [40], [41], the proposed method does not require iterative reconstruction; thus, it has a low computational complexity and deterministic performance. In contrast to AI-based methods [39], which necessitate significant amounts of training data and computation prior to implementation, this method has no training data requirements or specialized hardware requirements. Moreover, the proposed method provides better compression than any AI-based approach for real-time and/or low-resource applications. In conclusion, the findings show beyond a shadow of a doubt that the new method does indeed outperform current methods by achieving high CRs while preserving signal fidelity, as shown above. Therefore, since the new approach uses prediction modeling and sparse representation, it has been shown to be an efficient computational model to be used for emerging technologies, such as wearable monitoring devices, telecardiology systems, and IoT-based healthcare platforms.

Table 3. Performance comparison with the existing methods

Method	CR	PRD (%)	Remarks
Time-domain methods, e.g., DPCM, Delta coding, AZTEC, and TP [33]–[38]	3-10	4-8	Simple and low computational complexity; limited compression efficiency; may distort clinically significant features such as QRS complexes.
Orthogonal transformation method e.g., DWT, KLT, Fourier transform, DCT, Walsh transform, and Haar transform [37], [38]	3-20	3-6	Good energy compaction; effective for non-stationary signals; lack explicit temporal modeling; DWT provides the best performance among transforms.
Compressed sensing [40], [41]	10-25	5-10	Exploit signal sparsity; high compression potential; reconstruction is computationally expensive and may degrade diagnostic features.
AI-based methods [39]	8-35	2-6	High reconstruction quality; adaptive and data-driven; require large training datasets, high computational resources, and may lack generalization.
Proposed (LPC+RPE)	14-40	1.9-7.9	Very high compression efficiency; no training required; suitable for real-time and IoT applications.

4. CONCLUSION

In this paper, a new lightweight framework was developed for compressing ECG signal using LPC, RPE, and efficient parameter encoding and quantization schemes. Tested on the standard benchmark data sets from PhysioNet MIT-BIH Arrhythmia Database, the proposed approach shows excellent multi-rate performance without the need of any offline training of the model or codebook search. In terms of quantitative measures, the best setting range ($N=4$ to $N=6$) gives CR of 14.6 to 28.4 with SNR of 42.5 dB to 15.73 dB and frame-based PRD of 1.9% to 5.6% that maintains key diagnostic waveforms. In the case of maximum sub-sampling rate $N=10$, CRs go even up to 40.3 while PRD remains less than 9%. From practical point of view, the low complexity of the architecture allows to use it as an effective front-end for wearable devices and reduces transmission power usage in IoT telemedicine network. However, the present realization uses constant prediction order and sub-sampling factor that may produce some local fluctuations in signal fidelity during severe high-frequency ectopic arrhythmias. Future work could focus on the parameter selection adaptive approach and incorporating it into real-time embedded systems to expand the scope of this method in next-generation digital health care platforms.

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AUTHOR CONTRIBUTIONS STATEMENT

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Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Samer Alabed	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Mohammad Al-Rabayah		✓		✓		✓	✓	✓		✓		✓	✓	✓
Omar M. Bwaliez	✓					✓		✓		✓		✓	✓	

C : **C**onceptualization

M : **M**ethodology

So : **S**oftware

Va : **V**alidation

Fo : **F**ormal analysis

I : **I**nterpretation

R : **R**esources

D : **D**ata Curation

O : **O**riginal Draft

E : **E**diting

Vi : **V**isualization

Su : **S**upervision

P : **P**roject administration

Fu : **F**unding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The datasets used in this study are publicly available from the sources cited in the reference list [26]–[28].

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BIOGRAPHIES OF AUTHORS



Samer Alabed    is a professor of Electrical and Biomedical Engineering at the German Jordanian University (GJU), a strategic academic leader, and an expert in signal processing, internet of things, and artificial intelligence. Throughout his tenure at GJU, he has held several key academic and administrative leadership positions, including Head of Biomedical Engineering Department, Exchange Coordinator for the German Year Program, Director of the Accreditation and Quality Assurance Department, and Director of the E-Learning and Academic Performance Improvement Department. Prior to joining GJU, he served as an associate professor at the American University of the Middle East, Kuwait, from 2015 to 2022. He earned his Ph.D. in Electrical Engineering and Information Technology from TU-Darmstadt, Germany. From 2008 to 2015, he was also affiliated with TU Darmstadt, where he contributed to academic and research activities in electrical engineering, with a focus on digital signal processing and related technologies. He can be contacted at email: Samer.Alabed@gju.edu.jo.



Mohammad Al-Rabayah    earned his Ph.D. in Electrical Engineering from University of New South Wales. He is serving as an associate professor at American University of the Middle East (AUM), where he teaches a variety of courses, advises students, and contributes to departmental excellence. He was an assistant professor at Prince Sultan University. During his tenure, he taught courses in the Communication and Networks Department and played a key role in supporting the university's efforts to achieve ABET accreditation. He can be contacted at email: Mohammad.Alrabayah@aum.edu.kw.



Omar M. Bwaliez    is a professor at the Management Sciences Department of the Business School at the German Jordanian University (GJU), where he also serves as dean's assistant for accreditation and quality assurance. With over a decade of experience, he has excelled in teaching, research, training, and consultancy across various universities and companies in the Middle East and Europe. His scholarly contributions are reflected in numerous peer-reviewed articles featured in prestigious journals indexed by Scopus and Web of Science. He also holds multiple professional certifications in the fields of engineering management, Industry 4.0 technologies, quality management, higher education institutions assessment, and innovation. Prior to his academic career, he held key positions in Jordan's manufacturing sector, including industrial engineer, business development engineer, and quality assurance manager. He can be contacted at email: Omar.Bwaliez@gju.edu.jo.