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An Intelligent Hybrid Method for ECG Signal Compression Using Wavelet Transform and IWO Algorithm in Wireless Body Sensor Networks

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A B S T R A C T

Wireless Body Sensor Networks (WBSNs) are increasingly essential in healthcare, enhancing patient comfort and quality of life. These systems support patients, doctors, and medical teams through services such as continuous medical monitoring, medication and health information delivery, memory assistance, home device control, and emergency communication. This paper proposes a novel hybrid method for ECG signal compression, combining the Discrete Wavelet Transform (DWT) with the Invasive Weed Optimization (IWO) algorithm. DWT effectively decomposes the ECG signal into various frequency bands, capturing critical signal features, while IWO optimizes the selection of wavelet coefficients to achieve maximum compression with minimal data loss. The proposed approach was tested on standard ECG datasets, showing improved compression ratios compared to conventional methods. The results confirm that this technique maintains high signal quality, making it highly effective for real-time ECG monitoring in WBSNs. This ensures efficient data transmission and reliable performance in modern healthcare applications.

Keywords: *Body Sensor Networks, Medical Monitoring, ECG Signal Compression, Discrete Wavelet Transform, Invasive Weed Optimization.*

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1 Introduction

The revolution in information and communication technology has had a significant impact on all economic, security, and social sectors of countries [1-3]. With the development of information technology in the medical field, major transformations have occurred in the delivery of healthcare and medical services. Furthermore, recent advances in distributed networks, very small sensors, low-power microelectronics, and the development of body sensor networks have facilitated this progress [4-6]. The emergence of wireless sensor networks has enabled the monitoring and control of individuals in the surrounding environment. Continuous monitoring of body sensor networks enables early detection [7-10]. It can also be acknowledged that the internet has opened new ways to deliver healthcare services to the public. Overall, the focus on disease prevention and early detection of high-risk health disabilities is one of the main objectives of using body sensor networks. According to accurate statistics, the number of elderly individuals over the age of 65 in various societies is expected to reach 70 million by 2025. Therefore, the development of body sensor networks has made monitoring the elderly population easier, and it is also useful for the general population [11, 12].

Wireless Body Sensor Networks (WBSNs) consist of a series of heterogeneous biological sensors. These sensors are placed at different parts of the body and can either be worn on the body or implanted. Each of these sensors requires specific conditions to detect and record signs. In general, a sensor network can measure, sense, and sample an individual's vital signs. At the same time, it can also detect human emotions or physiological states. The wireless body sensor network communicates with a specific coordinator node that has the lowest energy consumption and the highest processing power. This node is responsible for transmitting biological signals to the patient (user) in order to provide immediate diagnosis and accurate decision-making [6].

Wireless body sensor networks are networks that use wireless sensors to monitor and collect biological and physiological data within or on the human body. These networks have numerous applications in the fields of medicine, sports, and improving quality of life. Below, we discuss some of the features, applications, and challenges of WBSNs. The important features of WBSNs are as follows:

1. Small and Wireless Sensors: WBSN sensors are typically very small, lightweight, and wireless, making them easy to place on the skin or inside the body.

2. Low Power: These sensors are designed to consume low energy to extend battery life and reduce the need for frequent battery replacements.

3. Ability to Measure Biological Data: Sensors can collect various physiological data such as temperature, heart rate, blood pressure, movement activities, and other biological parameters.

4. Wireless Connectivity: WBSNs can connect to other devices such as smartphones or computers, enabling wireless transmission of data.

Data compression of ECG (electrocardiogram) signals in WBSNs is highly important, as it helps optimize energy consumption, network bandwidth, and data storage. The significance of ECG data compression in WBSNs can be summarized as follows:

1. Energy Consumption Reduction: Wireless sensors in WBSNs typically have limited battery life. Compressing data helps reduce the volume of data that needs to be transmitted, thereby lowering energy consumption for data transmission and extending the sensor's battery life.
2. Bandwidth Optimization: WBSNs often face bandwidth limitations. Data compression can reduce the amount of data transmitted, enabling the network to transfer data more efficiently and at higher speeds. This is particularly crucial when there are many sensors or when continuous data transmission is required.
3. Increased Data Transmission Speed: Compressing ECG data reduces the time needed for transmission. This is critical for real-time applications, such as patient health monitoring, where quick responses are necessary.
4. Storage Efficiency: ECG data typically consumes a lot of storage space. Compression helps reduce the amount of storage required, which is beneficial for WBSN systems that need to store data over extended periods.
5. Maintaining High Data Accuracy: Some compression methods preserve the essential and important features of the ECG signal, while discarding less relevant data. This ensures that the compressed data retains its

key characteristics for medical analysis and disease diagnosis.

6. Reduced Network Congestion: By reducing the volume of data transmitted, compression minimizes the risk of network congestion and interference. This is particularly important in wireless networks, where signal interference can often occur.

Therefore, ECG data compression in WBSNs not only contributes to system efficiency but also enhances the overall performance of these networks in health monitoring and biological data transmission.

The paper is structured as follows: Section 2 reviews existing methods, discussing previous techniques, algorithms. Section 3 introduces the proposed method, detailing the new approach and its theoretical and practical aspects. Section 4 presents simulation results of the proposed method, comparing them with existing methods. Section 5 provides the conclusion of the paper.

2 Existing Methods

A high-performance VLSI design for a lossless ECG encoder tailored for wireless body sensor networks (WBSNs) is introduced in [2]. To minimize power consumption during wireless transmission, an innovative lossless compression algorithm for ECG signals has been developed. This algorithm integrates an adaptive predictor governed by fuzzy decision control alongside an entropy encoder utilizing a two-stage Huffman coding technique. Additionally, the design functions at 100 MHz while consuming only 28.3 µW of power. The proposed method achieves an average compression ratio of 2.53 when tested on the MIT-BIH arrhythmia database. Compared to existing ECG encoder implementations, the suggested VLSI design provides a higher compression ratio, reduced power usage, and lower hardware complexity. The fuzzy predictor is composed of five registers, three subtractors, a multiplexer, and a fuzzy decision controller. Despite advancements in ECG monitoring with WBSN integration, achieving optimal energy efficiency remains a challenge. Implementing ECG compression can enhance energy efficiency by reducing the transmission time over power-intensive wireless links. In [1], a compression model for sensor signals is introduced. The findings indicate that the proposed approach serves as a robust alternative to ECG compression techniques utilizing the Discrete Wavelet Transform (DWT) within WBSN-based ECG monitoring systems. It is shown that employing this method for ECG compression extends node lifetime by 37.1% compared to its DWT-based counterpart.

In [3], a wireless ECG acquisition and classification system is introduced, consisting of a BioSignal Processor (BSP), a transmitter-receiver unit, and a Digital Signal Processor (DSP). The BSP, designed with a low-complexity architecture, incorporates only a low-noise amplifier and a High Pass Sigma-Delta Modulator (HPSDM). The transmitter and receiver utilize On-Off Keying (OOK) for energy-efficient wireless communication and short-range transmission. Signal processing and analysis are handled by the DSP circuit at the receiver end. The entire system is fabricated using a 180-nanometer CMOS process with a 1.2 V supply voltage. The power consumption, including the BSP and transmitter, is a mere 587 µW, while at the receiver node, the total power consumption, including the receiver and DSP, amounts to 926 µW. In [6], a novel method for ECG signal compression in low-power ECG sensor nodes, utilizing the sparse characteristics of ECG signals in the frequency domain, is presented. The results show that this method achieves significantly better compression performance, with an average compression ratio (CR) of 65, while the existing method achieves a CR of approximately 40 at the same error rate. The impressive compression performance of the proposed approach provides a practical solution for minimizing energy consumption in the design of wireless ECG sensor nodes. In [5], a low-power capacitive ECG monitoring system has been implemented. The system operates with a 5 V supply voltage, and a low-power Bluetooth module is used to reduce power consumption during wireless data transmission. The total power consumption of the system is 16.4 mW.

Continuous heart signal monitoring via wearable IoHT devices helps reduce mortality but generates large ECG/VCG data, challenging due to limited storage, transmission, and power. The article [4] proposes low-power, resource-efficient VLSI architectures for multichannel ECG/VCG compression. Using the PTB database, the designs achieve high compression ratios (3.857 for ECG, 4.45 for VCG) with minimal power and area needs, making them ideal for wearable healthcare devices. Data compression helps reduce storage and boost transmission efficiency in wearable ECG systems.

The paper [7] presents an efficient compression method using wavelet transform (WT) and variable-length run-length encoding. WT is used to extract transform coefficients, followed by dead-zone quantization based on energy packing efficiency. Coefficients below a set threshold are discarded, and others are quantized and encoded. Tested on MIT-BIH arrhythmia database, the method achieved a 20.48 compression ratio and strong performance metrics like low PRD and high SNR, outperforming existing ECG compression techniques. The paper [9] proposes an ECG compression method with adaptive reconstruction quality using discrete cosine transform (DCT) and evolutionary algorithms. DCT decomposes the signal, and thresholding is optimized using PSO, FPA, ABC, and CS algorithms. Modified run-length encoding (MRLE) compresses the data, followed by decoding and inverse DCT. Results show effective compression with PRD between 1.02% and 4.95%, indicating excellent reconstruction and good compression performance.

In [8], a wireless ECG system is introduced, designed for real-time ECG monitoring in cardiac patients. The proposed device is lightweight (25 grams), wearable, and capable of wirelessly transmitting the patient's ECG signal via ZigBee to a mobile phone or personal computer. Thanks to its ultra-low power ECG chip, the device provides a battery life of approximately 26 hours during continuous operation. In [10], a low-power biosignal acquisition and classification system for body sensor networks is proposed. The biological signals are captured by BSP circuits, which convert them into digital form. These signals are subsequently transmitted by the transmitter, while the receiver and DSP handle the reception and processing of the data. In [11], a low-power analog circuit design for wireless ECG acquisition systems is introduced. Given the necessity for efficient communication within body sensor networks, the use of low-power analog ICs becomes essential. The proposed system for acquiring the ECG signal includes an ECG signal acquisition board, an on-chip low-pass filter, and an on-chip successive approximation analog-to-digital converter. Additionally, a quadrature oscillator along with a 2.4 GHz transmitter, which integrates a power amplifier and mixer, has been developed to wirelessly transmit the ECG signal.

3 Proposed Method

Since the proposed compression method is based on the wavelet transform and the invasive weed optimization (IWO) algorithm, the fundamental concepts of these techniques are first presented.

3.1 Wavelet Transform

Discrete Wavelet Transform (DWT) is a mathematical technique used for analyzing signals at different scales. This transform decomposes a signal into a set of coefficients that capture different aspects of the signal at various scales. Unlike the Fourier Transform, which analyzes a signal in the frequency domain, the wavelet transform provides information in both the time and frequency domains. This dual-domain capability makes DWT highly effective for processing non-stationary signals such as images and audio [13-15].

DWT works by applying low-pass (LL) and high-pass (HH) filters to decompose the signal into two main components: approximation (low-frequency component) and detail (high-frequency component), as shown in Figure 1. This process can be iteratively applied to reduce the data dimensions. One of the notable features of DWT is its high compression ability, which allows it to extract significant information while retaining quality and removing unnecessary data. The concept of multi-level decomposition can be formulated mathematically. The discrete-time signal s[n] can be decomposed based on the following relations:

$$y_h[m] = \sum_n s[n]\, g_h[2m-n] \quad (1)$$

$$y_l[m] = \sum_n s[n] g_l[2m-n] \quad (2)$$

y_h and y_l indicate the outputs of the high-pass and low-pass filters, respectively. Meanwhile, g_h and g_l are the impulse responses of the filters.

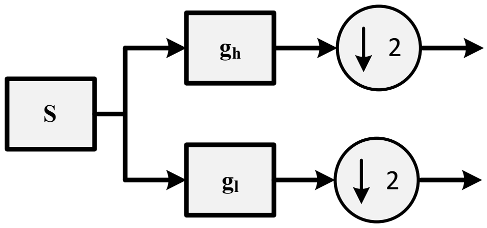


Figure 1. Discrete Wavelet Transform Process [15].

3.2 Invasive Weed Optimization Algorithm

The IWO algorithm (Figure 2) is inspired by the growth behavior of weeds in nature [16-19]. These plants, due to their rapid and aggressive growth, pose a serious threat to crops and agricultural plants. Weeds have a high ability to adapt to various environmental conditions, enabling them to thrive even under changing circumstances. This adaptability allows them to survive in most conditions. The IWO algorithm mimics these natural characteristics, especially in terms of search and optimization, by using the growth and resilience of weeds as an inspiration to design optimal methods for solving various problems. The steps of the IWO algorithm are as follows:

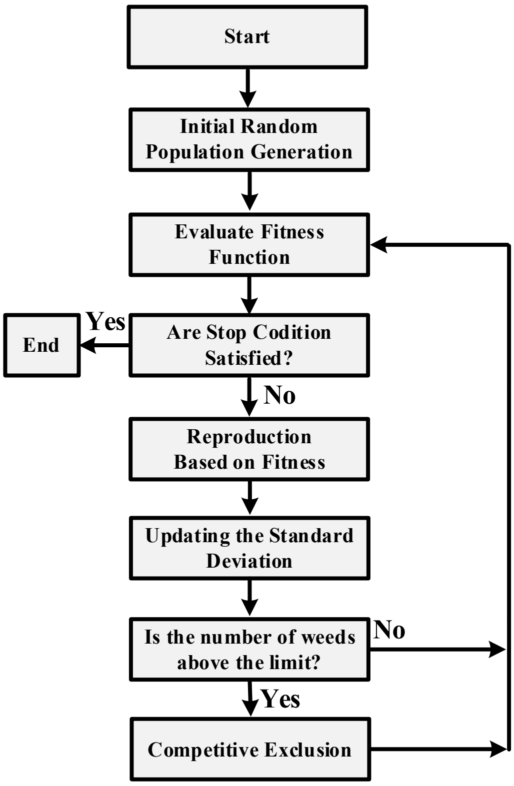


Figure 2. Invasive Weed Optimization Flowchart [18].

1. Random generation of the initial population and fitness evaluation: In this step, an initial population of solutions is generated randomly. Then, each solution is evaluated using the fitness function. The fitness function measures the performance of each solution based on a specific criterion, which is considered the "fitness" or "strength" of each individual in the population.
2. Reproduction based on fitness and standard deviation update: In this step, the reproduction process begins, which is directly related to the fitness of each individual. Individuals with higher fitness are more likely to participate in reproduction. After reproduction, the standard deviation (a key parameter in the IWO algorithm) must be updated. This update helps in adjusting the search domain and introduces diversity in the population. The generated seeds are dispersed in the search space, following a normal distribution with a mean of zero and a specified variance. The initial standard deviation is δ_{initial}, which gradually transitions to the final value of δ_{final}. Throughout the algorithm's execution, the standard deviation changes nonlinearly from its initial to final value. In other words, as the algorithm progresses, seeds are increasingly generated around the obtained solutions, leading to reduced dispersion. The standard deviation is updated according to equation (3).

$$\delta_{Iter_i} = \frac{(max\,It - Iter_i)^{pow} \times (\delta_{initial} - \delta_{final})}{(max\,It - 1)^{pow}} + \delta_{final} \quad (3)$$

where δ_{Iter_i} is standard deviation at the i-th iteration, $max\,I\,t$ is maximum allowed number of iterations, $Iter_i$ is the i-th iteration number and Pow indicates nonlinear adjustment factor.

3. Competitive elimination of weeds: In this step, a competition occurs among the weeds (solutions). Solutions with lower fitness are removed from the population. This step is akin to natural selection, where only the best individuals remain in the population.
4. Termination condition check: In this step, the algorithm checks if the termination conditions are met. These conditions may include reaching the maximum allowed number of iterations, achieving a satisfactory level of fitness, or obtaining an optimal solution. If the termination conditions are not met, the algorithm continues.

These steps are repeated continuously until the algorithm converges to an optimal or near-optimal solution.

3.3 Compression Process with Wavelet Transform and IWO Algorithm

In this Section, a new method for data compression is proposed. In the first step, a wavelet transform is applied to the original signal to extract the important information contained in the signal. Then, the wavelet coefficients that are below a certain threshold are removed. The threshold selection is performed by the IWO algorithm in such a way that the compression error is minimized. Further details of the proposed method are provided in the following. The proposed method is a combination of wavelet transform and the IWO algorithm, which is an intelligent approach for adaptive ECG signal compression. In this research, a new method for adaptively selecting the threshold is proposed. The threshold is chosen in such a way that the following cost function is minimized by IWO.

$$Cost = W_1 \times PRD + W_2 \times (1 - \mathrm{CC}) + W_3 \times 1/\mathrm{CR} \quad (4)$$

where Percent Root Difference (PRD), Correlation Coefficient (CC), and Compression Ratio (CR) are performance measures used to evaluate the quality of ECG signal compression.

PRD is a widely used metric for measuring the distortion introduced during the compression and reconstruction processes. It quantifies the difference between the original ECG signal and the reconstructed signal after decompression. Lower values of PRD indicate lower reconstruction error and better preservation of the original signal characteristics.

CC is a statistical measure that evaluates the similarity between the original ECG signal and the reconstructed signal. It reflects how well the waveform morphology is preserved after compression. A CC value close to one indicates a high degree of similarity and demonstrates that important ECG features, such as the P wave, QRS complex, and T wave, have been accurately maintained.

CR is a measure of compression efficiency and indicates the amount of data reduction achieved by the compression algorithm. Higher values of CR correspond to greater compression efficiency and lower storage and transmission requirements. The parameters W_1 , W_2 and W_2 are weighting coefficients that determine the relative importance of each objective in the optimization process.

The proposed method has several advantages that distinguish it from classical methods:

1. Optimal Threshold Selection with IWO: In conventional methods, the threshold is typically fixed or based on statistical criteria (such as hard or soft thresholding). However, here, the weed optimization algorithm is used to search for the optimal threshold value. This ensures that less important wavelet coefficients are removed while retaining the important information. Additionally, the compression is adaptive, with the optimal threshold value dynamically adjusted based on the type of signal.

2. Increased Compression Ratio with Minimal Quality Loss: Using IWO enables a higher compression ratio because the threshold is selected in such a way that the least amount of useful information is discarded. As a result, the reconstructed signal retains high quality, and the reconstruction error is reduced.

3. Noise Reduction and Improved Reconstruction Accuracy: By removing less significant wavelet coefficients, high-frequency noise is also eliminated. This feature is particularly beneficial for ECG signals, which are typically affected by muscle noise, power grid interference, and motion artifacts, leading to improved reconstruction accuracy and a cleaner signal.

4. Nonlinear Optimization and Global Search with IWO: Unlike gradient-based methods, the weed optimization algorithm can reach globally optimal solutions in the search space. This advantage ensures that the determined threshold provides the highest efficiency for compression.

Proposed method for ECG signal compression using Wavelet Transform and IWO algorithm is as shown in Figure 3. The main steps are described as follows:

Step 1: Decompose the ECG signal using a fixed multi-level Discrete Wavelet Transform (DWT).

Step 2: Generate a candidate threshold value using the IWO algorithm.

Step 3: Apply the threshold to the wavelet coefficients. Coefficients whose absolute values are smaller than the threshold are set to zero.

Step 4: Store the remaining non-zero coefficients together with their positions as the compressed representation of the ECG signal.

Step 5: Reconstruct the ECG signal by applying the Inverse Discrete Wavelet Transform (IDWT) to the thresholded coefficients.

Step 6: Evaluate the reconstructed signal using the objective function

Cost = W1 × PRD + W2 × (1 − CC) + W3 × (1 / CR)

where PRD measures reconstruction distortion, CC evaluates morphological similarity between the original and reconstructed ECG signals, and CR represents the achieved compression ratio.

Step 7: Update the IWO population according to the calculated cost value.

Step 8: Repeat Steps 2–7 until the stopping criterion is satisfied.

Step 9: Select the threshold yielding the minimum cost value.

Step 10: Output the compressed ECG representation consisting of the retained wavelet coefficients and their corresponding indices.

The computational complexity of the DWT and IDWT operations is O(N), whereas the overall complexity of the proposed method is approximately O(PGN), where P is the population size and G is the number of IWO generations.

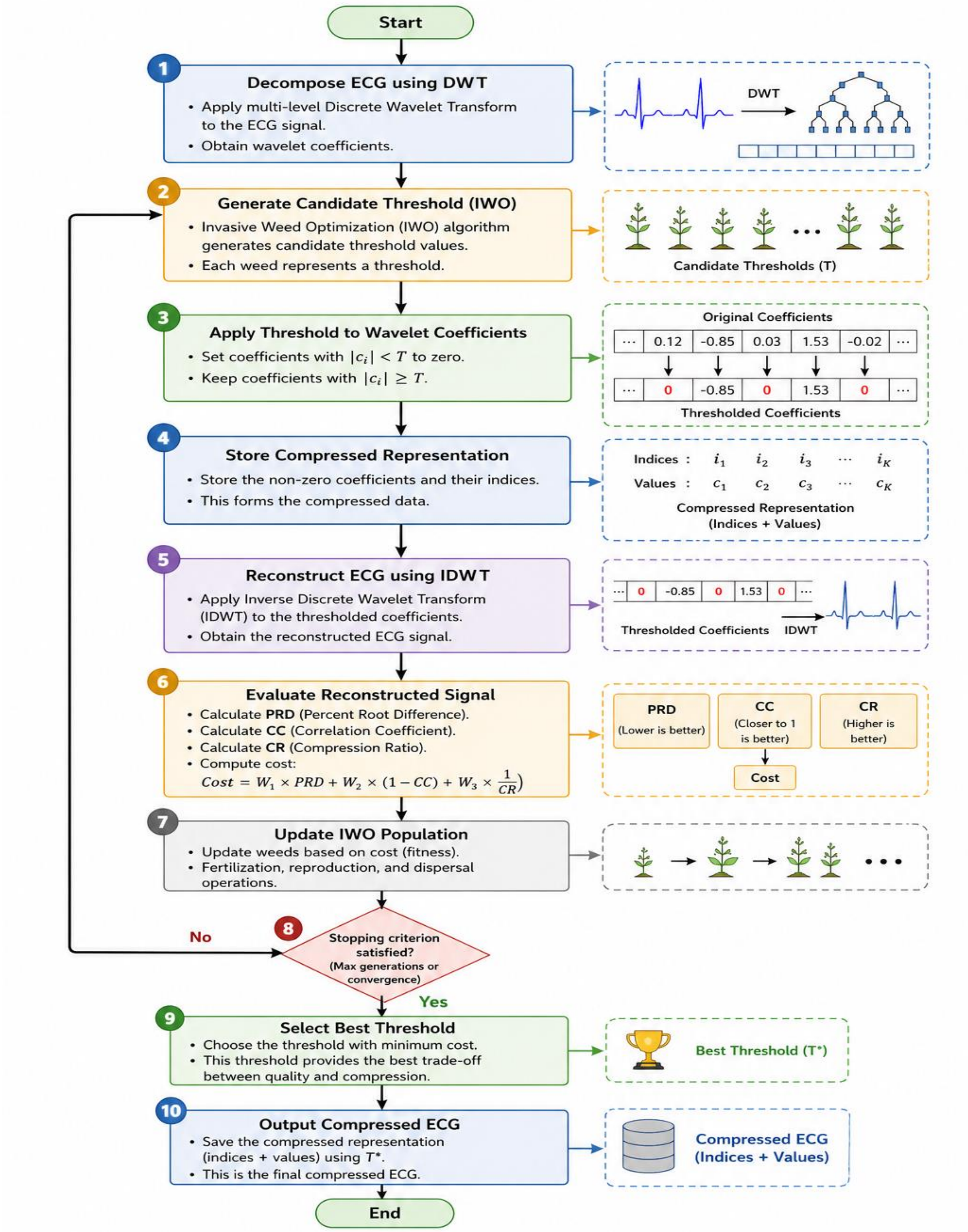


Figure 3. Proposed Method for ECG signal compression using DWT and IWO algorithm.

4 Simulation Results

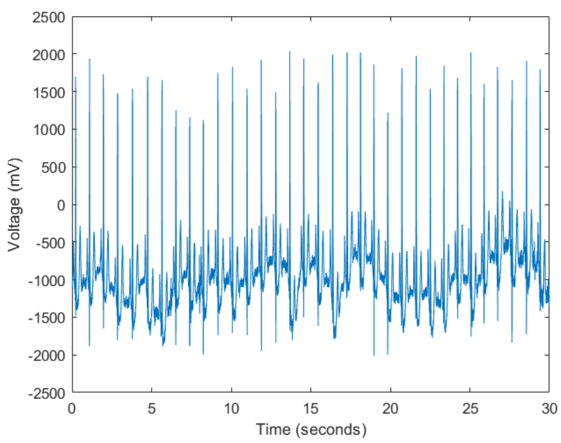
The algorithm of the proposed method and the existing method has been implemented using MATLAB software from MathWorks. The processor used is an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz with 16 GB of RAM. The parameters of the IWO algorithm are presented in Table 1. These parameters were chosen to create a trade-off between the speed and accuracy of the algorithm.

In this study, the MIT-BIH Arrhythmia Database is used to evaluate and validate the performance of the proposed method [20]. This database is one of the most well-known and widely used resources in the field of ECG (electrocardiogram) signal processing. It consists of 48 two-channel ECG records, each approximately 30 minutes long, with a sampling rate of 360 Hz. The database includes annotated recordings of various types of cardiac arrhythmias, such as premature ventricular contractions (PVC), left and right bundle branch blocks (LBBB and RBBB), atrial premature beats, and other rhythm disturbances. It serves as a standard benchmark for evaluating and comparing algorithms in areas like compression, classification, recognition, and analysis of ECG signals in scientific papers and medical engineering research.

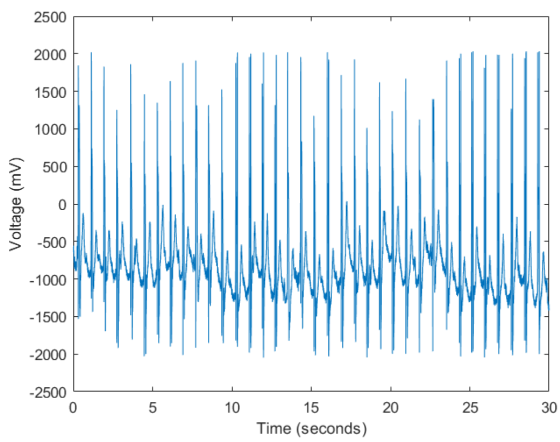
Table 1. Parameters of the Invasive Weed Optimization (IWO) Algorithm

Parameters	Values
N_{weed}	100
MaxIt	10
P_{max}	100
S_{max}	10
S_{min}	1
$\delta_{initial}$	0.3
δ_{final}	0.001
pow	3

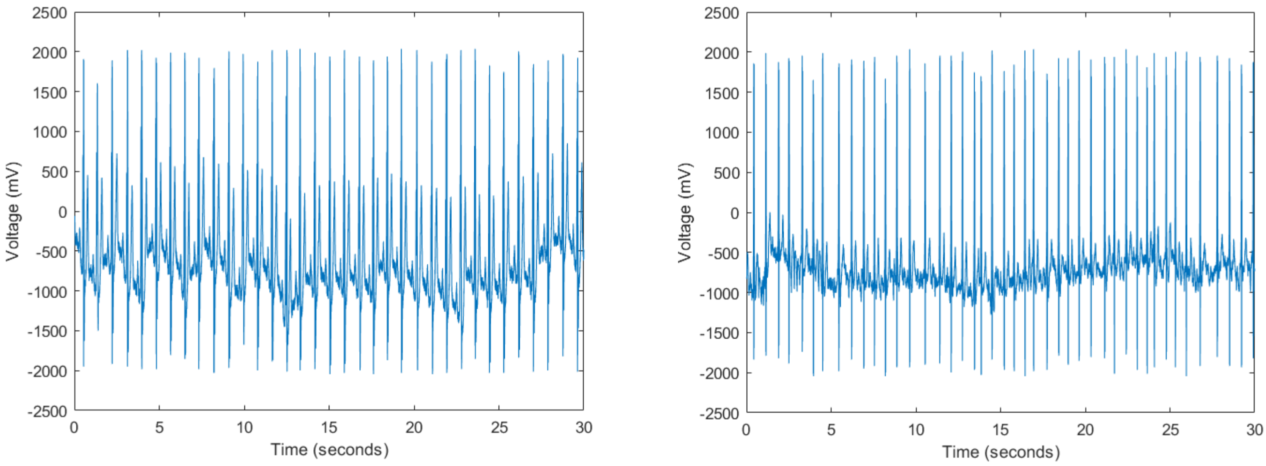
In Figure 4, several records from the MIT-BIH database, including records 101, 102, 111, and 201, are shown. These records are among the ECG signals used for evaluating various signal processing algorithms. Each of these records has its own unique characteristics, and the diversity in the types of arrhythmias present in them helps in the evaluation and analysis of the proposed algorithms. In Figure 5, the compressed signals obtained using the proposed method is displayed. In this method, the DWT is applied using the db4 wavelet and five levels of decomposition. This compressed signal demonstrates the successful compression and preservation of the original signal quality, which is crucial in ECG compression algorithms. Finally, the optimization process carried out in different stages of this method is depicted in Figure 6. This figure shows the process of selecting the optimal wavelet coefficients using the IWO algorithm, which aims to maximize compression while maintaining the integrity of the signal.



(a)

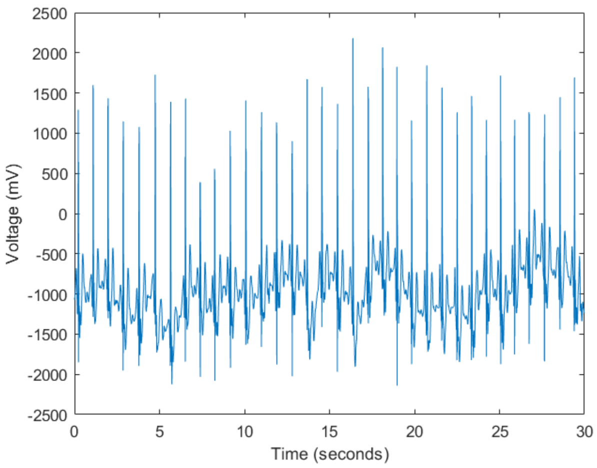


(b)

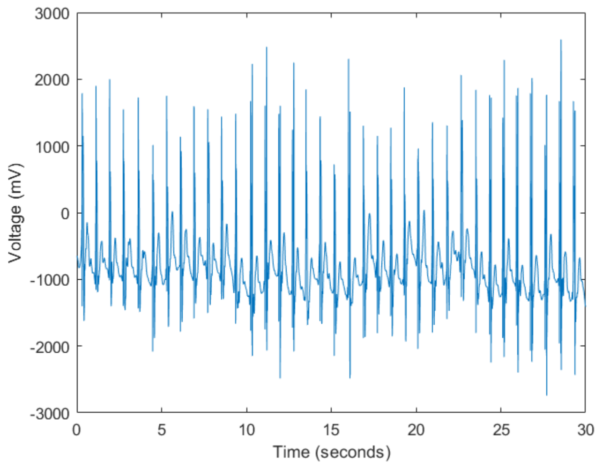


(c) (d)

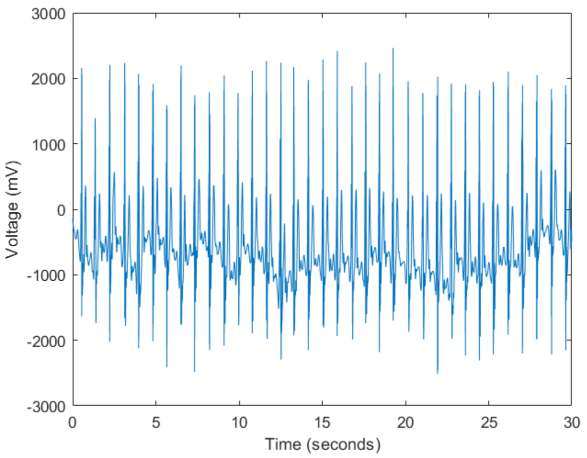
Figure 4: Examples of ECG signals from the MIT-BIH database: (a) Record 101, (b) Record 102, (c) Record 111, (d) Record 201.



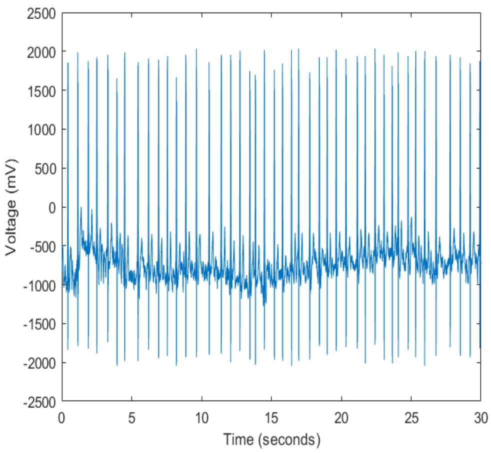
(a)



(b)



(c)



(d)

Figure 5: Compressed signals for each record using the proposed method: (a) Signal obtained for record 101, (b) Signal obtained for record 102, (c) Signal obtained for record 111, (d) Signal obtained for record 201.

Table 2 demonstrates that the proposed approach achieves an average CR of 21.8 while maintaining a low reconstruction error and high waveform similarity. The average PRD is 2.98%, indicating that the distortion introduced during the compression and reconstruction processes remains within clinically acceptable limits. Furthermore, the average CC reaches 0.991, confirming the high similarity between the original and reconstructed ECG signals and the effective preservation of important morphological features such as the P wave, QRS complex, and T wave. Among the evaluated records, Record 101 achieves the highest compression ratio of 24.8 with a PRD of 2.10% and a CC of 0.995, while Record 201 exhibits the largest reconstruction error with a PRD of 4.12%, although the reconstructed signal still maintains a high correlation coefficient of 0.985. Overall, the results indicate that the proposed method provides an effective compromise between compression efficiency and signal fidelity, making it suitable for ECG data transmission and storage in wireless body sensor network applications.

The performance of the proposed method is compared with existing methods in Table 3. As shown in Table 3, the method proposed in [12] achieves high compression ratio through online dictionary-based compression while maintaining a reconstruction error below 4%. Similarly, the EMD-based approach presented in [21] reports compression ratios of up to 25 with an error of approximately 5%. Although this method achieves a higher compression ratio, it relies on more sophisticated decomposition and dictionary-based processing frameworks. In contrast, the proposed DWT–IWO method achieves a compression ratio of 21.8 with a PRD of 2.98% and a correlation coefficient of 0.991, indicating high reconstruction quality and effective preservation of ECG morphology. Furthermore, the proposed method employs a relatively simple wavelet-based decomposition combined with adaptive threshold optimization, making it suitable for implementation in resource-constrained wireless body sensor networks.

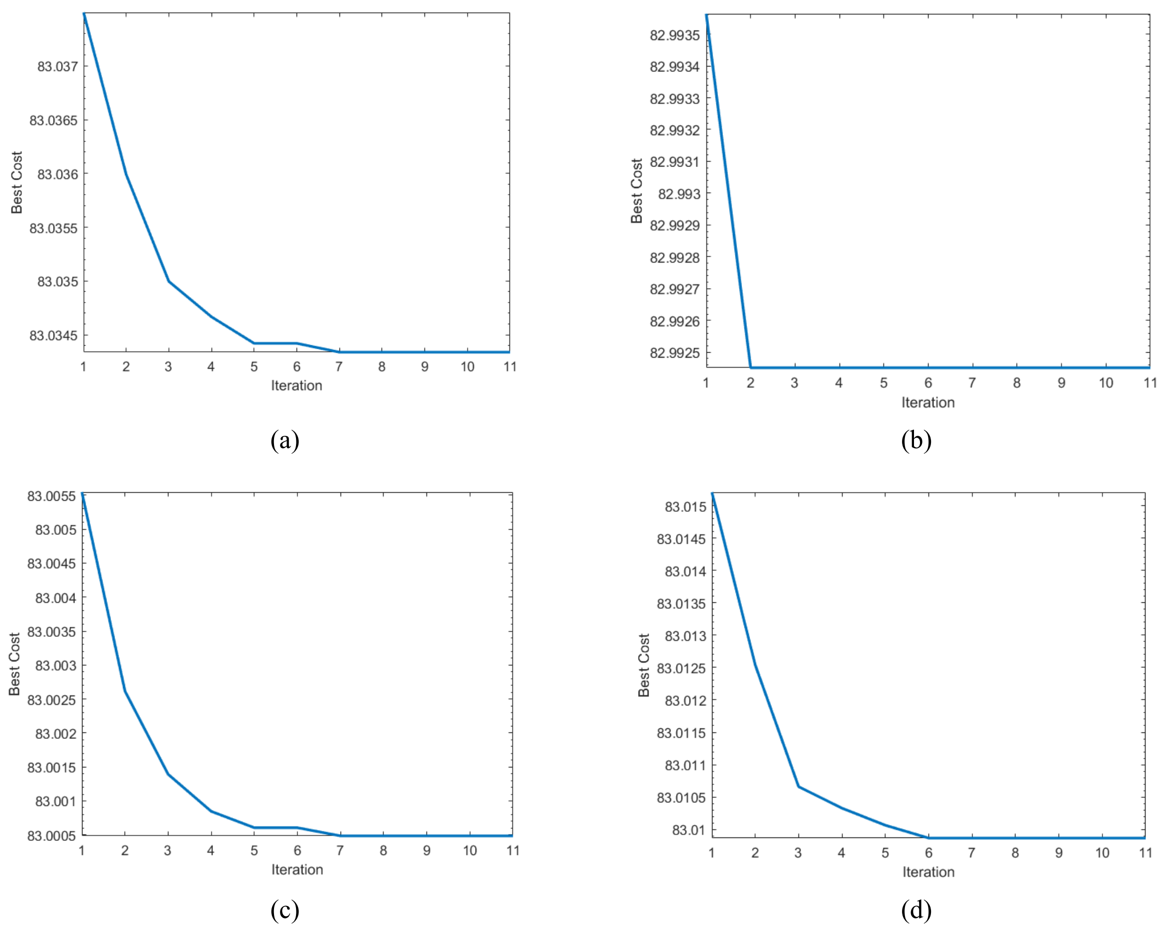


Figure 6. Optimization process using the IWO algorithm for wavelet coefficient selection: (a) Optimization process for record 101, (b) Optimization process for record 102, (c) Optimization process for record 111, (d) Optimization process for record 201.

Table 2. Compression Ratio and MSE for Each ECG Record

Record	CR	PRD (%)	CC
101	24.8	2.10	0.995
102	23.6	2.35	0.994
105	24.2	2.28	0.994
106	19.4	3.42	0.988
111	21.8	2.96	0.991
112	21.5	3.08	0.990
201	18.7	4.12	0.985
202	20.3	3.54	0.988
Average	21.8	2.98	0.991

Table 3. Comparison Results of the Proposed Method and Existing Methods.

Method	CR	PRD (%)	CC
Proposed Method	21.8	2.98	0.991
[12]	20	4	--
[13]	13.8	--	--
[14]	25	5	--

5 Conclusion

Compression of signals in wireless sensor networks not only helps reduce energy consumption and optimize bandwidth but also enhances data quality and network efficiency. Given the resource limitations in these networks, signal compression has become an essential tool for managing and optimizing the performance of wireless sensor networks. Signal compression in wireless sensor networks holds significant importance. In this study, a new method for signal compression based on wavelet transform is proposed. The wavelet transform removes redundant information from the ECG signal. The optimal threshold selection in wavelet transform is achieved through the IWO algorithm. The optimal threshold selection leads to improved performance of the proposed method. Simulation results demonstrate the superior performance of the proposed method compared to existing approaches.

Ethical Considerations

All procedures performed in this study were under the ethical standards.

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Conflict of Interest

The authors report no conflict of interest.

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