ISSN Online: 2821-1693

Transactions on Machine Intelligence

Journal Homepage: https://tmachineintelligence.ir/

ECG Signal Compression in Wireless Body Area Networks Using the Bat Algorithm

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ARTICLE INFO

Article History:
Received 4 May 2025
Received in revised form 10 August 2025
Accepted 2 September 2025
Available online 16 September 2025

Keywords:
Bat Algorithm, Signal Compression, ECG, Wireless Body Area Network (WBAN), PSNR.

ABSTRACT

Efficient compression of Electrocardiogram (ECG) signals is of considerable importance in wearable and remote healthcare systems, particularly in Wireless Body Area Networks (WBANs), where limitations in energy consumption, transmission bandwidth, and computational resources impose strict constraints on continuous physiological data monitoring. In this research, a novel ECG signal compression framework is proposed by integrating the Discrete Wavelet Transform (DWT) with the Bat Algorithm, a population-based metaheuristic optimization technique. In the proposed approach, the raw ECG signal is first decomposed into multiple frequency components in the wavelet domain, enabling an efficient representation of the signal in terms of a relatively small number of significant coefficients. Subsequently, the Bat Algorithm is employed to identify and select the optimal set of wavelet coefficients by maximizing the Peak Signal-to-Noise Ratio (PSNR) of the reconstructed signal. This optimization process allows the algorithm to preserve the coefficients carrying the most relevant morphological and diagnostic information while eliminating less significant components, thereby achieving effective data reduction without substantially degrading signal quality. The performance of the proposed method is evaluated using ECG recordings from the widely used MIT-BIH database. Experimental results demonstrate that the proposed DWT–Bat Algorithm framework achieves superior PSNR performance compared with conventional ECG compression techniques, indicating an improved trade-off between compression efficiency and reconstruction fidelity. The proposed approach therefore provides a promising solution for reducing the amount of transmitted ECG data while maintaining clinically relevant signal characteristics. Owing to its compression capability and potential for reduced communication overhead and energy consumption, the method can be considered suitable for real-time ECG monitoring applications in resource-constrained WBAN and wearable healthcare systems.

1. INTRODUCTION

The electrocardiogram (ECG) signal is one of the most vital physiological signals used in diagnosing and monitoring cardiac function. This signal provides invaluable information regarding the electrical activity of the heart and plays an essential role in detecting pathologies such as arrhythmia, ischemia, and myocardial infarction. With

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http://dx.doi.org/10.47176/tmi.2025.244862

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advancements in remote healthcare monitoring technologies and the expansion of Wireless Body Area Networks (WBANs), the demand for logging, storing, and transmitting high-volume ECG data has expanded significantly. Given the massive data volume generated, efficient ECG signal compression is vital to minimize storage requirements and transmission bandwidth while preserving signal reconstruction fidelity [1-3].

ECG signal compression finds widespread application in real-time patient monitoring, telemedicine systems, wearable devices, and cardiac alert systems. In these frameworks, patients' physiological data are gathered via body-mounted sensors and transmitted wirelessly to processing hubs or medical centers. Compression severely diminishes the volume of transmitted data, thereby reducing power consumption, communication latency, and the probability of data packet loss. Furthermore, in battery-constrained environments, data compression significantly extends system longevity and enhances overall network sustainability [4-7].

The paramount challenge in ECG signal compression is preserving the original waveform morphology during data reduction, as even minor distortions in amplitude or waveform shape can compromise clinical diagnosis. Additionally, classical compression techniques such as the Wavelet Transform or Discrete Cosine Transform (DCT) often demand meticulous parameter tuning and optimal coefficient selection, a process that is both time-consuming and inefficient. Another critical challenge is striking an optimal balance between compression ratio, reconstruction quality (typically quantified via the Peak Signal-to-Noise Ratio or PSNR metric), and computational complexity. These challenges take on heightened significance in real-time applications such as continuous patient monitoring.

To overcome these challenges, evolutionary algorithms such as the Genetic Algorithm (GA) and the Bat Algorithm (BA) have been deployed. Inspired by the natural behavior of living organisms, these algorithms exhibit robust performance in navigating complex optimization search spaces. In the context of ECG signal compression, evolutionary algorithms can intelligently select the effective wavelet transform coefficients or thresholding parameters to establish the best trade-off between compression performance and reconstruction quality. For instance, by combining local and global search mechanics, the Bat Algorithm can determine the optimal coefficients that maximize the PSNR value while minimizing information loss [8-10].

In summary, ECG signal compression is highly critical not only for saving power and bandwidth but also for bolstering data reliability within remote healthcare monitoring systems. Leveraging intelligent evolutionary algorithms facilitates adaptive, data-driven compression capable of responding to patient-specific profiles and dynamic network conditions. Fusing transform-domain methods (such as the DWT) with evolutionary optimization offers a powerful approach to achieving high-fidelity reconstruction using minimal computational resources. Consequently, this technology is poised to play an instrumental role in developing next-generation intelligent healthcare monitoring systems.

2. EXISTING METHODS

In study [1], an efficient VLSI design for an electrocardiogram (ECG) signal encoder in wireless body sensor networks is presented. To reduce power consumption during data transmission, a novel lossless encoding algorithm has been developed for ECG signal compression. This algorithm incorporates a fuzzy-logic-based adaptive predictor to estimate future signal values and a two-stage Huffman entropy encoder, which enhances compression efficiency and mitigates the required transmission power.

In paper [2], a novel paradigm for sensor signal compression is introduced. Experimental results indicate that the proposed method can serve as an effective and robust alternative to digital wavelet transform-based ECG compression techniques within ECG monitoring frameworks in wireless body sensor networks. Furthermore, the findings demonstrate that utilizing this approach yields a 37.1% increase in node longevity compared to the DWT-based approach.

In paper [3], a wireless system for cardiac signal acquisition and classification is presented, which comprises three primary modules: a bio-signal processor, a regenerative transceiver, and a digital signal processor. The bio-signal processor is designed with a simplified architecture, incorporating only a low-noise amplifier and a high-pass sigma-delta modulator. For low-power, short-range wireless communication, an on-off keying (OOK) scheme is implemented in the transceiver. The digital signal processor at the receiver handles signal processing and analysis.

The entire system is fabricated in 180 nm CMOS technology under a 1.2 V supply voltage and exhibits robust performance in cardiac signal acquisition and processing.

In study [4], a new method for cardiac signal compression in low-power sensor nodes is proposed, designed based on the sparse characteristics of signals in the frequency domain. The results indicate that this method delivers superior compression performance, achieving an average compression ratio of 65, whereas existing methods provide a compression ratio of only about 40% under the same error constraints. The high efficiency of this method offers a practical solution for significantly reducing energy consumption in the design of wireless cardiac sensor nodes.

In study [6], three distinct data transmission strategies are investigated: real-time transmission of all data, batch transmission of all data, and the transmission of detected events only the third model being the strategy proposed in this paper. To evaluate the impact of these strategies and ventricular fibrillation detection methods on energy consumption, a simulation environment and a generic power consumption model were developed.

3. PROPOSED METHODOLOGY

The proposed methodology is founded upon the Discrete Wavelet Transform (DWT) technique and the Bat Algorithm (BA). The constituent phases of the proposed framework are delineated in greater detail below.

3.1. Discrete Wavelet Transform (DWT)

The Discrete Wavelet Transform is a powerful mathematical tool for the analysis of non-stationary and complex signals, capable of providing simultaneous time and frequency domain representation. Unlike the Fourier Transform, which merely displays the spectral content of a signal averaged across the entire temporal horizon, the DWT captures frequency variations as they evolve over time. This attribute is exceptionally critical for biomedical signals such as ECGs, given that these biological signals are inherently non-stationary and their clinically significant features fluctuate dynamically over time [11-14].

In the discrete wavelet transform, the input signal is systematically passed through a series of low-pass and high-pass filters, followed by dyadic decimation (downsampling by a factor of two). The output of the low-pass filter yields the approximation coefficients (the coarse profile of the signal), whereas the high-pass filter isolates the detail coefficients (the high-frequency fluctuations). This decomposition process can be recursively repeated across multiple levels to resolve the signal into distinct frequency bands, allowing separate analysis and compression of disparate low-frequency and high-frequency features.

The DWT stands as one of the most prevalent techniques for ECG signal compression. In this application, the raw ECG trace is converted into wavelet coefficients, after which coefficients that contribute negligibly to signal reconstruction are either discarded or heavily attenuated via thresholding. Through this mechanism, data volume is compressed while strictly preserving the baseline morphology and clinical features of the cardiac waveform. Deploying the DWT for compression, particularly within wireless body area networks, substantially curtails energy expenditures and extends sensor node operating life.

The principal advantages of the DWT include its simultaneous time-frequency localization, high compression efficiency, and high-fidelity signal reconstruction. Nevertheless, selecting an appropriate wavelet basis function (mother wavelet), the optimal decomposition level, and the proper thresholding policy remains paramount to maximizing compression performance. Suboptimal parameter selection can induce degradation in reconstruction fidelity or escalate computational complexity; hence, fusing the DWT with intelligent frameworks or evolutionary metaheuristics for optimal coefficient selection has become widely adopted in contemporary research.

In conclusion, the Discrete Wavelet Transform constitutes a versatile and highly efficient instrument for bio-signal analysis and compression. It not only facilitates significant data reduction but also preserves the core diagnostic components of the signal, thereby enhancing the performance of remote health monitoring systems and decreasing power consumption in real-time execution. Given the architectural flexibility of the DWT to interface seamlessly with intelligent and evolutionary algorithms, it remains an optimal choice for ECG signal processing and compression.

3.2. Bat Algorithm (BA)

The Bat Algorithm is an evolutionary, swarm intelligence-based metaheuristic optimization algorithm. It was developed by mimicking the foraging behavior of bats and their capability to navigate and detect prey via echolocation. The underlying principle of the algorithm is that each bat represents a potential candidate solution within the problem search space. By moving through this space and dynamically updating its position and velocity, each bat searches for the global optimum [15-16].

In the Bat Algorithm, every individual bat is characterized by parameters such as flight frequency, velocity, position, and loudness. As the iteration count increases, the bats adjust their positions toward regions that offer superior objective function values. Concurrently, the loudness (A) of the bats decreases, while the pulse emission rate (r) progressively increases, thereby shifting the search focus toward local exploitation around the best objective function values. This dual-action mechanism empowers the algorithm with robust global exploration capabilities while ensuring fine-tuned local search in the vicinity of optimal solutions.

Due to its ease of implementation and high flexibility, the Bat Algorithm is extensively utilized in diverse applications, including neural network hyperparameter tuning, signal compression, resource allocation, and engineering design problems. Particularly in ECG signal compression, this algorithm can intelligently isolate the optimal wavelet transform coefficients or thresholding parameters to achieve the highest possible reconstruction quality with minimal data payload.

The primary advantage of the Bat Algorithm over other evolutionary computation techniques lies in its capability to seamlessly merge local exploitation and global exploration within a unified, elegant framework. This synergy yields rapid convergence speeds and prevents the population from getting trapped in local optima. Through the precise tuning of frequency, loudness, and emission rate parameters, this algorithm can effectively discover optimal solutions in complex and multi-objective optimization landscapes.

3.3. Core Phases of the Proposed Framework

The primary operational phases of the proposed method, which couples the Discrete Wavelet Transform and the Bat Algorithm for ECG signal compression, are seamlessly integrated as follows:

Pre-processing: The raw ECG signal collected from the sensor node is initially processed to eliminate ambient noise and unwanted physiological artifacts. This stage encompasses digital filtering and baseline normalization to guarantee high-fidelity input signal quality for subsequent operations.

Wavelet Decomposition: The pre-processed signal is subsequently decomposed into wavelet coefficients across various frequency sub-bands via the Discrete Wavelet Transform. The low-pass (approximation) coefficients capture the coarse morphology of the signal, while the high-pass (detail) coefficients capture structural details, facilitating the separation of clinical features from redundant components.

Objective Function Formulation: An objective function is formulated based on the Peak Signal-to-Noise Ratio (PSNR) reconstruction quality metric. The target of the Bat Algorithm is to select a subset of wavelet coefficients such that the reconstruction quality is maximized using the fewest coefficients possible, ensuring high-ratio signal compression while strictly preserving diagnostic ECG attributes.

Metaheuristic Optimization: The Bat Algorithm instantiates a population of candidate solutions, iteratively updating the position and velocity of each bat to identify the optimal configuration of wavelet coefficients. The dynamic interplay between bat loudness and pulse emission rates focuses the search on regions yielding the highest reconstruction fidelity, mitigating the risk of premature convergence.

Coefficient Selection and Compression: The optimized coefficients that contribute most significantly to signal reconstruction are preserved and prepared for transmission across the wireless body area network, whereas non-essential coefficients are zeroed out. This minimizes data volume and curtails the power consumption of the sensor nodes.

Inverse Transform and Reconstruction: At the receiver end, the ECG signal is reconstructed using the transmitted optimal coefficients via the Inverse Discrete Wavelet Transform (IDWT). The reconstruction accuracy is quantitatively evaluated using the PSNR metric to validate the performance of the proposed framework.

4. SIMULATION RESULTS

The proposed methodology and the existing comparative techniques were implemented within the MATLAB environment developed by MathWorks. The hardware testbed featured an Intel(R) Core™ i5-4460 CPU @ 3.2 GHz processor equipped with 16 GB of Random Access Memory (RAM). The operational parameters configured for the Bat Optimization Algorithm are compiled in Table 1.

Table 1. Parameters of the Bat Optimization Algorithm.

Parameter Name	Description	Value
r0	Initial Pulse Emission Rate	0.5
∝	Positive Constant 1	0.99
γ	Positive Constant 2	0.01
Population	Population Size	20
Iteration	Maximum Iterations	10

These parameters were tuned to establish an optimal balance between the convergence speed and the precision of the algorithm. The MIT-BIH Arrhythmia Database is one of the most reputable and widely used ECG signal datasets, specifically designed for research and development of signal processing algorithms and cardiac disorder detection. This database contains ECG signals recorded from patients with various cardiac conditions, where each record typically includes two signal channels sampled at 360 Hz.

In addition to the raw signals, precise annotations of cardiac events such as normal beats, various types of arrhythmias, and other abnormalities have been meticulously verified by cardiologists. This permits a standardized evaluation and benchmarking of compression and diagnostic algorithms. Utilizing the MIT-BIH database in ECG compression and analysis research standardizes experimental results and ensures high scientific credibility during the performance evaluation of proposed methodologies [17].

First, the original signal is loaded, as illustrated in Figure 1, where the horizontal axis represents the sample index and the vertical axis represents the signal amplitude. Compression is subsequently executed based on the predefined operational parameters of the Bat Algorithm. For the wavelet transform, a Daubechies 3 (db3) wavelet basis function with three decomposition levels is employed.

The compressed signal is depicted in Figure 2, and the optimization convergence curve driven by the Bat Algorithm is illustrated in Figure 3. The performance of the proposed framework is compared against existing state-of-the-art methods in Table 2. It is evident from the empirical results that the proposed methodology yields a demonstrably superior performance compared to alternative approaches. The primary limitation of the conventional methods lies in their suboptimal threshold selection.

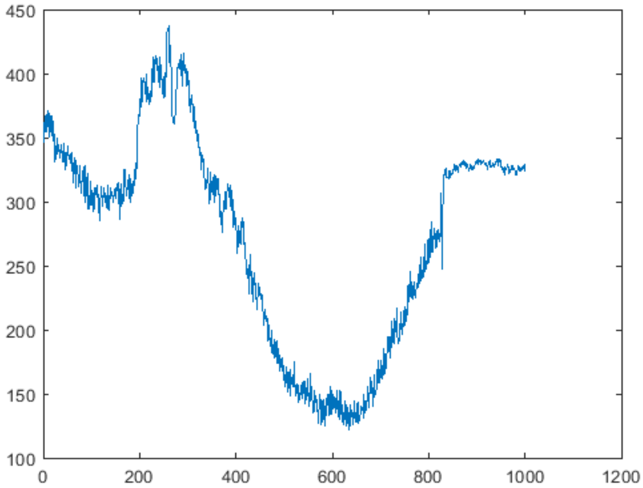

Fig. 1. Original ECG signal.

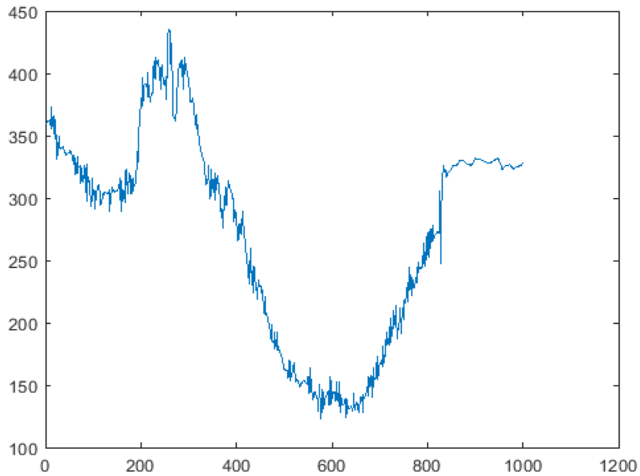

Fig. 2. Compressed ECG signal reconstructed by the proposed method.

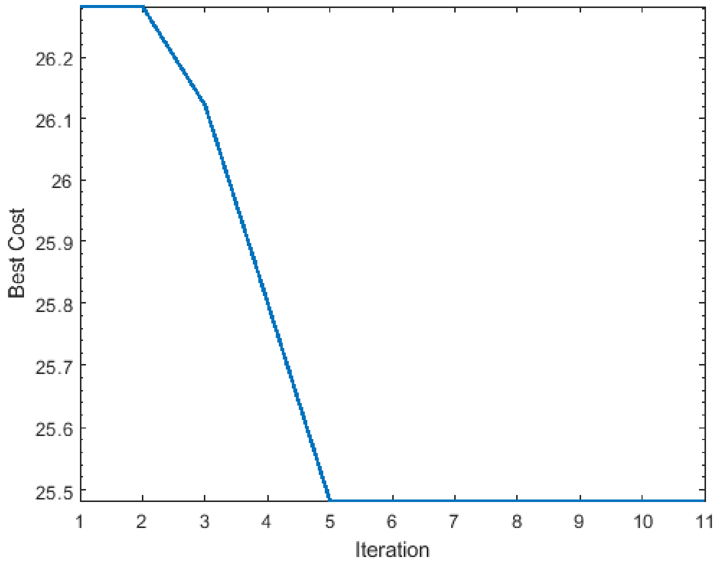

Fig. 3. Optimization convergence curve driven by the Bat Algorithm.

Table 2. Comparative performance results between the proposed method and existing methods.

Method	Average Compression Ratio
Proposed Method	**74.5**
Reference [8]	27.5
Reference [9]	13.8
Reference [10]	42.8

5. CONCLUSION

In this paper, a novel method for ECG signal compression is presented based on a hybrid approach combining the Discrete Wavelet Transform (DWT) and the Bat Algorithm (BA). The experimental results demonstrate that by isolating the optimal subset of wavelet coefficients, the Bat Algorithm maximizes the PSNR of the reconstructed signal while strictly preserving critical diagnostic features of the ECG waveform. Comparisons with classical DWT-based techniques indicate that the proposed methodology delivers a significantly higher compression ratio in addition to improving reconstruction fidelity. These findings highlight that the proposed framework offers an efficient, robust, and practical solution for real-time ECG signal compression within wireless healthcare monitoring systems.

Declaration

We acknowledge that we used ChatGPT to enhance the academic writing of our manuscript while ensuring the originality and integrity of our work.

Transparency Statement

The data supporting this study are available upon reasonable request to the corresponding author, subject to ethical and confidentiality considerations.

Acknowledgments

We would like to express our gratitude to all individuals who contributed to this project.

Declaration of Interest

The authors declare that they have no competing interests.

Funding

This research received no specific grant from any funding agency, commercial, or not-for-profit sectors.

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