



# A Detailed Survey of Electrocardiogram Signal Reduction Strategies: Evolutions, Hurdles, and Perspectives

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## How to Cite this Article:

Dev, O. (2026). A Detailed Survey of Electrocardiogram Signal Reduction Strategies: Evolutions, Hurdles, and Perspectives. International Journal of Creative and Open Research in Engineering and Management, <i>02</i>(04).  
<https://doi.org/10.55041/ijcope.v2i4.225>

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**Abstract**— With the rise of telehealth and long-term cardiac surveillance via wearables, the need for effective ECG compression has intensified. These techniques must balance the reduction of spectral bandwidth with the preservation of critical clinical markers. This paper surveys the landscape of ECG compression, comparing traditional algorithmic approaches with modern neural network architectures. Through a comparative analysis of metrics like Percentage Root Mean Square Difference and Compression Ratio, we highlight the evolution of the field, address persistent implementation challenges, and suggest future trajectories for research.

**Keywords**—ECG, Signal Compression, Wavelet Transform, Machine Learning, PRD, CR

## 1. INTRODUCTION

Electrocardiography (ECG) remains a fundamental instrument for assessing heart health. It is a vital diagnostic tool used to monitor cardiac activity. The proliferation of telemedicine and ambulatory sensors has led to an explosion in the quantity of cardiac data produced. Consequently, robust data reduction methods are imperative to minimize memory overhead and facilitate seamless live streaming while upholding clinical fidelity. To be effective, ECG data reduction must satisfy several criteria:

- **Superior Compression Ratios:** Maximizing data density.
- **Morphological Integrity:** Ensuring critical components like the QRS complex and P/T waves remain undistorted.
- **Algorithmic Efficiency:** Maintaining a low computational footprint suitable for on-chip processing.

An Electrocardiogram (ECG) serves as a temporal map of the heart's electrical conduction, captured through sensors placed on the patient's skin. In a typical healthy heart, this rhythm manifests as a predictable cycle of three primary waves i.e. P, QRS, and T, each tied to a specific mechanical movement of the cardiac muscle.



- **P Wave:** This initial deflection marks atrial depolarization. It occurs as electrical signals sweep through the heart's top chambers, triggering a contraction that pushes blood down into the ventricles.
- **QRS Complex:** This prominent spike represents ventricular depolarization. Due to the significant muscle density of the lower chambers, this signal is the most visible part of the trace. It represents the electrical force required to propel blood out toward the lungs and the rest of the body.
- **T Wave:** This follows the QRS and indicates ventricular repolarization. It is the electrical "reset" phase where the lower chambers recover and relax to prepare for the subsequent contraction.
- **U Wave:** Occasionally, a subtle U wave appears after the T wave. While not always present, it is generally associated with the recovery of the Purkinje fibers or papillary muscles, particularly during resting heart rates.

## 2. CLASSIFICATION OF ECG COMPRESSION METHODS

Methods for compressing ECG data are generally categorized by their ability to achieve bit-perfect reconstruction and the underlying strategies employed to eliminate data repetition.

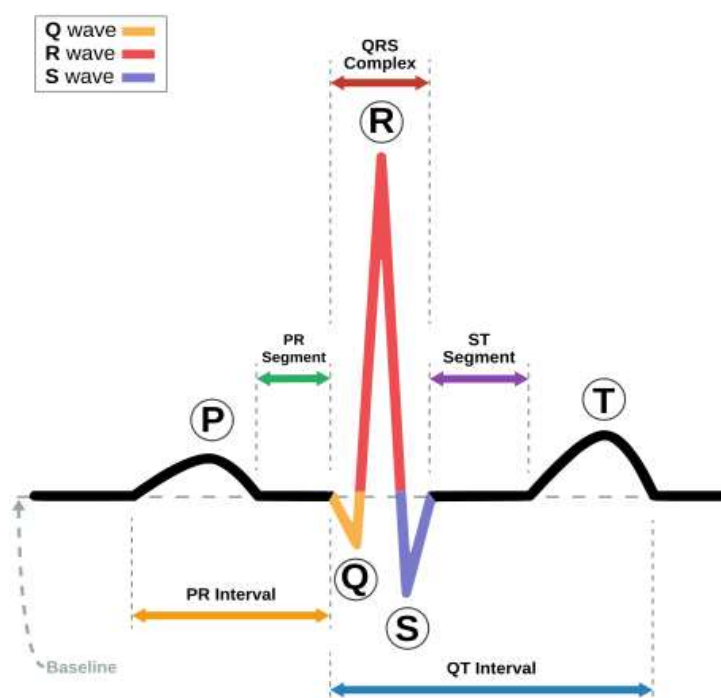
**2.1 Direct Time-Domain Methods:** These methods analyze successive samples directly to detect intra-beat redundancies.

**2.1.1 AZTEC (Amplitude Zone Time Epoch Coding):** The core logic of AZTEC is to convert the complex, continuous ECG waveform into a series of simplified horizontal lines (plateaus) and vertical slopes.

- Reduces signal into plateaus and slopes
- Simple but may distort signal morphology

**2.1.2 Turning Point (TP) Algorithm:** The algorithm functions by reducing the sampling rate of the signal by a factor of two (2:1 compression).

- Keeps alternate samples
- Moderate compression efficiency
- Limited diagnostic accuracy





**2.1.3 Fan Algorithm:** It uses slope-based approximation and has better than TP in preserving signal shape.

**Advantages:**

- Low complexity
- Suitable for real-time systems

**Limitations:**

- Lower compression performance
- Potential loss of diagnostic features

**2.2 Transform-Based Methods:** It converts the signal into another domain (spectral/energy) to concentrate energy into a few coefficients.

**2.2.1 Discrete Cosine Transform (DCT):** It translates the ECG signal from the time domain into a frequency-related domain where most of the "important" information is concentrated in just a few coefficients.

- Energy compaction capability
- Efficient for periodic signals

**2.2.2 Discrete Wavelet Transform (DWT):** The power of DWT lies in its ability to analyze the signal in both time and frequency simultaneously. DWT uses small, localized waves called wavelets that can vary in shape and duration.

- Multi-resolution analysis
- Highly effective for ECG due to non-stationary nature

**2.2.3 Fourier Transform based Methods:** These techniques treat the ECG signal as a summation of sinusoids (sine and cosine waves) of varying frequencies.

- Limited due to lack of time localization
- High compression efficiency
- Good signal reconstruction quality

**Limitations:**

- Higher computational complexity
- Requires careful parameter tuning

**2.3 Parameter Extraction Methods**

- Extract features such as QRS complex, intervals, amplitudes
- Store only clinically relevant parameters

**Advantages:**

- Very high compression ratios

**Limitations:**

- Not suitable for signal reconstruction
- Loss of full waveform

**2.4 Hybrid Methods**

- Combine time-domain and transform techniques
- Example: DWT + SPIHT (Set Partitioning in Hierarchical Trees)

**Advantages:**

- Improved CR and PRD trade-off
- Adaptive performance

**2.5 Machine Learning-Based Methods:** Adaptive models that learn the specific patterns of a patient's heartbeat. These methods are particularly effective because they can exploit non-linear correlations in the data that traditional methods miss.



### 2.5.1 Autoencoders

- Neural networks that learn compact representations
- Encoder compresses, decoder reconstructs

**2.5.2 Deep Learning Approaches:** It can learn the specific "vocabulary" of a heartbeat. By training on vast datasets, these models can identify and preserve subtle clinical features that simpler algorithms might blur.

- **CNN-based compression:** A CNN-based approach uses convolutional filters to automatically detect and preserve the unique "shapes" of the ECG, such as the sharp R-peak and the smooth T-wave.
- **RNN for temporal dependencies:** Unlike CNNs, which look at spatial shapes, RNNs focus on the temporal dependencies, how the signal at one millisecond relates to the signals that came before it.

**2.5.3 Compressed Sensing:** CS allows for the signal to be compressed during the acquisition process itself. The Core Philosophy is "Sense Less, Learn More". It reduces sampling rates below the Nyquist rate, often using Wavelet or Curvelet transforms to achieve sparsity.

- Exploits signal sparsity
- Reduces sampling rate and compression simultaneously

#### Advantages:

- High adaptability
- Potential for superior compression

#### Limitations:

- High computational requirements
- Need for training datasets

## 3. Comparative of ECG Compression Techniques

Method Type	Compression Ratio	PRD	Complexity	Suitability
Time-Domain	Low–Moderate	High	Low	Real-time
Transform-Based	Moderate–High	Low	Moderate	General use
Parameter Extraction	Very High	N/A	Low	Diagnosis
Hybrid	High	Low	High	Advanced
Machine Learning	Very High	Very Low	Very High	Research

## 4. Applications

- Telecardiology
- Wearable health monitoring systems
- Remote patient monitoring
- Cloud-based ECG storage systems

## 5. Challenges

### 5.1 Trade-off Between Compression and Quality

Maintaining diagnostic accuracy while achieving high compression remains difficult.

### 5.2 Energy Constraints

Wearable devices require low-power algorithms.

### 5.3 Real-Time Processing

Algorithms must operate efficiently with minimal delay.

### 5.4 Data Security and Privacy

Compressed ECG signals must be securely transmitted.



## 6. Future Directions

- Integration of AI-driven adaptive compression
- Edge computing for real-time ECG analysis
- Blockchain for secure ECG data transmission
- Personalized compression models based on patient-specific signals

## 7. Conclusion

Efficient ECG data handling is indispensable for contemporary medical telemetry. Although classic algorithms are prized for their simplicity, modern transform-based and integrated methodologies achieve higher fidelity. While burgeoning neural network approaches offer significant potential, refining them for energy-efficient, real-time execution remains a priority. Subsequent investigations must aim to harmonize data reduction rates with the computational demands and the preservation of critical diagnostic indicators.

## References

1. C.K. Jha, M.H. Kolekar, "Electrocardiogram Data Compression Techniques for Cardiac Healthcare Systems: A Methodological Review", IRBM, Volume 43, Issue 3, 2022, Pages 217-228.
2. <https://en.wikipedia.org/wiki/Electrocardiography>
3. Lijuan Zheng, Zihan Wang, Junqiang Liang, Shifan Luo, Senping Tian, "Effective compression and classification of ECG arrhythmia by singular value decomposition", Biomedical Engineering Advances, Volume 2, 2021.
4. Bukhennoufa, Nabil & Garah, Messaoud. (2026). Lossy ECG signal compression based on RR intervals detection with wavelet transform and optimized run-length encoding. Indonesian Journal of Electrical Engineering and Computer Science. Volume 41, pp: 109-118.
5. Thivya Anbalagan, Malaya Kumar Nath, D. Vijayalakshmi, Archana Anbalagan, "Analysis of various techniques for ECG signal in healthcare, past, present, and future", Biomedical Engineering Advances, Volume 6, 2023.
6. Mohamed Hammad, Asmaa Maher, Kuanquan Wang, Feng Jiang, Moussa Amrani, "Detection of abnormal heart conditions based on characteristics of ECG signals", Measurement, Volume 125, 2018, Pages 634-644.
7. João Paulo do Vale Madeiro, Paulo César Cortez, José Maria da Silva Monteiro Filho, Angelo Roncalli Alencar Brayner, "Developments and Applications for ECG Signal Processing" Academic Press, 2019, Pages 1-28.
8. E.B. Panganiban, A.C. Paglinawan, W.Y. Chung, G.L.S. Paa, "ECG diagnostic support system (EDSS): A deep learning neural network-based classification system for detecting ECG abnormal rhythms from a low-powered wearable biosensors" Sens. Bio-Sensing Res., 31 (2021), pp. 1-15
9. K.K. Patro, A.J. Prakash, S. Samantray, J. Pawiak, R. Tadeusiewicz, P. Plawiak, "A hybrid approach of a deep learning technique for real-time ECG beat detection" International Journal of Applied Mathematics and Computer Science, 32 (3) (2022), pp. 345-413
10. S. Naik, S. Debnath, V. Justin, "A review of arrhythmia classification with artificial intelligence techniques: Deep vs. machine learning, 2021 2<sup>nd</sup> International Conference for Emerging Technology (INCET)", (2021), pp. 1-14.