

# A Survey on Recent Research Trends Towards ECG Denoising for Sustainable Healthcare

**Prof. Ranganath B<sup>1</sup>, Meghana M Panedakatti<sup>2</sup>, Priyanka R L<sup>3</sup>**

Assistant Professor, Dept. of Electronics Engineering – VLSI Design and Technology, SKIT, Bengaluru, India<sup>1</sup>

Dept. of Electronics Engineering – VLSI Design and Technology, SKIT, Bengaluru, India<sup>2</sup>

Dept. of Electronics Engineering – VLSI Design and Technology, SKIT, Bengaluru, India<sup>3</sup>

**Abstract:** Cardiovascular diseases are a major cause of death and illness worldwide. This is why accurate Electrocardiogram (ECG) monitoring is so important for finding and treating these conditions early. Unfortunately, ECG signals can be unclear because of things like baseline drift, power line noise, movement, electrode issues, and electrical signals from muscles. This makes it harder to get a reliable diagnosis. To fix this, many methods have been developed to clean up ECG signals. These include digital filters, wavelet transforms, adaptive filters, deep learning, and empirical mode decomposition. When it comes to hardware, Field Programmable Gate Arrays (FPGAs) are a good choice for cleaning ECG signals in real time. They can process data in parallel, have low delay, can be reprogrammed, and use energy efficiently. This paper looks at recent methods for cleaning ECG signals using FPGAs. We compare their algorithms, how they are optimized for hardware, how complex they are to implement, what resources they use, and how well they remove noise. We also discuss how FPGAs are being used with Artificial Intelligence (AI), Edge Computing, the Internet of Things (IoT), and wearable health devices. Finally, we talk about the current research challenges and what needs to be done in the future to create ECG denoising systems that are scalable, use little power, and perform well.

**Keywords:** Electrocardiogram (ECG), FPGA, ECG Denoising, Wavelet Transform, Biomedical Signal Processing, Real-Time Signal Processing, Sustainable Healthcare, Wearable Healthcare.

## 1. INTRODUCTION

Cardiovascular diseases kill a lot of people worldwide, so we need ways to accurately and constantly monitor heart activity. Electrocardiography (ECG) is a common, non-invasive method that records the heart's electrical signals. It's really important for spotting heart problems. But, ECG signals recorded in hospitals or when people are moving around can pick up interference. This includes things like shifting baselines, power line noise, movement artifacts, poor electrode contact, and muscle electrical activity (EMG) noise. All of this makes the signal worse and can lead to wrong diagnoses. To deal with this, many ways to clean up ECG signals have been suggested. These include digital filters, adaptive filters, wavelet transforms, empirical mode decomposition, and deep learning. For hardware, Field Programmable Gate Arrays (FPGAs) are a popular choice for cleaning ECG signals in real-time. This is because they can do many calculations at once, have very little delay, can be reprogrammed, and use energy efficiently.

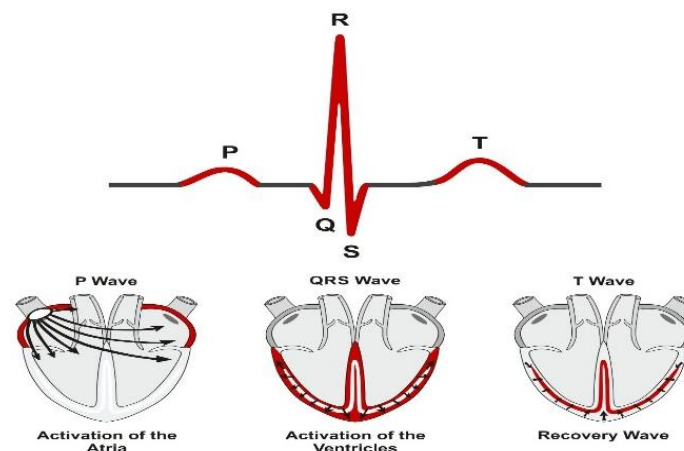


Figure 1. Electrocardiogram Signal

Recently, combining FPGAs with Artificial Intelligence (AI), Edge Computing, the Internet of Things (IoT), and wearable health systems has made patient monitoring smarter and more continuous. This paper looks at recent FPGA methods for

cleaning ECG signals. We examine their signal processing algorithms, hardware designs, optimization techniques, how complex they are to implement, how many resources they use, and how well they remove noise. We also point out current research problems, areas that haven't been explored much, and what needs to be done to create ECG denoising systems on FPGAs that can scale, use little power, and perform well. Denoising systems.

Figure 1 shows what a normal ECG looks like. It has a P wave, QRS complex, and T wave, which show the heart's electrical activity in one beat. The P wave is when the top chambers of the heart (atria) get electrical signals and contract. The QRS complex is the most important part; it shows when the main pumping chambers (ventricles) get signals and pump blood. The T wave is when the ventricles electrically recover. These parts of the signal tell doctors a lot about heart conditions like irregular rhythms, heart attacks, and problems with how electrical signals travel. However, when recording ECGs, the signal often gets messed up by baseline shifts, power line noise, muscle noise, movement, and electrode issues. This can change the shape and size of the P wave, QRS complex, and T wave, making diagnoses less accurate. So, the main goal of ECG cleaning is to get rid of noise while keeping these important signal features. FPGAs help with this by allowing fast, parallel processing with low delay and less power use. This means the ECG shape can be kept accurate in real-time, using hardware efficiently. This makes FPGAs great for wearable health devices, portable heart monitors, and continuous medical applications.

## 2. LITERATURE REVIEW

Recent work on cleaning ECG signals has focused on making the signals clearer while keeping the important heart features needed for accurate diagnosis. Older methods like FIR, IIR, adaptive filters, and wavelet transforms have been used a lot to reduce baseline shifts, power line noise, and movement artifacts. More recently, researchers have tried advanced methods like Empirical Mode Decomposition (EMD), sparse signal processing, combined algorithms, and deep learning to get better results. FPGA implementations have become very popular because they offer parallel processing, low delay, less power consumption, and efficient hardware use for real-time ECG processing. Current studies also focus on hardware optimization, pipelined designs, High-Level Synthesis (HLS), and edge computing to make systems faster and more scalable. This review looks at and compares these FPGA ECG denoising methods based on how accurate they are, how computationally complex they are, how efficient their hardware is, how many resources they use, and how well they work for wearable and sustainable health applications.

Liu et al. (2022) reviewed ECG denoising methods, dividing them into hardware design, digital signal processing, and machine learning. They noted that combining hardware improvements with better denoising algorithms makes ECG signals better, more efficient computationally, and useful for real-time healthcare.

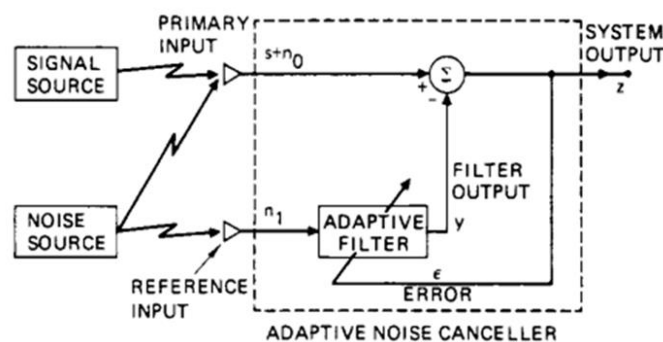


Figure 2. The adaptive noise cancelling concept.

Kaur (2024) reviewed advanced ECG filtering techniques, including EMD, wavelet transform, deep learning, and hybrid filters. They found that smart filtering methods improve the Signal-to-Noise Ratio (SNR), keep the ECG shape, and make diagnoses more accurate for wearable health systems.

Noskova and Tumakov (2024) studied ECG denoising using wavelet transforms and compared different wavelet types for reducing high-frequency noise. They found that choosing the best wavelet improves denoising and keeps important ECG features for reliable heart diagnosis. Xie et al. (2025) proposed an adaptive wavelet thresholding method for ECG noise reduction, testing different thresholding techniques and wavelet bases. Their results showed that adaptive thresholding with the right wavelet choice offers better noise reduction, improved ECG feature preservation, and is well-suited for real-time FPGA implementation.

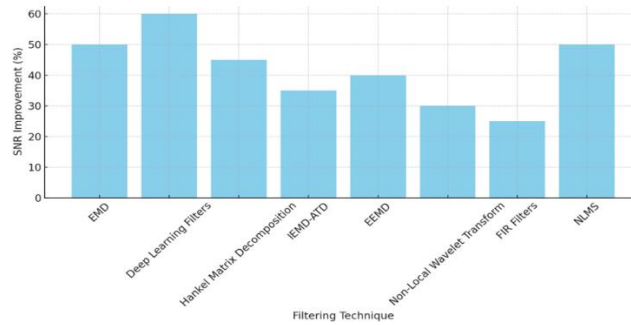


Figure 3. SNR Improvement by Filtering Technique.

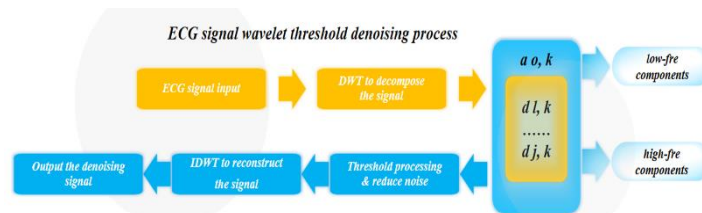


Figure 4. Wavelet thresholding denoising process of ECG signal.

| Filtering Technique                 | Noise Types Addressed                    | Metrics Used                 | Performance Improvement                                        |
|-------------------------------------|------------------------------------------|------------------------------|----------------------------------------------------------------|
| Empirical Mode Decomposition (EMD)  | High-Frequency Noise, Baseline Wander    | SNR, RMSE                    | 40-50% SNR improvement, notable RMSE reduction                 |
| Deep Learning Filters               | Baseline Wander, Electrode Noise         | SSD, MAD                     | 60% BW filtering effectiveness                                 |
| Hankel Matrix Decomposition         | Baseline Wander, Power Line Interference | SNRout, PRD                  | 45% noise reduction in high-noise conditions                   |
| IEMD-ATD                            | Gaussian Noise                           | SNR, Correlation Coefficient | 35% MSE reduction compared to EMD                              |
| EEMD                                | Gaussian Noise                           | MSE                          | MSE ratio 0.61 relative to FIR filters                         |
| Non-Local Wavelet Transform         | Additive White Gaussian Noise            | SNR, RMSE                    | SNR increase and RMSE decrease by 30%                          |
| FIR Filters                         | EMG Noise, Baseline Shifts               | PRD                          | Effective baseline correction; slight R-wave voltage reduction |
| Normalized Least Mean Square (NLMS) | High-Frequency Noise                     | SNR                          | Significant SNR improvement for real-time applications         |

Midani et al. (2025) reviewed traditional, wavelet-based, and AI-assisted ECG denoising methods. They emphasized that combined denoising approaches improve signal quality, reduce distortion, and help create efficient FPGA-based ECG processing systems for sustainable healthcare.

### 3. RESEARCH GAP

Even though many ECG denoising methods exist, creating efficient real-time healthcare systems still faces challenges. Most current studies focus on making denoising more accurate but pay less attention to how FPGAs are used, how much power they use, and hardware optimization. Many algorithms are designed to remove only one type of noise, making them less effective when multiple noises occur in real ECG monitoring. Also, advanced AI denoising methods often need a lot of computing power, making them hard to implement on cheaper FPGAs. There's also limited research on scalable FPGA designs that offer fast processing, low power use, and reliable ECG feature preservation. Therefore, we need an efficient FPGA-based ECG denoising system that can accurately remove noise while using hardware resources wisely and supporting sustainable real-time healthcare. While Differential Pulse Code Modulation (DPCM) has been studied for efficient image compression, several research issues remain. Most standard DPCM algorithms use fixed prediction models, which don't work well on images with complex textures, sharp edges, or fine details. Although adaptive and

hybrid DPCM methods have improved compression and image quality, they often increase computational complexity, making them less suitable for real-time and resource-limited applications. Furthermore, many studies focus mainly on grayscale images, with little research on color, high-resolution, multispectral, or hyperspectral image compression. How well DPCM works with noisy images and different image types has also not been studied enough.

#### **4. FUTURE SCOPE**

The future goal is to create a smarter and more efficient FPGA-based ECG denoising system by using advanced techniques like AI, machine learning, and adaptive filtering. The system could be improved to detect arrhythmias in real-time, process multiple ECG channels, and monitor patients continuously using wearable devices. By adding IoT and cloud technologies, ECG data can be securely sent to doctors for remote diagnosis and telemedicine. Further optimizing the FPGA design can lower power consumption, hardware needs, and processing delays, making the system suitable for portable, battery-powered medical devices. In the future, this approach could also be used for other medical signals like EEG and EMG, offering a complete and affordable healthcare monitoring solution for hospitals, clinics, and home care.

#### **5. CONCLUSION**

ECG signals are easily affected by noise and interference during recording, such as baseline shifts, power line noise, movement artifacts, poor electrode contact, and EMG noise. These unwanted signals can significantly reduce signal quality, hide important waveform features, and negatively impact the accuracy of both manual and automated heart diagnoses. Therefore, developing strong and computationally efficient denoising methods is crucial for accurate clinical assessment and reliable real-time monitoring. Implementing ECG denoising algorithms on Field Programmable Gate Arrays (FPGAs) provides an effective hardware solution that can meet the demanding computational needs of real-time medical applications. Due to their ability to perform parallel processing, reconfigurable architecture, predictable performance, and low latency, FPGAs allow for high-speed signal processing while efficiently using hardware resources and consuming less power. These features make FPGA implementations particularly suitable for portable and resource-limited healthcare systems. Moreover, the proposed FPGA-based framework offers a scalable and flexible platform for integrating new technologies, including advanced signal processing algorithms, Artificial Intelligence (AI), Edge Computing, the Internet of Things (IoT), and wearable health devices. This integration enables intelligent decision-making, continuous patient monitoring, and remote healthcare delivery while minimizing computational load and communication delays. Overall, this work shows how FPGAs can be used to create accurate, energy-efficient, and cost-effective ECG denoising systems, contributing to the development of next-generation cardiac monitoring solutions and advancing sustainable digital healthcare.

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