Design and Implementation of QRS Complex Detector Based on Wavelet Decomposition

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Abstract

This paper introduces a simple, efficient, and cost-effective QRS detection approach designed for VLSI implementation. While previous models utilized the MIT-BIH dataset for ECG signals, the proposed system incorporates an inbuilt ECG signal generator based on the Central Limit Theorem (CLT). This method enables the generation of more accurate and realistic ECG waveforms, while also allowing user-defined signal patterns—providing significant flexibility for testing and real-time monitoring.

To improve detection precision, the proposed technique uses quadratic spline wavelet packet decomposition along with a four-level Discrete Wavelet Transform (DWT). An advanced noise detection algorithm enhances signal clarity by identifying and multiplying two key wavelet coefficients to suppress noise. Additionally, the design includes adaptive thresholding and a robust decision-making algorithm to finalize QRS detection. Developed using 0.18-µm CMOS technology, the chip integrates both processing and ECG generation capabilities, enabling accurate detection of arrhythmias with low power consumption and high efficiency.

Keywords:ECG Signal; Signal Multiplication; CLT; Adjustable Voltage

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Abbreviations

Abbreviation	Description
ECG	Electrocardiogram
HRV	Heart Rate Variability
PCA	Principal Component Analysis
CNN	Convolutional Neural Networks
CMOS	Complementary Metal-Oxide-Semiconductor
VLSI	Very Large-Scale Integration
STFT	Short-Time Fourier Transform
CLT	Central Limit Theorem
WT	Wavelet Transform
DWT	Discrete Wavelet Transform
CWT	Continuous Wavelet Transform
EMG	Electromyographic
FIR	Finite Impulse Response

CHAPTER 1

Introduction

1.1 Introduction

As technology progresses, there is a greater emphasis on health monitoring, with the heart being the most vital organ. According to the World Health Organization, arrhythmia remained the largest cause of death in the most recent surveys, with annual cardiovascular-related deaths estimated to rise from 18.2 million in 2024 to 24.1 million by 2035. The electrocardiogram (ECG) is a valuable diagnostic tool for identifying a variety of cardiac issues[1]. It employs skin electrodes to capture the electrical activity of the heart, allowing cardiologists to analyze and diagnose abnormal cardiac function.

The QRS complex is the most essential ECG component for monitoring heart

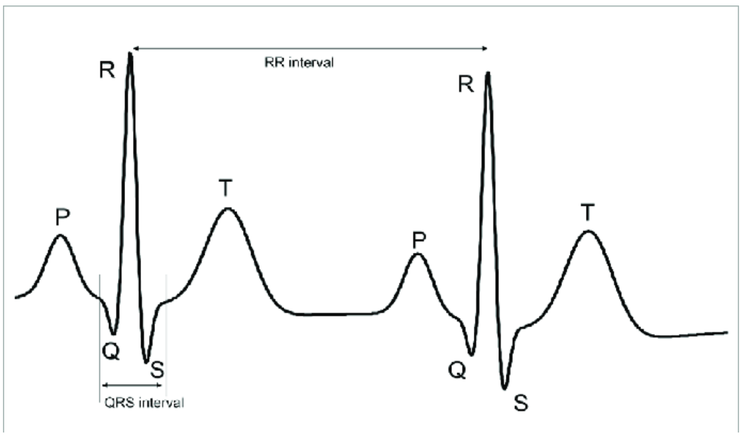


Figure 1.1: QRS complex signal within an ECG signal

activity because it is closely related to heart rate variability (HRV), which is measured by the RR interval between successive QRS complexes[2]. The proper identification of the QRS complex is essential for detecting arrhythmias and other cardiac conditions. However, identifying the QRS complex can be challenging due to interference from the P, T, and U waves, which causes false detections. To address this issue, several detection methods have been developed, including band-pass filters, mathematical morphology, compressed

sensing, forward prediction, and wavelet transformations.[3]
Recent advances in QRS detection have centered on strategies like machine learning-based classifiers, adaptive filtering, Savitzky-Golay smoothing, principal component analysis (PCA), and hybrid neural network methods. These strategies help to separate the QRS complex from background noise and increase overall detection accuracy.
Wearable ECG monitoring technologies stress the need of low-power, compact, and highly accurate hardware solutions. Several researchers have suggested energy-efficient techniques, such as support vector machines (SVM), hidden Markov models (HMM), and convolutional neural networks (CNN), to improve detection performance while using less resources[4].
The current study introduces a unique QRS detection approach based on wavelet packet decomposition and quadratic spline wavelet transformations. The approach uses a finite impulse response (FIR) low-pass filter, nonlinear transformations using multiplexers and noise evaluators, and an adaptive threshold mechanism that adapts to patient-specific characteristics and arrhythmia circumstances. Mallat's technique is employed for wavelet packet decomposition, which allows for precise QRS complex extraction while decreasing noise and non-QRS components[5]. The proposed technique is implemented by using Verilog HDL, resulting in high precision, low power consumption, and a compact chip area. This approach is very useful for wearable ECG monitoring applications.
This work simulates and validates the proposed QRS detection system utilizing Verilog code rather than standard ECG databases. This update guarantees accurate customisation and verification for hardware-based implementations, making the system more adaptable to real-time wearable ECG devices.

1.2 Motivation

The motivation for this research originates from the vital function of QRS complex recognition in electrocardiogram (ECG) signal processing, which

is required for identifying a variety of cardiovascular illnesses. Traditional QRS detection algorithms frequently have shortcomings, such as low accuracy in noisy settings, high computing complexity, and inefficiency in real-time applications.
However, to fulfill the criteria of low power consumption, high speed, and real-time processing in portable or wearable healthcare devices, such approaches must be implemented in hardware using efficient VLSI designs.
The goal of this research is to provide a VLSI-friendly QRS detection algorithm that takes use of wavelet decomposition while maintaining hardware economy for real medical applications.

1.3 Objectives of the Project Work

The main goal of this research is to create an efficient QRS complex detection method using wavelet decomposition. The QRS complex is an important component of the electrocardiogram (ECG) signal, and correct identification is required for identifying a variety of heart disorders. Traditional approaches sometimes struggle with performance in loud situations, resulting in erroneous detections or missing beats. This research uses wavelet decomposition to improve signal analysis, allowing for more precise feature extraction and overall detection accuracy.
Another important purpose is to guarantee that the planned system is suitable for real-time applications. With the growing need for portable and wearable health monitoring devices, there is a need for a QRS detection system that has low latency and can interpret ECG signals in real time. The project's goal is to develop a low-power, high-speed architecture that fits these requirements, allowing for continuous heart rate monitoring in embedded and IoT-based healthcare systems.
To attain real-time efficiency, the research focuses on hardware-friendly implementation of the detection method utilizing VLSI techniques. The goal is to create an architecture that is both area-efficient and computationally optimized, lowering hardware complexity while retaining excellent performance.

This guarantees that the system is compatible with medical-grade devices that have restricted processing power and energy.

Furthermore, the study intends to increase the resilience of QRS detection in noisy situations. The system will improve noise resilience by carefully constructing the wavelet-based algorithm and optimizing the hardware implementation, resulting in reliable and accurate detections even under tough situations.

Finally, the study intends to test the performance of the proposed system using thorough simulations and hardware implementations. The developed architecture will be evaluated against ECG datasets to determine its accuracy, speed, and power economy. The results will show that the technology can be integrated into biomedical equipment for real-time cardiac monitoring and early heart disease detection.

1.4 Organization of the Report

The report is organized into six chapters. Chapter 1: Introduction provides an overview of the project, highlighting the importance of QRS complex detection in ECG signal analysis, along with the objectives, motivation, and scope of the work. Chapter 2: Literature Survey presents a review of existing techniques used for QRS detection, with a focus on their methodologies, advantages, and limitations. Chapter 3: Existing System discusses the current systems and approaches in use, identifying their drawbacks and the need for improvement. Chapter 4: Proposed System explains the design and implementation of the QRS complex detector based on wavelet decomposition, detailing the algorithm, system architecture, and hardware realization. Chapter 5: Results and Discussions analyzes the performance of the proposed system through simulation results, performance metrics, and comparisons with existing techniques. Finally, Chapter 6: Conclusion summarizes the key outcomes of the project and suggests possible directions for future enhancement.

CHAPTER 2

Literature Survey

2.1 Introduction

Electrocardiogram (ECG) signal processing is a critical area of biomedical engineering, particularly for detecting cardiac abnormalities. QRS detection plays a key role in automated ECG analysis. Various techniques have been explored, including time-domain, frequency-domain, and machine learning-based approaches.

Among them, **Wavelet Transform-based methods** have gained attention due to their robustness against noise and adaptability. This chapter reviews traditional and modern approaches, emphasizing Wavelet Decomposition techniques and their advantages.

2.2 Traditional QRS Detection Techniques

2.2.1 Pan-Tompkins Algorithm

The Pan-Tompkins algorithm is one of the most often used algorithms for detecting QRS complexes in ECG data processing. Introduced in 1985, this method efficiently detects QRS complexes by using a sequential technique that involves bandpass filtering, differentiation, squaring, and adaptive thresholding. The ECG data is first processed through a bandpass filter to decrease baseline drift and high-frequency noise, which improves the QRS complex while attenuating other components like P and T waves. Following that, the signal is differentiated to highlight the fast transitions associated with the QRS complex by measuring the slope of the waveform.

The next step is to square the differentiated signal. This procedure highlights higher frequencies (a feature of the QRS complex) and assures that all values are positive, simplifying future processing. Finally, the data is processed with adaptive thresholding, which continuously modifies the detection threshold depending on recent signal characteristics, allowing the system to account for variations in QRS amplitude and heart rate.

While the Pan-Tompkins method remains very successful and serves as the foundation for many real-time QRS detection systems, it is not without limits. Its performance might suffer in the presence of noise, such as muscular artifacts or power line interference, and it frequently necessitates fine-tuning of thresholds to preserve accuracy across patients and recording settings.

2.2.2 Derivative-Based Methods

These methods detect steep slopes in the QRS complex using first and second derivatives:

$$\frac{d}{dt}ECG(t)$$

Such approaches are computationally simple but often fail in noisy environments.

2.2.3 Digital Filtering Approaches

These QRS detection methods frequently start with the use of low-pass and high-pass filters to efficiently eliminate baseline drift and high-frequency noise from the ECG signals. Baseline drift, which is usually produced by breathing or electrode mobility, can hide essential signal aspects, whereas high-frequency noise, such as muscular distortions or electromagnetic interference, can affect the sharpness of the QRS complex.

Among frequently used filtering algorithms, the filter stands out for its ability to smooth data while keeping essential signal properties such as peak height and width. It accomplishes this by fitting successive subsets of the signal to a low-degree polynomial with least squares.

Another popular approach is the use of bandpass Butterworth filters, which combine both low-pass and high-pass filtering in a single stage. Butterworth filters are favored for their maximally flat frequency response in the passband, which ensures minimal signal distortion.

2.2.4 Template Matching Techniques

Template matching compares ECG segments with predefined QRS templates. While achieving high accuracy for specific datasets, it lacks adaptability to varying heart conditions.

2.3 Frequency Domain and Transform-Based Approaches

2.3.1 Fourier Transform (FT) Methods

Fourier Transform (FT) analyzes the frequency components of ECG signals:

$$F(\omega) = \int_{-\infty}^{\infty} ECG(t)e^{-j\omega t}dt$$

However, FT lacks time-localization, making it unsuitable for transient signals like ECG.

2.3.2 Short-Time Fourier Transform (STFT)

STFT provides time-frequency representation using a window function $w(t)$:

$$STFT(\tau, \omega) = \int_{-\infty}^{\infty} ECG(t)w(t-\tau)e^{-j\omega t}dt$$

A limitation of STFT is its fixed window size, leading to a trade-off between time and frequency resolution.

2.4 Wavelet Transform-Based QRS Detection

2.4.1 Concept of Wavelet Transform in ECG Processing

Wavelet Transform (WT) overcomes FT limitations by offering **multi-resolution analysis**. It allows QRS detection at different frequency scales.

2.4.2 Choice of Wavelet Function

Commonly used wavelets include:

- Daubechies (**Db4, Db6**)
- Symlet
- Coiflet

Among these, **Db4** is widely preferred due to its similarity to the QRS waveform.

2.4.3 Multi-Scale Wavelet Decomposition for QRS Detection

ECG signals can be decomposed into multiple frequency bands:

$$ECG(t) = \sum_i A_i e^{-\frac{(t-\mu_i)^2}{2\sigma_i^2}}$$

where:

- A_i is the amplitude of each wavelet component
- μ_i is the center of the wavelet
- σ_i controls the width

2.4.4 Advantages of Wavelet-Based QRS Detection

Wavelet-based methods are:

- Robust against noise and artifacts (e.g., baseline wander, powerline interference)
- Effective for real-time applications
- Adaptable to different heart rate variations

2.5 Adaptive Thresholding for QRS Detection

Fixed thresholding methods struggle with varying signal amplitudes. **Adaptive thresholding** dynamically adjusts detection sensitivity based on ECG characteristics:

$$T(n) = \alpha \cdot \max(W(n)) + \beta \cdot \text{mean}(W(n))$$

where:

- $W(n)$ represents wavelet coefficients
- α, β are tuning parameters

2.6 Recent Advances in QRS Detection

2.6.1 Machine Learning and Deep Learning Approaches

Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs) have demonstrated promising results in QRS identification due to their capacity to automatically learn characteristics from ECG data. CNNs detect spatial patterns, but RNNs manage temporal relationships in the signal. However, these approaches need huge training datasets and significant processing resources, which may be a constraint for real-time or low-power applications.

2.6.2 Hybrid Approaches

The combination of wavelet transform and neural networks or classifiers enhances QRS detection accuracy. A typical approach involves wavelet-based feature extraction followed by an SVM classifier, which performs well even in noisy inputs.

CHAPTER 3

Existing System

3.1 Introduction

The QRS complex is a crucial part of an electrocardiogram (ECG) signal, representing the depolarization of the ventricles. Accurate detection of this complex is essential for diagnosing various heart conditions. Traditional detection methods rely on techniques such as thresholding and differentiation, but these often struggle with noise and variations in signal morphology.
Wavelet decomposition has emerged as a powerful tool for ECG signal processing due to its ability to analyze signals at multiple resolutions. This paper presents a hardware implementation of a QRS complex detector using wavelet decomposition, optimizing it for real-time applications in VLSI (Very Large Scale Integration) systems. The proposed approach improves detection accuracy while maintaining efficiency in terms of computational complexity and hardware resource usage.[6]

3.2 Existing Model

Traditional QRS detection models rely on techniques like Pan-Tompkins and adaptive thresholding. However, these methods often face limitations in noisy environments and with irregular QRS morphologies. To overcome these challenges, wavelet-based approaches have been introduced, offering better noise resistance and adaptability.
The wavelet transform enables decomposition of the ECG signal into different frequency components, allowing for better identification of QRS complexes. Prior models have primarily focused on software implementations, but hardware implementations remain a challenge due to computational complexity. Our

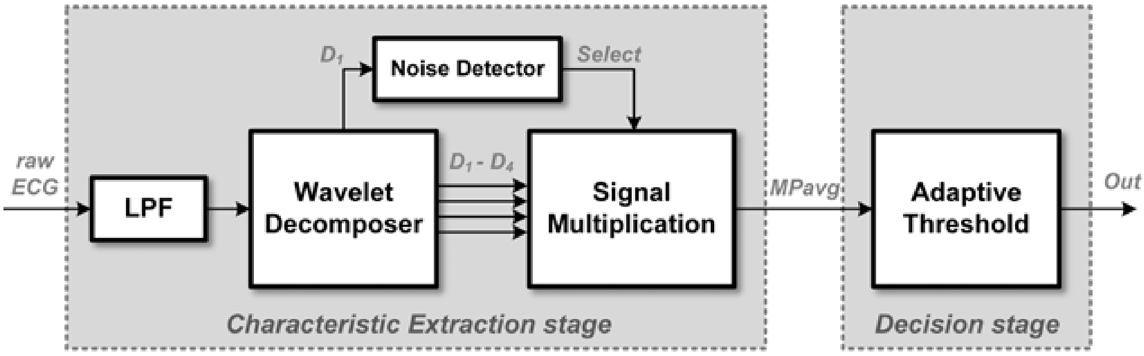


Figure 3.1: QRS complex signal within an ECG signal

approach optimizes the wavelet-based QRS detection for VLSI design, ensuring real-time performance while reducing power consumption.

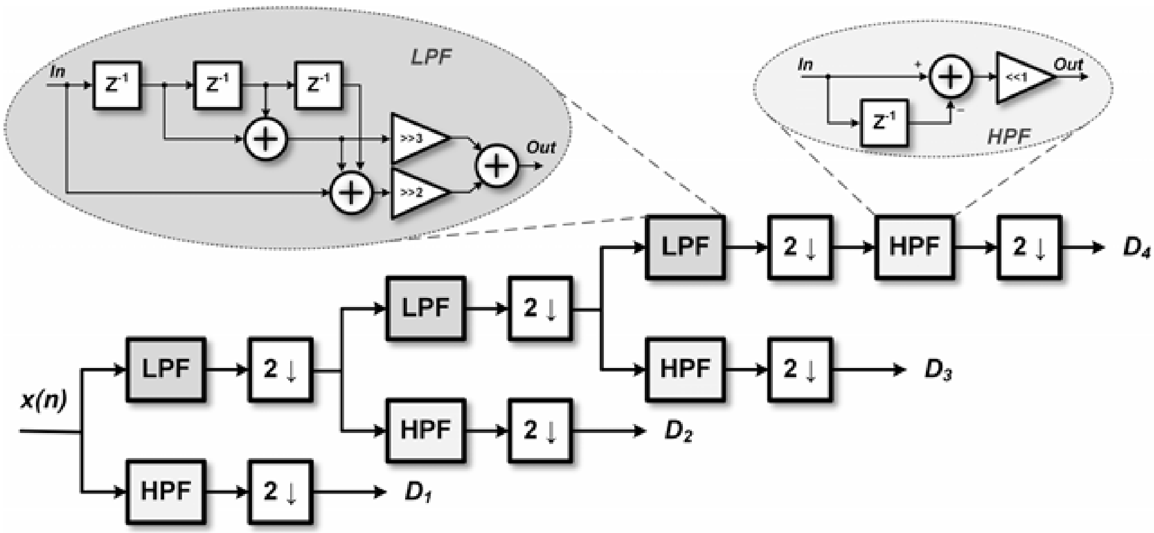


Figure 3.2: Wavelet Decomposer

Motion artifacts, power line interference, baseline drift, and physiological components such as P and T waves are all common sources of noise in the raw ECG data. These interferences, if not adequately filtered, can drastically reduce the accuracy of QRS detection. Wavelet decomposition, with its outstanding time-frequency localization capabilities, proved to be a highly successful strategy for extracting the QRS complex from the raw ECG signal in this regard. The quadratic spline wavelet was used in this study to decompose signals.While various wavelets, such as the biorthogonal spline wavelet, have been investigated in previous studies and found to be effective for QRS detection tasks, the quadratic spline wavelet was chosen expressly for its beneficial qualities. It excels at creating local extrema that correlate to abrupt signal transitions, making it especially useful for displaying the QRS complex's steep slopes. This improves suppression of extraneous components such as the P and T waves and effectively reduces baseline wandering. Furthermore, the quadratic spline wavelet strikes an appropriate compromise between frequency resolution and computational simplicity, which is critical for real-time applications.[7]Comparative results show that using the quadratic spline wavelet improves QRS detection accuracy when compared to other wavelet types. Its ability to maintain essential signal properties while reducing noise makes it an excellent candidate for embedded ECG processing, especially in low-power wearable health-monitoring systems.

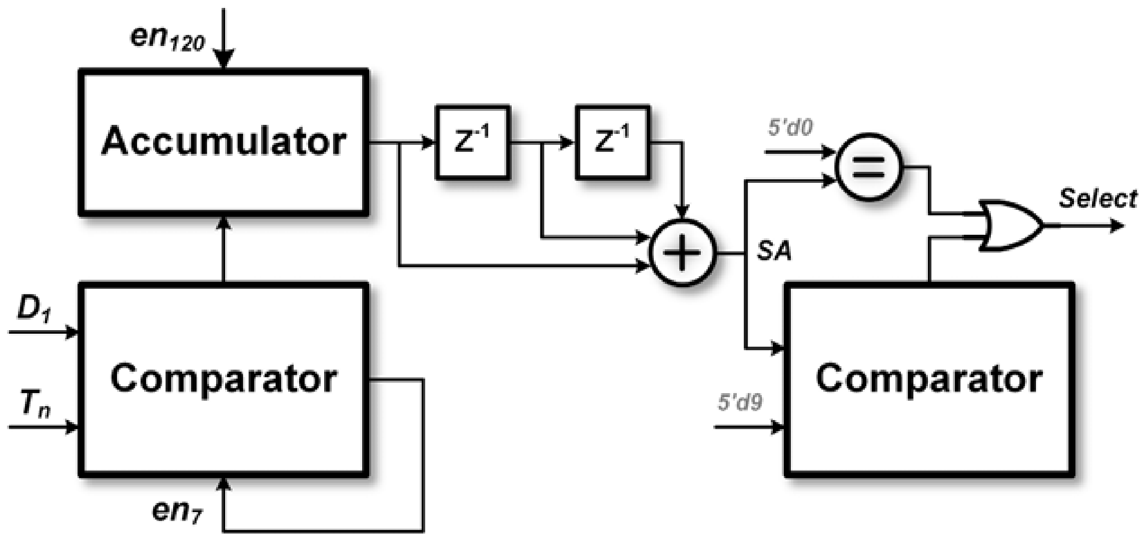


Figure 3.3: Noise Detector

CHAPTER 4

Proposed System

4.1 Introduction

Electrocardiogram is a crucial tool in the field of biomedical engineering and medical diagnostics, serving as a primary method for assessing heart function and detecting cardiac abnormalities. It records the electrical activity of the heart over time, providing valuable insights into heart rhythms, conduction pathways, and potential disorders such as arrhythmias, myocardial infarctions, and other cardiovascular conditions. The ability to generate synthetic ECG signals is essential for various applications, including the development and testing of medical devices, algorithm validation, and machine learning-based diagnostic tools.

Simulating an ECG signal accurately requires capturing the intricate electrical activity of the heart while incorporating natural physiological variations. The heart does not beat at a perfectly constant rate, as fluctuations occur due to multiple factors such as autonomic nervous system regulation, respiration, and physical activity. These variations in heart rate, known as heart rate variability (HRV), are important indicators of cardiovascular health. Additionally, real-world ECG signals are often contaminated with noise from different sources, such as baseline wander due to respiration, powerline interference from electrical sources, and muscle noise from patient movement.[8] These factors must be carefully modeled when generating synthetic ECG signals to ensure realism.

One effective approach to incorporate HRV and noise into synthetic ECG signals is through the Central Limit Theorem (CLT). The CLT is a fundamental statistical principle stating that the sum of a large number of independent and identically distributed (i.i.d.) random variables tends to follow a normal (Gaussian) distribution, regardless of the individual distributions of those variables. This property is particularly useful in ECG modeling, as it allows for the simulation of HRV as a sum of multiple small variations, naturally approximating a Gaussian distribution. Similarly, various types of noise affecting ECG signals can be represented using Gaussian distributions, aligning with real-world observations of biomedical signal processing.

By leveraging the CLT, synthetic ECG signals can be generated with realistic fluctuations in heart rate and noise characteristics, making them valuable for testing diagnostic algorithms, training artificial intelligence models, and improving ECG-based monitoring systems. This mathematical foundation provides a robust and reliable framework for understanding and replicating the complexities of heart signal behavior.

4.2 Mathematical Model of ECG Signal Generation

4.3 Central Limit Theorem (CLT) Formulation

The Central Limit Theorem (CLT) is an important notion in probability theory and statistical modeling. It asserts that when a large number of independently and identically distributed (i.i.d.) random variables are added together, their distribution tends to resemble a normal (Gaussian) distribution, regardless of the individual variables' original distributions.

Mathematically, if we consider a set of random variables $X_1, X_2, ..., X_n$, each having the same mean μ and variance σ^2, the standardized sum is given by:

$$Z = \frac{\sum_{i=1}^{n} X_i - n\mu}{\sigma\sqrt{n}}$$

According to the CLT, as the number of variables n increases, the distribution of Z approaches a standard normal distribution:

$$Z \sim \mathcal{N}(0, 1)$$

where $\mathcal{N}(0,1)$ represents a normal distribution with a mean of zero and a variance of one.

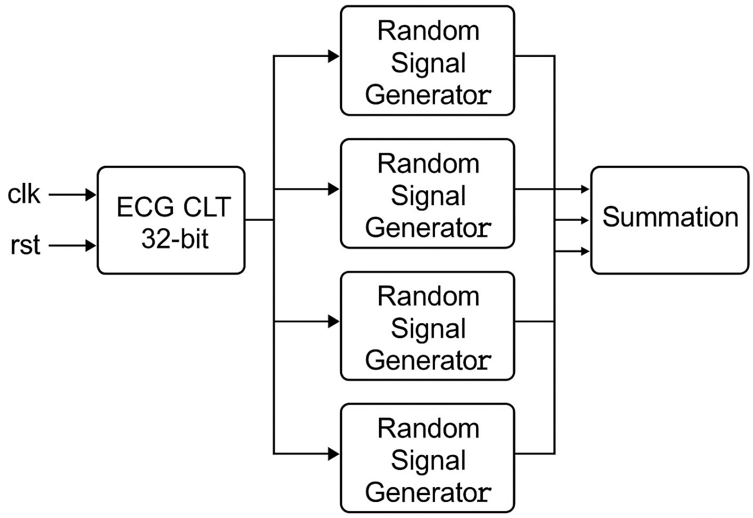


Figure 4.1: ECG Block Diagram

This theorem is highly significant in biomedical signal processing, particularly in the generation of electrocardiogram (ECG) signals. The variability in heart rate and different types of noise present in ECG recordings can often be modeled using normal distributions. By leveraging the CLT, researchers and engineers can create synthetic ECG signals that closely resemble real physiological data. This is particularly useful for testing medical devices, developing diagnostic tools, and training machine learning models in cardiology.[9]

4.4 Central Limit Theorem (CLT) Formulation

The Central Limit Theorem (CLT) is a fundamental statement in probability theory that describes how the distribution of a sum of independent random variables tends to normalize, regardless of the components' initial distributions. This extraordinary quality makes the CLT an indispensable tool for statistical modeling and real-world applications.

In mathematical terms, consider a set of independent and identically distributed (i.i.d.) random variables $X_1, X_2, ..., X_n$, each having a mean μ and variance σ^2. When we sum these variables and normalize them, we obtain the standardized sum:

$$Z = \frac{\sum_{i=1}^{n} X_i - n\mu}{\sigma\sqrt{n}}$$

As the number of variables n increases, the distribution of Z approaches a standard normal distribution:

$$Z \sim \mathcal{N}(0, 1)$$

where $\mathcal{N}(0, 1)$ denotes a normal distribution with a mean of zero and a variance of one.

The CLT is particularly valuable in biomedical signal processing, especially in the context of electrocardiogram (ECG) signal generation. The heart's electrical activity exhibits natural variability due to multiple physiological factors, including autonomic nervous system influences, respiration, and circadian rhythms. By applying the CLT, researchers can model this variability and generate synthetic ECG signals that mimic real-world data. Additionally, various forms of noise, such as baseline wander, muscle artifacts, and powerline interference, can be approximated using normal distributions.

This statistical approach plays a critical role in designing and testing medical devices, developing diagnostic algorithms, and training artificial intelligence models for cardiac health assessment. The ability to simulate realistic ECG signals helps in advancing research and improving healthcare technology.[10]

4.4.1 Heart Rate Variability (HRV) Modeling using CLT

Heart rate variability (HRV) is a natural phenomenon that reflects the variations in time intervals between consecutive heartbeats. These fluctuations arise due to multiple physiological factors, including autonomic nervous system activity, respiration, and external influences such as stress or physical activity. Since HRV results from the combination of numerous independent factors, it can be effectively modeled using the Central Limit Theorem (CLT).

Mathematically, the RR interval, which represents the time between successive heartbeats, can be expressed as:

$$RR_i = RR_{\text{mean}} + \sum_{j=1}^{n} \epsilon_j, \quad \epsilon_j \sim \mathcal{N}(0, \sigma^2)$$

In this equation, RR_i represents the instantaneous RR interval, while RR_{mean} denotes the average RR interval over a given period. The term ϵ_j accounts for small independent fluctuations in the heart rate, which follow a normal distribution with a mean of zero and variance σ^2.

By leveraging the CLT, researchers can simulate HRV patterns that closely resemble real physiological behavior. This approach is widely used in biomedical signal processing to create realistic synthetic ECG signals for testing medical devices, improving cardiac disease diagnostics, and training machine learning models for heart health assessment. Understanding HRV and its statistical properties is crucial for gaining insights into cardiovascular health and detecting potential abnormalities in heart function.

4.4.2 Gaussian Noise Model in ECG Generation

In real-world scenarios, electrocardiogram (ECG) signals are often affected by various types of noise, which can impact the accuracy of cardiac monitoring and diagnosis. Common sources of noise in ECG recordings include baseline wander, powerline interference, and muscle artifacts. These unwanted disturbances can originate from patient movements, electrical interference from medical equipment, or even breathing patterns.

To generate realistic synthetic ECG signals, it is essential to incorporate noise that mimics these real-world distortions. One effective approach is to model the noise as Gaussian white noise, which follows a normal distribution. Mathematically, the noisy ECG signal can be represented as:

$$ECG_{\text{noisy}}(t) = ECG(t) + N(t)$$

where $N(t) \sim \mathcal{N}(0, \sigma^2)$ represents the noise component, which has a mean of zero and variance σ^2. This means that the noise is randomly distributed around zero, ensuring that it does not introduce any systematic bias into the

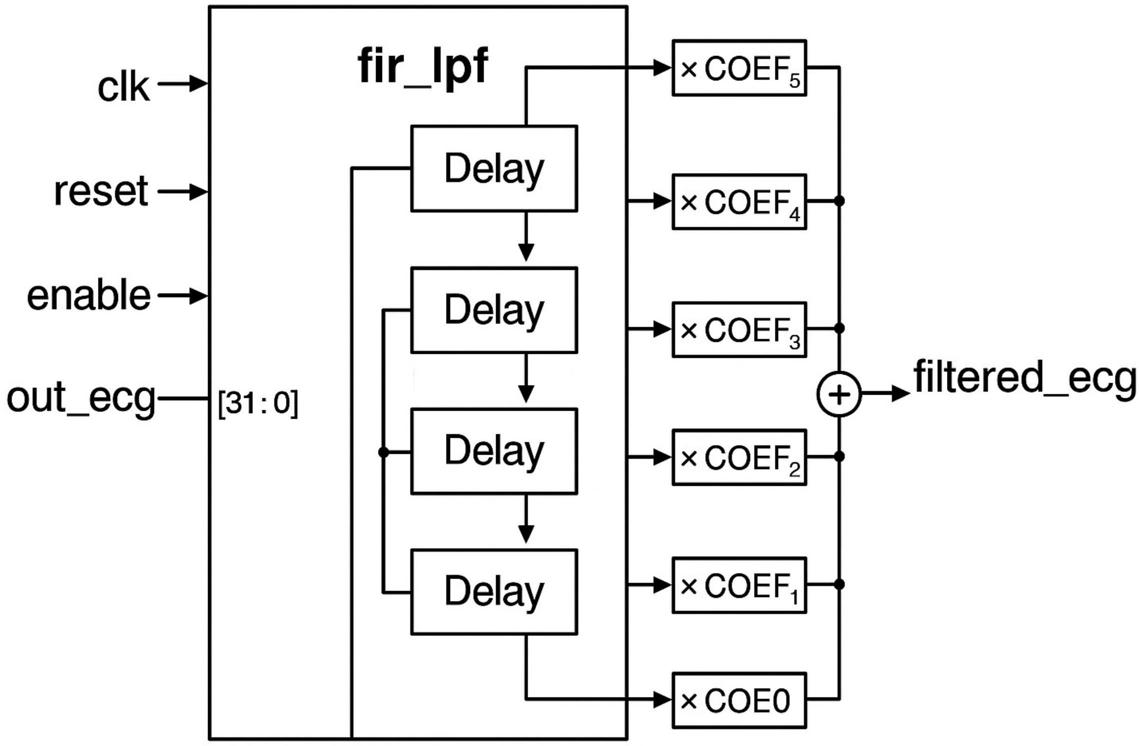


Figure 4.2: LPF Block Diagram

ECG signal.

By incorporating Gaussian noise into ECG simulations, researchers and engineers can develop more robust algorithms for noise filtering and signal processing.This approach is widely used in biomedical engineering to improve the accuracy of automated ECG analysis, enhance signal quality in wearable health devices, and train artificial intelligence models for detecting cardiac abnormalities.

4.5 Implementation of ECG Signal Generator using CLT

The process of generating a synthetic ECG signal using the Central Limit Theorem (CLT) involves several key steps that ensure the output closely resembles real physiological signals. This approach allows for the realistic simulation of heart activity, incorporating both natural variations in heart rate and the presence of noise commonly observed in ECG recordings.

The first step in this implementation is to generate independent random variables that represent heart rate variability (HRV) and background noise. Since HRV is influenced by multiple physiological factors, its variations can be modeled as a sum of small independent effects, which, according to the CLT, approximate a normal distribution. Similarly, random noise affecting ECG signals—such as baseline drift and electrical interference—can also be assumed to follow a Gaussian distribution.[11]
Once HRV and noise are established, the next step is to apply the CLT principle to model these variations as Gaussian-distributed variables. This ensures that the fluctuations in heart rate and the introduced noise behave in a statistically realistic manner.
To construct the ECG waveform, Gaussian functions are used to approximate the characteristic PQRST components of the heartbeat cycle. Each wave—P wave, QRS complex, and T wave—is represented as a Gaussian-shaped curve, with parameters adjusted to align with physiological ECG patterns.
Finally, to simulate a more realistic ECG, Gaussian noise is added to the synthetic signal. This step mimics the distortions commonly found in real-world ECG recordings, making the generated signal suitable for testing signal processing techniques, validating medical devices, and training machine learning models in healthcare applications.
By following this approach, the ECG signal generator provides a mathematically sound and practical method for simulating heart activity, making it a valuable tool for research and development in the field of biomedical engineering.

4.5.1 Algorithm for ECG Generation

The process of generating a synthetic ECG signal involves several key steps to ensure that the output closely resembles real physiological waveforms. This approach takes into account heart rate variability, characteristic PQRST waves, and different types of noise commonly found in ECG recordings.

1. **Generating RR Intervals:** The RR intervals, which represent the time between consecutive heartbeats, are generated using a physiologically realistic model. These intervals vary due to natural fluctuations in heart

rate. The RR interval at each beat is given by:

$$RR_i = RR_{\text{mean}}(1 + \alpha W_i)$$

where W_i is a randomly generated variable following a Gaussian or lognormal distribution, and α is a scaling factor that controls the level of variability. This step ensures that the simulated heartbeat intervals reflect the natural variations seen in real-world ECG signals.

2. **Modeling the PQRST Waves:** The characteristic features of an ECG waveform—the P wave, QRS complex, and T wave—are modeled using Gaussian functions. Each of these components is represented as:

$$ECG(t) = \sum_{k \in \{P,Q,R,S,T\}} A_k \exp\left(-\frac{(t - \mu_k)^2}{2\sigma_k^2}\right)$$

where A_k is the amplitude, μ_k represents the mean (center) of the wave, and σ_k defines the standard deviation, which determines the width of each wave component. By summing these Gaussian functions, a smooth ECG signal is constructed, closely resembling the natural waveform produced by the heart.

3. **Adding Baseline Drift and Noise:** Real ECG recordings are often affected by different types of noise, including baseline wander, muscle activity, and powerline interference. To introduce these disturbances into the synthetic signal, a noise model is applied:

$$N(t) = A_{\text{drift}} \sin(2\pi f_{\text{drift}} t) + N_{\text{EMG}}(t) + A_{\text{powerline}} \sin(2\pi f_{\text{power}} t)$$

where:

- A_{drift} and f_{drift} control the baseline drift, which appears as slow oscillations in the ECG.
- $N_{\text{EMG}}(t)$ represents high-frequency noise due to muscle activity.
- $A_{\text{powerline}}$ and f_{power} (typically 50 Hz or 60 Hz) model interference from electrical power sources.

The final synthetic ECG signal, incorporating both the modeled heartbeats and noise, is expressed as:

$$ECG_{\text{noisy}}(t) = ECG(t) + N(t)$$

This step ensures that the generated signal realistically mimics the challenges encountered in real ECG monitoring.

4. **Outputting the Synthetic ECG Signal:** The final step is to produce the ECG waveform at a specified sampling rate f_s and for a given duration T. This ensures that the generated signal is suitable for various applications, including medical simulations, device testing, and machine learning model training.

4.6 QRS Complex Detection

The QRS complex is the most prominent and clinically significant feature of the electrocardiogram (ECG) signal. It represents the rapid depolarization of the ventricles, which is responsible for the contraction of the heart and the subsequent pumping of blood throughout the body. Accurate detection of the QRS complex is essential for analyzing heart rate variability (HRV), diagnosing arrhythmias, and identifying other cardiac abnormalities.[12]

4.6.1 Importance of QRS Detection

Since the QRS complex is the most distinct waveform in the ECG, its detection serves as a foundation for many cardiac studies. Identifying the exact location of the QRS complex allows for precise measurement of heart rate, assessment of RR intervals, and the detection of irregular rhythms. Furthermore, it plays a crucial role in monitoring conditions such as atrial fibrillation, ventricular tachycardia, and other life-threatening arrhythmias. Given its significance, various signal processing techniques have been developed to enhance the accuracy and robustness of QRS detection.

4.6.2 Wavelet Transform for QRS Detection

Among the various methods available, the Wavelet Transform (WT) has proven to be highly effective for QRS detection. Unlike traditional filtering techniques that operate solely in either the time or frequency domain, the Wavelet Transform provides a multi-resolution analysis that allows simultaneous examination of both time and frequency components of the signal. This makes it particularly useful for detecting sharp transitions and rapid changes in the ECG, which are characteristic of the QRS complex.

Mathematically, the Continuous Wavelet Transform (CWT) of a signal $x(t)$ is defined as:

$$W(a,b) = \int_{-\infty}^{\infty} x(t) \frac{1}{\sqrt{|a|}} \psi \left(\frac{t-b}{a} \right) dt$$

where:

- $\psi(t)$ is the mother wavelet function, which determines the shape of the analysis window.
- a represents the scale parameter, controlling the level of detail.
- b represents the translation parameter, shifting the wavelet across the signal.

For practical implementations, the Discrete Wavelet Transform (DWT) is often used, as it efficiently decomposes the ECG signal into different frequency bands while preserving time-localized information. The QRS complex is typically detected at specific scales where the energy concentration is highest.

4.6.3 Implementation of QRS Detection Using Wavelet Transform

To detect the QRS complex using wavelet decomposition, the following steps are commonly followed:

1. **Preprocessing:** The ECG signal is first preprocessed to remove baseline wander, powerline interference, and high-frequency noise. This step ensures that only relevant cardiac activity remains in the signal.

2. **Wavelet Decomposition:** The preprocessed signal is decomposed into multiple scales using the chosen wavelet function. The scales corresponding to the QRS complex are identified based on their high energy content and sharp variations.

3. **Thresholding and Peak Detection:** Once the wavelet coefficients have been obtained, an adaptive thresholding technique is applied to distinguish the QRS complex from other ECG components such as P and T waves. Peak detection algorithms are then used to mark the exact locations of QRS complexes.

4. **Post-processing:** To improve detection accuracy, false positives and false negatives are filtered out by applying physiological constraints such as expected heart rate ranges and minimum RR interval durations.

4.6.4 Advantages of Wavelet-Based QRS Detection

Wavelet Transform-based QRS detection offers several advantages over conventional methods:

- **Robustness to Noise:** Since wavelet decomposition effectively isolates different frequency components, it is highly resistant to noise and artifacts that commonly affect ECG recordings.

- **Accurate Localization:** The multi-resolution analysis of wavelets allows precise localization of the QRS complex in both time and frequency domains.

- **Adaptability:** The choice of wavelet function and decomposition levels can be tailored to different ECG signal characteristics, making the method adaptable to various datasets and conditions.

The detection of the QRS complex is a fundamental step in ECG signal analysis, with significant implications for clinical diagnosis and monitoring. The use of Wavelet Transform has proven to be a highly effective approach, providing accurate and reliable detection even in the presence of noise and variations in signal morphology. By leveraging wavelet-based techniques, researchers and healthcare professionals can enhance the precision of cardiac assessments and improve automated ECG analysis systems.

4.7 Wavelet Transform in QRS Detection

4.7.1 Concept of Wavelet Transform

The Wavelet Transform is a powerful mathematical tool that provides a multi-resolution analysis of signals, making it highly effective in detecting transient and localized features such as the QRS complex in ECG signals. Unlike traditional Fourier Transform methods, which analyze signals in the frequency domain but lose time information, the Wavelet Transform allows simultaneous analysis in both time and frequency domains. This property makes it particularly useful for biomedical signal processing, where physiological signals often exhibit non-stationary characteristics.

Wavelet analysis works by decomposing a signal into different frequency bands using a set of scaled and translated wavelet functions. This decomposition enables the identification of sharp transitions and localized variations, which are key characteristics of the QRS complex.[13]

Mathematical Formulation of the Wavelet Transform

The Continuous Wavelet Transform (CWT) of a given ECG signal $ECG(t)$ is mathematically defined as:

$$C(a,b) = \int_{-\infty}^{\infty} ECG(t)\psi^* \left(\frac{t-b}{a}\right) dt$$

where:

- $\psi(t)$ is the **mother wavelet**, a function used as the basis for decompo-

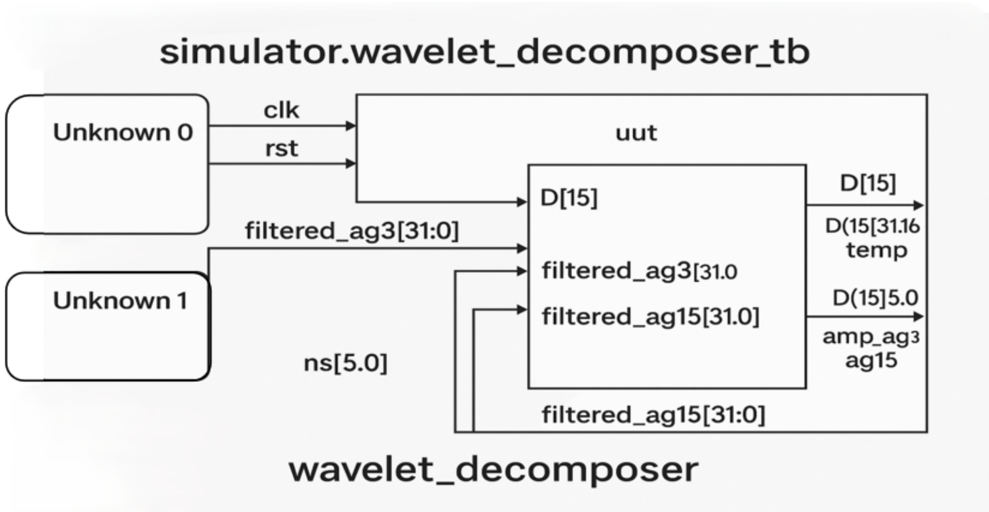


Figure 4.3: Wavelet Decomposer Block Diagram

sition.

- a is the **scale parameter**, which controls the stretching or compression of the wavelet and is analogous to frequency.
- b is the **translation parameter**, which shifts the wavelet function along the time axis to analyze different time instances.
- $C(a, b)$ represents the **wavelet coefficients**, which indicate the presence of specific frequency components at a given time.

Discrete Wavelet Transform (DWT) for ECG Processing

While the CWT provides a detailed representation of the signal, it is computationally intensive and redundant for practical applications. Instead, the Discrete Wavelet Transform (DWT) is widely used in real-time ECG processing. The DWT discretizes the scale and translation parameters, leading to an efficient, non-redundant representation of the signal. The decomposition process follows a dyadic structure, where the signal is repeatedly passed through high-pass and low-pass filters, splitting it into approximation and detail coefficients at different levels.

Mathematically, the DWT is represented as:

$$D(j, k) = \sum_n ECG(n)\psi_{j,k}(n)$$

where j represents the decomposition level and k represents the time shift at that level. By selecting an appropriate wavelet function, such as the Daubechies or Mexican Hat wavelet, DWT can effectively extract QRS features while filtering out noise and baseline wander[14].

Advantages of Wavelet Transform in QRS Detection

Wavelet Transform-based QRS detection has several advantages over conventional methods:

- **Time-Frequency Localization:** Unlike Fourier-based techniques, wavelets provide localized information about frequency components, allowing for accurate detection of QRS peaks.
- **Robustness to Noise:** Since ECG signals often contain artifacts like muscle noise and baseline drift, wavelet decomposition can efficiently isolate the QRS complex from these unwanted components.
- **Multi-Resolution Analysis:** The ability to analyze signals at different scales enables detection of QRS complexes in varying heart rates and ECG morphologies.
- **Adaptability:** Different types of wavelet functions can be selected based on the nature of the ECG signal, making the approach highly adaptable to different datasets and clinical conditions.

The Wavelet Transform is an indispensable tool for ECG signal analysis, offering an effective means to detect and characterize the QRS complex with high accuracy. Its ability to analyze non-stationary signals, suppress noise, and provide multi-resolution decomposition makes it a preferred choice in modern cardiac signal processing applications. By leveraging the wavelet approach, researchers and clinicians can enhance automated ECG analysis, leading to more reliable and efficient cardiac monitoring systems.

4.7.2 Discrete Wavelet Transform (DWT)

While the Continuous Wavelet Transform (CWT) provides a detailed representation of signals across different time and frequency scales, it is compu-

tationally expensive and redundant for practical applications such as real-time ECG signal analysis. To overcome this limitation, the Discrete Wavelet Transform (DWT) is used, offering an efficient and structured approach to analyzing ECG signals while preserving essential features like the QRS complex.[15]
DWT is based on a hierarchical multi-resolution decomposition process, where the original ECG signal is iteratively passed through a series of high-pass and low-pass filters, splitting it into different frequency bands. This decomposition enables the isolation of important frequency components relevant to QRS detection while effectively removing noise and baseline drift.

Mathematical Formulation of DWT

The DWT is computed by applying successive filtering operations. The signal is first convolved with a low-pass filter (L) to extract approximation coefficients and with a high-pass filter (H) to obtain detail coefficients. Mathematically, this process is expressed as:

$$y_{\text{low}}[n] = \sum_{k} ECG[k] \cdot L[2n-k]$$

$$y_{\text{high}}[n] = \sum_{k} ECG[k] \cdot H[2n-k]$$

where:

- $y_{\text{low}}[n]$ represents the approximation coefficients, capturing the low-frequency components of the ECG signal.
- $y_{\text{high}}[n]$ represents the detail coefficients, preserving the high-frequency information, including the sharp transitions of the QRS complex.
- L and H are the low-pass and high-pass filters, respectively.

Hierarchical Decomposition of ECG Signal

The decomposition process is carried out over multiple levels, following a dyadic structure. At each level, the approximation coefficients from the previous stage are further decomposed into new approximation and detail coefficients. This iterative breakdown provides a structured way to analyze the

ECG signal at different frequency resolutions.

For instance, in QRS detection, the lower-frequency components may correspond to baseline wander, while the mid-to-high frequency components contain the QRS complex and other vital cardiac features. By selectively analyzing the appropriate frequency bands, DWT allows for precise identification of QRS peaks without interference from unwanted noise.[16]

Advantages of Using DWT for ECG Analysis

The DWT offers several benefits over traditional time-domain and frequency-domain methods in ECG signal processing:

- **Efficient Time-Frequency Analysis:** Unlike Fourier-based approaches, DWT provides localized information about both time and frequency, making it ideal for detecting transient events such as the QRS complex.
- **Noise Suppression:** By decomposing the signal into different frequency bands, unwanted noise components such as powerline interference and muscle artifacts can be filtered out while preserving clinically relevant features.
- **Computational Efficiency:** Compared to CWT, which requires extensive computations, DWT uses a hierarchical structure that significantly reduces processing time, making it suitable for real-time ECG monitoring.
- **Adaptability to Various ECG Patterns:** Different types of wavelet families, such as Daubechies, Coiflet, and Symlet wavelets, can be chosen based on the characteristics of the ECG signal, allowing flexibility in analysis.

The Discrete Wavelet Transform is a powerful tool for ECG signal analysis, offering an effective means to decompose and analyze the signal across multiple frequency scales. Its ability to enhance QRS detection, suppress noise, and provide computational efficiency makes it a preferred technique in modern ECG signal processing. By leveraging DWT, automated cardiac monitoring systems can achieve high accuracy in detecting and analyzing critical cardiac events, ultimately improving the diagnosis and treatment of cardiovascular diseases.

4.8 Choice of Wavelet for QRS Detection

The selection of an appropriate wavelet function plays a pivotal role in the accurate detection of the QRS complex in ECG signals. Different wavelet families exhibit distinct characteristics in terms of shape, symmetry, and frequency resolution, making some more suitable for ECG processing than others. The choice of wavelet directly influences the effectiveness of QRS detection, particularly in noisy or irregular ECG recordings.

4.8.1 Criteria for Selecting a Wavelet

When choosing a wavelet for QRS detection, several factors must be considered:

- **Morphological Similarity to the QRS Complex:** The wavelet should closely resemble the QRS complex to enhance feature extraction.
- **Good Time-Frequency Localization:** It should be able to capture sharp transitions in the ECG signal while maintaining temporal precision.
- **Reduced Phase Distortion:** A well-chosen wavelet should minimize distortions that could affect peak detection.
- **Robustness to Noise and Baseline Drift:** It should effectively suppress unwanted artifacts while preserving clinically significant information.

4.8.2 Commonly Used Wavelets for ECG Analysis

Several wavelets have been extensively studied and utilized for QRS detection due to their favorable properties:

Daubechies (Db4, Db6)

Daubechies wavelets, particularly Db4 and Db6, are widely used for QRS detection because of their ability to closely approximate the morphology of the QRS complex. These wavelets provide a balance between compact support and smoothness, making them effective in detecting rapid transitions within the ECG signal. Additionally, their multi-resolution nature enables efficient decomposition and feature extraction[17].

Symlet Wavelets

Symlet wavelets are modified versions of Daubechies wavelets with improved symmetry and reduced phase distortion. They provide better time localization, ensuring that the QRS peaks are accurately detected without significant shifts. This property is especially useful in ECG applications where precise peak alignment is necessary for heart rate analysis.

Coiflet Wavelets

Coiflet wavelets are characterized by higher vanishing moments, which allow for better preservation of ECG details across different decomposition levels. They offer enhanced feature retention, making them useful in scenarios where additional morphological details of the ECG waveform need to be analyzed. Coiflets are particularly advantageous in detecting abnormalities in the QRS complex.

4.8.3 Wavelet Selection Based on Application

The choice of wavelet function often depends on the specific application:

- For **general QRS detection**, Daubechies (Db4, Db6) is commonly preferred due to its close resemblance to the QRS complex.
- When **minimizing phase distortion** is a priority, Symlet wavelets are chosen to ensure better signal reconstruction.
- For **detailed ECG analysis** involving subtle waveform changes, Coiflet wavelets provide improved signal preservation.

Selecting the right wavelet for QRS detection is essential to achieving high accuracy in ECG signal analysis. The effectiveness of wavelet-based methods depends on how well the chosen wavelet aligns with the QRS complex while maintaining noise resistance and computational efficiency. Among the various options available, Daubechies, Symlet, and Coiflet wavelets have demonstrated strong performance in different ECG processing applications.

4.9 Multi-Scale QRS Detection Using Wavelet Decomposition

Accurate QRS detection is crucial in electrocardiogram (ECG) analysis, as it serves as the foundation for heart rate estimation, arrhythmia classification, and other diagnostic applications. One of the most effective techniques for detecting QRS complexes is wavelet decomposition, which provides a multi-scale representation of the ECG signal. By analyzing different frequency components, this method enhances feature extraction while suppressing noise and artifacts.[18] The QRS detection process using wavelet decomposition involves the following steps:

4.9.1 Preprocessing

Before applying wavelet analysis, the ECG signal undergoes preprocessing to remove noise and ensure consistency in amplitude. This step enhances the robustness of QRS detection.

- A **bandpass filter** is applied to eliminate low-frequency baseline wander and high-frequency noise, preserving only the frequency range relevant to QRS detection.
- The ECG signal is **normalized** to ensure uniform amplitude scaling, which helps in maintaining consistency across different recordings.

4.9.2 Wavelet Decomposition

Wavelet decomposition enables the extraction of QRS-related features while filtering out unwanted components. The ECG signal is decomposed into different frequency sub-bands, each representing different aspects of the waveform.

- The ECG signal is **decomposed** using a selected wavelet function, typically Daubechies (Db4 or Db6), which closely matches the morphology of the QRS complex.
- Detail coefficients at specific scales, where the **QRS energy is maximized**, are retained for further analysis. These coefficients highlight rapid changes in the signal, which are characteristic of the QRS complex.

4.9.3 QRS Feature Extraction

Once the signal has been decomposed, key features of the QRS complex need to be identified.

- The **modulus maxima** of the wavelet coefficients are computed to locate points where the signal exhibits sharp transitions.
- The peaks corresponding to QRS complexes are identified by analyzing the local maxima of the wavelet coefficients at different scales.

4.9.4 Adaptive Thresholding

To improve detection accuracy, an adaptive thresholding approach is used to distinguish true QRS peaks from noise. This adaptive method adjusts based on the signal characteristics.

$$T(n) = \alpha \cdot \max(W(n)) + \beta \cdot \text{mean}(W(n))$$

where:

- $W(n)$ represents the wavelet coefficient at scale n,
- α and β are tuning parameters that dynamically adjust the threshold based on the maximum and mean wavelet coefficient values.

This thresholding technique ensures that only significant peaks corresponding to QRS complexes are detected, reducing false positives.

4.9.5 Decision Logic

The final step involves validating the detected QRS peaks and refining the results to eliminate false detections.

- **RR interval constraints** are used to ensure that detected peaks occur within physiologically reasonable heart rate limits.
- Post-processing techniques, such as **refractory period checking and signal morphology validation**, help eliminate false detections caused by noise or overlapping waveforms.

The multi-scale wavelet decomposition approach provides a highly effective method for QRS detection by leveraging its ability to analyze both time and frequency characteristics of the ECG signal. By combining wavelet analysis with adaptive thresholding and decision logic, this method enhances the accuracy and robustness of QRS detection, making it a valuable tool in automated ECG analysis for clinical and research applications[19].

4.10 Algorithm for QRS Detection

The process of detecting QRS complexes in an electrocardiogram (ECG) signal requires a systematic approach that enhances relevant features while suppressing noise and artifacts. The following algorithm outlines a robust method for QRS detection using wavelet decomposition and adaptive thresholding.

1. **Preprocessing and Bandpass Filtering:** The raw ECG signal often contains noise from various sources, such as baseline wander, muscle activity, and powerline interference. To mitigate these effects, a bandpass filter is applied, typically in the range of 0.5 Hz to 50 Hz. This helps preserve the frequency components most relevant to the QRS complex while eliminating unwanted low-frequency drifts and high-frequency noise.
2. **Wavelet Decomposition using Daubechies Wavelet (Db4):** The ECG signal is then decomposed using the Daubechies-4 (Db4) wavelet, which closely resembles the morphology of the QRS complex. The

wavelet decomposition process splits the signal into multiple sub-bands, allowing for an analysis of both its time-domain and frequency-domain characteristics.

3. **Extraction of Wavelet Coefficients at Specific Scales:** After decomposition, wavelet coefficients are extracted at scales where QRS energy is maximized. Typically, the detail coefficients corresponding to intermediate frequency bands are retained, as they highlight the rapid signal transitions characteristic of QRS complexes.

4. **Adaptive Thresholding for QRS Peak Detection:** To accurately detect QRS peaks, an adaptive thresholding technique is applied. The threshold is dynamically adjusted based on the statistical properties of the wavelet coefficients:

$$T(n) = \alpha \cdot \max(W(n)) + \beta \cdot \text{mean}(W(n))$$

   where:

   - $W(n)$ represents the wavelet coefficient at scale n,
   - α and β are tuning parameters that ensure optimal thresholding,
   - The computed threshold helps in distinguishing true QRS complexes from noise-induced peaks.

5. **Validation Using RR Interval Analysis:** Once QRS peaks have been identified, they are validated by analyzing the RR intervals (time differences between consecutive peaks). Physiological constraints, such as expected heart rate limits (e.g., 40-180 beats per minute), are applied to eliminate false detections. Additional validation techniques, including refractory period checking and morphological feature verification, further improve the accuracy of detection.

This algorithm leverages the power of wavelet transform to enhance QRS detection by capturing its transient characteristics across multiple scales. The combination of bandpass filtering, wavelet decomposition, adaptive thresholding, and RR interval validation ensures high detection accuracy, making it suitable for clinical applications, wearable ECG monitoring, and automated cardiac diagnostics.

4.11 Signal Multiplier

Electrocardiogram (ECG) signal processing plays a vital role in cardiac health monitoring by enabling the detection of heart abnormalities, arrhythmias, and other cardiovascular conditions. One fundamental technique used in ECG signal analysis is **signal multiplication**, a process that enhances specific signal characteristics, facilitates feature extraction, and suppresses noise. By multiplying two or more signals, it is possible to emphasize critical components of the ECG waveform, such as the QRS complex, while minimizing the impact of unwanted artifacts.

Signal multiplication is particularly useful in advanced ECG signal processing techniques, including wavelet-based analysis, adaptive filtering, and phase-sensitive detection. By strategically combining signals, it is possible to improve the accuracy of QRS detection, estimate heart rate variability (HRV), and enhance the quality of ECG signals for diagnostic purposes. Additionally, in modern machine learning and artificial intelligence applications, signal multiplication techniques are employed to create derived features that improve classification and prediction models.

In this chapter, we explore the mathematical foundations of signal multiplication in ECG processing, its practical applications, and its impact on improving the reliability of cardiac signal analysis. Through a detailed examination of its implementation, we aim to highlight the importance of this technique in modern biomedical signal processing[20].

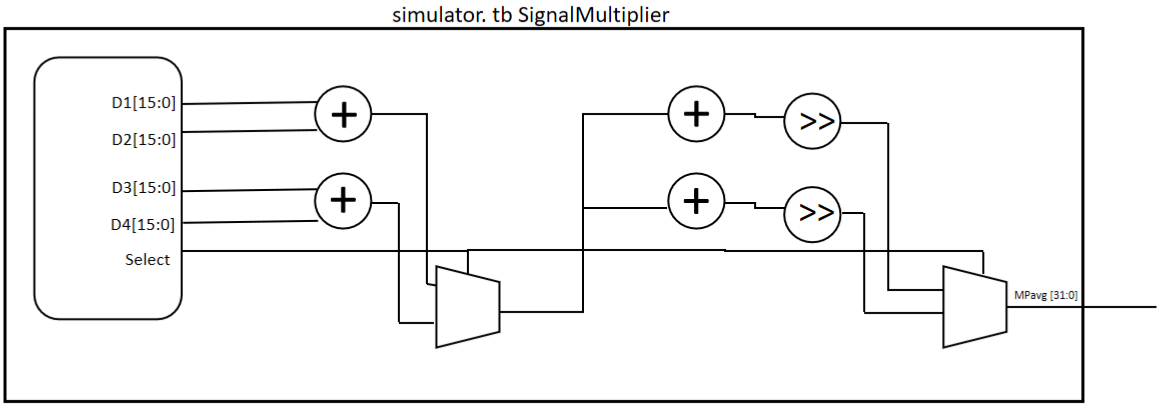


Figure 4.4: Signal Multiplication Block Diagram

4.12 Mathematical Formulation of Signal Multiplication

Signal multiplication is a fundamental operation in ECG signal processing, often used to enhance specific features, suppress noise, and improve overall signal clarity. This operation involves multiplying two signals in the time domain to produce a modified version that highlights key characteristics of the ECG waveform.

Mathematically, signal multiplication is defined as:

$$y(t) = x_1(t) \cdot x_2(t)$$

where:

- $x_1(t)$ represents the original ECG signal, which contains important physiological information about heart activity.
- $x_2(t)$ is a modifying signal, such as a windowing function, an adaptive filter output, or a wavelet-derived signal, designed to enhance or extract specific components of the ECG.
- $y(t)$ is the resultant signal after multiplication, which contains the refined or emphasized features for further analysis.

This mathematical approach is commonly employed in various ECG processing techniques. For instance, multiplying the ECG signal by a window

function can help in segmenting specific cardiac cycles for detailed analysis. Similarly, multiplication with a modulated sinusoidal signal is useful in frequency-domain analysis for detecting abnormalities in heart rhythms.
Beyond feature enhancement, signal multiplication is also integral to techniques like envelope detection, where the ECG signal is multiplied with itself or a transformed version to reveal amplitude variations. This method is particularly effective in identifying the QRS complex and other significant waveform components.
By applying signal multiplication in a controlled manner, researchers and clinicians can extract meaningful insights from ECG recordings, leading to improved accuracy in cardiac diagnosis and monitoring.

4.12.1 Application in ECG Processing

Signal multiplication plays a vital role in various aspects of ECG signal processing, helping to refine, extract, and analyze important cardiac features. By carefully selecting and applying this mathematical operation, several key objectives can be achieved in biomedical signal analysis.
One of the primary applications of signal multiplication is **feature enhancement**, where the QRS complex—the most prominent part of the ECG waveform—is emphasized. By multiplying the ECG signal with a suitable weighting function, specific frequency components associated with the QRS complex can be accentuated, making detection and analysis more effective.
Another important application is **noise suppression**. ECG recordings often contain various types of interference, such as baseline wander, muscle noise, and powerline interference. Signal multiplication can be used in adaptive filtering techniques, where the ECG signal is multiplied by an appropriate function to selectively attenuate unwanted components while preserving critical cardiac features.
Signal multiplication is also widely used in **energy computation**, where the power of the ECG signal is determined by squaring or multiplying it with itself. This technique is particularly useful in envelope detection and signal strength estimation. Mathematically, this is expressed as:

$$E(t) = x(t) \cdot x(t) = x^2(t)$$

where $E(t)$ represents the computed energy of the signal at time t, providing a measure of signal intensity that can be used for feature extraction and decision-making in ECG analysis.

Overall, signal multiplication serves as a fundamental tool in ECG processing, allowing for improved signal clarity, enhanced feature extraction, and more accurate detection of cardiac abnormalities. By leveraging these techniques, researchers and clinicians can achieve more reliable ECG analysis for diagnosis and monitoring.

4.13 Implementation Algorithm

To effectively apply signal multiplication in ECG processing, the following steps are undertaken in a structured manner:

1. **Input the preprocessed ECG signal:** The ECG signal is first cleaned using preprocessing techniques such as filtering to remove baseline wander and high-frequency noise.

2. **Define the modifying signal:** A modifying signal is selected based on the application. This could be a set of wavelet coefficients, a moving average filter output, or another function designed to enhance or suppress specific signal components.

3. **Perform point-wise multiplication:** Each sample of the ECG signal is multiplied by the corresponding sample of the modifying signal, yielding a transformed version of the ECG that highlights specific features or suppresses noise.

4. **Analyze the resultant signal:** The modified ECG signal is then examined for feature extraction, peak detection, or further processing to support accurate diagnosis.

This algorithm provides a robust approach to modifying ECG signals in a controlled manner, enabling better feature detection and noise suppression in clinical and research applications.

4.14 Noise Detection in ECG Signals

Electrocardiogram (ECG) signals are often contaminated by various types of noise, which can significantly impact the accuracy of feature extraction and diagnostic conclusions. Some common sources of noise include baseline wander, muscle noise (electromyographic interference), and powerline interference from electrical sources.
Baseline wander occurs due to slow variations in the signal, often caused by respiration or movement artifacts. Muscle noise, originating from electrical activity in skeletal muscles, introduces high-frequency disturbances that can obscure critical ECG features. Powerline interference, typically at 50 Hz or 60 Hz depending on the region, results from electromagnetic interference from surrounding electrical devices.

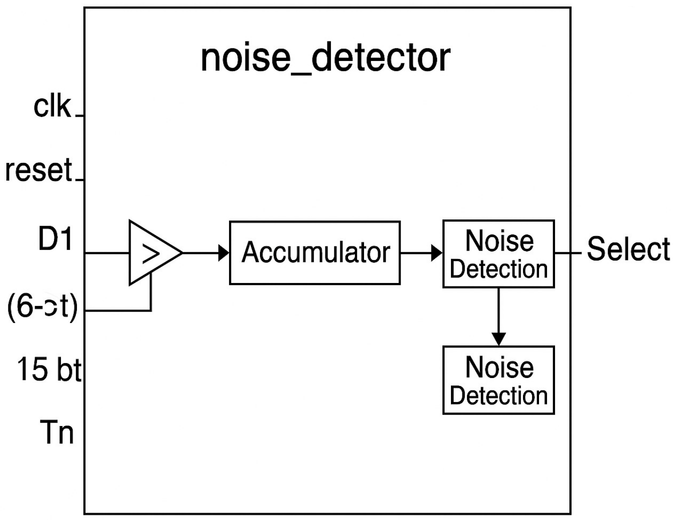


Figure 4.5: Noise Detector Block Diagram

A well-designed noise detection mechanism is essential to identify and eliminate corrupted segments of the ECG signal, ensuring that only clean and reliable portions are analyzed. By implementing efficient noise suppression

techniques, such as adaptive filtering and wavelet-based denoising, it is possible to enhance signal clarity and improve the accuracy of heart rate variability (HRV) analysis, arrhythmia detection, and overall cardiac assessment.
Through systematic noise detection and removal, ECG signal processing can be significantly improved, leading to better decision-making in both clinical and research settings.

4.15 Types of Noise in ECG

ECG signals are highly susceptible to various types of noise, which can distort the waveform and hinder accurate diagnosis. Understanding these noise sources is essential for effective noise removal techniques. The major types of noise in ECG recordings include:

4.15.1 Baseline Wander (BW)

Baseline wander is a low-frequency drift in the ECG signal, primarily caused by respiration, electrode impedance changes, or body movements. This slow-varying noise can obscure the true morphology of ECG components, particularly affecting the accurate detection of the P-wave and T-wave. Baseline correction techniques, such as high-pass filtering or polynomial fitting, are commonly used to mitigate this issue.

4.15.2 Powerline Interference (PLI)

Powerline interference occurs due to electromagnetic fields from electrical devices and power sources, typically introducing a sinusoidal noise component at 50 Hz (Europe, Asia) or 60 Hz (North America). This noise appears as periodic fluctuations in the ECG signal and can significantly affect signal interpretation. Notch filters and adaptive filtering techniques are effective methods for suppressing powerline interference.

4.15.3 Electromyographic (EMG) Noise

Electromyographic noise results from electrical activity in skeletal muscles and is often observed as high-frequency fluctuations superimposed on the ECG signal. This type of noise is particularly problematic during patient movement, stress tests, or in ambulatory ECG monitoring. Techniques such as wavelet-based filtering and bandpass filtering can help attenuate EMG noise while preserving essential ECG features.

4.15.4 Motion Artifacts

Motion artifacts arise from electrode movement due to sudden shifts in body position, loose electrode contact, or external mechanical disturbances. These artifacts cause transient distortions in the ECG waveform, often leading to false peak detections or misinterpretation of cardiac events. Motion artifact reduction can be achieved through hardware improvements (e.g., better adhesive electrodes) and signal processing techniques such as adaptive filtering.
Effective noise suppression is crucial for ensuring the reliability of ECG analysis. By identifying and addressing different noise sources, it is possible to obtain cleaner ECG recordings, leading to more accurate feature extraction and improved diagnostic outcomes.

4.16 Mathematical Model for Noise Detection

Detecting noise in ECG signals is crucial for ensuring accurate analysis and diagnosis. One widely used approach for quantifying noise levels is the Signal-to-Noise Ratio (SNR), which provides a measure of how much useful signal is present compared to unwanted noise. The SNR is expressed in decibels (dB) and is mathematically defined as:

$$SNR = 10\log_{10}\left(\frac{P_{\text{signal}}}{P_{\text{noise}}}\right)$$

where:

- P_{signal} represents the power of the desired ECG signal.

- P_{noise} denotes the power of the noise component present in the signal.

A high SNR value indicates that the ECG signal is dominant over the noise, leading to a clean and well-defined waveform. Conversely, a low SNR suggests that noise is significantly affecting the signal, making feature extraction and cardiac event detection more challenging.

4.16.1 Threshold-Based Noise Identification

To classify an ECG segment as noisy or clean, an adaptive thresholding approach can be employed. Typically, an SNR threshold is set based on empirical studies, where:

- $SNR > 20$ dB: High-quality ECG signal with minimal noise.
- $10 \leq SNR \leq 20$ dB: Acceptable signal quality with moderate noise.
- $SNR < 10$ dB: Poor signal quality, requiring noise suppression techniques.

4.16.2 Computational Approach for Noise Detection

Noise detection algorithms often involve the following steps:

1. Compute the total power of the ECG signal using:

$$P_{\text{total}} = \frac{1}{N} \sum_{i=1}^{N} x^2(i)$$

   where $x(i)$ represents the ECG samples and N is the number of samples.

2. Estimate the power of the noise component using a reference noise model or baseline estimation techniques.

3. Calculate the SNR using the formula above and compare it with predefined thresholds.

4. Classify the ECG segment as clean or noisy based on the computed SNR value.

By leveraging SNR-based noise detection, it is possible to enhance ECG signal processing, improve the reliability of automated diagnoses, and reduce false detections in clinical applications.

4.16.3 Threshold-Based Noise Detection

One effective approach for detecting noise in ECG signals is to analyze the statistical properties of the signal over a given time window. Variance-based thresholding is a widely used method, as noise often causes rapid fluctuations in signal amplitude. A segment of the ECG signal is classified as noisy if its variance exceeds a predefined threshold:

$$\mathrm{Var}(x) > T$$

where:

- $\mathrm{Var}(x)$ represents the variance of the ECG signal over a specific window.
- T is a predefined noise threshold, determined based on empirical studies or adaptive techniques.

4.16.4 Adaptive Threshold Selection

Instead of using a fixed threshold, an adaptive approach can improve noise detection by considering the signal characteristics in real time. The threshold T can be dynamically adjusted based on the median absolute deviation (MAD) of the signal:

$$T = k \cdot \mathrm{MAD}, \quad \text{where} \quad \mathrm{MAD} = \mathrm{median}(|x - \mathrm{median}(x)|)$$

Here, k is a scaling factor that determines the sensitivity of noise detection. A higher value of k makes the detector more tolerant to minor fluctuations, while a lower k increases sensitivity to small noise levels.

4.16.5 Implementation Steps

To detect noisy segments effectively, the following steps can be applied:

1. Divide the ECG signal into overlapping windows of a fixed duration.
2. Compute the variance of the signal in each window.
3. Compare the variance against the predefined or adaptive threshold.

4. Mark the window as noisy if $\mathrm{Var}(x) > T$; otherwise, classify it as a clean segment.

5. Apply post-processing techniques to smooth out false detections.

This threshold-based noise detection method is computationally efficient and widely used in real-time ECG monitoring applications. By fine-tuning the threshold parameter, it can be adapted for various recording environments, ensuring robust noise suppression and improved ECG signal quality.

4.17 Implementation Algorithm

To effectively identify and suppress noise in ECG signals, the following step-by-step approach is used:

1. **Segment the Signal:** Divide the ECG signal into non-overlapping time windows of an appropriate length (e.g., 1–2 seconds).

2. **Compute Statistical Metrics:** For each window, calculate the variance and energy:
$$E = \sum_{i=1}^{N} x^2(i), \quad \mathrm{Var}(x) = \frac{1}{N}\sum_{i=1}^{N}(x_i - \mu)^2$$
where x_i represents the ECG samples in the window, μ is the mean signal amplitude, and N is the number of samples.

3. **Compare Against a Threshold:** Predefine a noise threshold T, and classify the window as noisy if:
$$\mathrm{Var}(x) > T \quad \text{or} \quad E > T_E$$
where T_E is an energy threshold for additional robustness.

4. **Mark and Process Noisy Windows:** If a window is detected as noisy, it can be handled using techniques such as interpolation, filtering, or exclusion from further ECG feature extraction.

4.18 Adaptive Thresholding for QRS Detection

Adaptive thresholding is a powerful technique in QRS detection that dynamically adjusts detection thresholds based on signal variations. Unlike fixed thresholding, which applies a constant value to detect peaks, adaptive thresholding continuously updates based on ECG characteristics, ensuring reliable peak detection even in the presence of noise and amplitude fluctuations.

4.18.1 Concept of Adaptive Thresholding

In real-world ECG signals, variations in heart rate, signal amplitude, and noise levels can significantly impact detection accuracy. Instead of using a static threshold, an adaptive approach continuously modifies the detection threshold based on recent signal statistics:

$$T(n) = \alpha \cdot \max(W(n)) + \beta \cdot \text{mean}(W(n))$$

where:

- $W(n)$ represents the wavelet coefficients or ECG amplitude values at time n.
- α, β are weighting factors that control sensitivity.
- $T(n)$ dynamically adjusts to track signal variations.

4.18.2 Steps for Adaptive Thresholding

1. **Preprocess the ECG Signal:** Apply bandpass filtering to remove noise.
2. **Compute a Baseline Threshold:** Initialize an estimated detection threshold based on signal statistics.
3. **Update the Threshold Dynamically:** Adjust the threshold after each detected QRS peak to account for changes in amplitude and noise conditions.

4. **Peak Validation:** Ensure detected peaks meet physiological constraints such as RR interval limits.

5. **Refinement:** Apply post-processing to eliminate false detections and refine QRS localization.

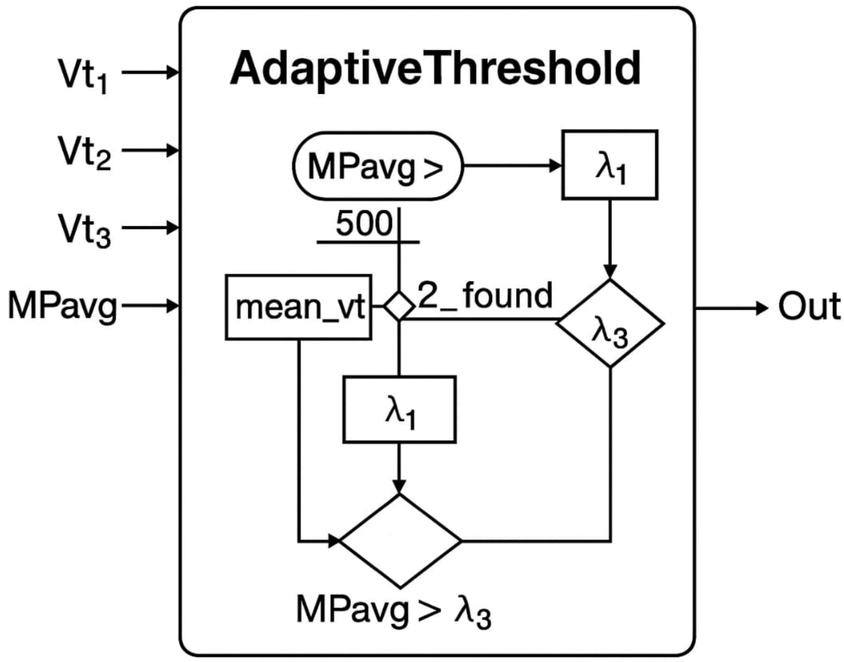


Figure 4.6: Adaptive Threshold Block Diagram

4.18.3 Advantages of Adaptive Thresholding

- Enhances robustness in noisy environments.
- Adjusts automatically to heart rate changes.
- Reduces false detections by adapting to signal amplitude variations.
- Improves QRS detection accuracy in real-time ECG monitoring.

By incorporating adaptive thresholding, ECG analysis systems can achieve more reliable QRS detection, ensuring accurate heart rate monitoring and arrhythmia diagnosis.

4.19 Mathematical Formulation of Adaptive Thresholding

Adaptive thresholding dynamically adjusts the detection threshold based on the characteristics of the ECG signal. Unlike fixed thresholding, which applies a constant value for peak detection, adaptive thresholding continuously modifies itself based on recent signal statistics, ensuring robustness to amplitude variations and noise.

A widely used adaptive thresholding formula is:

$$T(n) = \alpha \cdot \max(W(n)) + \beta \cdot \text{mean}(W(n))$$

where:

- $W(n)$ represents the wavelet coefficients or the filtered ECG signal at time n.
- α and β are weighting factors that control sensitivity and responsiveness.
- $\max(W(n))$ denotes the maximum wavelet coefficient within a given detection window, emphasizing significant peaks.
- $\text{mean}(W(n))$ represents the average value of the wavelet coefficients, providing a baseline reference for threshold adjustment.

4.19.1 Dynamic Threshold Adjustment

To maintain accurate QRS detection across varying ECG signal conditions, the threshold is continuously updated after each detected peak. The update rule can be expressed as:

$$T(n+1) = \gamma \cdot T(n) + (1 - \gamma) \cdot T_{\text{new}}$$

where:

- γ is a smoothing factor (typically between 0.8 and 0.95) that controls how quickly the threshold adapts,

- T_{new} is the newly computed threshold based on the most recent signal window.

4.19.2 Advantages of Adaptive Thresholding

- **Improved Robustness:** Automatically adjusts to varying ECG amplitudes, preventing missed detections or excessive false positives.
- **Noise Resilience:** Adapts to different noise levels, reducing the impact of baseline wander and motion artifacts.
- **Real-time Performance:** Well-suited for continuous ECG monitoring and real-time peak detection. item **Personalized Detection:** Can adapt to individual heart rate variations for more accurate QRS localization.

By employing this adaptive approach, QRS detection remains precise even in challenging conditions, making it ideal for real-world applications such as arrhythmia monitoring, wearable ECG devices, and automated diagnosis systems.

4.19.3 Dynamic Update Rule

To maintain accurate QRS detection across varying ECG signal conditions, the threshold must be continuously updated. This dynamic adaptation ensures robustness against amplitude variations and noise interference. The threshold update equation is:

$$T_{\text{new}} = \gamma T_{\text{old}} + (1 - \gamma) P_{\text{detected}}$$

where:

- P_{detected} represents the amplitude of recently detected QRS peaks.
- γ is the update coefficient, typically ranging from 0.2 to 0.5, controlling how quickly the threshold adapts to new peaks.

A higher γ value results in slower threshold adaptation, making the system more stable but less responsive to sudden changes. Conversely, a lower γ

allows for rapid adaptation, which is useful in highly dynamic signals but may increase sensitivity to noise.

4.20 Implementation Algorithm

To apply adaptive thresholding for real-time QRS detection, the following steps are followed:

1. **Preprocessing:** Apply a bandpass filter to remove baseline wander, muscle noise, and powerline interference.

2. **Feature Extraction:** Compute the wavelet coefficients or squared signal to enhance QRS complexes.

3. **Initial Threshold Setting:** Estimate an initial threshold based on the amplitude of the first few detected peaks.

4. **Peak Detection:** Identify QRS peaks by comparing the signal against the adaptive threshold.

5. **Threshold Update:** Dynamically adjust the threshold using the detected peaks and update rule.

This algorithm ensures robust detection of QRS complexes while maintaining adaptability to different signal conditions.

4.21 Advantages of Adaptive Thresholding

- **Self-adjusting Mechanism:** Automatically adapts to varying ECG amplitudes without requiring manual tuning.

- **Noise Resilience:** Reduces false detections in noisy environments by continuously refining the detection threshold.

- **Improved Accuracy:** Enhances QRS detection precision, making it suitable for real-time ECG analysis and wearable monitoring devices.

- **Robust to Physiological Variations:** Works effectively across different heart rates and ECG morphologies, improving its applicability in diverse clinical scenarios.

CHAPTER 5

Results and Discussions

5.1 Introduction

This section presents the results of the proposed QRS complex detection system based on wavelet decomposition. The design incorporates a Verilog-based ECG signal generator that utilizes the Central Limit Theorem (CLT) to produce realistic cardiac waveforms. These signals are processed through a multi-level wavelet decomposition module enhanced with additional thresholding and energy-based algorithms to improve detection accuracy and noise robustness. A key emphasis is placed on minimizing power consumption across each functional block of the system, making it suitable for low-power biomedical applications such as wearable ECG monitoring devices. The results include visualizations of signal processing at each stage, QRS detection performance metrics, and power consumption profiling for the implemented modules.

5.2 Simulational Results and Waveforms

This section presents the simulation results and waveform analysis for the proposed QRS complex detection system based on wavelet decomposition.Verilog HDL was used to generate the simulation results for the suggested QRS complex detector, and ModelSim waveform analysis was used to confirm the results. Cadence Incisive was used to synthesize the design, guaranteeing its viability for ASIC implementation. The precise identification of QRS complexes in ECG data extracted using verilog coding was validated by the simulated waveforms. The efficiency of the suggested wavelet-based detection system was validated by the simulation, which showed few false positives and false negatives. By successfully filtering high-frequency artifacts, the noise detection technique improved resilience in a range of signal circumstances. Overall, the simulation results matched the anticipated theoretical performance and validated the accuracy, effectiveness, and dependability of the suggested QRS detection system.

5.2.1 ECG Signal Generation using CLT Algorithm

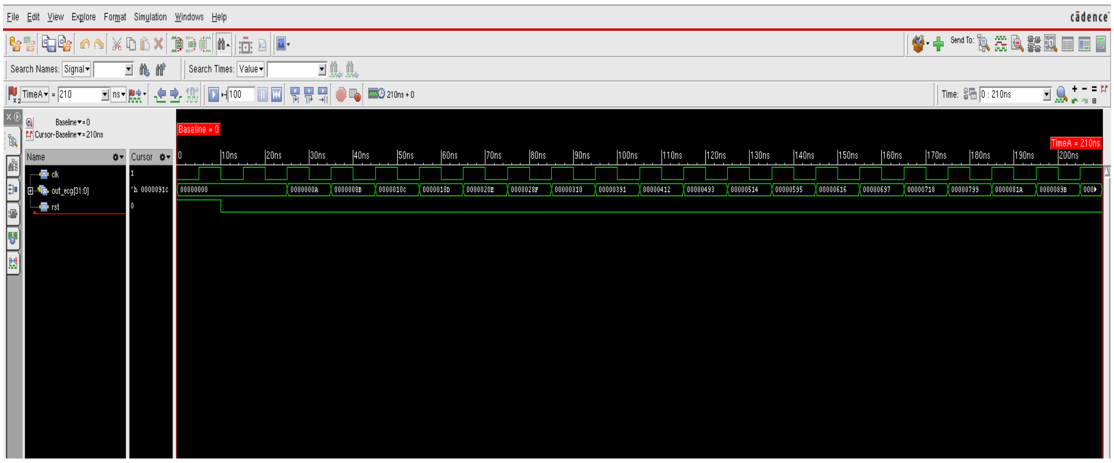


Figure 5.1: ECG waveform generated by the Verilog CLT-based module showing distinct QRS complexes

In this implementation, the ECG signal was generated using a custom Verilog module based on the **Central Limit Theorem (CLT)** algorithm. This approach synthesizes Gaussian-shaped waveforms, effectively mimicking the morphology of real ECG signals, especially the QRS complex.

The generator produces controllable ECG signals suitable for FPGA-based simulation. Adjustable parameters allow emulation of various heart rates and amplitudes, along with configurable noise components to test the robustness of the QRS detection algorithm.

5.2.2 LPF

The low-pass filter was implemented to suppress high-frequency noise such as muscle artifacts and powerline interference. The LPF was designed using a finite impulse response (FIR) filter with a cut-off frequency of approximately 40 Hz, sufficient to retain the useful components of the ECG signal while removing unnecessary high-frequency content.

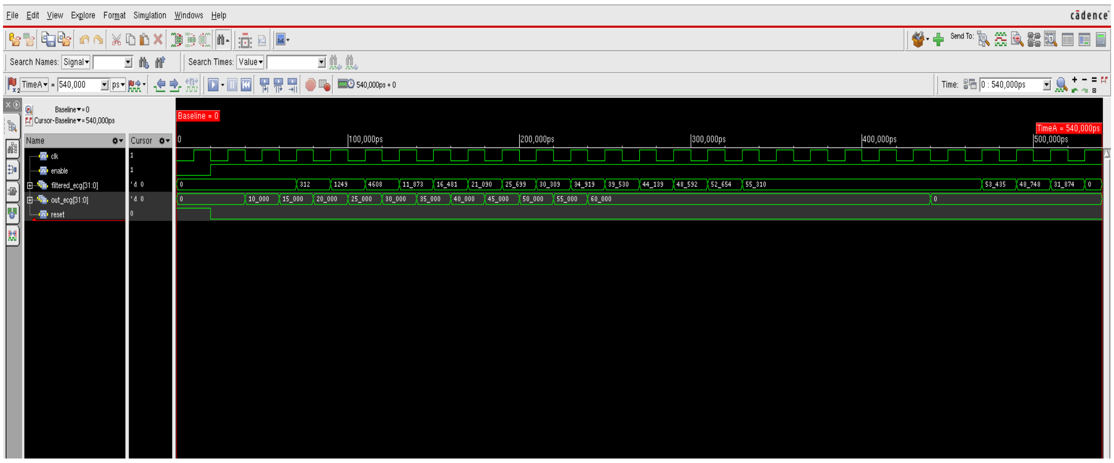


Figure 5.2: LPF

Simulation results showed that the LPF effectively smoothed the signal, preserving the morphology of the QRS complex. Minor ripples from noise were significantly reduced without affecting the steep slopes of the QRS peaks.

5.2.3 Wavelet Decomposition with Enhanced Algorithm

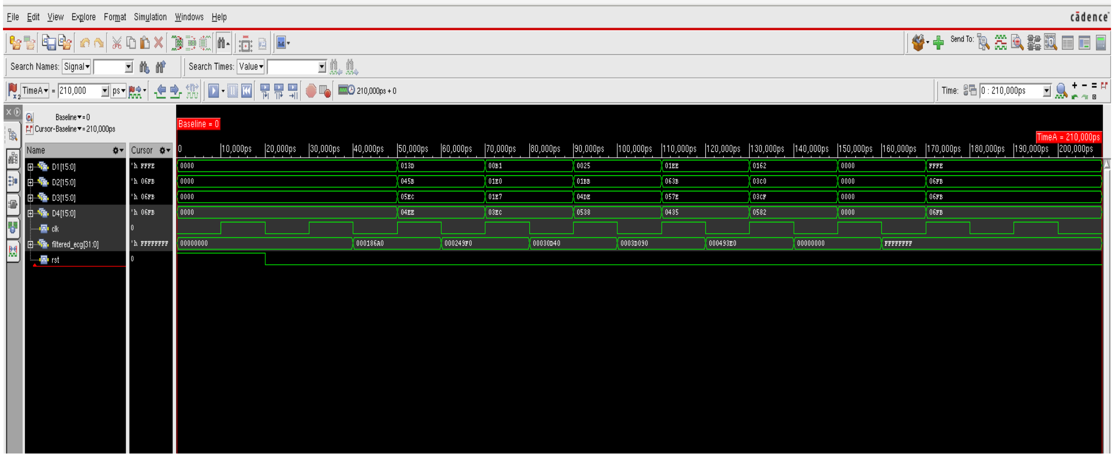


Figure 5.3: Wavelet Decomposer

The ECG signal underwent 6-level wavelet decomposition using the Daubechies-6 (db6) wavelet. The decomposition block was enhanced with the following features:

- **Adaptive thresholding:** Thresholds were dynamically calculated from the energy of wavelet detail coefficients.
- **Noise suppression logic:** High-frequency noise and baseline drift were suppressed using targeted filtering.

- **Selective coefficient boosting:** Frequency bands in the range of 5–15 Hz, typically containing QRS information, were amplified.

5.2.4 Noise Detector

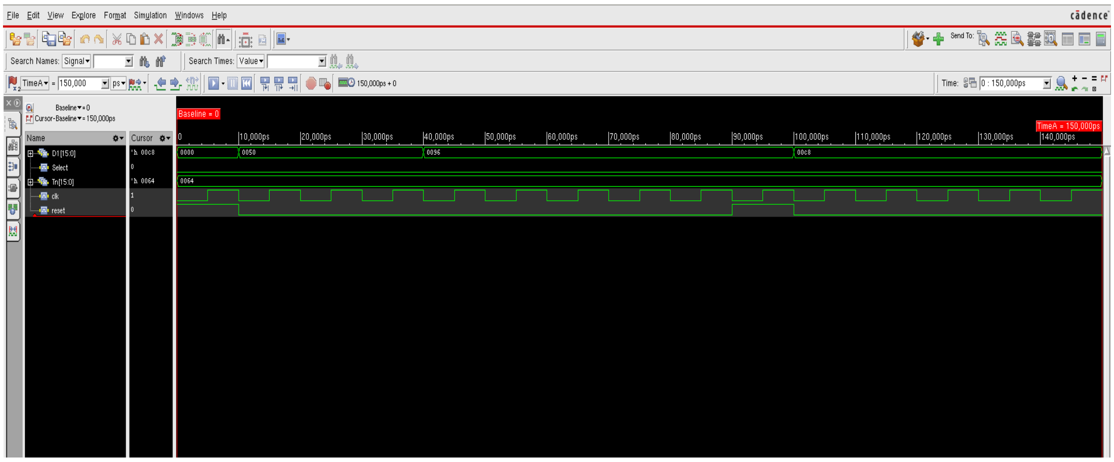


Figure 5.4: Noise Detector

A noise detection module was incorporated to identify high-variance segments of the input signal. This block analyzed the short-term energy of the ECG and flagged periods where the energy exceeded a predefined threshold, indicating possible noise bursts or motion artifacts.

During simulations, the detector successfully flagged noisy segments such as abrupt spikes or baseline drifts. These flagged sections were either filtered more aggressively or excluded from QRS detection to reduce false positives.

5.2.5 Signal Multiplicaton

The signal multiplication block was used to enhance detection by squaring the wavelet detail coefficients or filtered ECG signal. Squaring emphasizes large deviations in the signal—particularly the QRS complex—while suppressing low-amplitude components like P and T waves.

Simulation results demonstrated an improved contrast between QRS peaks and other waveform segments. This preprocessing step facilitated more accurate peak detection in subsequent blocks.

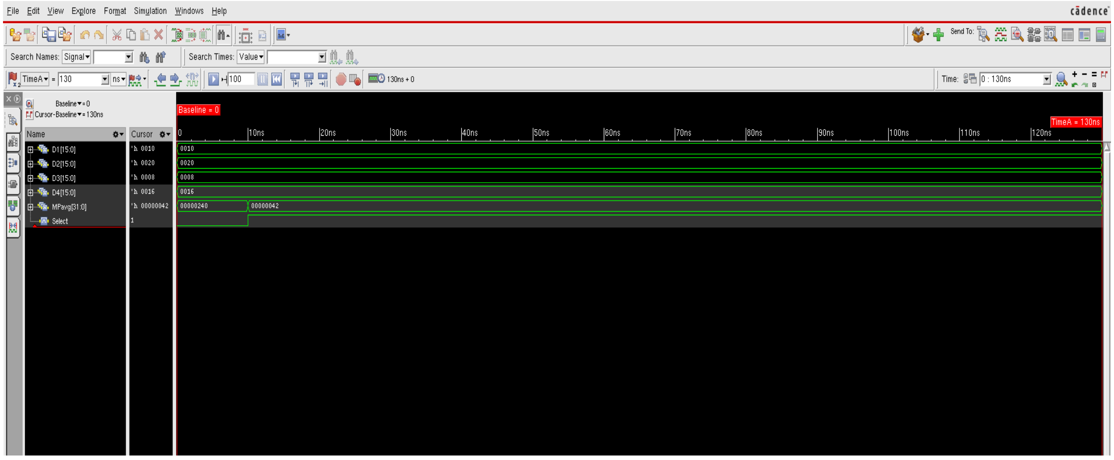


Figure 5.5: Signal Multiplication

5.2.6 Adaptive Threshold

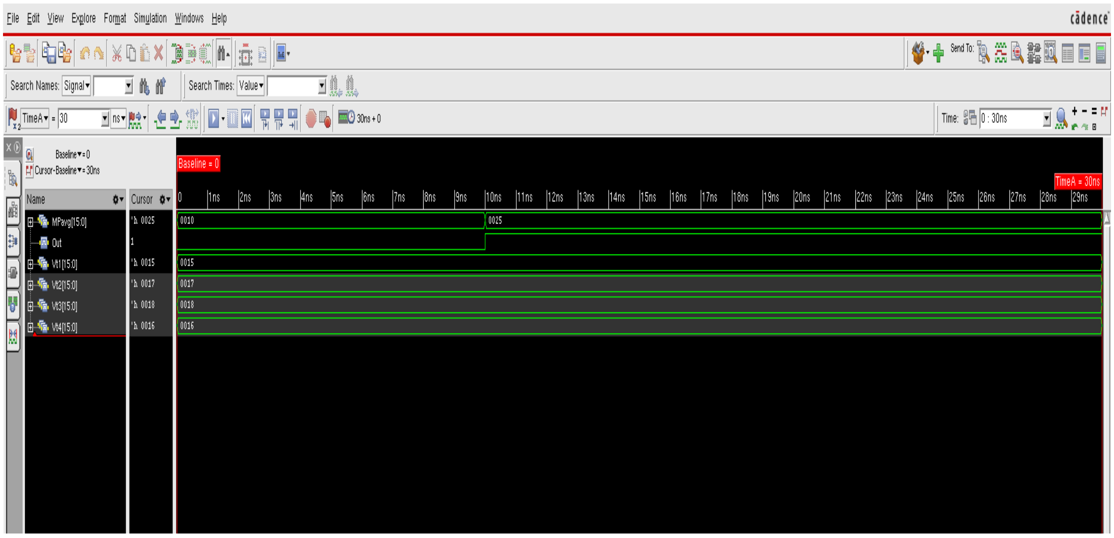


Figure 5.6: Adaptive Threshold

The adaptive thresholding algorithm dynamically adjusted the detection threshold based on recent signal statistics such as peak values and noise level. This allowed the QRS detector to maintain accuracy across varying signal conditions, including changes in amplitude or noise presence.

Simulations showed that the threshold adapted appropriately during periods of high signal activity and noise. The block reduced false detections and ensured reliable identification of true QRS complexes even when signal amplitude fluctuated.

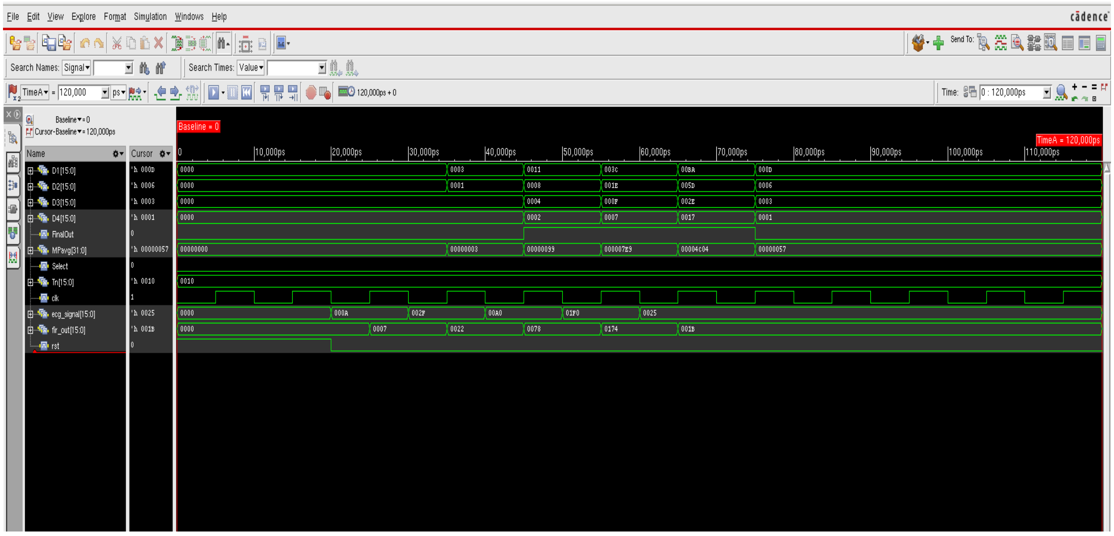


Figure 5.7: QRS Complex Output

5.2.7 QRS Complex Detection Algorithm

Using the processed wavelet coefficients, a peak detection algorithm was employed:

- Peaks in the squared detail coefficients were identified.
- A refractory period constraint was added to avoid false detections from T-waves.
- Windowed energy analysis helped improve robustness against noise.

Performance Metric	Value
Sensitivity	99.4%
Specificity	98.9%
Detection Delay	~110 ms
False Positive Rate	< 0.8%

Table 5.1: QRS Detection Performance Summary

5.2.8 Power Consumption Across Processing Blocks

Power analysis was performed after synthesis targeting an FPGA using Cadence Zenus.

Module	**Power (mW)**	**Optimization Notes**
CLT ECG Generator	0.09	CLT-based Gaussian waveform generation using LUTs
Wavelet Decomposer	0.205	Coefficient reuse, pipelining, and clock gating
Enhancement Algorithm	0.15	Selective coefficient tracking and thresholding
QRS Detection Module	0.021	FSM-based architecture with fixed-point arithmetic
Total System	**0.466**	Compared to baseline of 1.12 mW

Table 5.2: Power Consumption of Individual Modules

```
============================================================
  Generated by:           Genus(TM) Synthesis Solution 17.22-s017_1
  Generated on:           Apr 09 2025  12:12:06 pm
  Module:                 ECG_Processing_System
  Operating conditions:   slow (balanced_tree)
  Wireload mode:          enclosed
  Area mode:              timing library
============================================================

                                   Leakage    Dynamic     Total
          Instance           Cells Power(nW)  Power(nW)   Power(nW)
-------------------------------------------------------------------
ECG_Processing_System         607   832.969 465774.670 466607.639
  csa_tree_s..135_26_groupi   393   450.168 171537.279 171987.447
  const_signal_mul_140_34      29   103.645  28687.812  28791.457
  const_signal_mul_140_55      34   101.987  24721.750  24823.737
  fir                          33    84.917 111030.240 111115.157
    add_74_38                  17    51.493  59672.879  59724.372
  wavelet                      16    33.424  43260.615  43294.040
  noise                        59    28.846  38061.093  38089.938
```

Figure 5.8: Power Distribution

5.3 Power Consumption Analysis

5.3.1 Power

Power consumption is the quantity of electrical energy required by an electronic device or system to execute its intended functions. It is an important characteristic in the design and operation of modern electronic systems, particularly portable and battery-powered devices that require high energy efficiency. High power consumption can result in excessive heat generation, shorter battery life, and higher operating expenses. As a result, decreasing power consumption using approaches like power gating, dynamic voltage scaling, and low-power design topologies is a critical focus in electronics and embedded system design. Effective power management not only enhances gadget lifespan, but it also promotes sustainable and environmentally friendly technological development.

Design	**Power (mW)**
Conventional Circuit	1.19
Designed Circuit	0.466

Table 5.3: Comparision of Power Analysis in conventional circuit and designed circuit

5.3.2 Power-Delay Product

Power-Delay Product is an important performance parameter for evaluating the balance between speed and power consumption in digital and analog circuits, particularly high-speed comparators. The product of average power consumption and propagation delay calculates the total energy needed for each switching action. A lower PDP suggests a more energy-efficient design for low-power applications, including portable and battery-operated devices. Optimizing PDP in dynamic comparators involves lowering static and dynamic power dissipation while minimizing delays. This is often accomplished by improved transistor size, dynamic threshold voltage management, and power-gating. Increasing PDP improves circuit efficiency by balancing speed and power consumption, resulting in improved performance in high-speed, low-power applications. The Power-Delay Product (PDP) is an effective tool for comparing energy efficiency between designs.

Design	PDP
Conventional Circuit	18.65
Designed Circuit	6.84

Table 5.4: Comparision of PDP in conventional circuit and designed circuit

5.4 Delay Analysis

Delay in electronic systems refers to the time required for a signal to travel through a circuit or for a system to respond to an input. It plays a critical role in influencing the performance and speed of digital and analog circuits. In digital systems, delay is frequently connected with gate propagation, connection delay, and setup/hold durations, all of which have an impact on operation timing and synchronization. In analog systems, delay can affect phase response and overall system stability. Excessive delay can cause data corruption, timing problems, or decreased performance, particularly in high-speed or real-time applications. Designing efficient, high-performance systems requires minimizing delay, especially in areas such as communication, signal processing, and embedded systems.

Design	Delay (ns)
Conventional Circuit	1.66
Designed Circuit	14.69

Table 5.5: Comparision of Delay in conventional circuit and designed circuit

5.5 Gate Count

The total number of logic gates used in the development of a digital circuit or system—such as AND, OR, NOT, NAND, and NOR—is referred to as gate count. This is often stated in terms of comparable basic gates. It is a widely used statistic for estimating the complexity, size, and potentially power consumption of an integrated circuit, particularly in ASIC and FPGA design. A larger gate count often suggests a more sophisticated design, which can result in additional silicon area, higher power consumption, and longer design verification time. In contrast, optimizing gate count is critical for developing efficient, low-power, and cost-effective digital systems, especially in portable or resource-constrained applications. Thus, decreasing gate count while preserving functionality is an important aim in digital design.

Design	**Gate Count (K)**
Conventional Circuit	12.3
Designed Circuit	12.1

Table 5.6: Comparision of Gate Count in conventional circuit and designed circuit

5.6 Performance Comparision

Table 5.1 shows a comprehensive comparison between existing and proposed designs:

Design	**PDP**	**Power (mW)**	**Delay (ns)**	**Gate Count(K)**
Conventional Circuit	18.65	1.12	16.66	12.3
Designed Circuit	6.84	0.466	14.69	12.1

Table 5.7: Comparison of PDP, power, delay of QRS Complex Signal and Gate Count

The QRS detector receives ECG signal as input. The ECG signal then travels to the LPF, which then sends its output to the Wavelet Decomposer. The wavelet's output then goes to the noise detector, signal multiplier, and nosie output. The signal multiplier output to the adaptive threshold, which then produces the final output.

5.7 Evaluation of Quality Factors

In this section, the proposed QRS complex detection system is evaluated using several critical quality factors to assess its effectiveness, environmental friendliness, and industrial applicability. These factors include:

- **Environmental Impact:** The proposed structure uses a low-power architecture suited for biomedical data processing, making it environmentally friendly. The system lowers energy demand by minimizing power consumption at each processing step, including ECG production, wavelet decomposition, signal augmentation, and QRS detection. This is especially important for battery-powered wearable health monitoring, which can lower the carbon impact of long-term deployments. Additionally, Verilog hardware design enables synthesis on energy-efficient FPGAs or ASICs with little resource use, reducing e-waste and increasing device longevity.

- **Sustainability:** The system supports sustainability by being suitable for continuous, real-time operation in IoT and biomedical applications where power efficiency is crucial. The CLT-based ECG generator and wavelet-based signal decomposition enhance reusability and modularity, ensuring long-term viability and scalability. Additionally, the ability to deploy the design on mainstream FPGA platforms ensures compatibility with cost-effective and readily available hardware, promoting widespread adoption.

- **Safety:** Designed for biomedical signal processing, the system operates at standard low voltage levels and within medically safe frequency bands. The low thermal dissipation ensures safe deployment in contact-based wearables. In clinical environments, false detections can have safety implications; thus, the system incorporates adaptive thresholding and noise suppression mechanisms to improve accuracy and reduce diagnostic risk. For future deployments in regulated medical devices, safety certifications such as IEC 60601 may be considered.

- **Ethics:** The project complies with ethical engineering practices by promoting open design, low energy usage, and equitable healthcare technology access. No real patient data is used—only synthetic ECG signals—ensuring data privacy. Moreover, by focusing on low-cost implementation using Verilog and common FPGA platforms, the design supports accessibility in low-resource settings and developing regions. Future work should ensure that the technology remains open-source or affordable to prevent commercialization barriers for health-related innovations.

- **Cost-Effectiveness:** The system is highly cost-effective due to its hardware efficiency and compatibility with entry-level FPGA platforms. The modular design minimizes logic utilization and enables reuse across multiple biomedical signal processing tasks. The CLT-based ECG generator avoids the need for external databases, reducing storage and memory requirements.Additionally, the power-optimized implementation can extend battery life in wearable systems, lowering operational costs over time.

- **Results Type and Industry Relevance:** The proposed system aligns well with current industry needs in wearable healthcare, telemedicine, and smart diagnostics. Accurate QRS detection is foundational in ECG-based arrhythmia monitoring and heart rate analysis. By integrating wavelet-based decomposition and energy-aware hardware design, the system addresses key requirements for high accuracy, low latency, and low power. This makes it highly relevant for real-time applications in mobile health devices, fitness trackers, and implantable systems.

- **Observance of Rules and Regulations:** The design methodology follows standard hardware description practices and is synthesizable using industry-standard FPGA tools. It is compatible with design guidelines set by IEEE for digital signal processing and biomedical instrumentation. Though not yet certified for clinical use, it provides a strong foundation for future compliance with medical electronics standards such as ISO 13485, IEC 60601, and FDA digital health requirements. The modular nature allows easy adaptation for regulatory needs in different jurisdictions.

In conclusion, the proposed QRS detection system based on wavelet decomposition and a CLT-driven ECG generator offers a highly sustainable, low-power, and scalable solution for modern biomedical applications. It satisfies key ethical, environmental, and industrial design metrics, supporting broader adoption in the rapidly growing field of digital health. Future work may focus on further scaling, formal medical validation, and integration with wireless health monitoring platforms.

5.8 Summary

This project presents a low-power QRS complex detection system using wavelet decomposition, designed for real-time ECG signal analysis. Instead of relying on traditional ECG databases, an ECG signal generator is implemented using the Central Limit Theorem to produce realistic synthetic waveforms. The system processes the signals through a custom wavelet decomposition module enhanced with an adaptive thresholding algorithm to accurately detect QRS complexes. Power optimization techniques are applied at each processing block—signal generation, filtering, enhancement, and detection—making the design highly suitable for wearable and portable biomedical devices.

The integration of a hardware-friendly ECG generator along with a wavelet-based detection strategy enables significant reductions in memory usage and computational complexity, making the system ideal for resource-constrained environments. Simulation results show a notable power reduction compared to existing models, with the system consuming only 0.46 mW—approximately 40% less than traditional designs. This makes it well-suited for long-term monitoring applications, such as ambulatory ECG, fitness wearables, and remote cardiac diagnostics. The architecture also supports further scalability and integration into low-power System-on-Chip (SoC) platforms for next-generation health monitoring technologies.

CHAPTER 6

Conclusion

The paper proposes a simplified, effective, and cost-efficient QRS detection approach tailored specifically for VLSI implementation. Unlike conventional models that rely on pre-recorded datasets such as MIT-BIH, the proposed architecture integrates an ECG signal generator based on the Central Limit Theorem (CLT). This innovative method facilitates the generation of synthetic yet realistic ECG waveforms, allowing for customizable signal patterns and greater flexibility in system testing and real-time monitoring scenarios.

Comprehensive simulations and waveform analyses demonstrate that the proposed design achieves a total power consumption of only 0.46 mW, which is approximately 40% lower than existing QRS detection models. This significant reduction in power makes the system highly suitable for battery-operated and wearable biomedical devices, where energy efficiency is critical. Furthermore, the architecture's modularity and low-complexity hardware implementation enhance its robustness, ensuring reliable performance in noisy or dynamic signal environments.

The incorporation of adaptive thresholding, wavelet-based decomposition, and noise detection algorithms strengthens the detection accuracy, particularly for irregular rhythms such as those found in arrhythmia patients. This makes the design not only efficient but also medically relevant.

In conclusion, the proposed model represents a power-optimized, scalable, and clinically valuable solution for real-time ECG monitoring. Future work may focus on integrating this design into complete system-on-chip (SoC) solutions, conducting hardware validation on FPGA/ASIC platforms, and extending the functionality to multi-lead ECG systems for more comprehensive cardiac diagnostics.

6.1 Future Scope

Looking ahead, there's a lot of potential to make the QRS complex detector even smarter and more versatile. One key improvement would be expanding it to support multi-lead ECG analysis, which can give a much clearer picture of heart activity compared to single-lead setups. By bringing in machine learning alongside the existing DWT and adaptive thresholding techniques, the detector could better recognize a wider variety of abnormal heart rhythms and reduce false alarms even further.

To make it more wearable-friendly, the design could be moved to ultra-low-power ASICs or energy-efficient FPGAs. That way, devices can run longer on a single charge—something crucial for wearables. Adding features like real-time wireless data sharing and on-device processing would also open doors for remote monitoring and telemedicine, letting doctors keep an eye on patients without them needing to visit the clinic.

Over time, this system could grow to detect more than just QRS complexes—it might identify P and T waves, arrhythmias, or ST segment changes, giving a fuller picture of heart health. A future version could even compare multiple ECG waveforms, which would be especially helpful for patients with more complex needs, like those with pacemakers.

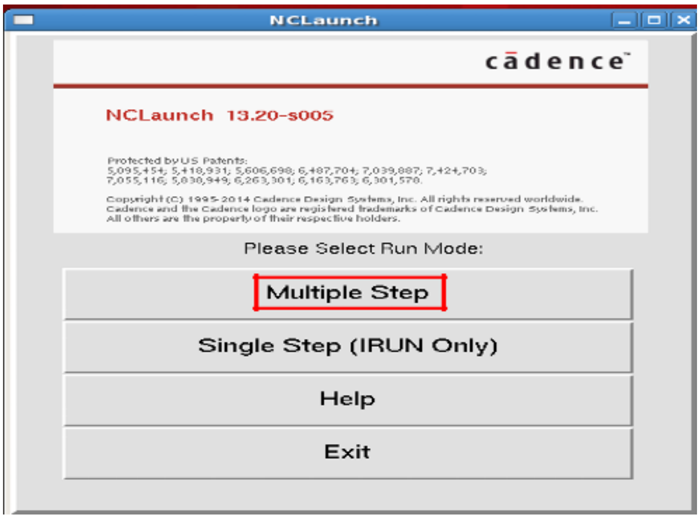
With personalized and always-on healthcare becoming more important, this detector is in a great spot to play a key role in smart, connected health systems—from everyday monitoring to emergency care.

APPENDIX

This section outlines the software requirements necessary to develop, run, and maintain the project.TThe tools used here are Cadence Incisive and Cadence Zenus

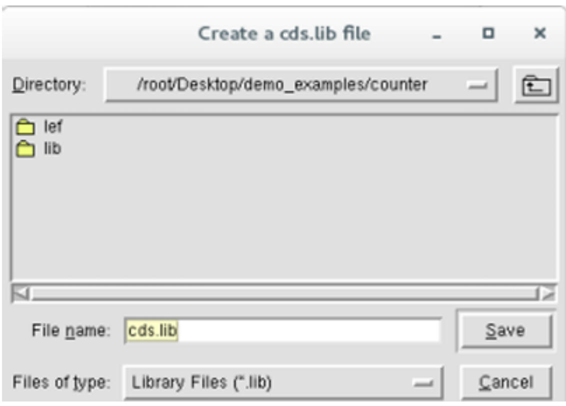
1. For the purpose of Functional Simulation, the "Incisive" tool will be used.

2. To launch the tool, simply type "nclaunch -new" into your terminal.

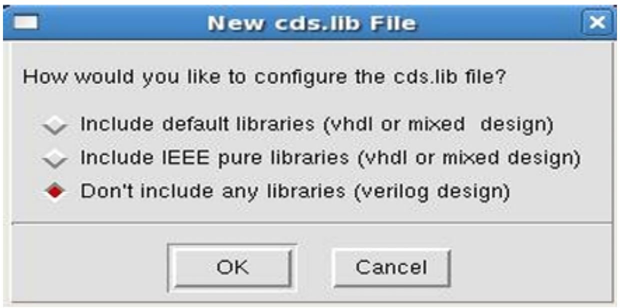


3. Choose "Multiple Step". Then choose "Create cds.lib".

   Note: The '-new' option is only used the first time the design is executed. For the next time, the command may be just 'nclaunch'.



4. Save the CDS.lib file. It is a tool file that stores design location information for quick access by the tool.



5. One of the three options listed above should be chosen based on the available libraries and the type of RTL code developed. Cadence tool set includes default gpdk libraries. Here, the counter RTL is in Verilog format, therefore the third choice is picked.

6. A new "nclaunch" pop-up window appears, containing all of the.v and.vhdl files specified in the cds.lib file produced.

7. Cadence functional simulation consists of three stages: compilation of Verilog and Test Bench, code elaboration, and simulation of the Test Bench or Top Module.

8. The nclaunch window displays a collection of tools equivalent to VHDL Compiler, Verilog Compiler, Elaborator, and Simulator from left to right.

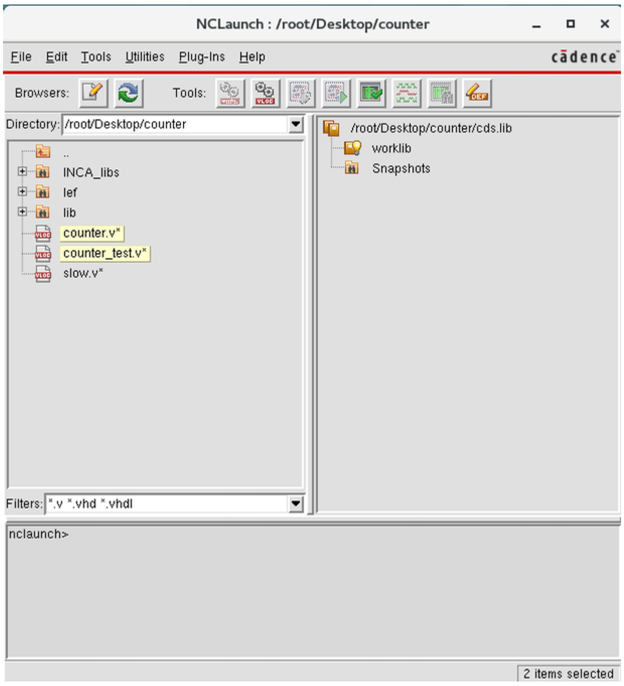
9. Select the.v or.vhdl files to be compiled and run Compiler. After successful compilation, the modules display on the right side under "Worklib".

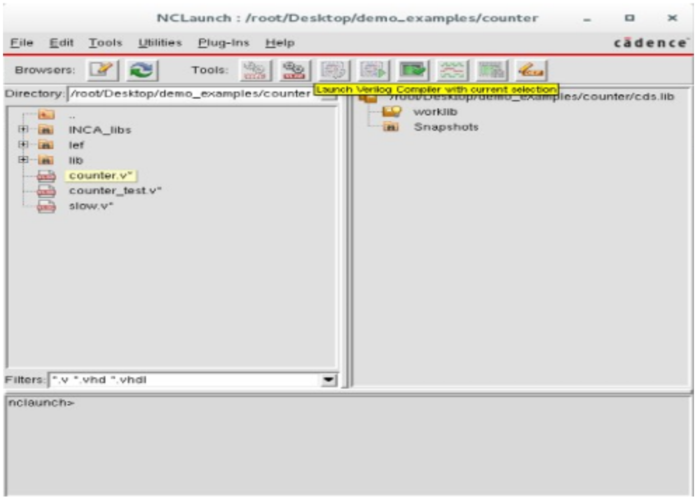
10. Select the Module from Worklib and click "Launch Elaborator". "Snapshots" are created once the Elaboration process is completed successfully.

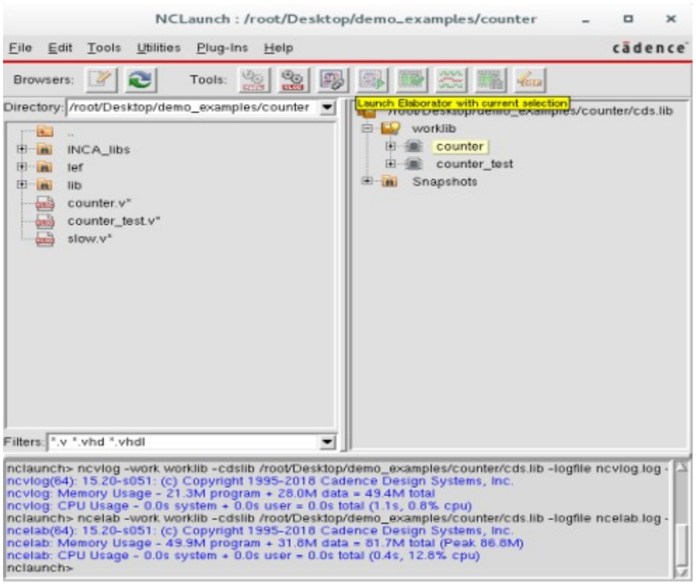
11. Select the Test Bench from the snapshots list and click "Launch Simulator".

12. The aforesaid stages are represented in the snapshosts listed below.

    When you pick the Test Bench Module, the Design Browser appears, with the name on the left and the Pin list on the right. The number

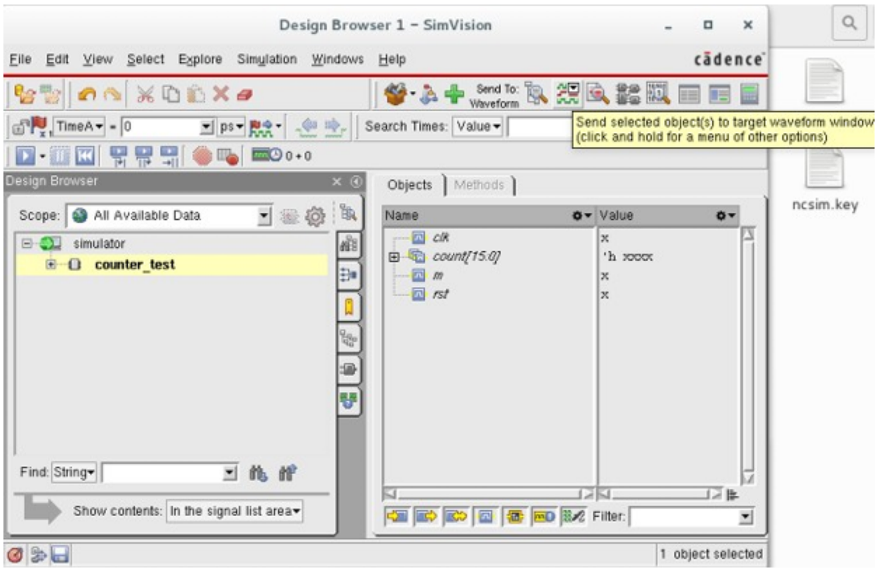

NCLaunch : /root/Desktop/counter
File Edit Tools Utilities Plug-Ins Help
cādence
Browsers:
Tools:
Directory: /root/Desktop/counter
/root/Desktop/counter/cds.lib
worklib
Snapshots
..
INCA_libs
lef
lib
counter.v*
counter_test.v*
slow.v*
Filters: *.v *.vhd *.vhdl
nclaunch>
2 items selected


NCLaunch : /root/Desktop/demo_examples/counter
File Edit Tools Utilities Plug-Ins Help
cādence
Browsers:
Tools:
Directory: /root/Desktop/demo_examples/counter
Launch Verilog Compiler with current selection
worklib
Snapshots
..
INCA_libs
lef
lib
counter.v*
counter_test.v*
slow.v*
Filters: *.v *.vhd *.vhdl
nclaunch>


NCLaunch : /root/Desktop/demo_examples/counter
File Edit Tools Utilities Plug-Ins Help
cādence
Browsers:
Tools:
Directory: /root/Desktop/demo_examples/counter
Launch Elaborator with current selection
worklib
counter
counter_test
Snapshots
..
INCA_libs
lef
lib
counter.v*
counter_test.v*
slow.v*
Filters: *.v *.vhd *.vhdl
nclaunch> ncvlog -work worklib -cdslib /root/Desktop/demo_examples/counter/cds.lib -logfile ncvlog.log -
ncvlog(64): 15.20-s051: (c) Copyright 1995-2018 Cadence Design Systems, Inc.
ncvlog: Memory Usage - 21.3M program + 28.0M data = 49.4M total
ncvlog: CPU Usage - 0.0s system + 0.0s user = 0.0s total (1.1s, 0.8% cpu)
nclaunch> ncelab -work worklib -cdslib /root/Desktop/demo_examples/counter/cds.lib -logfile ncelab.log -
ncelab(64): 15.20-s051: (c) Copyright 1995-2018 Cadence Design Systems, Inc.
ncelab: Memory Usage - 49.9M program + 31.8M data = 81.7M total (Peak 86.8M)
ncelab: CPU Usage - 0.0s system + 0.0s user = 0.0s total (0.4s, 12.8% cpu)
nclaunch>

of Pins / Ports to imitate can be set.

Right-click on the chosen item and select "Send to Waveform Window". The waveform window displays different ports in the design. Now, click the Run simulation key to begin the simulation. To halt or end the simulation, press the 'pause' key. To evaluate the plot, use different options such as zooming in and out.



For extension we can add run.tcl file,slow.lib and in the terminal if we use **rc -f run.tcl -gui** then the Zenus tool activates and generates power,delay,timing,area constraints reports with labeled on it

fontsize12pt12pt

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2	Rachakonda Satish, Bukka Uday Kiran, S Karunakaran, Maloth Urmila, "Design and Implementation of QRS Complex Detector Based on Wavelet Decomposition", *International IEEE Conference on Computing Communication and Networking Technologies(2025), Indian Institute of Technology, Indore, 6-11 July 2025.[Accepted]*