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VLSI Chip Design for Abnormal Heartbeat Detection: Review

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Abstract: ***The detection of irregular heart rhythms from electrocardiogram (ECG) signals is essential for the diagnosis and continuous monitoring of cardiac disorders, where the early identification of arrhythmias, such as premature ventricular contractions, ventricular tachycardia, and ventricular fibrillation, is critical for preventing sudden cardiac events [7]–[9]. ECG analysis is challenged by noise, baseline drift, and nonstationary behavior, necessitating robust preprocessing and feature extraction techniques, such as wavelet-based denoising and moving average QRS detection methods [3], [10], [13]. Advanced heart rate variability (HRV) analysis using compressed sensing and integral pulse frequency modulation (IPFM) models has demonstrated improved spectral resolution and prognostic value, particularly for unevenly sampled RR intervals [4]–[6], [14]. Statistical, machine learning, and deep learning approaches, including Bayesian frameworks, complexity-measure-based hypothesis testing, and convolutional neural networks, have further enhanced arrhythmia detection and classification accuracy [7]–[9], [11], [15]. To support continuous real-time monitoring, recent research has emphasized hardware-efficient implementations, with VLSI, FPGA, and ASIC-based architectures enabling low-power abnormal heartbeat detection through optimized neural networks and edge artificial intelligence, which are suitable for wearable and implantable devices [1], [12], [16]–[18].***

Keywords: Electrocardiogram (ECG), Abnormal Heartbeat Detection, Cardiac Arrhythmia, QRS Detection, Machine Learning, VLSI Design.

1. Introduction

Cardiovascular diseases remain a leading cause of illness and mortality worldwide, with cardiac arrhythmias, such as premature ventricular contractions, ventricular tachycardia, and ventricular fibrillation, posing significant and life-threatening risks. Therefore, the reliable and timely detection of abnormal heartbeats from electrocardiogram (ECG) signals is essential for clinical diagnosis, continuous patient monitoring, and emergency intervention systems [7], [8], [9].

The analysis of ECG signals is challenged by noise contamination, baseline wandering, and the non-stationary nature of cardiac activity. Accurate detection of ECG features, particularly the QRS complex, is critical for heartbeat analysis and arrhythmia detection in ECG signals. To address these issues, Chen *et al.* proposed a real-time QRS detection approach that integrates wavelet denoising with moving-averaging techniques, demonstrating robust performance under noisy conditions and suitability for real-time implementation [3].

Heart rate variability (HRV) analysis is valuable for assessing autonomic nervous system function and predicting cardiovascular outcomes. Advanced spectral estimation techniques based on compressed sensing have been introduced to overcome the limitations of traditional Fourier-based methods when dealing with unevenly sampled heartbeat intervals. In particular, reweighted ℓ_1-minimization and integral pulse frequency modulation (IPFM) model–based approaches have shown improved spectral resolution and estimation accuracy [4], [5]. The clinical significance of HRV has been further validated through prospective cohort studies, in which short-term HRV was identified as a strong predictor of long-term survival in patients undergoing chronic hemodialysis [6].

In addition to traditional signal processing techniques, machine learning–based methods have gained prominence in automatic arrhythmia detection and classification. Bayesian and complexity-measure-based detection frameworks have been proposed to enable robust real-time identification of abnormal cardiac rhythms [7], [9]. Recently, neural network–based approaches implemented directly on hardware platforms have demonstrated promising results in achieving low-latency and low-power operations. Chen *et al.* presented a Very Large-Scale Integration (VLSI) chip design utilizing a Data-Shifting Neural Network (DSNN) for abnormal heartbeat detection, highlighting the feasibility of deploying intelligent ECG analysis systems in resource-constrained biomedical devices [1].

2. Literature Review

Extensive research has been conducted on ECG signal processing and abnormal heartbeat detection using both traditional and advanced machine learning techniques. To ensure a dependable heartbeat analysis, it is crucial to identify the ECG characteristics, particularly the QRS complex, precisely. Chen *et al.* proposed a real-time QRS detection method that integrates moving-average filtering with wavelet denoising to suppress noise and baseline artefacts while maintaining a low computational complexity suitable for real-time biomedical applications [3]. The robust detection of specific abnormal beats has also been explored using probabilistic models. Sayadi *et al.* introduced a wave-based Bayesian framework for detecting premature ventricular contractions, demonstrating enhanced robustness against ECG morphological variability and noise [7].

Beyond feature detection, heart rate variability (HRV) analysis has been widely recognized as an important tool for evaluating cardiac autonomic regulation and predicting cardiovascular outcomes. Traditional spectral analysis techniques often suffer from performance degradation when applied to unevenly sampled heartbeat interval datasets. To address this limitation, Chen and Chao proposed a reweighted ℓ_1-minimization–based compressed sensing framework for HRV spectral estimation, achieving improved frequency resolution with sparse signal representations [4]. In further work, the same authors introduced an IPFM-based compressed sensing approach that more accurately models heartbeat dynamics and enhances HRV spectral estimation reliability [5]. The clinical relevance of HRV metrics was confirmed in a prospective cohort study by Kuo *et al.*, in which short-term HRV parameters were found to be significant predictors of long-term survival in patients undergoing chronic hemodialysis [6].

In recent years, considerable effort has been devoted to the real-time detection and classification of life-threatening cardiac arrhythmias. Chen proposed a complexity-measure-based sequential hypothesis testing approach that enables rapid identification of lethal arrhythmias with minimal computational overhead, making it suitable for real-time monitoring systems [9]. Machine learning approaches have further improved arrhythmia classification performance. Li *et al.* applied supervised learning techniques to distinguish between ventricular fibrillation and ventricular tachycardia, achieving high classification accuracy and robustness across diverse ECG conditions [8].

Recently, the focus has shifted toward hardware-efficient implementations that can support continuous ECG monitoring using wearable and implantable devices. Chen *et al.* presented a VLSI chip design utilising a Data-Shifting Neural Network (DSNN) for abnormal heartbeat detection, significantly reducing memory access and computational costs while maintaining reliable detection performance [1]. This study highlights the growing trend of integrating neural network–based algorithms directly into hardware architectures to achieve real-time low-power biomedical sign Extensive research has been conducted on ECG signal processing

3. Studies and Findings

The reliable identification of the QRS complex is a fundamental requirement for heartbeat segmentation and rhythm analyses. Chen *et al.* developed a real-time QRS detection technique combining moving-average filters with wavelet denoising, achieving robustness against noise and baseline drift while maintaining low computational complexity suitable for real-time implementation [3]. The classical Pan–Tompkins algorithm established one of the earliest and most influential real-time QRS detection methods using digital filtering, differentiation, and adaptive thresholding [10]. Further improvements have introduced adaptive baseline removal and morphology-based processing to enhance the robustness across diverse ECG conditions [13].

Heart rate variability (HRV) analysis has been widely used as a noninvasive measure of autonomic nervous system regulation and of cardiovascular health. Conventional Fourier-based spectral estimation techniques often perform poorly with unevenly sampled RR intervals. To overcome this limitation, Chen and Chao proposed a compressed sensing–based HRV spectral estimation using reweighted ℓ_1-minimization, enabling a high-resolution frequency-domain analysis with sparse sampling [4]. This approach was extended using an integral pulse frequency modulation (IPFM) model to better represent the physiological heartbeat dynamics and improve estimation reliability [5]. Clinical studies have further validated the diagnostic value of HRV metrics in various diseases. Kuo *et al.* demonstrated that reduced short-term HRV is strongly associated with increased long-term mortality in patients undergoing chronic hemodialysis [6], while the International Task Force guidelines have standardized HRV measurement and interpretation [14].

Significant progress has been made in the detection and classification of abnormal and life-threatening arrhythmias. Sayadi *et al.* introduced a wave-based Bayesian framework for robust detection of premature ventricular contractions, achieving improved performance in noisy environments [7]. Chen proposed a complexity-measure-based sequential hypothesis testing approach that enables fast real-time detection of lethal arrhythmias with minimal computational complexity [9]. Machine and deep learning techniques have further improved the accuracy of arrhythmia classification methods. Li *et al.* demonstrated effective ventricular fibrillation and tachycardia classification using supervised learning methods [8], whereas recent convolutional neural network–based approaches have achieved near-cardiologist-level performance, highlighting the potential of data-driven methods for automated ECG analysis [11], [15].

4. Challenges & Constrains

Despite significant advances in ECG-based detection of abnormal heartbeats, several challenges and limitations remain. ECG signals are highly susceptible to noise, baseline wander, motion artefacts, and electrode placement variations, which can significantly degrade detection accuracy in real-world and ambulatory environments [3], [10], [13]. The nonstationary and patient-specific nature of ECG signals further complicates the generalization of detection and classification algorithms [7], [8]. Although machine learning and deep learning techniques have shown high accuracy, their performance often depends on large labelled datasets and high computational complexity, limiting their applicability in real-time and resource-constrained systems [11], [15]. Additionally, HRV spectral analysis methods face challenges when dealing with unevenly sampled data and short recording durations, despite the improvements offered by compressed sensing approaches [4], [5]. From an implementation perspective, hardware constraints such as limited memory, power consumption, and processing capability pose significant challenges for wearable and implantable devices, requiring careful trade-offs between accuracy, latency, and energy efficiency [1], [12].

5. Future Scope

Despite significant advances in ECG-based detection of abnormal heartbeats, several challenges and constraints persist. ECG signals are highly susceptible to noise, baseline wander, motion artefacts, and electrode placement variations, which can significantly degrade detection accuracy in real-world and ambulatory environments [3], [10], [13]. The nonstationary and patient-specific nature of ECG signals further complicates the generalisation of detection and classification algorithms [7], [8]. Although machine learning and deep learning techniques have shown high accuracy, their performance often depends on large labelled datasets and high computational complexity, limiting their applicability in real-time and resource-constrained systems [11], [15]. Additionally, HRV spectral analysis methods face challenges when dealing with unevenly sampled data and short recording durations, despite the improvements offered by compressed sensing approaches [4], [5]. From an implementation perspective, hardware constraints such as limited memory, power consumption, and processing capability pose significant challenges for wearable and implantable devices, requiring careful trade-offs between accuracy, latency, and energy efficiency [1], [12].

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