ADDHard: Arrhythmia Detection with Digital Hardware by Learning ECG Signal

Sai Manoj Pudukotai Dinakarrao
George Mason University
Fairfax, USA
spudukot@gmu.edu

Axel Jantsch
TU Wien, Institute for Computer Technology
Vienna, Austria
axel.jantsch@tuwien.ac.at

ABSTRACT

Anomaly detection in Electrocardiogram (ECG) signals facilitates the diagnosis of cardiovascular diseases i.e., arrhythmias. Existing methods, although fairly accurate, demand a large number of computational resources. Based on the pre-processing of ECG signal, we present a low-complex digital hardware implementation (*ADDHard*) for arrhythmia detection. *ADDHard* has the advantages of low-power consumption and a small foot print. *ADDHard* is suitable especially for resource constrained systems such as body wearable devices. Its implementation was tested with the MIT-BIH arrhythmia database and achieved an accuracy of 97.28% with a specificity of 98.25% on average.

CCS CONCEPTS

• **Hardware → Full-custom circuits**; On-chip sensors;

KEYWORDS

Arrhythmia detection; FPGA Design; ECG analysis; Digital design

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1 INTRODUCTION

According to World Health Organization (WHO) cardiovascular disease (CVD) statistics 2015 [1], CVDs are the major cause of death globally. Hence, arrhythmia detection (anomaly in Electrocardiogram signal (ECG) acquired from heart) have gained interest among researchers and practitioners.

To perform arrhythmia detection, the structure and characteristics of an ECG signal have to be understood. An ECG signal obtained from each sensing lead reflects the behavior of corresponding part such as arteries, ventricles [6]. An ECG signal is a time series with few millivolts amplitude with a frequency of 0.01-250 Hz [20]. Figure 1 shows a pseudo ECG signal and highlights the five major components P, Q, R, S and T. Spatial and temporal properties such as time intervals, width of these components individually or when combined are used for arrhythmia detection, like variation in T component morphology, ST segment duration, and the R-R interval [6]. The terminology used in this paper to refer to ECG signal properties is defined below:

Component: The components of the ECG signal are the P, Q, R, S and T peaks.

Feature: Features of a component refer to its inherent characteristics such as time period, amplitude, width. For instance, R-R interval can be seen as a feature, similarly the width of the QRS complex, or the amplitude of the R peak.

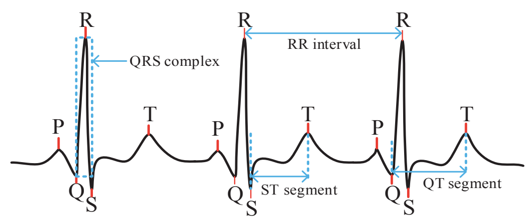

Figure 1: A pseudo ECG signal and its components

Despite of the progress achieved in component detection and feature extraction of ECG signal, Arrhythmia detection with low-complexity and area overheads remain unanswered.

1.1 Challenges in Arrhythmia Detection

Some of the challenges in the arrhythmia detection are: Symptoms of arrhythmia do not show-up all the time; Artifacts and noise from the mechanical components influence the accuracy of anomaly detection; and the characteristics of ECG signal vary among different persons and even vary for same person with time. Thus, there exists no standard rule(s) that can effectively fit everyone. Hence, arrhythmia detection needs to be carried out based on the ECG signal features (time period, amplitude and so on).

1.2 Contributions

We propose *ADDHard* (**A**rrhythmia **D**etection with **D**igital **Hard**ware) to perform arrhythmia detection and address the above mentioned challenges. The proposed method achieves an accuracy of 97.28% on average [12] and has a form factor that fits to be a body wearable device. The contributions of *ADDHard* are:

- A lightweight extracted features dependent analysis of ECG signal is carried out for arrhythmia detection. *ADDHard* circumvents the need for training phase or assumptions required to process ECG signal.
- *ADDHard* effectively detects sinus arrhythmias such as sinus bradycardia, sinus tachycardia, and atrial-ventricular fibrillations. Note, that the aim of this work is to detect the arrhythmia, rather than classification.

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2 RELATED WORK

A vast amount of research is carried out in arrhythmia detection, and a few relevant works are reviewed here.

For detecting arrhythmias, especially ventricular, R-R interval based techniques [13] are popular because of the large amplitude of the R peak. Based on the variations in R-R intervals, statistical parameters such as mean, variance are derived for R-R intervals and the presence of arrhythmia can be determined based on statistical parameter values. Additionally, techniques employing correlation [2], outlier detection [13] and other variants are proposed. Advanced predictors and regression techniques with high efficiency [8], such as auto-regressive integrated moving average (ARIMA) techniques are also used to detect the arrhythmia. These methods are prone to noises as they impact the outcome of regression.

Advancements in machine learning (ML) led to its use for arrhythmia detection. A three-layer feedforward neural network is proposed for arrhythmia detection in [3]. A generalized feedforward neural network trained with static back propagation to detect arrhythmia is proposed in [15]. For the ease of implementation on FPGAs, a block-based neural network (BbNN) structure is often chosen. In general, the BbNNs are trained using evolutionary algorithms such as genetic algorithms (GA). Hermite basis function is one of the efficient feature extraction methods for ECG signals [9]. A BbNN with Hermite expansion coefficients along with R-R intervals as inputs is proposed for ECG arrhythmia classification in [16]. Similarly, arrhythmia detection using different variants of neural networks have been proposed [11, 19]. Neural networks are efficient to detect and classify arrhythmias. However, most of them are computationally expensive due to floating point operations, and complex activation functions. Other ML techniques such as Support Vector Machines (SVM) have been employed for arrhythmia detection [17]. Irrespective of the ML technique used, in addition to the involved complex computations, the system needs to be trained every time a test needs to be carried out on a different person.

Compared to the existing works, *ADDHard* does not need to have an explicit training or specific assumptions about ECG signal or the patient, instead it extracts the features from components and uses them for Arrhythmia detection. In terms of complexity, *ADDHard* makes use of standard hardware blocks such as adders, and comparators; a smaller hardware foot print is sufficient.

3 PROBLEM AND SYSTEM DESCRIPTION

3.1 Problem Formulation

The problem of arrhythmia detection in an ECG signal can be divided into two sub-problems. To have an optimal usage of utilized resources, it is important to find the components of interest, extract and analyze their features for arrhythmia detection. As such, the first sub-problem is defined as:

Sub-problem 1: Detection of a set of components in the ECG signal efficiently, and extract the features of the components.

$$\begin{aligned} D &\subset I(x_1, x_2, ..., x_n) \\ C(D) &= features. \end{aligned} \tag{1}$$

Here, $I(x_1, x_2, ..., x_n)$ represents the input ECG signal, with x_i representing the ECG sample at i-th time instant. Detected components are given by D with extracted features as $C(D)$. .

Once the incoming ECG signal's features are extracted, the system needs to learn the behavior of the signal based on which it could analyze the ECG signal to detect the arrhythmia, which is the second subproblem.

Sub-problem 2: Differentiate the normal and abnormal patterns of ECG signal based on the previously extracted features and the features of ECG signal under test.

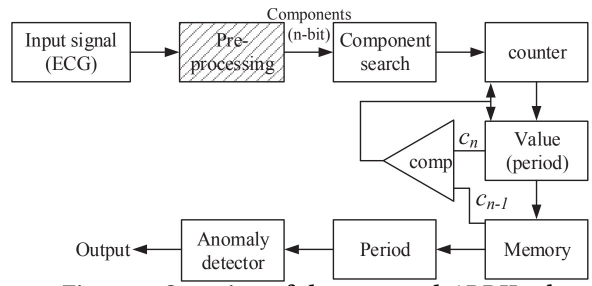

Figure 2: Overview of the proposed *ADDHard*

3.2 System Overview

The block diagram of the proposed *ADDHard* system is presented in Figure 2. The ECG signal is provided as input to the pre-processing block for noise removal and component detection. Functional description of pre-processing stage is presented in Section 4.1. Once the components are detected, they are digitally represented in the form of n-bits. It uses a simple look-up-table to represent the detected components. The component search block receives the digitally represented components from the pre-processing block and searches for a particular component (R component here). Once the component is found in the sequence, it activates the counter. The frequency of the component is found out using simple counters. This frequency or the time interval (c_n) between the components is transferred into the memory. Using the previously analyzed and stored features (c_{n-1}) and the extracted components of the ECG signal (c_n), the variations in features of the ECG and the presence of arrhythmia is signalled. This feature storing, comparing with previously analyzed features are carried out with the aid of standard comparators and registers. Further, this stored period or frequency keeps updating with the input. For better understanding, clock and reset are not shown in Figure 2.

4 PROPOSED ADDHard

Arrhythmia detection using *ADDHard* is performed in three steps, namely: pre-processing and component detection, feature extraction and updation, and signalling arrhythmia.

4.1 Pre-processing and Component Detection

To avoid processing and memory overheads, it is vital to find the components of interest, before extracting the features from a signal. Hence, we perform removal of noises such as baseline wandering, and component detection using *Discrete Wavelet Transform (DWT)* (on software). As wavelet analysis provides a good estimation of time-frequency localization, this method is considered for pre-processing and component (QRS) detection, based on implementation in [18]. Some of the major obstacles to accurate ECG analysis are the baseline wandering and 60Hz interference noise. These are initially filtered using the bandpass filters.

Wavelet transform is a convolution of the signal $f(t)$ with the wavelet function $\psi(t)$, given by

$$X_{j,j} = \int_{-\infty}^{\infty} f(t) \cdot \psi_{j,k}(t)dt \tag{2}$$

here, $(j, k) \in Z^2$. We use Daubechies wavelet (db6) as the mother wavelet and further perform QRS localization and detection using different coefficients. Daubechies wavelets have similar physical properties as QRS complex, hence can detect the QRS effectively. For pre-processing and component detection, the signal is decomposed into 8 levels ($d1$ to $d8$). Coefficients $d3$, $d4$, and $d5$ are used to identify the QRS complex and R components as the maximum points.

4.2 Feature Extraction and Update

Once the components are detected, it is essential to determine the features of detected components for further processing. In this work, the major features of interest are the amplitude, time interval, and period of the detected components. This extraction is performed using simple counters in Figure 2. A sample feature set will be like:

$$C(D) = \{t_{PP}, t_{QQ}, t_{RR}, ..., t_{QRS}\} \tag{3}$$

Here $C(D)$ represents the extracted features of the components; t_{RR} indicates the R-R interval in the ECG signal, and the same goes for Q-Q, P-P and QRS components. As such, the features are extracted without any assumptions or explicit training.

Once these features are extracted from the ECG signal, they are compared with the previously stored values and if they are similar i.e., have smaller difference, then it is stored in the memory for reference. We use t_{RR} as the feature in this work. To address the challenge of robustness and being prone to noises, the system monitors features for four consecutive cycles, and if there is no large deviation, an average is considered as the feature that will be used for reference. The rationale to consider four continuous cycles is, in ECG signals most of the irregular heartbeats (arrhythmia) can be detected by observing four consecutive cycles [6].

The characteristics of an ECG signal changes with time and hence needs to be monitored and updated. Update of these characteristics happens gradually in *ADDHard*. For every heartbeat, the features of incoming signal is analyzed and if it is similar to the stored features, an averaging operation is performed and the stored feature value is updated with this new average. Significant variations in the width or any distortion in morphology of an individual component is dealt in pre-processing stage and leads to different digital representation by the component detector. Thus, the *subproblem 1* of feature learning and updation is performed.

4.3 Signaling Arrhythmia

To perform the arrhythmia detection, *ADDHard* makes use of the extracted features from the signal. The arrhythmia detection block validates the features of incoming signal with the features that are stored in the memory. Unlike machine generated signals, biosignals will have some variances in the period, amplitudes. For instance, a peak can occur at 0.70s, followed by peaks after 0.69s and 0.72s. Hence, a tolerance is incorporated into this validation mechanism. When the time interval of a component is similar to the value stored in the memory, i.e., previously extracted feature, system does not signal anomaly and updates the stored value, i.e., feature update (as in Line 11 of Algorithm 1). However, when the stored feature value and the analyzed feature value of the incoming ECG signal differ significantly, i.e., more than tolerance, *ADDHard* signals anomaly.

For R-R feature, for example, the anomaly detection output can be mathematically given as

$$anomaly = \begin{cases} 0, & |St_{RR} - t_{RR}| < \varepsilon \\ 1, & |St_{RR} - t_{RR}| > \varepsilon \end{cases} \tag{4}$$

where St_{RR} represents the R-R time interval stored in memory and t_{RR} indicates the R-R interval of the beat under analysis. The tolerance is given by ε. The assumption of this process is that the anomalies do not occur at the beginning of the process. In case of anomalies in the first few samples, i.e., at the beginning of the setup, the intervals post anomaly will be used as the stored feature values are reset, i.e., there will be a slight delay in learning the features.

Thus, the *Subproblem 2* for ECG arrhythmia detection is solved using extracted and updated features from the ECG signal and circumvents the need for explicit training. Arrhythmia detection with *ADDHard* is summarized in Algorithm 1.

Algorithm 1 *ADDHard* for arrhythmia detection in ECG Signal

Require: ECG signal from sensor ($I(x_1, x_2, ..., x_n)$)
Ensure: Arrhythmia detected or not signal $anomaly$

1: **Component Detection:** $DWT(I)$ as given in (2) using Daubechies wavelet
2: Obtain QRS complex, as in Section 4.1
3: **Feature Extraction** using counters, as in Section 4.2
4: For next cycles, extract the features, $C(DD)$
5: **if** $|C(DD) - C(D)| < \varepsilon$ **then**
6:     anomaly ← '0'
7:     **update();**
8: **else**
9:     anomaly ← '1'
10: **end if**
11: **update(){**
12:         $St_{RR} \leftarrow (St_{RR} + t_{RR})/2$ }

5 SIMULATION RESULTS

5.1 Simulation Setup

The simulations and synthesis are performed in Xilinx Vivado. MIT-BIH Arrhythmia database from PhysioNet [12] is used for periodicity detection simulations. Each ECG record is of 30 minutes duration and the pre-processing, i.e., component detection using discrete wavelet transform is performed in Matlab, and digitized to 8-bit data. A 10-bit counter is used in simulations. The tolerance for validation, i.e., ε is set to 15% of the corresponding feature. This value is chosen based on different evaluations to yield best accuracy.

We extracted the power and area information from Design compiler tool for Global Foundry (GF) 65 nm node. *ADDHard* occupies an area of nearly 158.04 μm^2 and consumes nearly 18.69 μW dynamic power. The above mentioned area and power does not include the component detection in Matlab. However, some of the ASIC implementation for pre-processing and component detection algorithms like Pan-Tompkins is presented in [5]. It is reported to have an area of nearly 74,000 μm^2 (0.07 mm^2) for 65 nm CMOS technology for pre-processing. This makes the whole system's are i.e., pre-processing and *ADDHard* less than 0.1 mm^2, which is an ideal fit for body wearable device.

5.2 Component Detection

As *ADDHard* relies on extracted features of the signal from the detected components, it is non-trivial to evaluate the component detection performance as a first step. Hence, we compare the utilized discrete wavelet transform based component detection with the widely used Pan-Tompkins algorithm. The annotations that are required to derive the conclusions are taken from the MIT-BIH database. Both techniques are run on MATLAB for component detection. Table 1 presents the comparison results in terms of false positive and false negatives. One can observe that both of the techniques perform similarly good, but employed DWT technique slightly outperforms the Pan-Tompkins algorithm based component detection.

Table 1: Component Detection Performance

Parameter	DWT	Pan-Tompkins
False negative (%)	0.75	1.40
False positive (%)	0.47	0.47

5.3 Arrhythmia Detection

The arrhythmia detection performance of the proposed *ADDHard* is summarized in Table 2. *ADDHard* has an accuracy of 97.28%, specificity of 98.25% and sensitivity of 78.70%. Sensitivity indicates the percentage of sick people who are correctly identified as having arrhythmia and specificity indicates the percentage of healthy people who are identified as healthy. A low sensitivity is achieved due to more number of false negatives resulting from the existence of fusion beats (which resembles QRS complex), bigeminy and trigeminy ventricular rhythms. However, critical arrhythmias like Atrial and Ventricular premature contractions are efficiently detected.

Table 2: Arrhytmia detection performance of *ADDHard*

Accuracy	Specificity	Sensitivity
97.28%	98.25%	78.70%

5.4 Comparison

Table 3 compares our results (Accuracy and Specificity) with respect to several published works.

Table 3: Arrhythmia detection performance

	Acc.	Spec.	Note
ADDHard	97.28%	98.25%	Extracted features based analysis
[4]	70.00%	-	Bayesian classifier
[11]	98.10%	99.78%	Probabilistic ANN
[14]	99.00%	-	Beat-filtering and matching
[3]	98.60%	-	3-layer Feedforward NN
[19]	98.80%	99.96%	BPNN
[16]	97.35%	98.8%	Evolvable BbNN
[7]	93.20-99%	-	FCM-PCA-NN

One can observe that our method performs on par with some of the existing works, but neural network implementations are superior in terms of accuracy. However, the difference is limited to 2.5%, and our method does not need training in a clinical environment. Further, *ADDHard* extracts the features from the detected components, and does not require training with patient specific data. Hence, it is more generic. The number of operations involved are less complex and smaller in number compared to a neural network implementation, at the cost of slight reduction in accuracy. Some wearable devices for arrhythmia detection are proposed in [10, 13]. They sense the ECG signal and transmit the partially processed data to a remote end for further processing, which implies higher overhead in terms of power consumption due to more communication. In case of *ADDHard*, the circuit can off-load the communication load of the wearable device by avoiding continuous transmission of the data. Instead, it can be configured to transmit only when an arrhythmia is detected and at periodic instants (considerably less frequent than in traditional devices) for verification by the physician or analyst. This will bring additional power savings due to significantly lower communication needs.

6 CONCLUSION

In this work, a digital implementation for arrhythmia detection, *ADDHard* is proposed. *ADDHard* makes use of the extracted features to perform the arrhythmia detection. The extracted features are also updated to cope with changes. The benefits of *ADDHard* comes from its lightweight hardware footprint, less complex computations and no need of explicit training. As such it is a more generic ECG signal analyzer. *ADDHard* was tested on MIT-BIH Arrhythmia database and achieved an accuracy of of 97.28%. *ADDHard* occupies an area of 158.04 μm^2 and consumes 18.68 μW power in a 65 nm GF process CMOS node (excluding pre-processing).

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