A Wearable Long-Term Single-Lead ECG Processor for Early Detection of Cardiac Arrhythmia

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Abstract— Cardiac arrhythmia (CA) is one of the most serious heart diseases that lead to a very large number of annual casualties around the world. The traditional electrocardiography (ECG) devices usually fail to capture arrhythmia symptoms during patients' hospital visits due to their recurrent nature. This paper presents a wearable long-term single-lead ECG processor for the CA detection at an early stage. To achieve on-sensor integration and long-term continuous monitoring, an ultra-low complexity feature extraction engine using reduced feature set of four (RFS4) is proposed. It reduces the area by >25% compared to the conventional QRS complex detection algorithms without compromising the accuracy. Moreover, RFS4 eliminates the need for complex machine learning decision logic for the detection of premature ventricular contraction (PVC) and nonsustained ventricular tachycardia (NVT). To ensure correct functional verification, the proposed system is implemented on FPGA and tested using the MIT-BIH ECG arrhythmia database. It achieves a sensitivity and specificity of 94.64% and 99.41%, respectively. The proposed processor is also synthesized using 0.18um CMOS technology with an overall energy efficiency of 139 nJ/detection.

I. INTRODUCTION

Cardiac arrhythmia (CA) is a malfunction in the electrical impulses in the human heart causing irregular heartbeat rhythms [1]. The most severe case of CA occurs when these irregular rhythms originate in the bottom chambers of the heart, the ventricles, known as ventricular arrhythmia (VA). VA accounts for ~0.3 million annual deaths in the US only [2]. More than 80% of VAs are caused by the coronary heart disease, hypertension, or cardiomyopathy. VA is classified into premature ventricular contraction (PVC), Ventricular Tachycardia (VT), and Ventricular Fibrillation (VF). PVC can be considered as an early alarm for the patient of being at higher risk of developing VT or VF if left untreated. VT is an abnormal Electrocardiogram (ECG) rhythm consists of unifocal or multifocal PVCs [3] which can lead to sudden death [4]. VT is divided into two types based on its duration; the Non-sustained Ventricular Tachycardia (NVT) and Sustained Ventricular Tachycardia (SVT). NVT is referred as 3 or more consecutive PVCs with a peak-to-peak (RR) interval of < 600ms or 100 bpm (beats per min) [5]. Frequent PVCs are associated with higher risk of instance strokes and deaths [5]. Failing to timely detect, diagnose, and treat an NVT/PVC, may lead to sudden death [1]. Currently, there is no patient-friendly early detection solution for this alarmingly CA disease. This paper proposes an early NVT/PVC detection system to take preemptive measures that will potentially lead to saving human lives.

In the current medical practice, the cardiologist adopts the ECG signal recordings and patient's questionnaire for the initial evaluation of the patient's condition. However, this approach may fail to capture the severity of the disease due to the limited duration of ECG recordings and the intermittent nature of CA. To resolve this issue, a long-time continuous monitoring is required to record the abnormal ECG activities for CA cases. For this monitoring system, utilizing the wireless link for continuous transmission of ECG recordings is not an energy–efficient solution that severely impacts the monitoring [6], [7] . Signal compression can be a solution to reduce the huge amount of transmission data [8], but the large compression ratio degrades the signal quality. Ref [9], [10] extract and transmit specific features like R peaks or interval, to lower down transmission power which severely impacts the correct diagnosis. Moreover, both solution requires continuous interaction between data acquisition unit (Real-time ECG) and expert unit (Cardiologist). An alternative and promising approach is to adopt the on-sensor processing that includes extracting the key features of ECG and detecting the NVT/PVC. This approach reduces the energy requirements of the system and provides timely detection of CA.

A prime factor in detecting NVT/PVC in real-time ECG depends on the correct selection of the minimum set of features corresponds to CA. Therefore, having a reduced feature set along with low-complexity detection processor is very crucial for energy efficient operation. This paper proposes a reduced feature set of 4 (RFS4) features for CA detection. Figure 1 shows the proposed wearable ECG System on Chip (SoC) for the timely detection of CA. The main focus of this work is the ECG processing part for CA features extraction and detection.
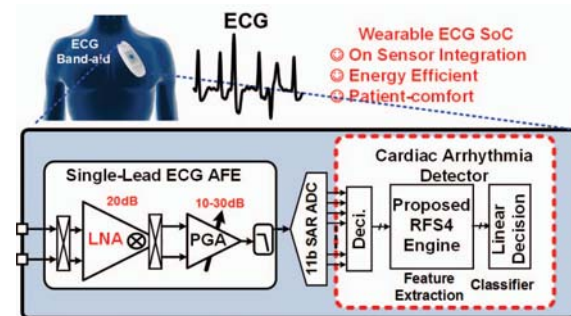

Figure 1. Proposed wearable ECG SoC for Cardiac Arrhythmia Detection

II. SYSTEM OVERVIEW

The accurate classification usually involves two parts, features extraction, and classifier [11]. A wide range of feature sets have been devised in past decades, e.g. spectral [12], temporal [13] and complexity measure [14]. For higher accuracy machine learning techniques like neural networks [15] and support vector machine (SVM) [16], [17] have been

used. Although these algorithms exhibit high classification accuracy for the PVC and NVT but at the expense of extremely high computational power and huge hardware resources. Moreover, the classifiers based on the neural networks and SVM often require high storage capacity for the data buffering and processing which further elevates system power consumption.
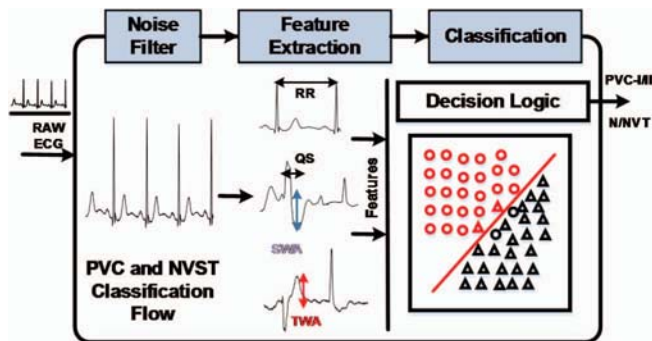

Figure 2. Generic flow of ECG classification system with focus on proposed features.

A. Recent Trends

Several biomedical signal processors have been devised for accurate ECG analysis and classification in real time. The main target is to reduce the power consumption for longer battery life and achieve small form factor for the wearability. Ref [18] utilizes low power ECG acquisition system along with off-sensor field programming gate array (FPGA) for various heart disease identification. The time-domain morphological analysis is used for the feature extraction and classification; detection performed on the basis of ST segment. High classification accuracy (96.6%) was achieved but not suitable for real-time implementation due to the predefined fixed window size for the localization of S and T fiducial points. A cardiac sensor SoC was designed for multiple cardiac syndrome detections using ECG [19]. Significant features were extracted and multiple classifiers were adapted to improve the classification accuracy to 95.8%. In addition, power gating and voltage scaling techniques were used to reduce the leakage power, but large memory utilization led to overall high system power consumption of 20.1 µW.

Ref [20] and [21] target application specific integrated circuits (ASIC) design with wireless transmission to reduce the power consumption. An invasive atrial fibrillation detection has been proposed with hardware and software optimization to reduce the area and power consumption [20]. Moreover, fully integrated low-power processor is designed to predict VA at least three (3) hours before the electrical onset [21], but the results are simulation based and achieves low prediction accuracy for the VA.

B. This Work Contribution

This paper proposes a low power ECG processor for PVC and NVT detection for on-sensor monitoring systems. Both algorithm and architecture are optimized to improve the power efficiency. Feature selection is in-direct relation with the detection complexity and classification accuracy,

therefore thorough analysis is conducted to compute the desired features. In this work R-R interval, Q-S interval and S wave amplitude (SWA) are utilized to completely describe the QRS morphology and T wave amplitude (TWA) is selected for the electric instability of the heart. Most of the previous works [15]-[21], faced significant power consumption issues due to the addition of machine-learning classifier. Therefore, in this work four robust features with thresholds are utilized to classify the beats into normal and PVC without any machine-learning classifier. The same classified beats are used to detect the NVT rhythm. To achieve energy-efficient implementation, a small moving average window has been used and real-time classification of beats is performed with every incoming beat. In addition, no training data is required for the classifier therefore small buffer (1KB) is used instead of large-sized memory which further enhances the energy efficiency.

III. REDUCED SET OF FOUR (RFS4) CLASSIFICATION

The proposed system is helpful in early diagnosis of the small-scale myocardial infarction; death of heart cells and helps cardiologist to treat a patient in early stages. Every incoming PQRST beat is immediately classified based on the simple and adaptive thresholds. Moreover, due to reduction in power consumption (battery-life will enhance) the proposed system is suitable candidate for the on-sensor ECG analysis; hence facilitates long-term ECG data acquisition and processing.

The proposed system consists of three main stages of ECG noise filtering, feature extraction, and classification as shown in Figure 2. In the ECG noise filtering; the incoming ECG signal is processed through filters and moving window integral to remove the ADC noise and additional unwanted signals. In the feature extraction, the four features are extracted from the clean ECG signal and grouped together to formulate a unique set of four. The classification section utilizes the feature set along with the simple and robust threshold-based decision logic to classify the ECG signal. The thresholds vary from person-to-person, therefore self-adaptive mechanism is proposed to make them robust against amplitude or beat-frequency variations. The beats which satisfy PVC conditions are recorded as abnormal and other beats are normal. NVT rhythm is detected based on the continuous occurrence of the PVC pattern. If more than three (3) continuous PVC's are registered, then the pattern is classified as NVT and other rhythms are registered as normal. The proposed classification successfully replaces the machine learning algorithm requirement and reduces the computation load on the system.

A. Feature Depiction

Features selection and extraction are both equally important for effectiveness and performance of the classification system. Moreover, the feature dimensionality directly effects the memory requirement and the power consumption for any processing system, therefore intelligent choice of features results in robustness and fidelity of the system.

This work focuses on an optimized RFS4 implementation. Interval information has been proven to be the most used for

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the last few decades in differentiating the PVC beats from the normal beats [22]. The PVC appears earlier than the normal beats with smaller RR interval [6], therefore can be treated as a sufficient condition for the PVC detection.
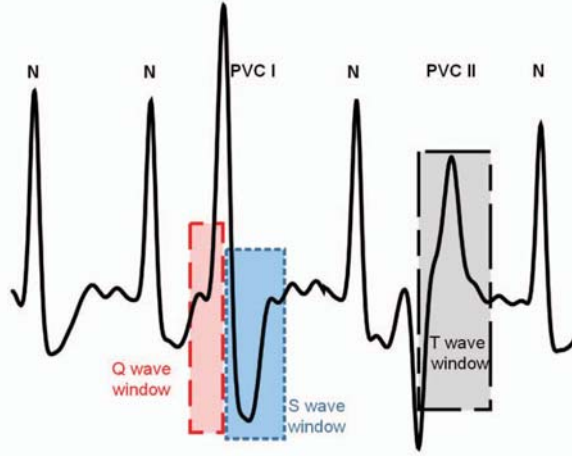

Figure 3. PVC types and formulation of search windows for features extraction.

Furthermore, PVC type I beats have a wider QRS complex and usually ends with a gentler slope along with a QRS followed by ST-segment depression [23], therefore, QRS behavior is an important feature for the correct PVC detection. Hence QS interval is calculated to represent the wider QRS complex and S-peak to show ST segment depression. The 4th feature TWA is to detect the PVC type II which has normal but negative QRS complex followed by a high TWA. Both PVC I and PVC II are depicted in the Figure 3. The selected RFS4 don't require any further principal component analysis (PCA) for dimension reduction, therefore, an additional computational power is saved. The main advantage of these features is they ensure multifocal PVC detection. The extraction of the feature set is based on R peak location and all other waves are calculated relatively.

IV. HARDWARE ARCHITECTURE

The hardware architecture of the proposed processor is shown in the Figure 4. ECG data with a sampling frequency of 360 Samples/sec from the ADC with 11-bits resolution, is processed in the proposed system for preprocessing, feature extraction and classification. Small RAM of size 1 KB is used to maintain the noise-free data of previous two seconds. The data is fed to an expert system which extracts features and provides features set to decision logic.

A. Signal Preprocessing

Power-line interference, baseline wander, muscle artifacts and electrode motion artifacts are some noises added in ECG data acquisition stage. Thus, noise cancellation is necessary before feature extraction. We used band pass filtering for raw ECG signal to isolate predominant QRS energy usually centered at 10 Hz. Cascade of LPF and HPF is used with cut-off frequencies of 0.5 Hz and 10 Hz respectively.

B. Feature Extraction

1) Peaks Detection:

The state logic algorithm is implemented as shown in the Figure 5. The algorithm works on thresholds and slope changes in search windows. In state zero, mean of 2 seconds absolute and real data is calculated for R wave and T wave adaptive thresholds, named $BUFF_{MEAN}$ and $BUFF_T$, respectively, which are used for real-time calculation of R and T wave thresholds.

$$BUFF_{MEAN} = \frac{\sum_{k=0}^{n} |X(k)|}{n} \qquad (1)$$

$$BUFF_T = \frac{\sum_{k=0}^{n} X(k)}{n} \qquad (2)$$

Where k is an integer variable varying from 0 to n, n is twice the sampling frequency, and $X(k)$ is the incoming filtered EEG data.
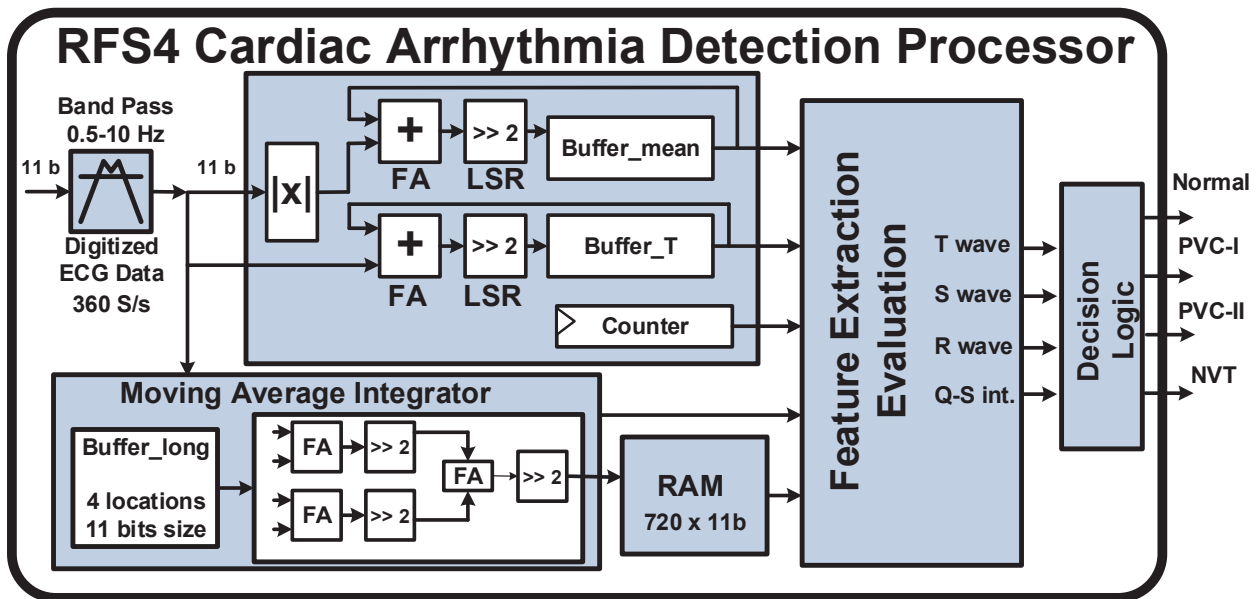

Figure 4. Architecture of proposed processor.

Further, moving average integral with a window size of 4 samples, named as Mean$_{ONLINE}$, is used to improve signal quality, which can be varied. The Smaller window size is used to reduce latency and computational load while not compromising on signal quality.

$$TH_R = BUFF_{MEAN} \times Weight \qquad (3)$$

$$Mean_{ONLINE} = \frac{\sum_{k=0}^{r} X(k)}{r} \qquad (4)$$

Where TH_R has used R wave detection, Weight is a patient-specific integer value with a nominal value of 2, and r is the window size used in the algorithm for a specific patient. To avoid large RAM size only last two seconds data is saved. After every two seconds, RAM is flushed keeping most recent 30 samples for keeping system pipeline working. After calculating R wave adaptive threshold, if online mean exceeds this threshold state is changed to R wave detection. Slope change with local maxima or minima is detected and registered as R wave. Search window for Q wave is created from R wave location to 0.1s before. This approach makes Q wave detection non-descriptive and fixed search windows like [18] are avoided for both Q and S waves. In this search window, the local minima with negative slope change is reported as Q wave. After Q wave detection if QRS is positive system moves to S wave detection. Search window of 0.4s after R wave location is used for S wave; negative slope change in this window is recorded as S wave. After successful S wave detection, the adaptive threshold for T wave is calculated; which is updated on every successive system iteration.

$$TH_T = BUFF_T - |S_{PEAK}| + \left(\frac{3}{4}\right) \times |S_{PEAK}| \qquad (5)$$

TH$_T$ is the T wave threshold and S$_{PEAK}$ is the amplitude of latest detected S wave. The system is put on sleep after T wave until next QRS complex appears, to save computations and improving system power efficiency. At each upcoming QRS complex, both thresholds for R and T wave are updated and further calculations are performed on the base of these adaptive thresholds.

2) Feature Set Extraction
After the successful recording of peaks novel morphological features like RR and QS interval are calculated. Last RR interval (LRRI) is calculated keeping in count whether R peak is positive or negative. Last QS interval (LQSI) is defined as the QS interval of the last QRS complex and ST segment depression. These two features combine with S and T peaks to form Feature set for decision logic. On the basis of this robust feature set normal and PVC beats are differentiated; which further classify rhythms into normal and NVT for proper detection.

C. Decision Logic
Based on feature set devised in previous state, decision logic firstly classifies beats using thresholds instead of machine learning techniques. In the decision logic, detection is performed with simple and adaptive but robust thresholds which update after every four successive QRS complexes.

$$TH_S = \frac{\sum_{l=0}^{m} S_{Detect}(l)}{m} \qquad (6)$$

$$TH_{QS} = \frac{\sum_{l=0}^{m} \{Q_{Detect}(l) - S_{Detect}(l)\}}{m} \qquad (7)$$

Where, TH$_S$ is used in the decision logic, TH$_{QS}$ is mean of four consecutive QS intervals, represented by m, used in PVC detection, Q$_{DETECT}$ and S$_{DETECT}$ are locations of Q and S wave to calculate a number of samples between Q and S wave for finding QS interval.
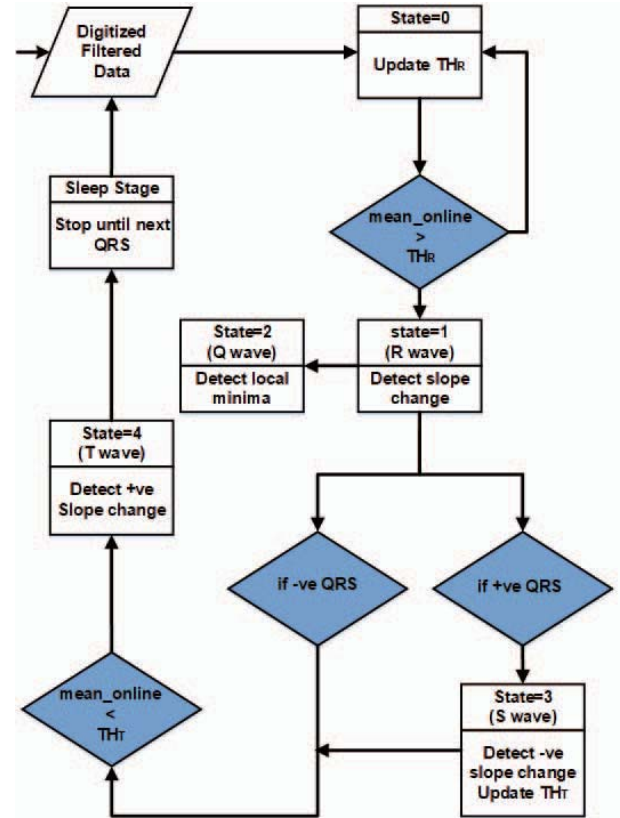

Figure 5. State logic diagram of the algorithm.

All forms of PVC have relatively very smaller RR interval, almost half, as compared to normal beats, therefore, it's taken as a basic parameter for detection. Furthermore, one form (PVC I) has wider QRS with positive R peak; followed by ST-segment depressing with a gentler slope, and other (PVC II) has negative R peak followed by high TWA. Hence for successfully differentiating both forms of PVC, we need different parameters because of morphology difference.

Since both PVC forms have the unique feature of smaller RR interval so, last RR interval (LRRI) is used for basic judgment. RR interval for the positive QRS complex is represented by variable name P-LRRI and similarly N-LRRI is used for the negative QRS complex. For PVC I, TH$_S$ and TH$_{QS}$ are used together to test if wider QRS and ST segment depression exist forming LQSI. While in PVC II, high (HTWA) is detected when TWA is greater than TH$_R$

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represented by a variable. The total of four variables is used for multifocal PVC detection. $LQSI_V$ and $LQSI_N$ are the boundaries of LQSI for PVC and normal beats respectively. Likewise, other variables also have decisions boundaries as shown in Figure 6.

All these parameters are estimated during online processing on ECG data. They separate 2D plane into two regions, normal and PVC beats. If a positive QRS complex appears with P-LRRI value less than $P\text{-}LRRI_V$ and LQSI exceeds $LQSI_V$, which satisfies PVC I characteristics, and the beat is classified as PVC I. Similarly, if a negative QRS is registered with N-LRRI less than $N\text{-}LRRI_V$ and the HTWA is greater than $HTWA_V$, the beat is classified as PVC-II. Each upcoming PVC triggers the NVT mode on and the number of PVC beats appears consecutively is calculated. If more than three PVC beats appear together rhythm is classified as NVT otherwise normal.
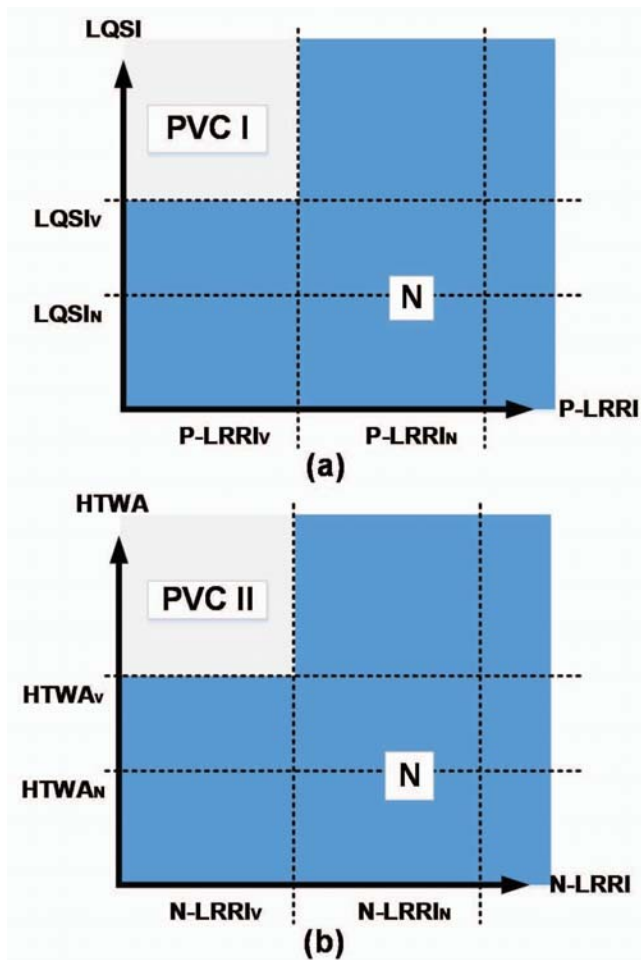

Figure 6. Decision rule based on (a) LQSI, P-LRRI for detection of PVC I from normal (N) beats and (b) N-LRRI and HTWA for detection of PVC II from normal (N) beats.

V. PERFORMANCE AND RESULTS

A. Implementation

The proposed RFS4 CA detection processor is synthesized using the 0.18μm process to compute the energy efficiency of the system. To measure the real-time performance and working, the complete implementation is also done on the FPGA. The overall power consumption of the RFS4 processor is 5.04μW @ clock speed of 1 KHz. MIT BIH arrhythmia database [24] is used for a testing proposed system having ECG data of 11 bits-resolution sampled at 360 Samples/s. Records with more proportion of PVC beats and NVT appearance are chosen for the testing. For each record whole record of duration 35 min each is fed into the system and classification results are determined.

B. Classification Accuracy

Detection performance for simple decision logic without any machine learning algorithm is tested; an average sensitivity (Se) and specificity (Sp) of 94.64% and 99%, respectively, is achieved for PVC, whereas an accuracy of 100% is reported for NVT detection.

Figure 7 shows the accuracies of individual patients in the database. Some of the patients with record number 119, 203, 221 and 233 are classified with 100% accuracy even for PVC. The patient record 203 is the noisiest among all records [23], but due to the proposed adaptive and robust proposed classification system high accuracy is achieved even on this record compared to the [21].
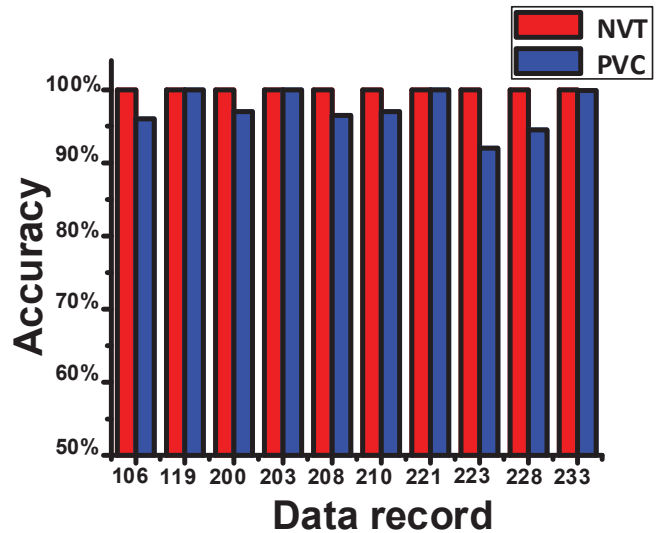

Figure 7. Classification accuracy of an adaptive threshold based decision logic.

C. Comparison against Previous Works

The detection performance of the proposed system is comparable to the state of the art-works of [25] and [26], while using much less number of feature set. The feature set in the proposed implementation is similar to that in [27] with slightly improved specificity and without utilization of any machine learning classifier.

Table I shows the comparison of the proposed system with the state of artworks. The proposed work achieves better classification accuracy than machine-learning based [19], [21], and comparable performance to the [28] by using simple threshold-based logic with power consumption of 5.04uW @ clock frequency of 1KHz..

VI. Conclusion

An energy-efficient CA processor is presented for PVC and NVT detection using ECG data. Only single-lead ECG is used to perform the detection, without using any machine learning classifier; instead, a decision logic based on adaptive thresholds is used for classification. Four novel morphological features, which simplifies computations for both feature extraction and classification, reduces overall system power consumption. Despite using simple decision logic instead of classifier a comparable accuracy of 97.02% is achieved. The RFS4 processor is synthesized using 0.18um CMOS process with an energy usage of 139nJ/detection.

Table I. Comparison with the state-of-the-art-works ECG implementations.

	S. Y. Hsu et al. JSSC'14 [19]	S. Y. Lee et al. JBHI'15 [28]	N. Bayasi et al., TVLSI'16 [21]	This Work
Technology (nm)	90	180	65	180
Supply Voltage (V)	0.5	1.2	1.0	1.0
Area (mm^2)	4.989	2.465	0.112	NA
Classifier	Machine Learning	MCS	Naive Bayes	Threshold-based
Frequency (Hz)	25M	120	10K	1K
Power (uW)	20.1	5.97	2.79	5.04
Accuracy (%)	95.8	97.25	86.0	97.02
Type	SoC	SoC	ASIC	SoC

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