

# Design of Low Power ECG Prediction Processor for Ambulatory Ventricular Arrhythmia

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**ABSTRACT:** Cardiac arrest is quoted as the major contributor to the unforeseen death rate around the race. A system that warns the person about the onset of disorder in prior automatically is a boon to the terrene. This is achievable by deploying advances in technology to the previous and existing patient monitoring system. The proposed work presents a novel method in high level prediction of Ventricular arrhythmia to find out all the fiducial points using Electrocardiogram Signal Processor (ESP) with onset recording of the electrical activity of the heart beats over by implementation signal of ESP with unique set of features classified by Naïve Bayes classifier. A real time adaptive technique for detection and delineation on the P-QRS-T waves and boisterous with any variations in the ECG signals are to be investigated with high sensitivity and precision. To evaluate the performance of the processor database of the heart signal were obtained from MIT-BIH Arrhythmia. Based on the Field Programmable Gate Array (FPGA) simulation results, the overall classification accuracy was found to be 98% on the out-of sample validation data. The PAT algorithm modifies the delineation and thereby finding out the intervals of P-QRS-T peak sets. The proposed architectural method is designed in VHDL and simulated in Modelsim, and synthesized in Xilinx FPGA S6LX9, and also analyzed the logic size, area and low power

**KEYWORDS:** Electrocardiogram (ECG), Low power, Field Programmable Gate Array (FPGA), P-QRS-T wave, Classifier

## I.INTRODUCTION

Cardiovascular disease kills almost seventeen million people around the globe each year along with twenty million people at a risk of sudden heart failure. An ECG is a recording of the electrical activity on the body surface generated by the heart. ECG measurement information is collected by electrodes placed at designated locations on the body. Most ventricular arrhythmia is abnormal heart rhythms of persons that originate in the bottom chambers of the heart called the ventricles. These rhythms can occur as results of damage to the heart muscle from a heart attack or cardiomyopathy. A normal heart rate is 60 to 100 beats per minute at rest. Ventricular tachycardia is faster than normal heart rate that begins in the heart's lower chambers. [1] "Towards the ECG data signals with onset of Ventricular Arrhythmia Prediction signals prediction over detection for Heart attack," Physionet is a publicly available repository of physiological signals such as MIT-BIH MALIGNANT Ventricular Arrhythmia, using this data base to test the signals of Ventricular Arrhythmia in this paper. All training and validation are approved and performed on ECG data base available.

## II.RELATED WORK

The Implementation of ECG based Arrhythmia has been considered the best protection against of sudden death from ventricular arrhythmias in high risk patients. Long term of ECG monitoring is the criterion standard for the diagnosis of ventricular arrhythmia. By extracting and monitoring the intervals, amplitudes and waveform morphologies of the different P-Q-R-S-T waves, the on-set of the ventricular arrhythmia can be detected. [3] "A Low-Power ECG based Processor with High Configurable Embedded Machine Learning Accelerators for High-

Order and Adaptive Analysis of Medical-Sensor Signals,” The specific design features the following existing technological advances in detection over arrhythmias:

1) Dynamic model adaptations are enabled in the background through a hardware accelerator for embedded active learning. This enables scalable patient-model customization by minimizing the burden on human experts. An in-place algorithm for active learning enables hardware sharing for kernel functions by minimizing the overhead of context switches in the presence of real-time detection.

2) Medical applications and algorithms are implemented and tested (using clinical datasets), showing the use of the processor for continuous, patient adaptive monitoring within a network (via a Radio frequency interface)

### III.REAL TIME DETECTION

The previous design is a life savior of patients who are susceptible to ventricular arrhythmia by alerting them for immediate attention to their medical condition with aims to design and develop the integrated biomedical processor that is capable of acquiring ECG signals from the heart along with processing and analyzing it on the same chip without any external interaction as shown in Fig.1. Thus the patient would have the immediate alert of his/her situation to be very important, especially in critical situations. Many algorithms and methods for the automatically generating ECG feature extraction and determination of scaled features depended on uniqueness is specified with QT interval measurement in particular have been already developed. However, the formalization of the QT interval measurement process remains insufficient and requires further investigation [4]. As the preparation for the detection of the ECG features, the ECG signal is filtered and differentiated. The Previous patient monitoring system architecture predominantly consists of three main stages, which are the ECG preprocessing, feature extraction, and classification, as shown in Fig.1. In the first stage, the ECG preprocessing is responsible for three tasks:

- 1) ECG filtering(Bandpass);
- 2) QRS complex detection(PAT);
- 3) T and P wave delineation(Naïve Bayes algorithm).

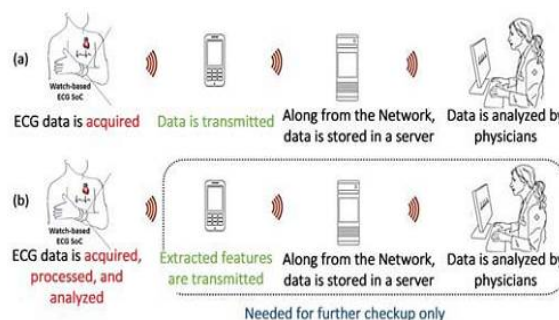


Fig.1 Comparison between (a) commonly implemented system and (b) Proposed system

The ECG filtering removes the noise coupled with the ECG signal and prepares it for further analysis. After that, the QRS complex is detected using the Pan and Tompkins (PAT) algorithm. The feature extraction consists of two main steps: the detection of characteristic points (QRS complex or rather R peak, P wave peak and T wave peak) and the determination of the waveform boundaries (on- and offsets). Finally T and P wave are delineated, and the corresponding fiducial points (P onset, P peak, P offset, T onset, T peak, and T offset) are extracted. In the second stage, the intervals to be find out between the fiducially points and they are RR, PQ, QP, RT, TR, PS and SP intervals. In the final stages, naïve Bayes algorithm is used to identify the signals that are susceptible to

ventricular arrhythmia, and find out the attach with simplest classification method that can be easily implemented in Hardware [1],[8],[10].

#### IV. PROPOSED DESIGN OF ECG BASED PROCESSOR

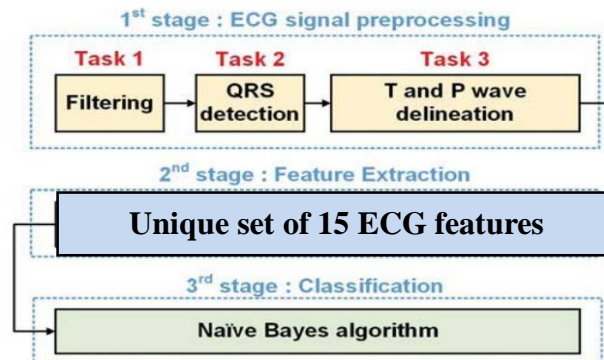


Fig.2 Proposed System representation with T, P, Q and S wave delineation of ventricular arrhythmia prediction system.

In the proposed method, of ventricular arrhythmia of preprocessing the delineation point to be added compare to existing system, such as the delineation point in existing system of T and P wave, its requires the first the detection of QRS complex. This is done using the algorithm proposed by Pan and Tompkins (PAT) which consists of filtering, differentiating, squaring and averaging of the ECG signals [12]. This delineation point to be added with T, P, Q and S, is based on novel technique proposed system method. The data is to identify based on adaptive search windows along with adaptive thresholds to accurately distinguish T and P peaks from noise peak. In each heartbeat, the TPQRS complex is used as a reference for the detection of T, P, R, Q, S waves in which two regions are demarcated with respect to R peaks. The region are then used from the forward and backward search windows of the T, P, Q and S waves, respectively, as shown in Fig.3. The ECG data need to identify the lowest peak in the heart beat testing of unique feature extraction.

#### V. PREDICTION OVER DETECTION

The Finite state machine of ECG based processor, is initialized on “LOAD samples”, this data will be taken from test bench, of Physionet MIT-BIH data set of hexadecimal values, to be loaded at the speed of 100 Hz, once the data ready will be high, the data will be given to ECG filtering. The ECG filtering preprocessing stage will be designed Band pass filtering of the raw ECG signal is the first step in which the filter isolates the predominant QRS energy centered at 10Hz, and attenuates the low frequencies characteristic of the P, Q, T and S waves baseline drift, and higher frequencies associated with electromyographic noise and power line interference. The main important point is not to lose the information carried by the ECG signal after being filtered out. The difference equations of the cascaded LPF and high-pass filter (HPF) are given in (1) and (2), respectively. The cutoff frequency of the LPF filter is 11 Hz, and it introduces a delay of six samples, whereas the HPF has a cutoff frequency and delay of 5 Hz and 16 samples, respectively. The coefficients of the filters are all integers it generated from FDATool on MATLAB, and the filter architecture of LPF and HPF of Finite impulse response (FIR) is shown in Fig

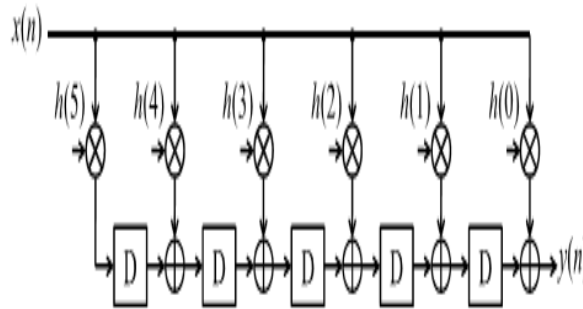


Fig.3 Finite impulse response (FIR) design of LPF and HPF

QRS Detection, to detect the complex QRS values of PAT method, which is based on the amplitude threshold technique exploiting the fact that R peaks have higher amplitudes, compared with other ECG wave peaks. With proper filtering of the signals, the method is highly capable of detecting the R peaks in every heartbeat using two threshold levels. After filtering, the PAT algorithm is decomposed into four steps. Differentiation of the filtered signal is used to distinguish the QRS complex from other ECG waves by finding high slopes. Then, a nonlinear transformation is performed thorough point-to-point squaring of the filtered ECG signal in which it is important to emphasize the higher frequencies in the signal obtained from the previous step, which are normally characteristic of QRS complex. After that, integration is carried out by a moving time window to extract additional feature, such as the QRS width. Finally adaptive amplitude threshold are applied to the averaged signal to detect R peaks. Both the band pass filtered signal and the averaged signal are stored in separate SRAMs for further analysis. The process repeats itself, and the threshold is adjusted to the last detected R peak. The last step in the QRS complex detection is to find the corresponding R peaks in filtered signal, which is done by subtracting the delay encountered due to the filters. However multiple features were necessary to enhance the robustness of the system, and thus, we constructed this unique set of ECG intervals and used it as input for the final stage. This feature extraction combination has never been used in any published detection or prediction method, yet it was proved to be the most significant combination.

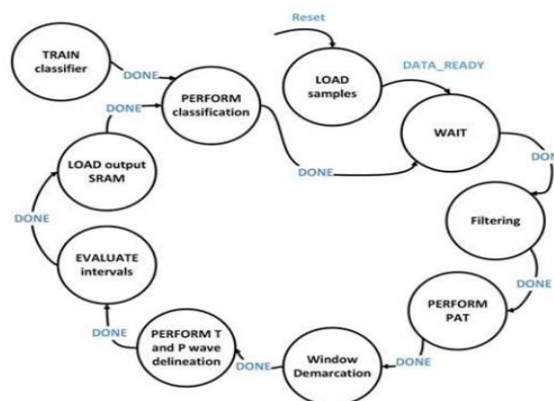


Fig.4 Main FSM processor

After the operation of feature extraction, the final stage, naïve Bayes algorithm is used to identify the signals that are susceptible to ventricular arrhythmia. There are many reasons for choosing the naïve Bayes. First, the ECG features have shown potential in the prediction of ventricular arrhythmia with a p-value <0.001. Second, it was intended to investigate the performance of the system without introducing the strong biasing effect of a classifier Naïve Bayes algorithm provides a way of calculating posterior probability  $P(c|x)$  from  $P(c)$ ,  $P(x)$  and  $P(x|c)$ .

$$P(c/x) = P(x/c).P(c) / P(x) \dots(1)$$

$$P(c/x) = P(x_1/c) \times P(x_2/c) \times \dots \times P(x_n/c) \times P(c)$$

Where,

- P(c|x) is the posterior probability of class (c, target) given predictor (x, attributes)
- P(c) is the prior probability of class.
- P(x|c) is the likelihood which is the probability of predictor given class.
- P(x) is the prior probability of predictor.

### VI. DESIGN FLOW

The Design flow of ECG based Processor of Ventricular Arrhythmia with the modules of three stages along with a main FSM that controls the flow of the data between the different stages as show in Fig.4. In the naïve bayes algorithm, is a set of data set to initialize the ECG ventricular arrhythmia attach, initially the data set to be converted in hexadecimal file of frequency table, and create the table by finding the probabilities like overcast probability =0.29 and probability of playing is 0.64, and finally the naïve bayes is an equation to calculate the posterior probability for each class, this class is the highest posterior probability is the outcome of prediction.

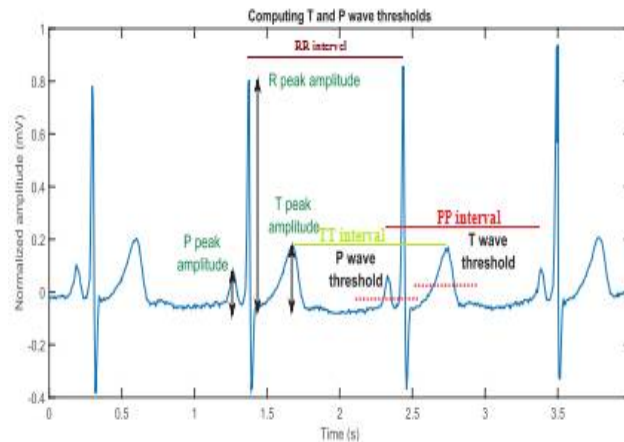


Fig.5 Computing T and P wave thresholds based on the previously detected T peak, P peak, and R peak values

The maximum value among these samples is set as an initial R peak and used to compute the initial value of the threshold, Th, which is set to 50% of the peak value.

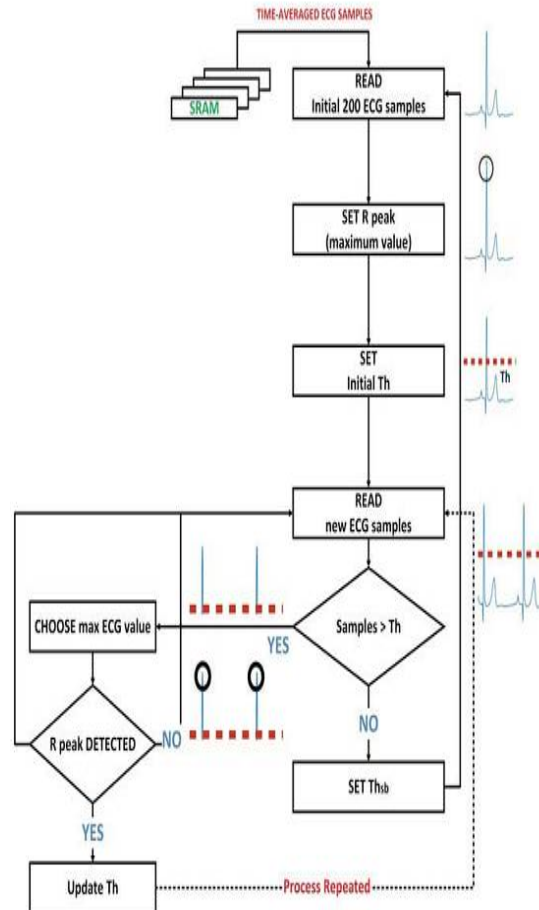


Fig.6 Flowchart of PAT detection technique

Then the value of every incoming sample is compared with  $Th$ , and only the sample value, which is greater than the threshold, is used in the next step. If none of the samples have a higher value than  $Th$ , the algorithm redefined the value of the threshold and set it to 30% of the peak value ( $Th_{sb}$ ). As soon as the demarcation of the samples that exist in the QRS complex region is done, the maximum value among them is set as a new R peak, and the threshold is updated accordingly (50% of the last detected R peak). The process repeats itself, and the threshold is adjusted to the last detected R peak. The last step in the QRS complex detection is to find the corresponding R peaks in filtered signal, which is done by subtracting the delay encountered due to the filters.

## VII. EXPERIMENTAL RESULTS

The evaluated simulation result of the proposed ESP for prediction over is obtained with Modelsim and synthesized in Xilinx FPGA S6LX9 using VHDL language. The proposed ESP achieved an outstanding capability of predicting the arrhythmia up to 2 h before the onset. A prediction accuracy of 98% was obtained on the out-of-sample validation data. The logic synthesis of power and area has been reported. The obtained results of the system are compared and validated by an expert cardiologist.



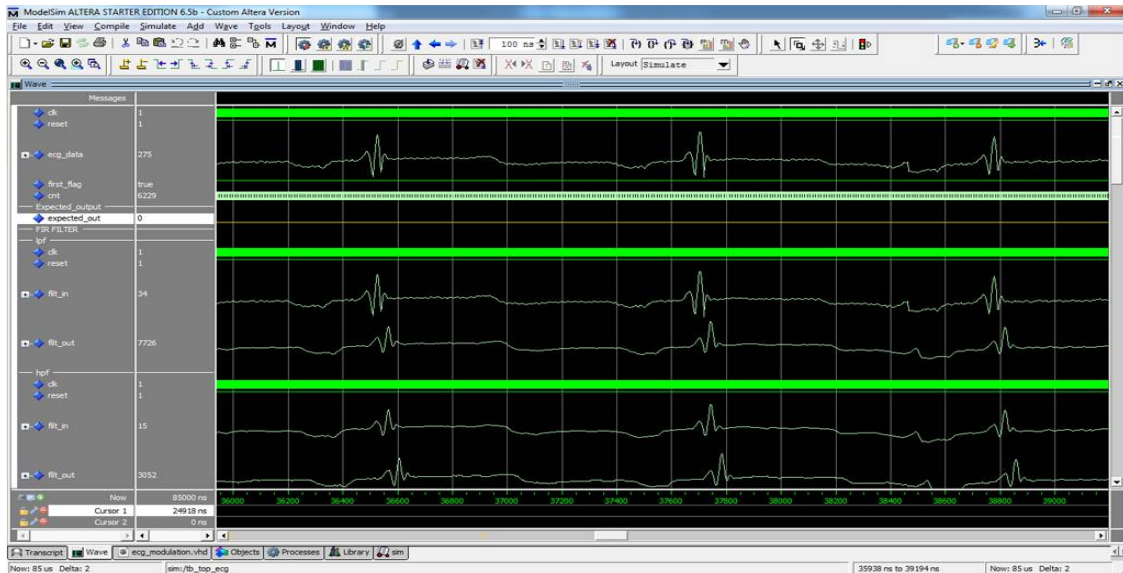


Fig.7 ESP Processor P-QRS-T wave delineation in Modelsim

## POWER REPORT

The input signal is a digitized ECG data sampled at 250 Hz, At an operating frequency of 10 kHz is more than sufficient to adequately process an ECG signal. At this frequency, our proposed system consumed around 105.28mW.

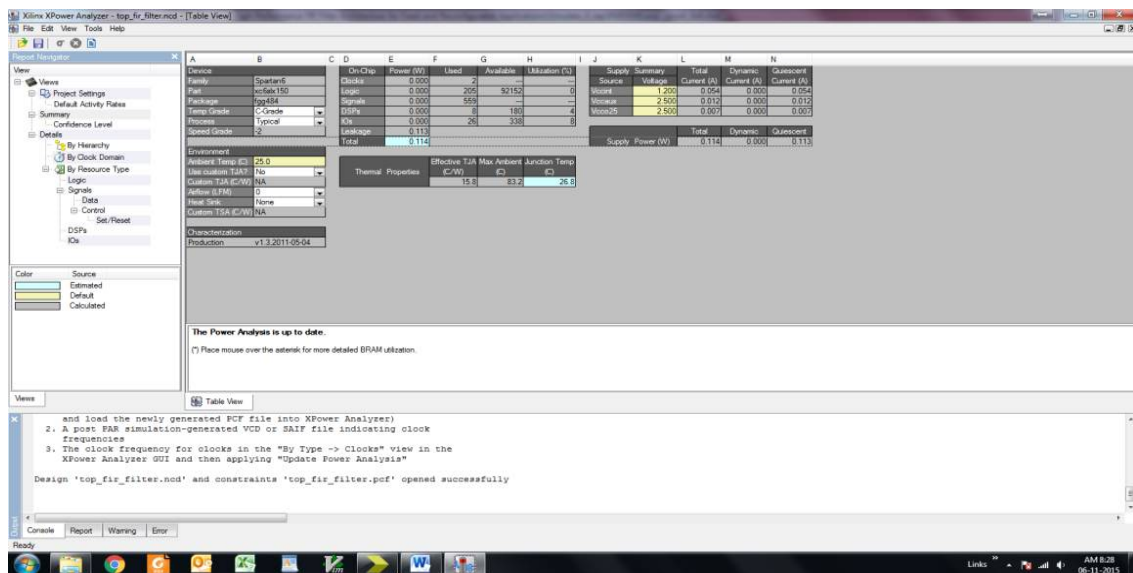


Fig.8 Power report.

## VIII.CONCLUSION

A fully integrated digital ESP for the prediction of ventricular arrhythmia that combines a unique set of ECG features with naive Bayes was proposed. Real-time and adaptive techniques for the detection and delineation of the P-QRS-T waves were investigated and employed to extract the fiducial points. The intervals of these waves

RR, PT, TP, QT, TQ, ST, TS, RP, PR, TR, RT, QR, RQ, SR, RS are checked and extracted and used as input of naive Bayes to classify the each heartbeat as normal or abnormal. The overall architecture is designed to make it suitable for a low-power application. The small area, low power, and high performance of the proposed ESP make it suitable for inclusion in system on chips targeting wearable mobile medical devices.

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