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Design And Implementation Of A Low Power Ecg Based Processor

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***Abstract* - This paper introduces the plan of an electrocardiogram (ECG) based processor (ESP) for the detection of ventricular arrhythmia utilizing a novel arrangement of ECG features and a radial basis function as a classifier. Constant and versatile systems for the identification and the depiction of the P-QRS-T waves were researched to extract the fiducial points. Those systems are hearty to any varieties in the ECG flag with high precision and accuracy. Two databases of the heart-beat recordings from the MIT PhysioNet and the American Heart Association were utilized as an approval set to assess the execution of the processor. The proposed system compares the heart signal recordings with the normal heart-beat signals so as to classify whether the heart-beat is normal or abnormal. Based on simulation results and synthesis using FPGA, the proposed system consumes a low power of 203 mW.**

Index Terms: Electrocardiogram (ECG), Ventricular Arrhythmia, Radial Basis Function (RBF), Classifier, Field Programmable Gate Array (FPGA), low power.

I.INTRODUCTION

SUDDEN cardiovascular passing records for around 300000 deaths in the United States every year, and, as a rule, is the last consequence of ventricular arrhythmias, counting ventricular tachycardia (VT) or ventricular fibrillation (VF) [1]. Ventricular arrhythmia is an anomalous ECG beat and is in charge of 75%–85% of sudden deaths in people with heart issues unless treated within seconds [1]. Most ventricular arrhythmias are caused by coronary illness, hypertension, or cardiomyopathy, and if not precisely analyzed nor treated, quick death occurs [2]. VT is a quick beat of more than three back to back beats beginning from the ventricles at a rate more than 100 beats/min [3]. VF is another beat described by the disordered activation of ventricles, and it causes quick discontinuance of blood dissemination and worsens further into a pulseless or flat ECG signal showing no cardiovascular electrical movement.

The implantable cardioverter-defibrillator has been considered as the best security against sudden demise from ventricular arrhythmias in high-chance people. Be that as it may, most sudden deaths happen in people who don't have high-hazard profiles. Long haul ECG checking is the measure standard for the analysis of ventricular arrhythmia. The 12-lead ECGs are acquired and investigated to distinguish any progressions in the qualities of the ECG flag. By extracting data about intervals,
amplitudes, and waveform morphologies of the diverse P-QRS-T waves, the onset of the ventricular arrhythmia can be recognized. An extensive variety of strategies were produced to distinguish ventricular arrhythmia in light of morphological [4], [5], spectral [6], or mathematical [7] features extracted from the ECG signal. Machine learning procedures, for example, neural systems [8] and support vector machine (SVM) [9] have additionally been recommended as a helpful device to enhance the detection effectiveness. Inspite of the fact that these techniques have displayed preferences in the recognition of ventricular arrhythmia, they have a few inadequacies. Some are as well hard to actualize or register, some have low specificity in segregating amongst typical and strange conditions, and all keep up late location interim, which is typically not enough to make a move.

II BASICS OF ECG SIGNAL PROCESSOR

Signal processing today is performed in most by far of frameworks for ECG investigation and understanding. The target of ECG signal processing is complex and involves the change of estimation exactness and reproducibility (when contrasted and manual estimations) what's more, the extraction of data not promptly accessible from the signal through visual evaluation. In numerous circumstances, the ECG is recorded amid ambulatory or, on the other hand strenuous conditions with the end goal that the signal is polluted by various sorts of noise. Hence, noise reduction is another important concern of signal processing.

ECG signal is the process of recording the electrical action of the heart over some undefined time frame

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utilizing terminals put on the skin. These cathodes recognize the small electrical changes on the skin that emerge from the heart muscle's electrophysiologic pattern of depolarizing and repolarizing amid every pulse. It is a regularly performed cardiology test.

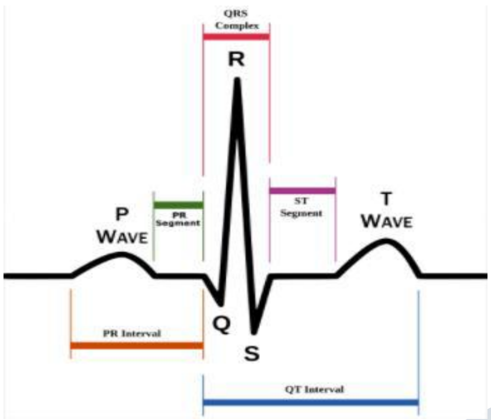

Figure 1: ECG Signal Of a heart of Normal beat

In an ordinary 12-lead ECG, 10 terminals are set on the patient's appendages and on the surface of the chest. The general extent of the heart's electrical potential is then measured from 12 distinct points ("leads") and is recorded over some stretch of time (for the most part 10 seconds). Along these lines, the general extent and course of the heart's electrical depolarization is caught at every minute all through the cardiovascular cycle.[4] The graph of voltage versus time created by this noninvasive restorative technique is alluded to as an electrocardiogram. The ECG signal of a heart of normal sinus rhythm is shown as reference in fig1.The basic ECG signal processor is shown in Fig2, which includes individual components, explained briefly below.

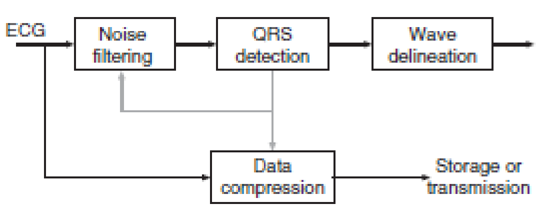

Figure 2: Block diagram of basic ECG Signal processing

Noise Filtering:

The filtering methods are basically utilized for preprocessing of the signals and have all things considered been actualized in a wide assortment of frameworks for ECG investigation. It ought to be recollected that separating of the ECG is relevant and ought to be performed just when the coveted data stays undistorted. This essential knowledge might be exemplified by separating for the expulsion of powerline interference. Such filtering is appropriate in a framework for the examination of heart rate inconstancy but is inappropriate in a system for analyzing the micropotentials as they overlap with the powerline interference.

QRS Detection:

The presence of a heart-beat and its occurrence time is essential data required in a wide range of ECG signal handling. As the QRS complex is that waveform that is most effectively recognized from the ECG, beat detection is synonymous to the detection of QRS complexes. The design of a QRS detector is of pivotal significance in light of the fact that poor detection execution may proliferate to resulting processing steps and, therefore, constrain the entire performance of the system. Beats that stay undetected constitute a more extreme mistake than do false detections; the former kind of mistake can be hard to rectify at a later stage in the chain of handling calculations, though, ideally, false detections can be eliminated by, for instance, performing classification of QRS morphologies.

A QRS detector must have the capacity to distinguish a huge number of various QRS morphologies keeping in mind the end goal to be clinically helpful and ready to take after sudden or continuous changes of the prevailing QRS morphology. Moreover, the detecter must not lock onto certain sorts of rhythm, but rather treat the next possible occasion as though it could happen at whenever after the most as of late distinguished beat. A few detector critical sorts of noise and artifacts exist dependent upon the ECG application of interest. The noise might be profoundly transient in nature or be of a more determined nature, as exemplified by the nearness of powerline obstruction.

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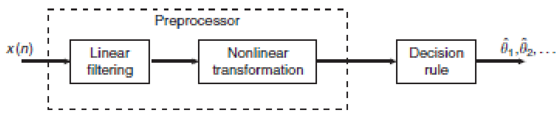

Figure 3: Structure of a common QRS detector

The structure of a common QRS detector is shown in fig 3. The linear filter is intended to have band-pass qualities with the end goal that the basic substance of the QRS complex is safeguarded, while undesirable ECG segments for example, the P and the T waves are smothered. The center frequency of filter changes from 10 to 25 Hz and the bandwidth from 5 to 10 Hz. Rather than different sorts of ECG filtering, waveform distortion is not a critical issue in QRS detection.
The nonlinear transformation improves the QRS complex in regards to the noise as well as changing the QRS complex into a positive peak which is well considered for threshold detection.
The decision rule considers a test to know the presence of QRS complex by taking the output of the preprocessor.

Wave Delineation:
Once the QRS complex has been detected, the T wave can be broke down in light of the fact that ventricular repolarization dependably takes after depolarization. On the other hand, the P wave does not lend itself as effortlessly to examination in light of the fact that atrial and ventricular rhythms might be free of each other.
However, atrial and ventricular rhythms are related so P wave identification might be in view of a regressive inquiry in time, starting at the QRS complex and completion toward the finish of the first T wave.
A technique for wave outline decides the limits of each wave inside the PQRST complex so that, with the subsequent time moments, distinctive wave spans can be registered. Once a wave has been depicted, different measures portraying the wave, for example, adequacy and morphology, can be effortlessly registered. Such a strategy should likewise have the capacity to distinguish when a certain wave is absent; this circumstance is normally experienced since, for instance, just the R wave or the S wave is available in specific leads or pathologies.

Data Compression
As an extensive variety of clinical examinations include the recording of ECG signals, huge measures of information are created for quick investigation, as well as for capacity in a database for future recovery and survey. It is understood that the accessibility of one or a few past ECG recordings enhances demonstrative exactness of different heart issue, including myocardial localized necrosis. Today, such serial ECG correlation incorporates brief term recordings gained amid rest, however may later on include long flags, for instance, obtained amid stretch testing or wandering checking. Eventhough hard circle innovation has experienced emotional enhancements in late years, expanded circle measure is paralleled by the ever increasing wish of doctors to store more data. Specifically, the consideration of extra ECG drives, the utilization of higher testing rates and better adequacy determination, the consideration of other, noncardiac signals, for example, pulse and breath, etc., prompt quickly expanding requests on plate measure. It is obvious that productive techniques for information pressure will be required for a long time to come.

III Proposed System:

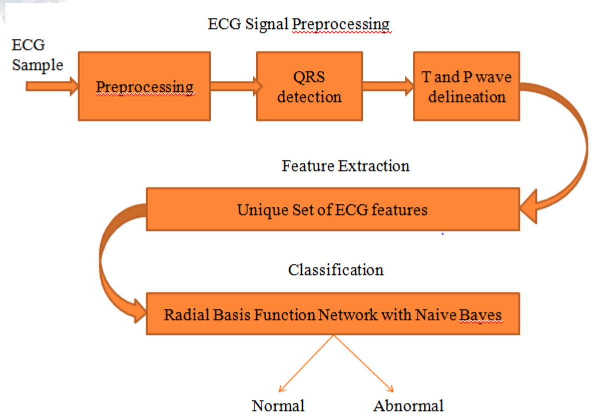

Figure 4: Block diagram of proposed System

The system consists of 3 steps namely, ECG signal preprocessing, Feature extraction and classification.

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ECG Preprocessing

1) Filtering / Preprocessing:

One of the most critical steps in ECG DSP is noise filtering .This is because ECG signals are noisily affected by different noises such as baseline wander, EMG interference and power line noise.This project is to implement a filter to reduce high frequency noise and power-line interference. Filtering is carried out so as to reduce the noise in the signal. The information carried by the ECG signal should not be lost even after filtering is done.

2) QRS Detection:

For detecting QRS complex, the PAT algorithm is used[15]. This is a common method used for exploiting the fact that R has high amplitude when compared to the other ECG signal peaks.

After filtering the ECG signal, the algorithm is divided into four steps. Differentiation is carried out to differentiate the QRS complex from the other waves by finding high peaks. At that point, a nonlinear change is performed through point-to-point squaring of the filtered ECG signal in which it is vital to emphasize the higher frequencies in the signal acquired from the previous step, which are regularly normal for QRS complex. After that, integration is done by a moving time window to extract extra features, for example, the QRS width. At last, adaptive amplitude thresholds are applied to the averaged signal to recognize R peaks.

For real time implementation, we have adjusted the peak detection method, as appeared in Fig.5. At first, the design reads the initial 250 ECG samples from the SRAM. 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. 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 (Thsb). 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 according 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.

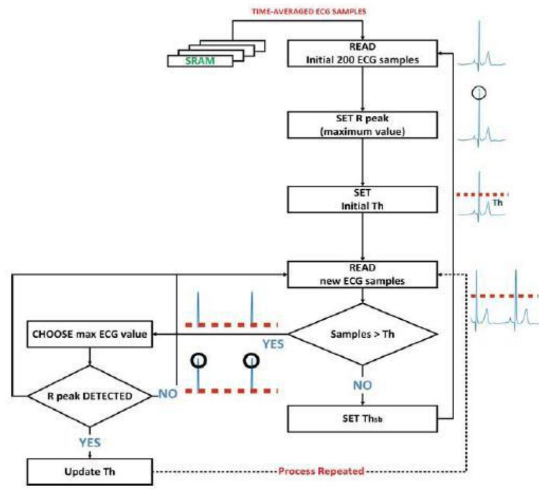

Figure 5: Flowchart of PAT technique

3) T and P Wave Delineation:

The T and P wave delineation is mainly on a novel technique which is proposed in [17] and is based on adaptive search windows to correctly distinguish T and P peaks. In each heartbeat, the QRS complex is used as a reference for the detection of T and P waves in which two regions are demarcated with respect to R peaks. These regions are then used to form the forward and backward search windows of the T and P waves, as shown in fig.6.

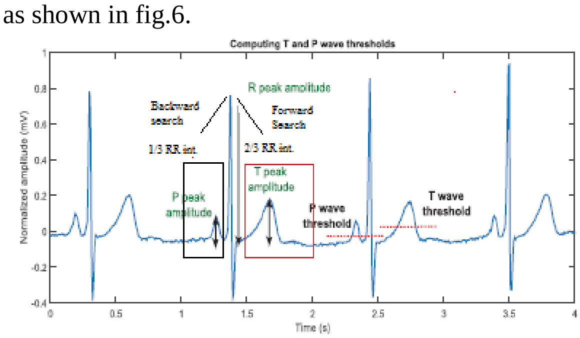

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Figure 6: Formulation of T and P wave search windows and thresholds

The thresholds as in (1) and (2) are modified in each heartbeat based on the recent values detected in the last 3 s

$$T_{wave\ th} = (T_{peak} / R_{peak})\ t_{thresh\ in} \quad (1)$$

$$P_{wave_{th}} = (P_{peak} / R_{peak})\ p_{thresh\ in} \quad (2)$$

Feature Extraction:

The two fundamental parameters that must be considered while developing a detection (or prediction) system are the complexity and accuracy of the feature extraction method in giving the best outcomes. For instance, if the method that is utilized for the feature extraction requires complex change or, data analysis of the ECG signal, this would expand the total cost and complexity of the system, and it will not be appropriate for wearable biomedical gadgets. For instance, a method detailed in [18] depends on ECG morphology also, RR intervals, prompting a basic and effectively feasible detection system. Besides, the extracted ECG features should demonstrate a noteworthy importance in the detection (or prediction) of the directed arrhythmia to ensure keeping up a high precision. For the most part, there is a tradeoff between the complexity and accuracy. For example, the accuracy of the system in [18] is lower when compared to the other introduced in [19] and [20].
The result of such examination yielded in a one of a kind arrangement of ECG features, which were observed to be the most demonstrative qualities of ventricular arrhythmia with a basic to realize system and high precision accuracy. The features incorporate RR, PQ, QP, RT, TR, PS, and SP intervals. Fig.7 demonstrates these intervals on ECG record. It merits specifying that the features are extracted from two consecutive heartbeats, dissimilar to different techniques that process every pulse independently.

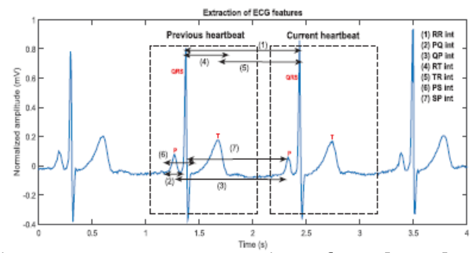

Figure 7: Feature Extraction of two heartbeats

Classification:

The classifier used here is Radial Basis Function Network. In mathematical modelling, RBFN is an artificial neural network that uses RBF as activation function. It was Formulated in 1988 by Broomhead and lowe. It has 3 layers – input, hidden with non-linear RBF activation function and linear output layers.

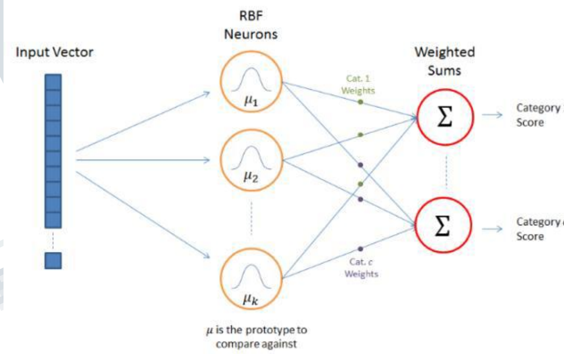

Figure 8: Architecture of Radial Basis Function as a Classifier

One of the frequently cited favourable circumstances of the RBF organize is its simplicity – there is no nonlinear optimization plan required. However, a number of the sophisticated methods for center placement and width determination are more included and increment the computational complexity of the model considerably. By and by, the basic RBF can give adequate performance for some applications.
Radial basis functions are easy to build, simple to train and discover an answer for the weights quickly. They give an extremely adaptable model and give great performance over an extensive variety of issues, both

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for discrimination and for functional approximation. The RBF model utilizes a number of the standard pattern recognition building blocks.
The computations will be more if done separately. So RBF network is used as a classifier along with Naive Bayes classifier.

IV Implementation Results

Apart from MATLAB simulations, VHDL simulations for each stage are done using Modelsim for verifying the design. Modelsim is considered as verification and a simulation tool.
ECG recordings from Physionet and AHA databases are considered as references. One of the ECG recordings is considered from MATLAB where the files are loaded from Physionet. These are saved in text format. The samples in the form of text are filtered to get a noise free signal. The simulation after the pre-processing stage is shown in figure9.

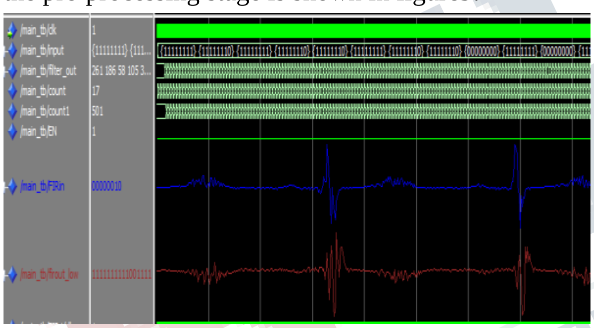

Figure 9: Simulation result after preprocessing

Now, after filtering, the output is given to QRS detection and feature extraction stage and the simulation of the second stage is shown in below figure 10.

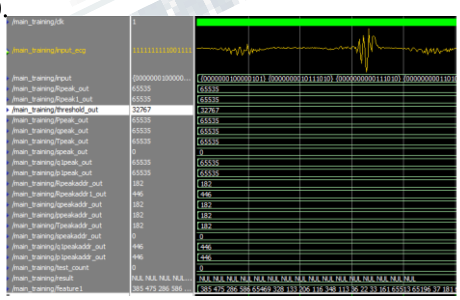

Figure 10: Simulation result for QRS complex and feature extraction

Finally, after passing it to the classifier, this specifies the heartbeat as normal/abnormal. The abnormal heartbeat indicates that the person has ventricular arrhythmia.

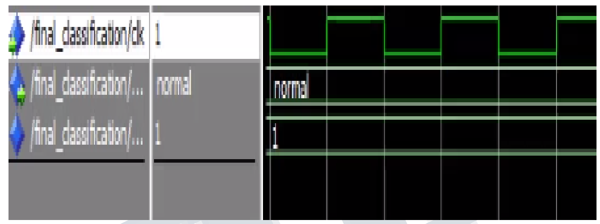

Figure 4: Simulation result after classification

The device utilization summary of the proposed system is

Table 1: Device utilization summary

Device Utilization Summary			
Logic Utilization	**Used**	**Available**	**Utilization**
Number of 4 input LUTs	6,372	29,504	21%
Number of occupied Slices	5,379	14,752	36%
Number of Slices containing only related logic	5,379	5,379	100%
Number of Slices containing unrelated logic	0	5,379	0%
Total Number of 4 input LUTs	10,232	29,504	34%
Number used as logic	6,372		
Number used as a route-thru	3,860		
Number of bonded IOBs	8	376	2%
Number of MULT18X18SIOs	36	36	100%
Average Fanout of Non-Clock Nets	1.44		

The above table shows the area occupied by the processor. The power can be obtained using Xpower analyzer tool in Xilinx

Table 2: On-chip power utilization

On-Chip	Power (W)	Used	Available	Utilization (%)
Logic	0.000	9502	29504	32
Signals	0.000	14937	---	---
MULTs	0.000	36	36	100
IOs	0.000	8	376	2
Leakage	0.203			
Total	0.203			

The power consumed is 203mW.The proposed system is compared with the existing system i.e., SVM classifier.

Table 3: Comparison between proposed and existing

Parameter	Existing	Proposed
LUT's count	17,648	6,372
Power (mW)	224	203

This shows that the proposed system has less power and area.

V CONCLUSION

An ECG based processor is implemented for detecting ventricular arrhythmia making use of features and the radial basis function as a classifier. Simulations of each stage are carried out for the ECG recordings taken from the databases in VHDL code, verified using Modelsim. By comparing the existing and proposed systems, it is clear that the proposed has less power and area. Hence it has high accuracy and performance.

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