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Predicting Ventricular Arrhythmia By using Naive Bases classification Algorithm

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*Abstract***— this paper presents the design of a fully integrated electrocardiogram (ECG) signal processor (ESP) for the prediction of ventricular arrhythmia using a unique set of ECG features and a naive basis classifier. Real-time and adaptive techniques are used for detection and delineation of the P-QRS-T waves. And also detect all intervals in the ECG signal and compared with stored record. Ventricular arrhythmia is predicted by analyzing ECG signal. Four methods are used to analysis the ECG signal namely the methods are ECG preprocessing, QRS complex detection, feature extraction and classification. By using above methods an accurate and noise free ECG Signal is obtained. Proposed architecture of this project analysis the logic size, area and power consumption**

*Index Terms***—Adaptive techniques, classification, electrocardiograph (ECG), feature extraction, low power, ventricular arrhythmia.**

I. INTRODUCTION

SUDDEN cardiac death accounts for approximately 300 000 deaths in the United States per year, and, in most cases, is the final result of ventricular arrhythmias, including ventricular tachycardia (VT) or ventricular fibrillation (VF) [1]. Ventricular arrhythmia is an abnormal ECG rhythm and is responsible for 75%–85% of sudden deaths in persons with heart problems unless treated within seconds [1]. Most ventricular arrhythmias are caused by coronary heart disease, hypertension, or cardiomyopathy, and if not accurately diagnosed nor treated, immediate death occurs [2]. VT is a fast rhythm of more than three consecutive beats originating from the ventricles at a rate more than 100 beats/min [3]. VF is another rhythm characterized by the chaotic activation of ventricles, and it causes immediate cessation of blood circulation and degenerates further into a pulseless or flat ECG signal indicating no cardiac electrical activity.

The implantable cardioverter-defibrillator has been considered as the best protection against sudden death from ventricular arrhythmias in high-risk individuals. However, most sudden deaths occur in individuals who do not have high-risk profiles. Long-term ECG monitoring is the criterion standard for the diagnosis of ventricular arrhythmia. The 12-lead ECGs are obtained and analyzed to detect any changes in the characteristics of the ECG signal. By extracting information about intervals, amplitudes, and waveform morphologies of the different P-QRS-T waves, the onset of the ventricular arrhythmia can be detected. A wide range of methods were developed to detect ventricular arrhythmia based on morphological [4], [5], spectral [6], or mathematical [7] features extracted from the ECG signal. Machine learning techniques, such as neural networks [8] and support vector machine (SVM) [10] have also been suggested as a useful tool to improve the detection efficiency. Although these methods have exhibited advantages in the detection of ventricular arrhythmia, they have some shortcomings. Some are too difficult to implement or compute, some have low specificity in discriminating between normal and abnormal conditions, and all maintain late detection interval, which is usually not enough to take an action.

A. Literature Review

1. The existing [17] introduce an adaptive T and P wave delineation technique which takes into account different waveform morphologies of T and P waves. By using an adaptive size of search window along with adaptive threshold, this method accurately detect peak, onset, and offset locations of T and P wave in each heartbeat. an efficient and accurate technique to estimate the T- and P-wave delineation is presented. The technique is robust and adaptive for different waveform morphologies. In addition to the simplicity of this new technique, it is very suitable to real-time analysis, avoiding any complex operations required by the available similar delineation algorithms

2. The main benefit of such approach is that the impact of a person's motion and his daily activities is dramatically reduced. Chen *et al.* [14] proposed a syringe-implantable ECG system for arrhythmia classification based on the state-of-the-art 65-nm CMOS process. The system acquires the ECG signal, filters it, amplifies it, and digitizes it

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through the analog front-end (AFE) module. The AFE contains a low-noise instrumentation amplifier, a variable gain amplifier, and a successive approximation register analog-to-digital converter. The Arrhythmia detection is performed using two approaches. The first approach evaluates the variance of the RR interval and applies a simple threshold technique to distinguish between normal and abnormal intervals. In the second approach, the ECG signal is transformed into the frequency domain, and the variation in the spectrum is analyzed.

B. Previous work of this paper

This paper proposes a fully integrated low-powered ESP for the prediction of ventricular arrhythmia up to 3 h before the onset, and to the best of our knowledge, this is the first solution that performs prediction instead of detection. Previous VT-/VF-related research was mainly concerned with the detec- tion of the VT/VF condition on and after it occurs [4]–[6], while our proposed solution performs prediction of it. In VT/VF detection, the ECG segment (or features extracted from it) that follows the onset of VT/VF is used to train the classifier in order to distinguish between normal and abnormal cases. Of course, the detection of such arrhythmia is critical, because the waveform of the ECG signal changes dramatically without following a consistent pattern, as shown in Fig. 1; however, this detection is not enough to save lives as the patient is left with a very few seconds to die. On the other hand, an early prediction of VT/VF would improve the quality.

C. Proposed System

The proposed system is a life savior for patients who are susceptible to ventricular arrhythmia by alerting them for immediate attention to their medical condition.

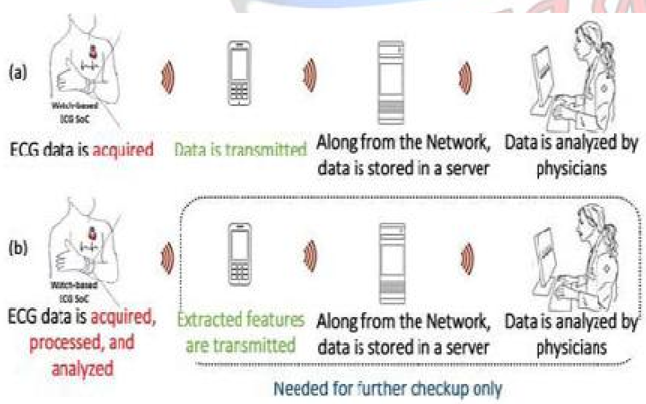

Figure 1.1: Comparison between (a) commonly implemented systems and (b) proposed one.

Unlike other systems that acquire the ECG signal and transmit it for further analysis, the proposed system aims to design and develop an integrated biomedical processor that is capable of acquiring the ECG signal from the heart along with processing and analyzing it on the same chip without any external interaction, as shown in Figure 4.1. Thus, the patient would have immediate alert to his situation and that is very important, especially in critical situations. Furthermore, the local processing of the data would reduce the amount of the data to be transmitted in case of any further checkup.

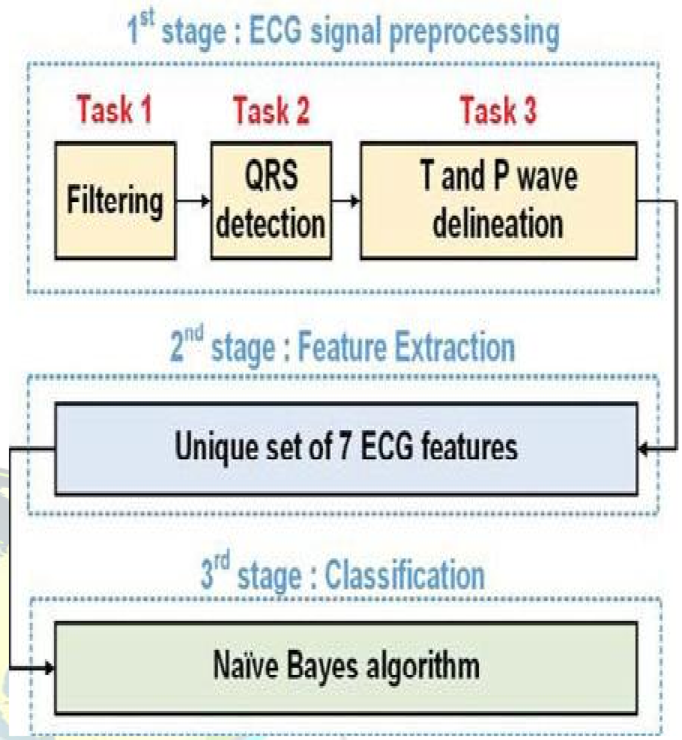

Figure 1.2: Proposed System

The proposed system consists of three main stages, which are the ECG preprocessing, feature extraction, and classification, as shown in Figure4.1. In the first stage, the ECG preprocessing is responsible for three tasks: 1) ECG filtering; 2) QRS complex detection; and 3) T and P wave delineation. 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 [15]. Finally, T and P waves are delineated, and the corresponding points (P onset, P peak, P offset, T onset, T peak, and T offset) are extracted. New techniques are presented in this stage to increase the robustness of the system, and this is by utilizing adaptive search windows and thresholds to accurately detect the points in each heartbeat.In the second stage, seven features are extracted from the ECG signal and grouped together to construct a unique set. All the features represent different intervals from the ECG signal, and they are RR, PQ, QP, RT, TR, PS, and SP intervals. Usually, the reported systems in the literature build their systems depending on one feature only, such as the heart rate interval [4], the variability of the timing delay of the ECG segments [5], or the QT interval variability [16]. 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. The combination of these features has never been used in any published detection or prediction method, yet it was proved to be the most significant combination.In the final stage, naive Bayes algorithm is used to identify the signals that are susceptible

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to ventricular arrhythmia. There are many reasons for choosing the naive Bayes. First, the ECG features have shown strong 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. Finally, naive Bayes is the simplest classification method that can be easily implemented in hardware.

ECG Preprocessing Stage

ECG Filtering: The block diagram of the preprocessing stage is shown in Figure1.3. Band pass filtering of the raw ECG signal is the first step in which the filter isolates the predominant QRS energy centered at 10 Hz, and attenuates the low frequencies characteristic of the P and T waves, baseline drift, and higher frequencies associated with electromyography noise and power line interference.

QRS Detection: To detect the QRS complex, the PAT method was used. The PAT is a widely used 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 signal, the method is highly capable of detecting the R peaks in every heartbeat using two threshold levels.

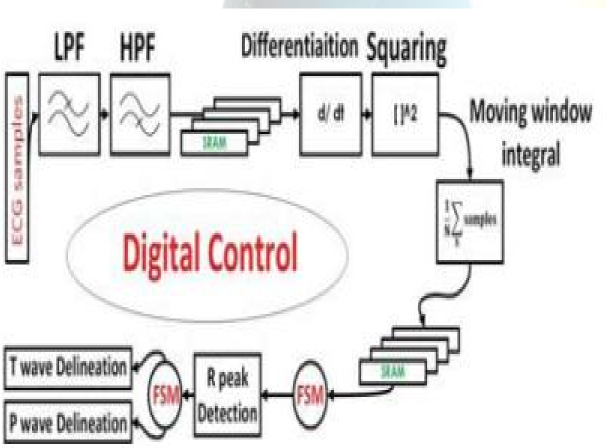

Figure 1.3 Block diagram of preprocessing stage, which contains filtering, QRS detection, and P and T wave delineation.

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 through 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 features, such as the QRS width. Finally, adaptive amplitude thresholds 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. [9] discussed about an eye blinking sensor. Nowadays heart attack patients are increasing day by day."Though it is tough to save the heart attack patients, we can increase the statistics of saving the life of patients & the life of others whom they are responsible for.

T and P Wave Delineation: The delineation of T and P waves is based on a novel technique proposed. The method is based on adaptive search windows along with adaptive thresholds to accurately distinguish T and P peaks from noise peak. 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, respectively, as shown in figure4.3.A forward search window is assumed to contain the T wave, and the boundaries are extended from the QRS offset to two third of the previously detected RR interval. Similarly, a backward search window for the P wave is identified and extended from the QRS onset backwardly to one third of the previous RR interval.

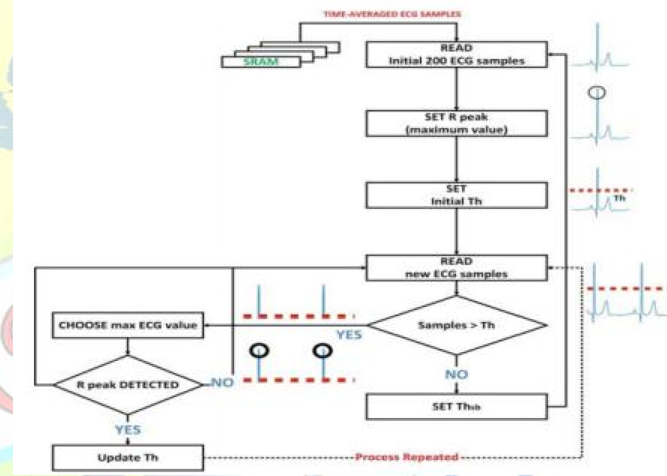

Figure 1.4. Flowchart of PAT peak detection technique.

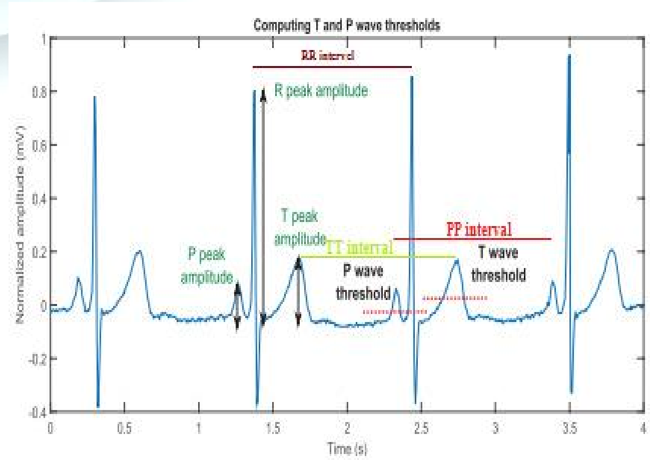

Figure1.5: Computing T and P wave thresholds based on the previously detected T peak, P peak, and R peak

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values. The position of T and P peaks is demarcated in their respective search windows by finding the local maximum or/and local minimum that are above the associated thresholds. The thresholds are modified in each heartbeat based on the most recent detected values in the last 3 the technique of computing the thresholds is shown in Figure1.5. By comparing the local maximum or/and the local minimum points with the thresholds, the waveform morphology of each wave is identified [positive monophasic, inverted, or biphasic (+, −)/(−, +)]. If the value of T or P peak is greater than the associated threshold, then the T or P wave has a positive monophasic waveform, and the local maximum is stored to give a probable position of the peak. Otherwise, the waveform is identified as inverted, and the local minimum of the ECG signal within the same window is the correct peak. In case of biphasic wave, both the local maximum and the absolute value of the local minimum should be greater than the threshold.

Onset and Offset Point Delineation:

The method traces the onset and offset values of the P-QRS-T waves by finding the sample corresponding to the zero slope of the entitled ECG signal. The sample point that has a zero slope and former to the peak is identified as the onset point. Similarly, the offset point is determined at other side of the peak. Sometimes, however, a derivative sign change occurs, which reflects a false indicator. To solve this, the method adds another criterion for a correct delineation of the wave boundaries based on the fact that the fiducial points tend to merge smoothly with the isoelectric line. The isoelectric line is approximated as the average value of the beat signal after removing the QRS complex. This idea is utilized and combined with the zero slope for an accurate and reliable delineation of the fiducial points.**Feature Extraction Stage**

The two main parameters that must be considered while developing a detection (or prediction) system are the complexity and the accuracy of the feature extraction technique in providing the best results. The result of such analysis yielded in a unique set of ECG features, which were found to be the most indicative characteristics of ventricular arrhythmia with a simple-torealize system and high prediction accuracy. The features include interval between P, Q, R, S, T peak values. Figure 4.5 shows these intervals on ECG record. It is worth mentioning that the features are extracted from two consecutive heartbeats, unlike other methods that process each heartbeat independently

Classification Stage

The choice of classifier in this paper was the naive Bayes. The naive Bayes classifier is easy to build with no complicated iterative parameter estimation, which makes it particularly useful for hardware implementation. It assumes naive and strong independent distributions between the feature vectors, and this assumption was met, since all the extracted ECG Independently analyzed and assessed from the beginning. The architecture of the classifier is implemented, as shown in fig1.6

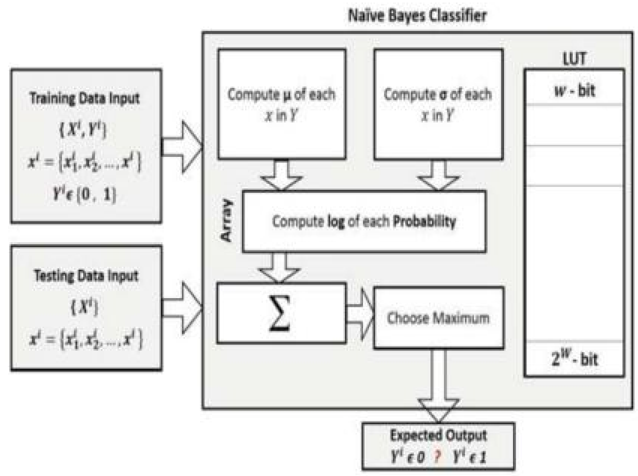

Figure1.6. Architecture of naive Bayes classifier

D .Simulation results

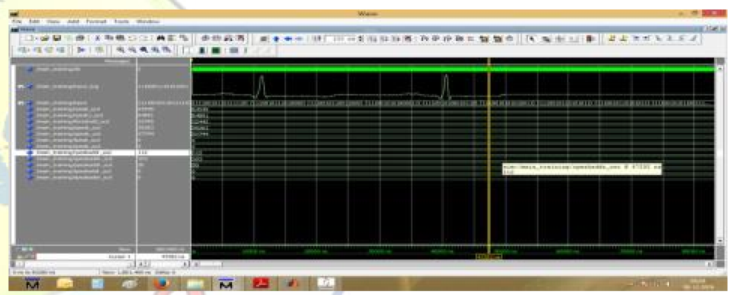

FIGURE 1.6 SIMULATION ECG INPUT SIGNAL

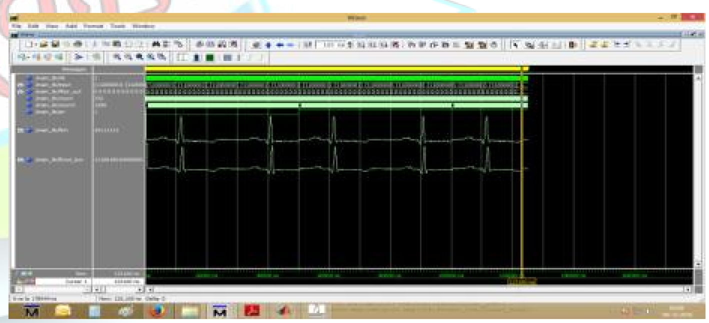

FIGURE 1.7 SIMULATION OF THE ECG FILTERING SIGNAL

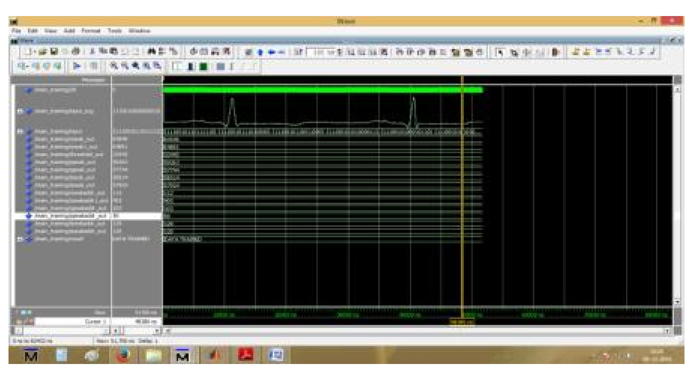

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FIGURE 1.8: SIMULATION OF THE CLASSIFIED ECG SIGNAL

CONCLUSION:

In this work, 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 points. Furthermore, seven features that represent different intervals of the ECG signal were extracted and used as input to the naive Bayes to classify each heartbeat as normal or abnormal. The combination of these features has never been used in any previous detection or prediction system. The small area, low power, and high performance of the proposed ECG system make it suitable for inclusion in system on chips targeting wearable mobile medical devices.

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