Arrhythmia Detection in Single-lead ECG by Combining Beat and Rhythm-level Information

Vinod Pathangay and Satish Prasad Rath

Abstract— **In this paper, we propose a method for detecting arrhythmia in single-lead electro-cardiogram (ECG) signal. By applying a sequence of pre-processing steps (filtering, baseline correction), beat classification and rhythm identification, six different beat-types and four abnormal rhythms are detected. Beat classification uses fast Fourier transform (FFT) as the feature and a support vector machine (SVM) classifier. Subsequently rhythm identification uses a deterministic finite state machine to detect abnormal rhythms. We evaluate the performance of our technique on the MIT-BIH database, to obtain 97% beat classification accuracy and perfect rhythm identification result.**

I. INTRODUCTION

Long term ambulatory ECG monitoring with a number of connected leads are not very comfortable for the patient as it can restrict the natural day-to-day movement. With the recent development of smaller *patch* form factors, the ECG sensor is attached on the chest with an adhesive patch with embedded terminals. However such devices are capable of acquiring only single-lead ECG data in favor of ease-of-use. It is therefore needed of detect arrhythmia automatically using single-lead ECG signal. Figure 1 shows a commercial ambulatory ECG devices. Although such devices can provide 3-lead ECG, it is computationally efficient to analyze single-lead ECG signal (lead-II) to detect presence of arrhythmia events.

Figure 2 shows the flow chart of the method presented in this paper. At the first level, bradycardia and tachycardia are detected using the calculated heart rate. FFT feature is used with a trained support vector machine (SVM) for beat classification. Subsequently other arrhythmia conditions are detected using the rhythm identification step which uses the results of beat classification. The diagnostic tree for proposed arrhythmia detection method is shown in Figure 3. The arrhythmias are detected at beat-level and at rhythm-level.

Section II presents a survey of recent arrhythmia detection methods. In section III, we discuss beat classification which is followed by rhythm identification in section IV. Section V concludes the paper and gives directions of future work.

Figure 1. Wipro Assure Health™ ECG necklace with five electrodes to sense three-lead ECG and connects to a smart phone using Bluetooth radio.

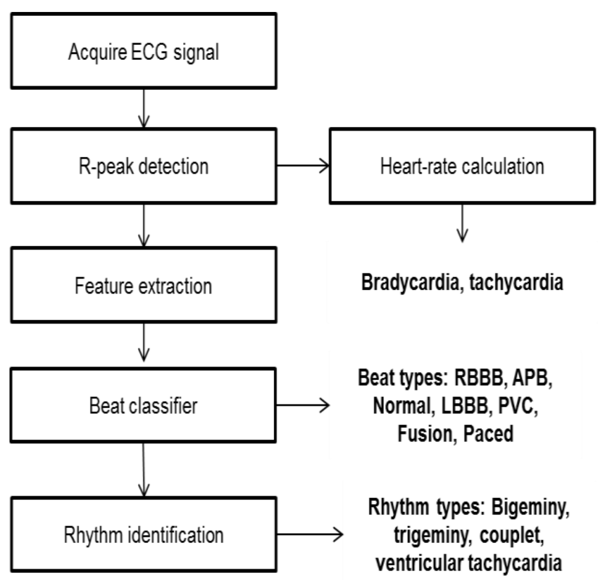

Figure 2. Sequence of steps for the showing the use of beat classifier output by the rhythm identification module for arrhythmia detection.

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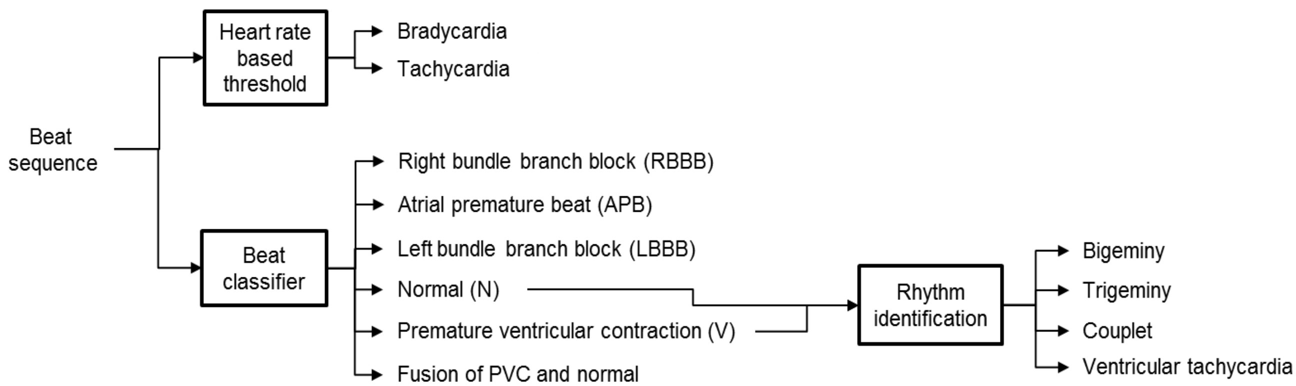

Figure 3: Diagnostic tree of the proposed approach.

II. Related Work

Arrhythmia detection methods can be roughly categorized as those based on time domain or frequency domain features. The time domain features are typically derived out of intervals between the PQRST waves in the ECG signal, but such segmentation of the ECG signal is often not reliable as the detection of waves other than the R-peaks can be difficult. The use of RR intervals with knowledge-base for arrhythmia detection is presented in [6]. However frequency domain features can be extracted more reliably after detecting R-peaks. Use of Wavelets features [5] has also been proposed.

Beat-level classification using support vector machine (SVM) classifier [1], [2], [3] and extreme learning machine [4] have been reported for arrhythmia detection. Although the beat classifier can identify the type of abnormal beat based on the features extracted at the beat-level, it also required to identify the rhythm-level arrhythmias. A method for detecting bigeminy and trigeminy rhythms using distribution pattern model is reported [7].

III. Beat Classification

The ECG signal is baseline corrected using morphological filtering [8]. This helps in improving the performance of subsequent R-peak detection [9]. The location of the R-peaks are used to segment the ECG signal into beats. The signal segment between two successive RR intervals is used for feature extraction. The beat segment is transformed to frequency domain using fast Fourier transform (FFT). The magnitude and phase of FFT output are used as the features to train the beat classifier.

The classifier is trained for seven beat types taken from MIT-BIH database [11]. These are normal beat, pre-ventricular contraction (PVC), right bundle branch block beat, atrial premature beat, left bundle branch block beat, fusion of PVC-normal. The libSVM tool [10] is used for beat classification experiments. The output of the beat-classifier is a sequence of beat-symbols. For beat-level arrhythmia, an alert is generated if the abnormal beat is detected at rate that is higher than a pre-defined threshold.

IV. Rhythm Identification

In order to identify rhythm-level arrhythmia beat-symbol sequence from the beat classifier is presented as input to a finite state machine. The state-machine is designed to determine the four rhythm-level arrhythmia: bigeminy (B), trigeminy (TR), couplet (coup), ventricular tachycardia (VT). The input beat symbols are normal (N) and ventricular (V) beats.

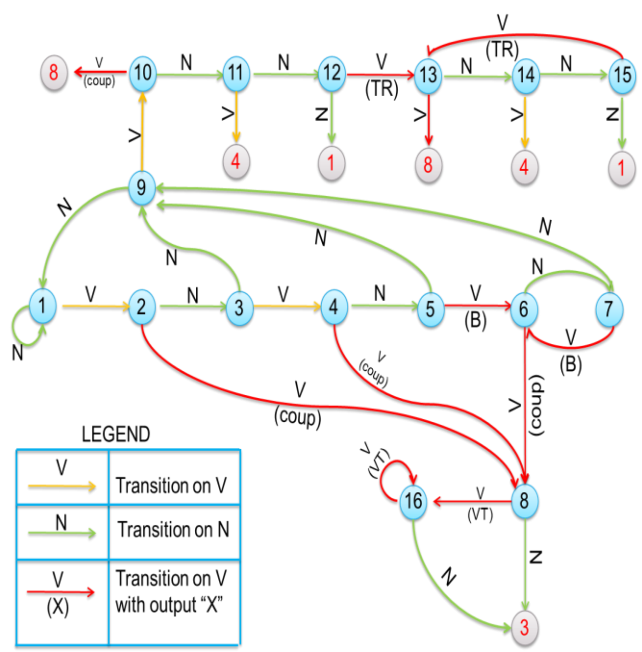

Figure 4. State transition diagram for identification of rhythm-level arrhythmia (N – normal, V – ventricular beat).

Figure 4 shows the transition diagram of the state-machine of the rhythm identification step. There are 16 states with state '1' as the entry state. For each input as ventricular (V) or normal (N) beat, the transition can be silent or with an output. The sate transitions are designed such that outputs (1) couplet *coup* is obtained for sequence *VV, (2) bigeminy *B* is obtained for the input sequence *NV, (3) trigeminy *TR* is obtained for the input sequence *NNV and (4) ventricular tachycardia *VT* for the input sequence *VVV. The transitions with output are shown as red arrows whereas the green and yellow arrows show the silent transitions. Given the deterministic nature of finite state machine, the errors in rhythm identification occur only when the beat symbols are incorrect.

V. Experimental Results

In this section, the experiments performed for beat classification module are presented. The experiments were performed to (1) find the optimal feature size, (2) find the best kernel parameters for the beat classifier and (3) evaluate enhanced feature-set. These experiments are discussed in the following subsections.

A. Feature Size Determination

For beat classification, features are extracted from the segment between the R peaks. This is resampled to a normalized length of 100 samples. Different lengths of FFT coefficients are extracted from this normalized segment for experimentation, as denoted by 'fft*N*' where *N* represents the number of FFT coefficients. These features are evaluated using the libSVM classifier [10] with default parameters. Figure 3 shows classification performance of the FFT features in terms of the receiver operating curves (ROC). It can be seen that fft35 shows the best ROC. Therefore fft35 is used for all the subsequent experiments as this is more compact and less computationally intensive than using the complete FFT output, i.e. fft100.

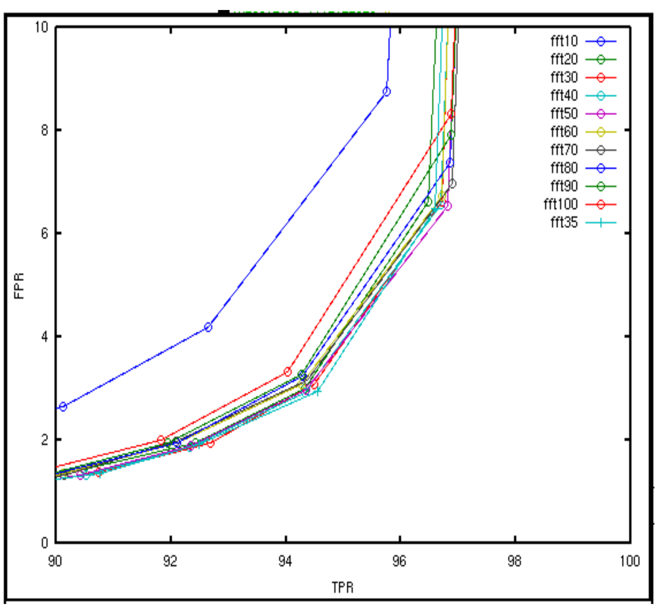

Figure 5. Receiver operating curves (TPR true positive rate vs. FPR false positive rate) for FFT features of different lengths extracted from the beat interval. Best ROC obtained for fft35.

B. Kernel Optimization

Two types of kernel functions were considered: 3rd degree polynomial and radial basis function. Optimization of kernel parameters to obtain an increased cross-validation accuracy is performed. The results of the grid search applied over the parameters of the polynomial kernel are shown in Figure 6. It can be noted that there is an increasing trend in the accuracy for different combinations of kernel mapping function coefficient (*r)* and cost parameter (*c*). With parameters $r = 13$ and $c = 15$, the 2-fold cross-validation accuracy reaches a maxima of 91.75%. Similarly a grid search performed for RBF kernel gave a maximum 2-fold cross-validation accuracy of 93.63% with kernel parameters $\gamma = 0.5$ and cost $c = 32$. Therefore RBF kernel gave the best performance. Figure 7 shows the corresponding confusion matrix generated. Hence RBF kernel with the selected parameters was used for the next set of experiments on combining different sets of features.

C. Feature-set Combination

This set of experiments evaluated the performance of an enhanced feature-set by including FFT phase information and normalized RR-intervals. The results in terms of 2-fold cross-validation accuracies are shown in Table 1. The baseline experiment (row 1) uses the fft35 magnitude feature. On concatenating the feature vector with the FFT phase information (row 2), it can be seen that there is an increase in accuracy to 95.24%. Similarly by including the normalized RR intervals to the feature vector (row 3), the accuracy increased to 96.01%. In the last experiment (row 5), the FFT window is shifted such that the R-peak is at the center of the window for each beat. This provides the best accuracy of 97.05%. This shows that the windowing scheme for feature extraction significantly affects the performance of the beat classifier. The results obtained with the proposed method is comparable with the 98% accuracy reported in [12] with similar training and testing set partition.

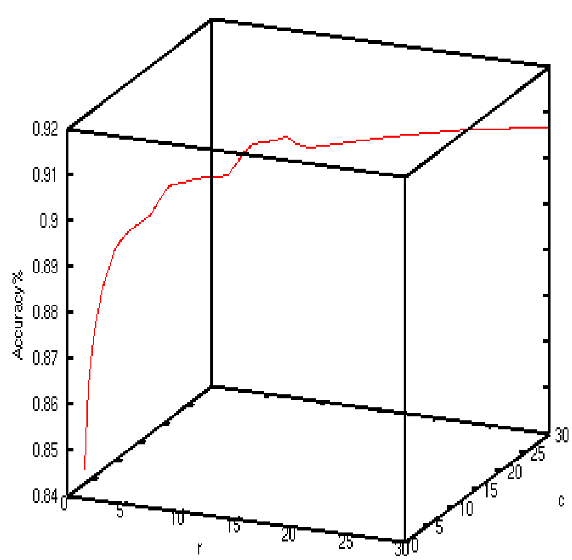

Figure 6. Grid search for finding the best set of parameters showing an increasing trend for the cross-validation accuracy.

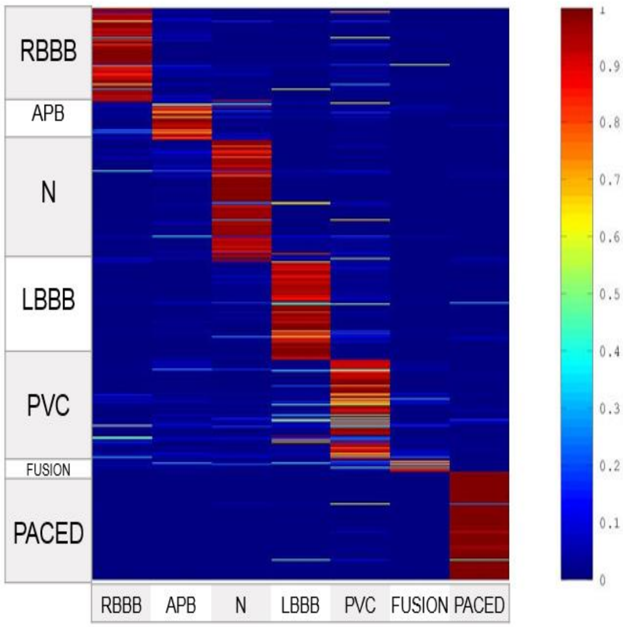

Figure 7. Confusion matrix of the beat classifier for seven different beat types: right bundle branch block (RBBB), atrial premature beat (APB), normal (N), left bundle branch block beat (LBBB), premature ventricular contraction (PVC), fusion of normal and PVC, paced beat.

TABLE I. PERFORMANCE OF ENHANCED FEATURE-SET

S. No.	Feature set	Accuracy (%)
1	fft35 magnitude	93.63
2	fft35 magnitude, phase	95.24
3	fft35 magnitude, RR interval	96.01
4	fft35 magnitude, phase, RR interval	95.58
5	R-peak centered fft35 magnitude, phase, RR interval	**97.05**

VI. CONCLUSION AND FUTURE WORK

The paper presents an arrhythmia detection method for single-lead ECG. The ECG signal is segmented into beats which are classified into normal and six types of ectopic beats. This helps to determine beat-level arrhythmia. For identifying rhythm-level arrhythmia, the beat symbol sequence is parsed using a state-machine. This helps in identifying four types of abnormal rhythms. Thus by combining the beat level and rhythm level information, ten types of arrhythmia events can be detected. As the rhythm identification is based on a deterministic finite state machine, it is not tolerant to errors in the beat symbols from the beat classification stage. A probabilistic state machine can be used to overcome this problem.

Although the proposed method in this paper was trained and tested on MIT-BIH data, it is further under the process of training and testing on a large scale ECG data collected from a trial using the Wipro Assure Health^{TM} ambulatory ECG device. This will ensure that the classifier will adapt to the device specific signal characteristics.

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