Enhancing Accuracy of Arrhythmia Classification by Combining Logical and Machine Learning Techniques

Vignesh Kalidas, Lakshman S Tamil

The University of Texas at Dallas, Richardson, USA

Abstract

This paper is a contribution to the Physionet/Computing in Cardiology Challenge 2015. The aim is to reduce the occurrence of false alarms in the ICU during the detection of asystole, extreme bradycardia, extreme tachycardia, ventricular fibrillation and ventricular tachycardia.

Robust classification of each arrhythmia is achieved using a combination of logical and SVM-based machine learning techniques. Information from electrocardiogram and photoplethysmogram signals, sampled at 250Hz, is used for logical analysis and to form the feature set. This information includes time-domain and frequency-domain data such as R-R intervals, power spectrum density, autocorrelation plots and standard deviation values. Pan-Tompkins algorithm is applied to ECG signals for QRS complex detection.

1. Introduction

This paper aims at improving the prediction accuracy of five life-threatening arrhythmias, namely, asystole (ASY), extreme bradycardia (EBC), extreme tachycardia (ETC), ventricular fibrillation (VFB) and ventricular tachycardia (VTA). This is a contribution to the Physionet/Computing in Cardiology Challenge 2015 [1].

Robust classification of each arrhythmia was achieved with a combination of logical and Support Vector Machine (SVM) based machine learning techniques. Information from electrocardiogram (ECG) and photoplethysmogram (PPG) signals, sampled at 250Hz, was used for logical analysis and to form the feature set vectors. These were derived from time and frequency-domain data including R-R intervals, power spectrum density, and statistical properties such as autocorrelation, standard deviation, etc.

2. Method

Our algorithms were developed using Matlab R2014a version. For machine learning based classification, SVM based supervised learning was performed using the “fitcsvm” and “predict” functions from Matlab’s Statistics and Machine Learning Toolbox. For all SVM based classifiers, the “fitcsvm” command was used for learning using Gaussian kernel. Since the training data was unbalanced, the training examples for each classifier were hand-selected from the original training set such that approximately equal number of positive and negative classes were trained for each arrhythmia. Depending on the spatial and spectral characteristics, the number and type of features differed for each arrhythmia. Classification was performed using the “predict” function. The predict function outputs two parameters, namely, the class label and a score value that indicated the confidence of prediction, which depended on the training features and was different for each arrhythmia. The function rdmat(), from the challenge’s “entry.zip” software folder [1] was used to extract the signal information from the corresponding header files for each record, using which the sampling frequency and gain corrected ECG and PPG signals were obtained.

2.1 Signal Pre-processing

Prior to performing logical analysis and feature vector formation for arrhythmia classification, the ECG and PPG signals were subjected to signal quality analysis and baseline wander removal. For quality analysis, the signals were checked for presence of flat lines and zigzag lines that could have resulted from improper electrode placement, loss of contact, etc., and not an actual cardiac abnormality, such as asystole.

Flat/zigzag lines are segments of signals having almost zero electrical activity. Segments of signal, having zero amplitude difference between two consecutive samples, for a duration of minimum two seconds, were classified as being “flat lines”. Segments of signal, having alternating positive and negative slopes between two successive samples, for a duration of minimum seconds, were classified as having zigzag lines.

For baseline wander removal from ECG, our algorithm first applied a second order bidirectional Butterworth low-pass filter with a cut-off frequency of 1Hz to the ECG signals. The resulting filtered signal was subtracted from the original signal to give a signal with approximately zero baseline wander, sufficient to detect R-peaks and other

ECG features relevant for classifying the five arrhythmias.

2.2 Arrhythmia Classification

A separate algorithm was used for each arrhythmia. Since the alarms were triggered within ten seconds of the arrhythmia event having been detected [1,2], our algorithm used only the last ten seconds i.e. from 4:50 to 5:00 of each signal from a particular recording. For retrospective analysis, the subsequent twenty seconds of data were used to determine if the classified alarm was a false positive or not. Pan-Tompkins algorithm was applied to ECG signals for QRS complex detection [3,4]. For each QRS complex the R-peak was identified as the sample with maximum amplitude located between the corresponding QRS onset and offset locations. The R-R interval was calculated as the difference between consecutive R-peak indices. The PPG peaks were detected using first order differentiation of PPG signal and the peak-to-peak intervals (PPI) correlated with ECG's R-R intervals, with a linear time shift [5].

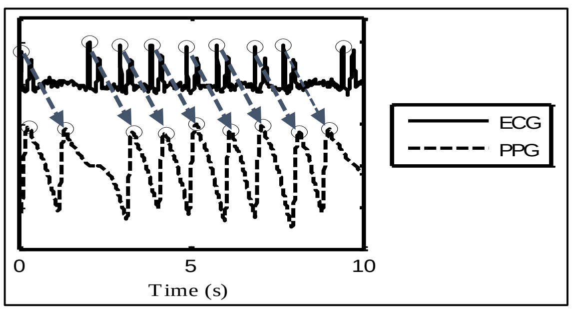

Figure 1. Correlation between R-peaks and PPG peaks

Classification of EBC, ETC and ASY involved analysing both ECG and PPG signals. For VFB and VTA, analysis was restricted to only ECG signals as PPG data was highly irregular to assist in any reasonable prediction.

If a signal was identified as possessing flat/zigzag lines, then the particular signal was not included in the analysis. If both ECG and PPG signals were detected with flat/zigzag lines, then no alarm was raised for that record.

2.2.1 Extreme Bradycardia (EBC)

Extreme Bradycardia is a type of cardiac arrhythmia where the heart rate is very slow i.e. less than 40 bpm for five consecutive beats [1].

Using the ECG R-peaks, a sliding window with six peaks per window was formed and its average R-R interval was calculated. The minimum of the average R-R intervals was determined and labelled as "min_ebpm". A similar approach was used in determining the average PPI value from the PPG signal, from which the minimum value was determined as "min_pbpm". The values of "min_ebpm" and "min_pbpm" were used to form the feature vector to train an SVM binary classifier. A beat sequence was classified as having bradycardia (class 1) if min_ebpm and min_pbpm were less than 42 bpm i.e. (40 bpm + (0.05%)).

Prior to determining min_pbpm, the standard deviation of PPG's PPI values was calculated, and if it exceeded a certain threshold, then the signal was considered as noisy. In that case, "min_ebpm" was assigned to "min_pbpm".

The records in the test were classified using a trained SVM model. For those records that were classified as bradycardia, if beat-to-beat intervals had heart rate below 42 bpm, then the alarm was suppressed. Else the alarm was retained

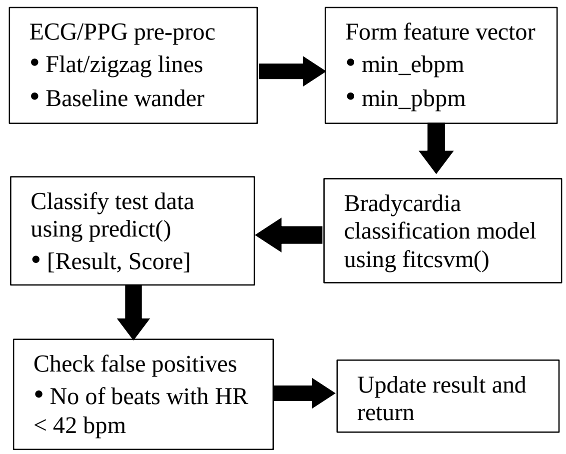

Figure 2. Bradycardia classification

2.2.2 Extreme Tachycardia (ETC)

Extreme Tachycardia is a type of cardiac arrhythmia with very high heart rates i.e. greater than 140 bpm [1]. Our algorithm for tachycardia classification was similar to that of bradycardia, except for the thresholds. A window of eighteen peaks was used to calculate the maximum R-R intervals and PPG PPI values. Here "max_ebpm" was determined which was equal to the maximum average R-R interval value. And similarly, max_pbpm was computed, which was equal to the maximum average PPI value. These values were then used to form a feature vector to train an SVM binary classifier. A beat was associated with tachycardia (class 1) if both max_ebpm and max_pbpm were greater than 133 bpm i.e. (140 bpm – (0.05%)). For records that were classified as having tachycardia, if less than five beat-to-beat intervals had heart rates exceeding 133 bpm, then the alarm was suppressed. Otherwise the alarm was retained.

2.2.3 Asystole (ASY)

Asystole [1] is the absence of QRS activity for atleast four seconds and is different from the flat line artefact.

In our algorithm, the ECG signals were used to form sliding windows of four seconds. For each window, a feature vector was formed using the following steps:

1. Calculate the number of samples in the window with magnitude exceeding 0.1mV. (Feature 1)
2. Calculate successive difference between locations of samples found in step 1 and store it in an array.
3. Determine maximum value of the array. (Feature 2)

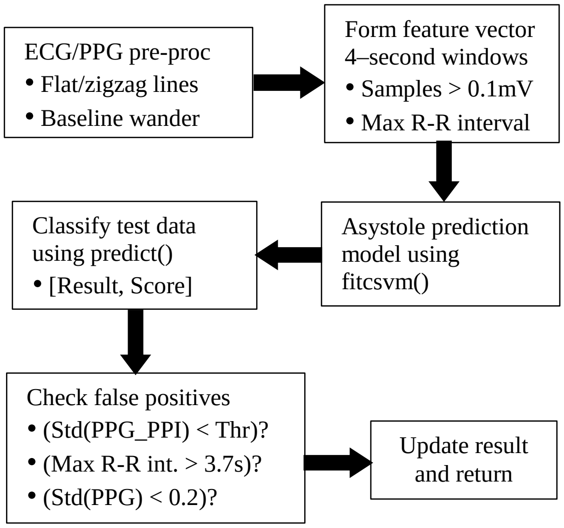

Figure 3. Asystole classification

A threshold of 0.1mV was chosen for Step 1 after it was found that in a majority of the records, ECG segments with asystole had a maximum amplitude whose magnitude did not exceed 0.1mV. The second feature refers to the maximum length of samples in a segment that had very low electrical activity i.e. magnitude less than 0.1mV. In a majority of records, the value of this feature exceeded 850 samples i.e. approximately 3.4 seconds, indicative of asystole. These features were used to train an SVM binary classifier. A training example was classified with asystole (class 1) only if its values for Feature 1 was less than 70 and for Feature 2 was above 850.

For test records that were classified as normal or having asystole using the above ECG analysis, the PPG PPI was analysed, and if its standard deviation was found to be less than a certain threshold (indicating regular PPG activity), the alarm was suppressed. Else, for higher standard deviation values, if any one of the intervals exceeded 3.7 seconds and the standard deviation of the PPG signal in that interval was less than 0.2 (indicating little PPG activity or blood flow), an alarm was raised.

2.2.4 Ventricular Tachycardia (VTA)

Ventricular tachycardia is a broad complex tachycardia originating in the ventricles, characterised by heart rates greater than 100 bpm [1]. The VTA segments in an ECG recording can be seen as either qR/qS complexes with heart rates exceeding 100 bpm and lacking any T or P wave presence. Hence these segments are composed of mainly a singular frequency component, approximately 1.6Hz to 5Hz, corresponding to a heart rate of 100 to 300 bpm.

Using ECG, our algorithm implemented a combination of SVM-based learning, autocorrelation and statistical analysis methods to detect VTA. A sliding window of two seconds was used. In the first stage, the normalized power spectrum density (nPSD) of the window was computed. The values of the nPSD from 0Hz to 20Hz were input to an SVM binary classifier. The classifier was trained such that windows whose nPSD values concentrated only around 1.6 to 5Hz were classified as exhibiting VTA (class 1), ensuring detection of records that had a 1.6Hz to 5Hz primary frequency component persisting for two seconds or more, indicating VTA symptoms.

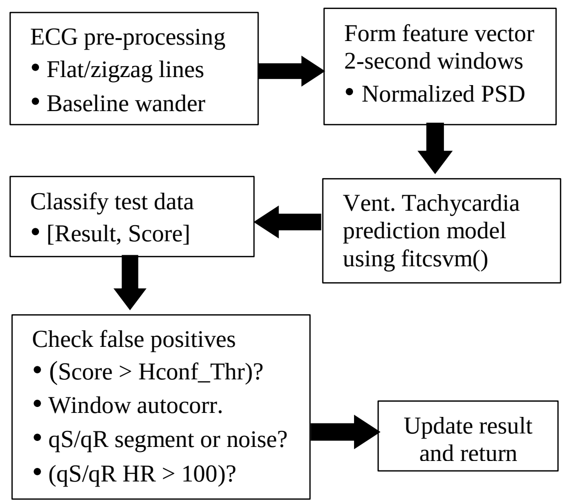

Figure 4. Ventricular Tachycardia classification

The above model misclassified some records, which were actually normal, as having VTA. This was due to the noisy nature of the signals which was reflected on the signal's spectral characteristics. To reduce such false positive classification, the segments classified as having VTA with the highest confidence scores were extracted from each ECG signal and their normalized autocorrelation was computed, whose peak amplitudes and intervals were analysed to check if the alarm was due to qR/qS complexes or other factors such as P, T waves and/or noise. The heart rate for the qS/qR complexes was computed to see if it exceeded 100 bpm. These steps decided if the alarms raised by the SVM classifier were to be retained or suppressed.

2.2.5 Ventricular Fibrillation (VFB)

Ventricular Fibrillation is a type of cardiac arrhythmia characterised by uncoordinated contraction of ventricular muscles, making them quiver. The ECG during VFB lacks presence of any fiducial points and is characterised by sinusoidal waveforms with dominant frequencies in the range of 3 to 8 Hz corresponding to a heart rate of 200 to 500 bpm approximately.

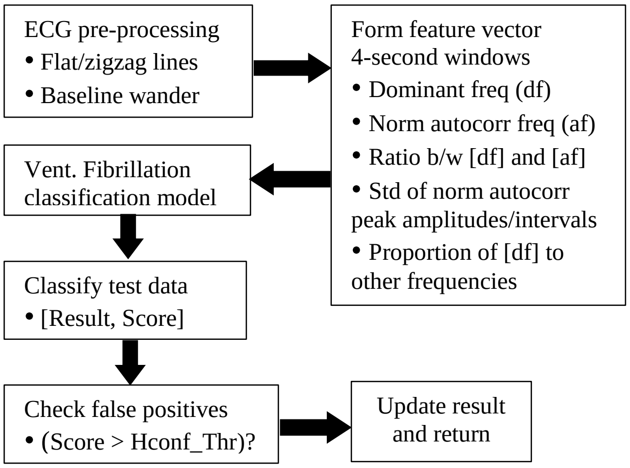

Figure 5. Ventricular Fibrillation classification

For predicting VFB, a feature vector was formed from the ECG using a sliding window of four seconds [1]. The features were derived from normalized power spectrum density analysis and autocorrelation plots [6]. They included frequencies present in each window, the frequency derived from the autocorrelation plot using peak-to-peak interval information, the correlation between PSD frequency and autocorrelation frequency, the standard deviation of peak amplitudes and standard deviation of peak intervals of the autocorrelation plot. These features were input to an SVM binary classifier. Of the records that were classified as exhibiting VFB, only those records that had a high confidence score of positive prediction were classified as exhibiting VFB.

3. Results

Our algorithm was tested on the Physionet Challenge training and test datasets consisting of 750 and 500 records respectively [1]. The results are summarized below:

Table 1. Classification statistics for training and test data.

Arrhythmia	Training Set		Test Set	
	TPR	TNR	TPR	TNR
EBC	100%	93%	87%	86%
ETC	100%	89%	100%	80%
ASY	100%	86%	78%	91%
VTA	84%	85%	90%	82%
VFB	100%	65%	100%	69%
Real-Time	96%	86%	94%	82%
Retrospective	94%	85%	94%	86%

TPR – True Positive Rate; TNR – True Negative Rate

4. Conclusion

The algorithms described in this paper classify five arrhythmias with very good accuracy as observed in the results table (Table 1). Using the scoring mechanism of the challenge [1], scores of 79.44 and 81.85 were achieved for real-time and retrospective datasets respectively. Since the algorithms use only ten seconds of ECG and/or PPG data, the speed of arrhythmia detection is reasonably high. This also ensures that alarms are raised within ten seconds of an event having occurred, which is in accordance with the ANSI/AAMI EC13 Cardiac monitor Standards [2]. Using information from both ECG and PPG helps in identifying arrhythmias better than in the presence of either signal alone. The primary disadvantage of the methods can be attributed to non-usage of PPG signals for VTA and VFB, and not checking for presence of random noise, which could increase false alarm rates.

References

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Address for correspondence:

Vignesh Kalidas
Quality of Life Technology (QoLT) Lab
Department of Electrical Engineering
The University of Texas at Dallas
800 West Campbell Road
Richardson, TX 75080
United States of America
vignesh.kalidas@utdallas.edu