A Switching Feature Extraction System for ECG Heartbeat Classification

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Abstract

This study compared two methods for extracting ECG waveshape features useful for heartbeat classification. The first method (segmented waveshape features) sampled the ECG waveshape between the P and T waveform boundaries, calculated QRS and T wave durations, and used RR-interval features. The second method (fixed interval waveshape features) used a fixed window to capture the ECG waveshape and RR-interval features.

Data were obtained from the MIT-BIH arrhythmia database. We investigated the problem of discriminating between normal, supraventricular (SVEB), ventricular (VEB), fusion and unknown beat classes. When the P, QRS and T wave boundaries could be found reliably, the segmented waveshape features resulted in more balanced performance for discriminating SVEB and VEB beats than the fixed interval waveshape features. A hybrid approach using segmented and fixed interval features when waveform boundaries could be reliably found, and fixed interval features otherwise was the most robust solution. Using the AAMI recommendations for cardiac rhythm disturbances the hybrid approach resulted in a sensitivity of 69%, a positive predictivity of 31% and a false positive ratio (FPR) of 6.6% for SVEB class. For the VEB class the sensitivity was 80%, the positivity predictivity was 85% and the FPR was 1.0%.

1. Introduction

The electrocardiogram (ECG) is a non-invasive test that can be used to detect arrhythmias. To successfully capture some arrhythmias up to a month of ECG activity may need to be recorded. Detection of non-life-threatening arrhythmias is an important area of study as many of these arrhythmias may require therapy to prevent further problems. A characteristic of many arrhythmias is that they appear as sequences of heartbeats with unusual timing or ECG waveshape. The rhythm of the ECG signal can be determined by knowing the classification of consecutive heartbeats in the signal [1] and an important step towards identifying an arrhythmia is the classification of heartbeats.

Automated processing of the annotation of beat types is helpful to the clinician as it may save many hours of tedious work manually annotating the beat types of multiday ECG recordings.

There are numerous publications on ECG beat classification e.g. [2-15]. Approaches considered include using Hermite functions [9,11,13], statistical features [6,13], waveshape [2,3,4,6,7,12,15,16] and wavelets [8,10,16] as discriminating features between the heartbeat classes. Classification methods include artificial neural networks [8,9], decision trees [15], linear discriminants [1,3,4,12], self organizing feature maps [11], support vector machines [10,13,16] and other statistically motivated approaches [6,7].

2. Methods

2.1. Data

Data from the 48 recordings of the MIT-BIH arrhythmia database [17] were used in this study. Each recording containing two ECG lead signals (denoted lead A and B). The four paced beat recordings were removed from the analysis as per AAMI recommended practice [18,19].

The data is bandpass filtered at 0.1-100Hz and sampled at 360Hz. There are 109,492 labeled ventricular beats from 15 different heartbeat types which were remapped to the five AAMI heartbeat classes [18,19] using the mapping in [3].

We note the error of mapping the atrial escape beats and nodal (junctional) escape beats to the normal class in Tables I and II in [3]. These two beat types are allocated to supraventricular ectopic beat class as stated in [18]. We have used this updated beat type mapping for this study.

After remapping, there were five heartbeat classes. Class N contained beats originating in the sinus node (normal and bundle branch block beat types), class S contained supraventricular ectopic beats (SVEB), class V contained ventricular ectopic beats (VEB), class F contained beats that result from fusing normal and VEBs, and class Q contained unknown beats including paced beats.

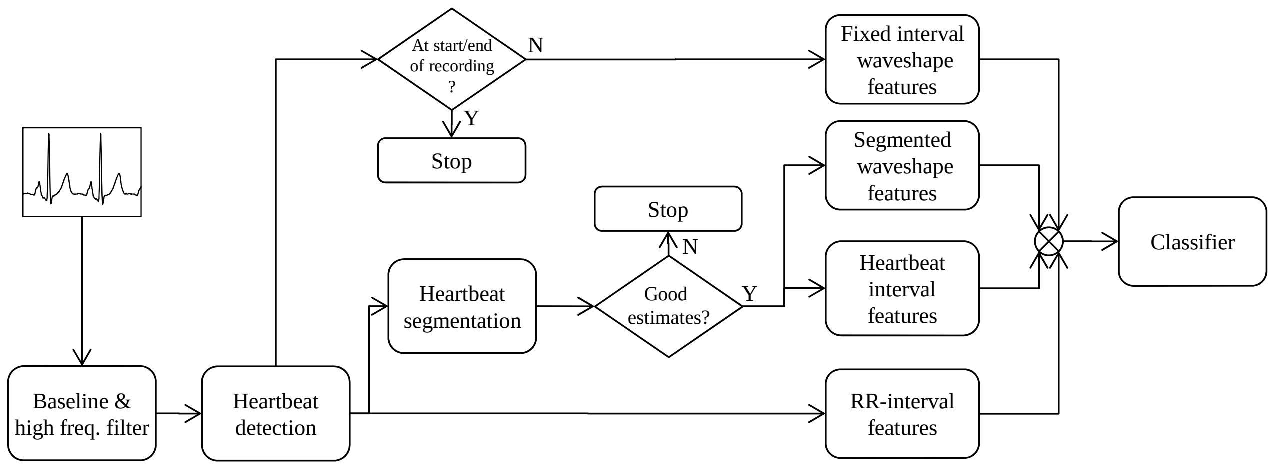

Figure 1: A schematic of a switching feature extraction system used in this study. Note the schematic shows the processing for one lead. There is an identical system for the second ECG lead used in this study.

2.2. Feature extraction

We had previously observed that features that captured the amplitude information of the ECG and utilised the P, QRS and T wave boundary information provided satisfactory classification performance [3]. The issue with this feature extraction method is that waveform boundary information cannot always be determined for every beat. In our previous study [3] when a waveform boundary could not be determined we replaced the resulting missing feature values with average values. The purpose of this study was to improve this step by using fixed interval amplitude information when waveform boundaries cannot be determined. Figure 1 shows a schematic of our system. It can be best described as a switching feature extraction system with 3 outputs.

1) When both waveform boundaries and fixed interval boundaries cannot be determined the system makes a classification based on RR-intervals only. This only occurs when a beat is very close to the start or the end of a recording.
2) When waveform boundaries cannot be determined and the fixed interval boundaries can be determined the system uses fixed interval waveshape and RR-interval features.
3) When waveform boundaries can be determined the system used fixed interval waveshape, segmented waveshape, heartbeat interval and RR-interval features.

The other modules of Figure 1 are discussed below. The first stage receives a digital ECG signal and removes artefact signals by applying a filtering stage. Artefact signals include high frequency noise, power line interference and baseline wander. Filters for this stage are described in [3]. The next stage provides heartbeat detection and heartbeat segmentation. In this study we used the manually verified heartbeat fiducial point times provided with the MIT-BIH arrhythmia database. The ECG heartbeat segmentation program of Laguna *et al.* was used to provide estimates of the QRS onset and offset and T-wave offset times; a Boolean value indicating the presence/absence of a P-wave and, if present, the P-wave onset and offset time. Validation of the program has been done on the CSE multilead database [20] and the MIT-BIH QT database [21]. The accuracy of the segmenting program was comparable with the inter-expert variation.

We followed the methods closely of the feature extraction in [3] with the enhancement of expanding the waveshape windows to include the P wave. Features were extracted as follows.

RR-interval features: Four features were extracted from the RR sequence. The pre-RR-interval was the RR-interval between a given heartbeat and the previous heartbeat. The post-RR-interval was the RR-interval between a given heartbeat and the following heartbeat. The average RR-interval was the mean of the valid RR-intervals for a recording and had the same value for all heartbeats in a recording. Finally, the local average RR-interval was determined by averaging the valid RR-intervals of the ten RR-intervals surrounding a heartbeat.

Heartbeat interval features: Three features per ECG lead were calculated. The QRS duration was the time interval between the QRS onset and the QRS offset. The T-wave duration was defined as the time interval between the QRS offset and the T-wave offset. The third feature was a Boolean variable indicating the presence or absence of a P-wave.

Segmented waveshape features: The segmented waveshape features contained amplitude values of the ECG signal determined by sampling windows between

Feature Set	Multiway performance		Sensitivities					AAMI performance measures: SVEB				VEB			
	Acc	Kappa	N	S	V	F	Q	Acc	Se	+P	FPR	Acc	Se	+P	FPR
Segmented waveshape	84.8	0.51	86	68	77	88	0	92.5	68	31	6.4	97.3	77	80	1.3
Fixed interval waveshape	87.5	0.56	89	65	80	73	14	91.3	65	27	7.5	97.5	80	82	1.2
Segmented and fixed interval waveshape	90.3	0.63	92	69	80	85	0	92.4	69	31	6.6	97.8	80	85	1.0
Config IX in [4]	84.7	0.50	86	70	77	90	0	93.6	70	36	5.4	97.4	77	82	1.2
Config IX in [4]*	85.9	0.53	87	76	78	89	0	94.6	76	38	4.7	97.4	78	82	1.2

*Same beat type mapping as [3]. See section 2.1 further details

Table 1: Classifications results obtained in this study. All results except for kappa are expressed as percentages. For comparison the equivalent results from configuration IX in [3] are shown in the 4th and 5th rows using the corrected and the original class mapping.
Abbreviations: Acc- accuracy, F-fusion, FPR – false positive rate, N- normal, +P- positive predictivity, Q- unknown, S-supraventricular, Se –sensitivity, SVEB – Supraventricular ectopic beat, V-ventricular, VEB – ventricular ectopic beat

the P wave onset and offset, the QRS onset and offset and the QRS offset and the T-wave offset points.

Fixed interval waveshape features: The fixed interval waveshape features contained amplitude values of the ECG signal obtained by a sampling window between the QRS detection point minus 250 milliseconds to the QRS detection point plus 500 milliseconds.

Classifier: Classifier models based on linear discriminants [22] were utilised throughout this study.

Performance Estimation: The data division scheme presented in [3] was used. Classifier training was achieved using data from 22 recordings of the database (DS1 in [3]) and performance assessment was determined using the other 22 recordings (DS2 in [3]). Performance measures considered include the 5-way accuracy, sensitivity and specificity performance metrics. We also calculated the accuracy, sensitivity, positive predictivity and false positive ratio for VEB and SVEB beat classes as per AAMI recommendations [18]. The kappa value [23] was also considered

3. Results and discussion

Three feature sets were assessed. The first feature set contained RR-intervals, heartbeat intervals and segmented waveshape features. The second feature set contained RR-intervals and fixed interval features. The third feature set contained RR-intervals, heartbeat intervals and segmented and fixed interval waveshape features.

Table 1 shows the multiway and the AAMI recommended performance measures for the three feature sets. For reference we have also included the equivalent results for configuration IX from our published system in [3] at rows four and five of Table 1. Comparing the results in rows four and five shows the effect of the updated beat type mapping described in section 2.1. It shows there was about a 1% drop in the normal class specificity and a 6% drop in the SVEB sensitivity. All other specificities are equivalent. The cause of this performance drop is likely due to the atrial escape beats and the nodal escape beats being misallocated by the system (whereas they were previously correctly allocated).

Rows one to three of Table 1 show the classification results of the configurations used in this study. The segmented waveshape feature set in row one is an equivalent system to configuration IX in [3]. Comparing the results of row one and row four shows the systems produce similar results. The small differences are due to the system in this study utilising P-wave information in the waveshape features.

Comparing the performance results for the fixed interval and the segmented waveshape features reveals that the fixed interval waveshape features had higher overall accuracy (87.5% cf. 84.8%) but less balanced performance for discriminating SVEB (91.3% cf. 92.5%) and VEB (97.5% cf. 97.3%) beats than the fixed interval waveshape features.

The switching system using the segmented and fixed interval waveshape features returned the best multiway performance figures (Acc–90.3%, N-92%, S-69%, V-80%, F-85%, Q-0%). It also had the highest kappa value of 0.63 for the multiway classification task. Using the AAMI performance measures this feature set returned a sensitivity of 69%, a positive predictivity of 31% and false positive ratio of 6.6% for SVEB class. For the VEB class the sensitivity was 80%, the positivity predictivity was 85% and the false positive rate was 1.0%.

4. Conclusion

A hybrid approach using segmented and fixed interval waveshape features resulted in the best multiway classification performance. Using the AAMI performance measures to assess the hybrid approach resulted in an accuracy of 92.4%, a sensitivity of 69%, a positive predictivity of 31% and false positive ratio of 6.6% for SVEB class. For the VEB class the accuracy was 97.8%, the sensitivity was 80%, the positivity predictivity was 85% and the false positive rate was 1.0%.

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