Heartbeat Classification System using Adaptive Learning from Selected Beats

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Abstract

An adaptive system for the automatic processing of the electrocardiogram for the classification of heartbeats into beat classes that learns from selected beats is presented. A first set of beat labels is produced by the system by processing an incoming recording with an unadapted classifier. The beat labels are then ranked by a confidence measure calculated from the posterior probabilities estimates associated with each beat classification. An expert then validates and if necessary corrects a fraction of the least confident beats of the recording. The system adapts by first training a classifier using the newly annotated beats, and then combining the outputs with the unadapted classifier to produce an adapted classification system. The adapted system then updates the remaining beat labels of the recording. Data was obtained from the heartbeats obtained from the 44 non-pacemaker recordings of the MIT-BIH arrhythmia database classified into one of eleven classes.

With no adaptation a classification accuracy of 63% was achieved. By adapting the classifier, classification accuracy could be increased to over 91%. Our results show that a significant boost in classification performance of the system is achieved even when a small number of selected beats are used for adaptation.

1. Introduction

Arrhythmias of the heart are due to any change in the rate, regularity, origin or conduction of the cardiac electric impulse. The consequence can be anywhere from immediately life threatening (e.g. ventricular fibrillation) to a non-discernable event by the patient. The electrocardiogram (ECG) is a simple non-invasive test that can be used to detect arrhythmias. A characteristic of many arrhythmias is that they appear as sequences of heartbeats with unusual timing or ECG waveshape. By labelling the sequence of beats in an ECG recording using established classes, the rhythm of the ECG signal can be determined from the resulting sequence [1].

Some arrhythmias can be very difficult to detect and up to a month of ECG activity may need to be recorded and analysed to successfully capture them. Automated processing of the beat labels is helpful to the clinician as it may save many hours of tedious work manually labelling multiday ECG recordings.

Automated ECG beat classification algorithms been a popular topic for many years e.g. [2-14]. The published approaches differ in three main respects 1) methods used for calculating discriminating features, 2) classifier model and 3) adaptive or fully automatic operation.

The best reported performance of fully automatic methods is a labelling accuracy of 92% when labelling the beats as normal, supraventricular ectopic or ventricular ectopic beats [13]. In order to improve performance of beat classification systems, research attention has been directed to patient adaptive arrhythmia detection i.e. the classifier uses expert knowledge about a section of the recording under analysis to improve the classification rate on the rest of the recording. Llamedo [13] et al. reported classification performance improvement of at least 6.9% with an adapting system using a system that combined a linear discriminant based automatic system with a clustering system. Other approaches to adaptation include Jiang et al. [7] who used a blocked based neural network and adapted the network using the first five minutes of each record. Ince et al. [8] used a feedforward neural network also adapted using the first five minutes of data of each record.

Adaptation is achieved by incorporating a human expert's knowledge of a section of the recording for a particular patient into the training of the classifier with the objective of increasing the classification performance of the heartbeat labelling system on the rest of the recording. The benefit of adaptation systems is the increased classification performance. The downside is that the fully automatic operation of the system is lost as a human expert must manually check the labels of a selection of sample beats of the recording under investigation.

Many of the adaptive systems published process the data in two passes. In the first pass an unadapted classifier is used to annotate the beats. In the second pass a selection of the beats annotated in the first pass are presented to a human expert for expert labelling. These newly labelled beats are then used to train an adapted classifier which is then used to label the remaining beats in the recording.

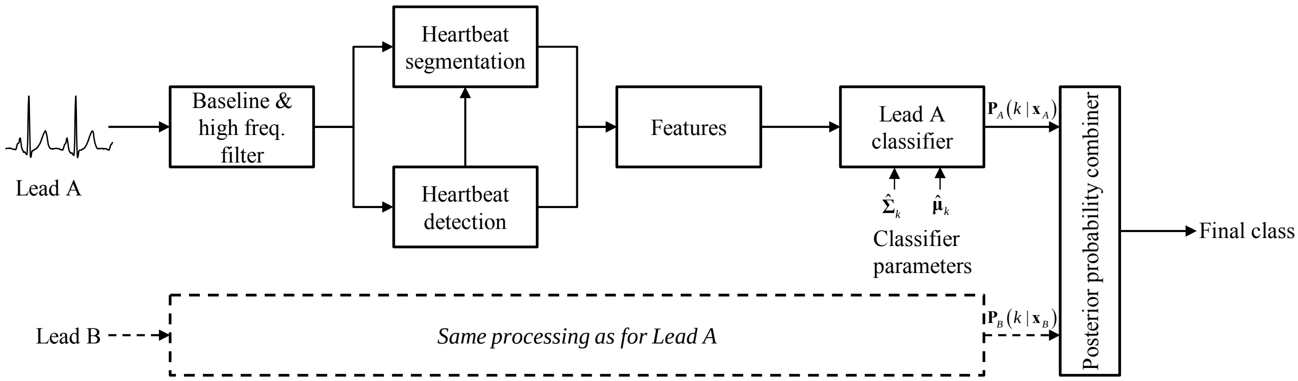

Figure 1. A schematic of the system for heartbeat classification. The classifier parameters determine if the system performs as an unadapted or adapted-classifier.

In this paper we offer an innovation to the selection of beats for presentation to the expert. We deliberately select beats that the unadapted classifier had most difficulty in classifying. The intuitive idea is that learning for the adapted classifier is best achieved by learning from hard cases rather than easier cases. We have previously shown that this method was of benefit when processing beats labelled according to AAMI guidelines [15]. The purpose of this study was to explore the utility of the method when using the full set of beat labels available with the MIT-BIH arrhythmia database.

2. Methods

Data from the 44 non-pacemaker recordings of the MIT-BIH arrhythmia database [16] were used in this study. Each recording contains two ECG lead signals (denoted lead A and B). The data is bandpass filtered at 0.1-100Hz and sampled at 360Hz. There are 100,731 labelled ventricular beats from thirteen beat classes. The classes (and class size) are normal (74,548), left (8,074) and right (7,259) bundle branch blocks, atrial escape (16), nodal escape (229), atrial premature (2544), aberrated atrial premature (150), nodal premature (83), supra-ventricular premature (2), premature ventricular contraction (6902), ventricular escape (106), fusion (803), and unclassified beats (15).

2.1. Data processing

We used independent records for training and testing our system (see section 2.3). This introduced a requirement that a beat class needed to be present in two or more records in order to be able to estimate its performance. As the supraventricular premature and atrial escape beats were present in one record they were merged with the atrial premature class. This resulted in eleven beat classes for all subsequent processing.

A schematic of our classification system is shown in Figure 1. It implements the unadapted and adapted classification systems. The baseline and high frequency filtering, heartbeat detection and heart beat segmentation are described in [4]. The features used by our system are shown in Table 1. An incoming record is processed in a number of steps as follows. The unadapted set of classifier parameters are used in the first step. These parameters have previously calculated using a large training dataset independent of the incoming record. The incoming record is processed with these classifier parameters to produce the initial set of beat labels. A selection of labelled beats is then presented to an expert who, if necessary, corrects the labels. The corrected labels are then used to calculate a new set of classifier parameters. The next step is to combine the unadapted and the new set of classifier parameters to produce an adapted set of classifier parameters. The system then uses the adapted parameters to process the incoming record beats that have not been annotated by the expert.

Table 1. List of features processed by the classifier.

Features
Pre- and post-RR interval, Average and local avg. RR-interval.
QRS duration (QRS offset - QRS onset) of leads A and B.
T-wave duration (T-wave offset - QRS offset) of leads A and B.
P wave flag for leads A and B.
ECG shape between QRS onset and offset of leads A and B.
ECG shape between QRS offset and T-wave offset of leads A and B.

2.2. Adaption

Figure 2 shows the adaptation steps used by our system. We based our classification system on linear discriminants as we previously achieved good results using them for ECG beat classification, they return probabilistic outputs, and training is achieved in a single iteration. Details of our adaptation algorithm follow.

The classifier parameters (class means $\boldsymbol{\mu}_k$ and common covariance $\mathbf{\Sigma}$) for linear discriminants can be determined from the training data examples using

$$\boldsymbol{\mu}_k = \sum_{n=1}^{N_k} \mathbf{x}_{kn} \Big/ N_k \ , \boldsymbol{\Sigma}_k = \sum_{n=1}^{N_k} \left(\mathbf{x}_{kn} - \boldsymbol{\mu}_k\right)\left(\mathbf{x}_{kn} - \boldsymbol{\mu}_k\right)^T \Big/ N_k \ ,$$

$$\text{and } \boldsymbol{\Sigma} = \sum_{k=1}^{c} N_k \boldsymbol{\Sigma}_k \Big/ \sum_{n=1}^{c} N_k \ . \qquad (1)$$

where the number of classes is c (11 in our case), the number of training examples in class k is N_k, the feature vector of the nth training example belonging to class k is denoted $\mathbf{x}_{kn}$, and $\boldsymbol{\Sigma}_k$ is the class-conditional covariance matrix. Note that the total number of beats used for training is $N = \sum_{n=1}^{c} N_k$. The training data is used to determine the $\boldsymbol{\mu}_k$'s and $\boldsymbol{\Sigma}$. A feature vector x is classified by calculating the estimated posterior probabilities, $P(k \mid \mathbf{x})$ for the kth class using

$$P(k \mid \mathbf{x}) = \exp(y_k) \Big/ \sum_{l=1}^{c} \exp(y_l) ,$$

$$\text{where } y_k = -\tfrac{1}{2}\boldsymbol{\mu}_k^T \boldsymbol{\Sigma}^{-1} \boldsymbol{\mu}_k + \boldsymbol{\mu}_k^T \boldsymbol{\Sigma}^{-1} \mathbf{x} \qquad (2).$$

The final classification of the system is the class with the highest posterior probability estimate.

During development of the system training is performed once on a large database and the unadapted classifier parameters $\overline{\overline{\boldsymbol{\mu}_k}}$'s and $\overline{\overline{\boldsymbol{\Sigma}_k}}$'s are then fixed.

After processing the incoming record with the unadapted parameters, beats are selected (see below) and presented to the expert for labelling. These selected beats are then used to determine the $\overline{\boldsymbol{\mu}_k}$'s and $\overline{\boldsymbol{\Sigma}_k}$'s using (1). The adapted parameters $\hat{\boldsymbol{\mu}}_k$ and $\hat{\boldsymbol{\Sigma}}$ are calculated using

$$\hat{\boldsymbol{\mu}}_k = K_k \overline{\boldsymbol{\mu}_k} + (1 - K_k)\overline{\overline{\boldsymbol{\mu}_k}} \ , \ \hat{\boldsymbol{\Sigma}}_k = K_k \overline{\boldsymbol{\Sigma}_k} + (1 - K_k)\overline{\overline{\boldsymbol{\Sigma}_k}} \ ,$$

$$\text{and} \qquad \hat{\boldsymbol{\Sigma}} = \sum_{k=1}^{c} N_k \hat{\boldsymbol{\Sigma}}_k \Big/ \sum_{k=1}^{c} N_k \ . \qquad (3)$$

where K_k is the class conditional weighting value and varies between 0 and 1.

2.3. Beat selection, combining classifiers and performance measurement

Our goal was to minimise the number of beats to be presented to the expert. To select beats to train the adapted-classifier we first ran the unadapted-classifier over the record and used (2) to calculate the posterior probabilities of each class for each beat. We graded the confidence of the classifiers decision for the ith beat by value of its highest posterior.

$$R_i = \max_{k=1..c}\left(P(k \mid \mathbf{x}_i)\right). \qquad (4)$$

Beats that have been classified with a high degree of confidence by the unadapted classifier have a large value for R_i while beats classified with a low degree of confidence will have a low value of R_i. To select beats for adaptation training we ranked the R_i's from lowest to highest value and then present the lowest ranked beats to the human expert for evaluation.

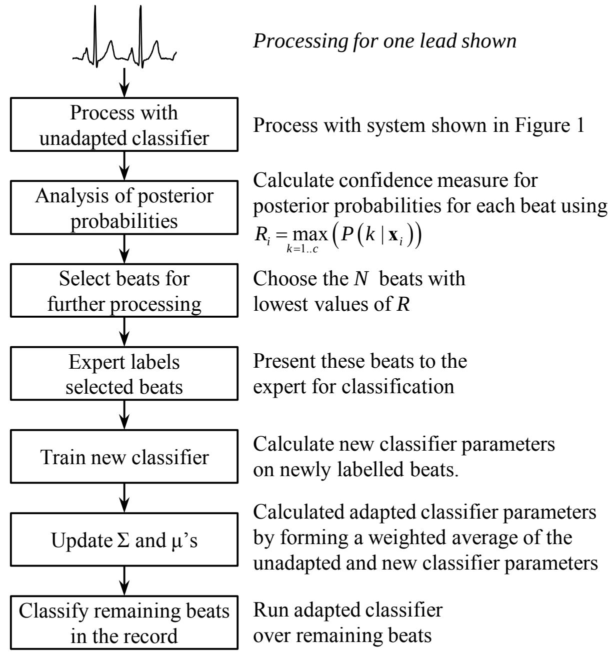

Figure 2. Adaptation algorithm.

To combine the outputs from processing lead A and lead B we multiplied posterior probability estimates calculated using equation (2) and rescaled so probabilities sum to one. The final output was the class with the highest combined posterior probability.

We used a leave-one-record-out cross validation process to estimate classifier performance. This provided 43 records for training the unadapted classifier and one record for testing classifier performance. Performance measures considered were the accuracy, sensitivity, and specificity measures. To obtain unbiased measures of performance we tested the performance on test data beats not used for adaption.

3. Results and discussion

All prior probabilities were set equal to 1/11. The class conditional weighting values were set to 0.5. The number of beats labelled by the expert for adaption was varied between 1 and 500 beats. Figure 3 shows the accuracy of classification system versus the number of beats used for adaption on the test data. Table 2 shows the class sensitivities on the test data of the unadapted and an adaption system requiring the expert to label 20 beats of an incoming record.

The results in Figure 3 demonstrate the benefit of adaption. The accuracy increases from 63% (no adaption) to over 91% using 500 beats for adaption. Table 2 demonstrates some of challenges of working with ECG beat labelling. Even with adaption the beat classes with a very small overall representation such as NP, VE and U have sensitivities below 30%. We also note that adaption decreased the sensitivity of the fVN class which is due to the similiarity of the waveshape of this class to normal

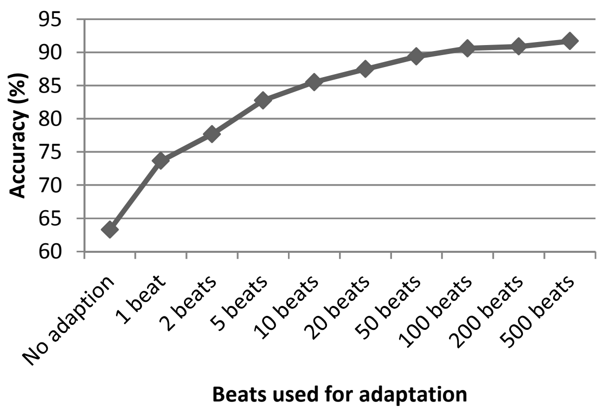

Figure 3. Classification accuracy as a function of beats used for adaptation.

beats. Other researchers in adaptive systems [7,8,13] have considered a much smaller set of a beat labels so it is difficult to compare results directly. They have reported accuracies of between 96% and 99% for separating normal from abnormal beats (2 class problem) so our result of above 90% for separating 11 classes appears favourable.

4. Conclusion

We have shown that adaptation can markedly improve the system performance but we note that this has come at the expense of fully automatic operation of the system.

Acknowledgements

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