An Adapting System for Heartbeat Classification Minimising User Input

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***Abstract*— An adaptive system for the processing of the electrocardiogram (ECG) for the classification of heartbeats into beat classes that seeks to minimize the required input from the user is presented. A first set of beat annotations is produced by the system by processing an incoming recording with a global-classifier. The beat annotations 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 then adapts by first training a local-classifier using the newly annotated beats and combines this with the global-classifier to produce an adapted classification system. The adapted system is then used to update beat annotations. Our results show that we can achieve a significant boost in classification performance of the system by using a small number of beats for adaptation.**

I. 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. 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. [2-14]. 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.

Approaches considered for calculating discriminating features have been motivated by observations that aberrant heartbeats normally have unusual timing and/or unusual ECG waveshape. Authors considering unusual timing features have used RR-intervals [3,6,7,8,9,10,12,13,14] in the immediate vicinity of the heartbeat under analysis to capture this information. Authors have also considered intrabeat timing changes by looking at P, QRS and T wave interval information [3,6,10]. Waveshape has been characterized using a wide variety of methods. For example it has captured directly by sampling the ECG waveform [3,5,6,10,11] and indirectly with dimension reducing functions such as Hermite functions [2,7,10], wavelets [8,9,12,13,14] and other higher order statistical functions [5,10]. It is not obvious from the presented results that any method has a clear advantage over others. Llamedo also considered multilead ECG features inspired by vectorcardiographic [12,13] analysis.

In order to improve performance of heartbeat 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 detection 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. Jiang et al. [7] 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.

Many of the adaptive systems published so far rely on a human expert labelling a contiguous series of heartbeats. While this is relatively easy to implement, it does not use the human expert's knowledge in the most efficient manner. In this paper we offer a new approach to the problem of adaption by forcing the classifier to learn from beats that it has had the most difficulty in classifying. We assess difficulty by looking at the posterior probabilities of each classification determined from a global-classifier and choosing beats where there is a small difference between the probability of the chosen class and the other classes. The intuitive idea is that learning is best achieved by using learning from hard cases rather than easier cases.

II. Methods

A. Data

Data from the MIT-BIH arrhythmia database [15] was used in this study. The database contains 48 recordings each containing two ECG lead signals (denoted lead A and B). Following AAMI recommended practice [16,17] the four paced beat recordings were removed from the analysis. The data is band-pass filtered at 0.1-100Hz and sampled at 360Hz. There are over 109,000 labeled ventricular beats from 15 different heart-beat types which were remapped to the five AAMI heart-beat classes [16]. 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

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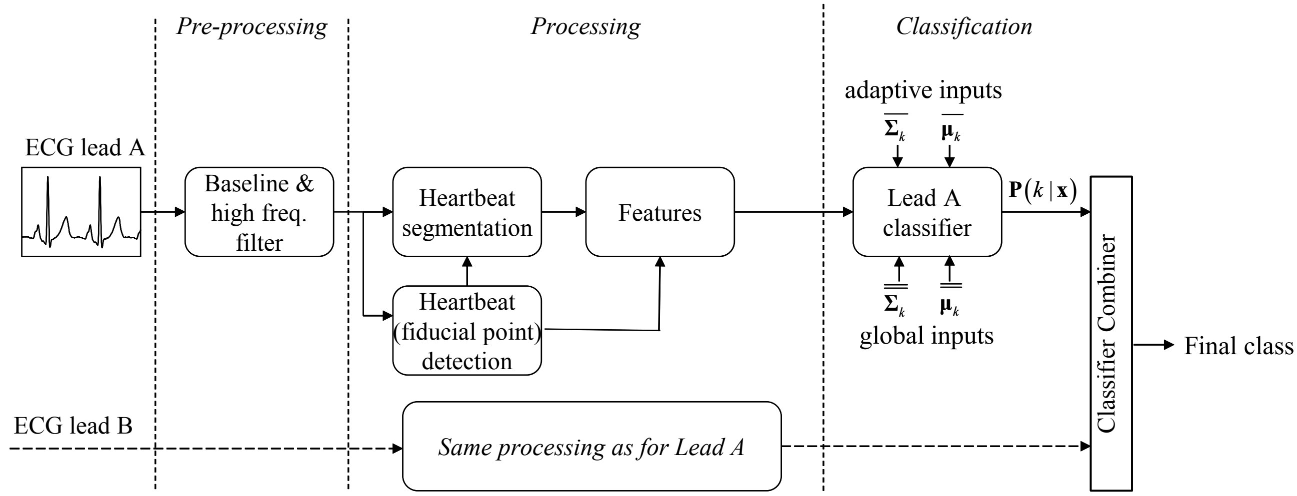

Figure 1: An Adaptive Heartbeat Classifier system. Note there is a parallel identical system processing ECG lead B.

beats (VEB), class F contained beats that result from fusing normal and VEBs, and class Q contained unknown beats including paced beats.

B. Data Processing

Figure 1 depicts our classification system. An incoming record is processed as follows. Initially, a global-classifier trained on a large dataset independent of the incoming record processes the recording to produce the initial set of beat annotations (in Fig. 1 this is achieved by switching off the adaptive inputs). A selection of annotated beats is then presented to an expert who, if necessary, corrects the annotations. The corrected annotations are then used to train a local-classifier. Adaptation is achieved by combining the outputs of the global-classifier and local-classifier to produce an adapted classification system. The adapted system is then used to update the annotations of the beats that have not been annotated by the expert.

The pre-processing and processing stages are identical to configuration IX described in [4] and the reader is referred to this reference for details. The features used by our system are shown in Table 1.

TABLE I: THE FEATURES CONSIDERED IN THIS STUDY.

Features
Pre-RR interval, Post-RR interval, Average RR-interval, 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 morphology (10 samples) between QRS onset and QRS offset of leads A and B.
ECG morphology (9 samples) between QRS offset and T-wave offset of leads A and B.

The feature extraction phase calculates a vector of measurements (feature vector) from each heartbeat that are processed by the classifier stage. The classifier stage selects one of the required classes in response to the input feature vector. The classifier contains parameters that are set during the system development to optimise the classification performance. The parameters are determined from a combination of local and global training. A combiner then unites the decisions of the classifier-units from the two ECG signal to form the final decision of the system.

C. Adaption

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 local 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 annotations of a selection of sample beats of the recording under investigation.

Our adaptation system is based on linear discriminants [18]. We have chosen this classifier as they return probabilistic outputs, training is achieved in one computation iteration and we have achieved good results with them previously for ECG heartbeat classification. Linear discriminant classifier parameters are determined with the training data using weighted maximum likelihood estimators as described in [18]. For a c class problem the classifier parameters (class means $\boldsymbol{\mu}_k$ and common covariance $\boldsymbol{\Sigma}$) can be determined from the training data examples using

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

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

where 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.

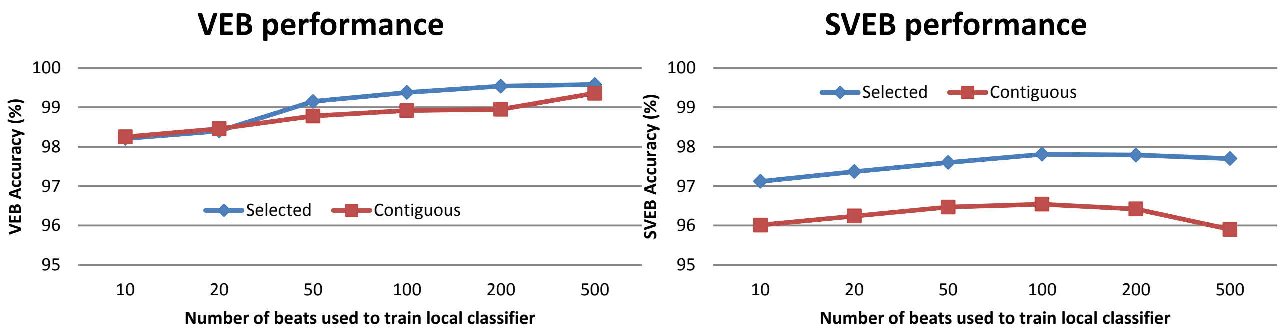

Figure 2: VEB and SVEB accuracy of the adaptive system. “Selected” indicates that beats for training the local classifier have been chosen using posterior probability values of the global classifier. “Contiguous” indicates the beats have been chosen sequentially be beat number.

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, $P(k\,|\,\mathbf{x})$ for the kth class using

$$P(k\,|\,\mathbf{x}) = \exp(y_k) \Big/ \sum_{l=1}^{c} \exp(y_l),$$
$$\text{where } y_k = -\tfrac{1}{2}\boldsymbol{\mu}_k^T\boldsymbol{\Sigma}^{-1}\boldsymbol{\mu}_k + \boldsymbol{\mu}_k^T\boldsymbol{\Sigma}^{-1}\mathbf{x}\,. \qquad (2)$$

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

Classifier parameters are calculated separately for the local- and global-classifiers and then the parameters are merged to form the final adapted system parameters. In the following the modifier $\overline{\overline{}}$ indicates data or parameters for the global-classifier, $\overline{}$ indicates local-classifier data or parameters, and $\hat{}$ indicates adapted classifier parameters. The global training data is used to determine the $\overline{\overline{\boldsymbol{\mu}_k}}$’s and $\overline{\overline{\boldsymbol{\Sigma}_k}}$’s for the global-classifier using (1) above. During development of the system global training is performed once on a large database and the global-classifier parameters are then fixed. The local data is used to determine the $\overline{\boldsymbol{\mu}_k}$’s and $\overline{\boldsymbol{\Sigma}_k}$’s for the local-classifier using (1). The parameters of the local and global classifier are combined to form the adapted classifier as follows:

$$\widehat{\boldsymbol{\mu}_k} = K_k\overline{\boldsymbol{\mu}_k} + (1-K_k)\overline{\overline{\boldsymbol{\mu}_k}}\,,\ \widehat{\boldsymbol{\Sigma}_k} = K_k\overline{\boldsymbol{\Sigma}_k} + (1-K_k)\overline{\overline{\boldsymbol{\Sigma}_k}}\,,$$
$$\text{and } \hat{\boldsymbol{\Sigma}} = \sum_{k=1}^{c} N_k\widehat{\boldsymbol{\Sigma}_k} \Big/ \sum_{k=1}^{c} N_k\,. \qquad (3)$$

where K_k is the class conditional weighting value and varies between 0 and 1 and is set using the training data. The total number of beats used in training of the local-classifier is given by $\overline{N}$.

Our goal was to minimise $\overline{N}$ by designing an adaptive classification system that selects the best heartbeats for review by the human expert. To select heartbeats to train the local-classifier we first ran the global-classifier over the record and used (4) to calculate the posterior probabilities of each class for each beat. We graded the confidence of the classifiers decision for the ith heartbeat by determining the ratio (R_i) of its highest posterior probability to sum of the other posterior probabilities. Using the fact that posterior probabilities sum to one for a heartbeat we get

$$R_i = \max_{k=1..c}\left(P(k\,|\,\mathbf{x}_i)\right) \Big/ \left(1 - \max_{k=1..c}\left(P(k\,|\,\mathbf{x}_i)\right)\right). \qquad (4)$$

Beats that have been classified with a high degree of confidence by the global 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. By forcing the adaptive system to focus on the difficult cases, we expected the adaptive learning to be achieved with a smaller number of beats.

D. Combining Classifiers

To combine the outputs from processing lead A and lead B we averaged the posterior probability estimates calculated using equation (2) and then chose the class with the highest combined posterior probability.

E. Performance Estimation

Classifier training was achieved using data from 22 recordings of the database (DS1 in [4]) and performance assessment was determined using the other 22 recordings (DS2 in [4]). Performance measures considered were the accuracy, sensitivity, positive predictivity and false positive ratio of the VEB and SVEB heart beat classes. Definitions for these measures may be found in [16] and procedures for calculating are given in [4]. We note that these calculation methods vary from standard definitions for accuracy, sensitivity, positive predictivity and false positive ratio. This is because the AAMI recommendations exclude unknown beats from true positive (TP) and false positive (FP) calculations for the SVEB and VEB measures and fusion beats are excluded from TP and FP calculations for VEB measures. This point is often overlooked by other researchers in the area.

III. Results And Discussion

We varied the number of beats used for adaption between 10 and 500. Figure 2 shows the accuracy of classification system for SVEB and VEB detection using beats selected by global classifier posterior probabilities. For reference we have shown the accuracy of the system when contiguous beats are chosen.

The results in fig. 2 demonstrate the performance benefit of selecting beats for local classifier training using global classifier probability estimates over sequential selection of beats. When using between 10 and 500 beats to train the local classifier it outperformed sequential selection for VEB and SVEB accuracy. This result suggests by forcing the adaptive system to focus on the difficult cases, faster learning has been achieved.

The full set of SVEB and VEB classification performance figures are shown in table 2 for the adaptive system processing 100 beats. It has been compared with other published systems.

Table II: Performance (%) of the adaptive system using 100 beats to train the local classifier. Abbreviations: acc-accuracy, sens-sensitivity, +P – positive predictivity, and FPR- false positive rate.

	VEB				SVEB			
	Acc	Sens	+P	FPR	Acc	Sens	+P	FPR
Our method	99.4	93.4	97.0	0.2	97.8	94.0	62.5	2.1
Unadapted [4]	97.4	77.7	81.9	1.2	94.6	75.9	38.5	4.7
Llamedo [12]	-	93	97	-	-	92	90	-
Jiang [7]	98.1	86.6	93.3	0.7	96.6	50.6	67.9	1.2
Ince [8]	97.6	83.4	87.4	1.3	96.1	62.1	56.7	1.0

The performance of our adapted system clearly outperforms the unadapted system processing the same features presented in [4]. The VEB accuracy has increased 2% to 99.4% and the SVEB accuracy has increased 3.2% to 97.8%. The performance increase is also seen in the other performance measures. Results show that our adaptive system exceeds the performance of the adapted systems of Jiang [7] and Ince [8] except for the false positive ratio (FPR) of the SVEB class. The reason for this is that the performance our system is tuned to provided balanced sensitivity and specificity (note specificity = 1- FPR). The systems of Jiang and Ince appear to be tuned for better specificity at the expense of reduced sensitivity. The VEB performance is equivalent to the performance of Llamedo's system [12]. For SVEB we achieve a higher sensitivity (94.0% cf. 92%) but a lower positive predictivity (62.5% cf. 90%).

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

IV. Conclusion

This study has shown that an adapting heartbeat classification system can achieve higher classification performance by selecting hearts that are hard to classify to train the local classifier. Selection of beats was performed by first processing the record with a global classifier and then selecting heart beats based on a confidence measure calculated from the posterior probabilities estimates.

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