Automatic ECG Arrhythmia Detection in Real-Time on Android-based Mobile Devices

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Abstract. Early detection of arrhythmic beats in the electrocardiogram (ECG) signal could improve the identification of patients at risk from sudden death, for example due to coronary heart disease. We present a mobile, hierarchical classification system (three stages in total) using complete databases with the aim to provide instantaneous analysis in case of symptoms and–if necessary–the recommendation to visit an emergency department. In this work, we give more details about the training process of the second stage classifier. The Linear Regression classifier achieved the smallest false negative rate of 14.06% with an accuracy of 66.19% after feature selection. It has to be investigated whether the hierarchical classification system has–in its entirety–better performance orientating on the false negative rate or the accuracy for the second stage classifier. The complete hierarchical classification system has the potential to provide automated, accurate ECG arrhythmia detection that can easily be integrated in daily life.

Keywords: Electrocardiogram; Pan-Tompkins algorithm; hierarchical classification; pattern recognition

1 Introduction

Early detection of arrhythmic beats in the electrocardiogram (ECG) signal could improve the identification of patients at risk from sudden death, for example due to coronary heart disease. Mobile and unobtrusive monitoring of the ECG signal combined with an automatic interpretation and analysis algorithm could provide instantaneous analysis in case of symptoms and may trigger–or prevent–presentation to an emergency department. Mobile devices (smartphones, tablets) are an integral part of daily life [6] and could be the basis for an automatic classification algorithm.

Three research groups, Yen et al. [17], Oresko et al. [9], and Gradl et al. [3], performed an embedded arrhythmia classification on mobile devices. Yen et al. [17] used a back-propagation neural network for the classification of seven different ECG beat types (normal; left bundle branch blocks; right bundle branch blocks (RBBB); premature ventricular contractions (PVC); ventricular ectopic beats; ventricular flatter waves). They achieved an average recognition rate of 98.34% using 15 selected records from the MIT-BIH Arrhythmia database [8]. Oresko et al. [9] trained a multilayer perceptron for the classification of five different ECG beat types (normal; RBBB; PVC; paced beats; fusion of normal and paced beats). They achieved recognition rates between 81% and 99% using 5421 heartbeats from the MIT-BIH Arrhythmia [8] database. Gradl et al. [3] used a decision tree classifier for the classification of two different ECG beat classes (normal; abnormal). They achieved a sensitivity of 89.5% and a specificity of 80.6% using the MIT-BIH Arrhythmia [8] and the MIT-BIH Supraventricular [4] database excluding 15 datasets.

In previous work, it was shown that it is possible to distinct various heartbeat types using selected databases/heartbeats. In this work, we present a mobile, hierarchical classification system based on complete databases with the aim to provide instantaneous analysis in case of symptoms and–if necessary–the recommendation to visit an emergency department. In this work, we focus on the second stage classifier.

2 Methods

2.1 Data and Beat Classes

We used the MIT-BIH Arrhythmia [8] and the MIT-BIH Supraventricular [4] databases available on the PhysioNet website [2] excluding paced beats. The remaining heartbeats were assigned to the following three classes: normal, pathological I, and pathological II. The class normal comprises all beats with no pathological appearance. The class pathological I comprises the following beats: bundle branch block beats; PVC; ventricular escape beats. The class pathological II comprises the following beats: atrial/aberrated atrial/nodal (junctional)/supraventricular (atrial or nodal) premature beats; ectopic (atrial or nodal) beats; fusion of ventricular and normal beats; atrial/nodal (junctional)/supraventricular escape beats.

2.2 Feature Extraction

We implemented the Pan-Tompkins algorithm [10] for real-time QRS complex detection based on the work by Gradl et al. [3]. Afterwards, we calculated 18 features (8 statistical, 6 heartbeat, and 4 template-based features) (Table 1). We used a window size of 400 ms around the R-peak for calculating statistical and template-based features. A more detailed description about the template-based features was published previously by Gradl et al. [3].

2.3 Hierarchical Classification System

For the recommendation of professional medical care, we suggest a hierarchical, three-stage classifier. In the first stage, a decision tree classifier detects RR-interval changes between consecutive heartbeats. In the second stage, single heartbeats are divided into the previously defined three classes: normal, pathological I, and pathological II. In the third stage, the prevalence of detected pathological beats is investigated in the course of the ECG signal. In the following, we only go into details about the training of the second stage classifier.

Training of Second Stage Classifier We randomly assigned 70% of each database to the training phase of the second stage classifier. The remaining 30% of each database remain for testing, however, we did not consider the testing dataset in this work. Due to the uneven distribution of the heartbeats in the three classes (150 493 heartbeats in class normal, 22 627 heartbeats in class pathological I, and 12 222 heartbeats in class pathological II) and the importance of detecting all pathological beats, we decided to give double weights to the pathological classes [15]. Thus, we randomly assigned 6 111 heartbeats to the class normal using the SpreadSubsample provided by WEKA [5], 12 222 heartbeats to the class pathological I, and 12 222 heartbeats to the class pathological II.

As preprocessing step, we rescaled all feature vectors to the range [0,+1] to avoid features in larger numeric ranges having a higher impact on the classification and dominating those features in smaller numeric ranges. As no single classifier is suitable for all classification tasks (No Free Lunch Theorem) [1], we compared five classification systems for the stage 2 of the hierarchical classification system [1,14] using the Embedded Classification Software Toolbox (ECST) [11]: C4.5, Linear Regression, Naïve Bayes, PART, and Support Vector Machine (SVM).

We chose the adjustable parameters as default parameters according to WEKA [5] with the following modifications: we determined in a grid search the optimum parameters for the minimum number of instances per leaf for the C4.5 ($n_{C4.5}$) and the PART (n_{PART}) classifier and the optimum parameter for the cost parameter c for the SVM classifier. The parameters for $n_{C4.5}$ and n_{PART} were {2, 4, 8, 16, 32} and for c were {1, 10, 100, 1000}.

The selection of these classification systems was based on preliminary work [7]: The best performing classifier Nearest Neighbor was excluded due to the high amounts of computational costs and memory consumption. Multilayer Perceptron was excluded due to the greater computational costs compared to the other classifiers. AdaBoost M1 was excluded as the current implementation of this classifier in the ECST is only able to distinct two classes.

We did not apply a feature selection step to the features. After consideration of the first results, we only used the best classifiers and applied a k-Feature Selection ($k = 5$) (5-FS), in forward search direction, to the features. The criterion value for the feature selection and for training the second stage classifier was the accuracy as defined in section 2.4. For evaluation, we applied ten-fold cross-validation. The feature selection procedure was evaluated using five-fold cross-validation in the inner loop (of the ten-fold cross-validation).

2.4 Performance Measure

We calculated the accuracy (ACC), also known as overall success rate, (eq. 1) and the false negative rate (FNR) (eq. 2) for comparing the different classification systems. The abbreviations are explained in Table 2.

$$\mathrm{ACC} = \frac{\mathrm{TP} + \mathrm{TN_{I,I}} + \mathrm{TN_{II,II}}}{30\ 555} \cdot 100\% \ . \tag{1}$$

$$\mathrm{FNR} = \frac{\mathrm{FN_I} + \mathrm{FN_{II}}}{\mathrm{TP} + \mathrm{FN_I} + \mathrm{FN_{II}}} \cdot 100\% \ . \tag{2}$$

The total number of feature vectors was 30 555.

3 Results

Table 3 shows ACC and FNR for the five different classifiers using the complete feature set. The optimum parameters for training the classifiers without feature selection for $n_{C4.5}$ was 4, for n_{PART} was 4, and for c was 1. Table 4 shows ACC and FNR evaluated using feature selection for three best classifiers visible in Table 3. The optimum parameters for training the classifiers with feature selection for $n_{C4.5}$ was 8 and for n_{PART} was 2.

Table 1. Set of 18 features for each heartbeat.

Statistical features	Heartbeat features	Template-based features
1. Mean	9. QRS-width	15. Maximal cross-correlation coefficient to template 1
2. Minimum value	10. RR-interval	16. Maximal cross-correlation coefficient to template 2
3. Maximum value	11. Previous RR-interval	17. Area difference to template 1
4. Standard deviation	12. QR-amplitude	18. Area difference to template 2
5. Kurtosis	13. RS-amplitude	
6. Skewness	14. QRST-area	
7. Variance		
8. Energy		

Table 2. Confusion matrix for the three classes normal (N), pathological I (P I) and pathological II (P II).

		Predicted class		
		N	**P I**	**P II**
Actual class	**N**	TP	FP_{I}	FP_{II}
	P I	FN_{I}	$TN_{I,I}$	$TN_{I,II}$
	P II	FN_{II}	$TN_{II,I}$	$TN_{II,II}$

Table 3. Accuracy (ACC) and false negative rate (FNR) (as defined in eq. 1 and eq. 2) using the ECST [11] for the complete feature set.

Classifier	**ACC** [%]	**FNR** [%]
PART	86.69	18.22
C4.5	87.18	19.78
Linear Regression	69.07	23.89
SVM	72.49	27.78
Naïve Bayes	48.64	67.86

Table 4. Accuracy (ACC), false negative rate (FNR) (as defined in eq. 1 and eq. 2), and selected feature numbers (SFN) (as defined in Table 1) using the ECST [11] with feature selection.

Classifier	**ACC** [%]	**FNR** [%]	**SFN**
Linear Regression	66.19	14.06	{2, 5, 9, 15, 18}
C4.5	84.61	22.10	{5, 9, 10, 14, 15}
PART	83.51	23.20	{5, 9, 10, 14, 15}

4 Discussion

We presented a three stage, hierarchical classification system based on the ECG signal to provide instantaneous analysis in case of symptoms. In this work, we focused on the second stage classifier. The FNR for the different classification systems without feature selection ranged from 18.22% (PART) to 67.86% (Naïve Bayes). The corresponding ACC ranged from 86.69% (PART) to 48.64% (Naïve Bayes) (Table 3).

Applying feature selection procedures has these two advantages: minimizing the computational costs and maximizing the classification performance as features might contain redundant information and could therefore decrease the generalization capability and the classification performance of the classifiers [1, 14]. Based on the results shown in Table 3, we decided to further investigate with feature selection the three best classifiers regarding the FNR: PART, C4.5, and Linear Regression.

The FNR for the different classification systems with feature selection ranged from 14.06% (Linear Regression) to 23.20% (PART). The corresponding ACC ranged from 66.19% (Linear Regression) to 83.51% (PART) (Table 4). In this case, the feature selection could reduce the FNR, although ACC was also reduced.

The training of the different classification systems as well as the feature selection procedure was based on ACC and not on the FNR. Consequently, all classification systems were trained to achieve a high ACC, disregarding the FNR. In the case of arrhythmia detection, where it matters to detect all abnormal (beats belonging to classes pathological I and pathological II), the particular FNRs could further be decreased if FNRs are considered in the training process. We decided to use ACC for training as both measures are important and addressed this issue assigning double weights to the pathological classes. It has to be investigated whether the final hierarchical classification system has–in its entirety–better performance orientating on the FNR or ACC for the second stage classifier.

Regarding arrhythmia detection, commonly the number of normal heartbeats exceeds the number of abnormal heartbeats. Woo et al. [16] tackled this problem using one-class support vector machine (OCSVM) [12]. They achieved an accuracy above 92% using selected records of the PhysioNet website [2]. The main idea behind OCSVM is to design a classifier using only one class and detect a new/different class as this class does not belong to the trained class. This procedure is called "novelty" detection. For this application, this would result in training the OCSVM using only normal heartbeats and afterwards detect abnormal (novel) heartbeats. This would require to add a hierarchy to the proposed classification system in this work: after the distinction between normal and abnormal heartbeats, the abnormal heartbeats have to be divided into pathological I and pathological II. In future work, we want to investigate whether OCSVM improves the hierarchical classification system.

The final hierarchical classification system and the QRS detection algorithm have to be further evaluated on data acquired in a clinical study and not only on databases. Therefore, we acquired long-term ECG recordings in patients suffering from heart conditions using one SHIMMER (Shimmer Research, Dublin, Ireland) sensor node. ECG data were obtained with four electrodes, placed at the upper torso, connected to the sensor node. In the future, we are planning to integrate the arrhythmia detection in devices like the FitnessSHIRT (Fraunhofer Institute for Integrated Circuits IIS, Erlangen, Germany). In the FitnessSHIRT, two textile electrodes are sewed into a tight fitting shirt for measuring a single-channel ECG signal [13]. This modality enables an unobtrusive measurement of ECG signals without the need of additional electrodes and could further enable a faster ECG data acquisition in case of symptoms.

5 Conclusion

This application has the potential to provide automated ECG arrhythmia detection that can easily be integrated in daily life. Especially in developing countries, where medical experts are scarce but mobile devices become widely available, such an application may have tremendous impact.

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