An Efficient Approach for Heartbeat Classification

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Abstract

In this paper an efficient heart beat classification algorithm for mobile devices is presented. A simplified ECG model is used for feature extraction in the time domain. QRS complex is modeled by two straight lines while P and T waves are modeled by parabolas. The T wave asymmetry is achieved using a fourth degree parabola, whereas the P wave is modeled by the second degree parabola. The model parameters are estimated using the linear least squares fitting technique.

Heart beats are classified using the following classes: Normal, Supraventricular and Ventricular ectopic beats. Classification of model parameters is done using a feed-forward neural network. The inputs used by the classifier are the following: QRS slopes, duration, P wave coefficients, adjacent and averaged RR intervals. Patient specific adaptation is achieved using a dominant heart beat as an additional classifier input. A series of tests have been performed to evaluate the classification algorithm. Three model sets were used for that purpose. The first one contains QRS parameters only. The second one contains the dominant QRS model as well and in the third model set the P wave and appropriate dominant P wave model are included.

Training and testing is done using the MIT BIH arrhythmia database ECG signals subset and expressed in sensitivity (Se), specificity (Sp) and accuracy (Acc). It can be concluded that the best results are achieved when applying the classification algorithm on the third model set. The following results were obtained: SeN = 99.15% (sensitivity for normal heart beat); SpN = 97.5%; AccN = 98.65%; SeV = 94.69% (ventricular heart beat), SpV = 95.66%; AccV = 95.31%, SeS = 928%; SpS = 96.41%; AccS = 94.48%.

1. Introduction

ECG analysis is still one of the most common procedures in the heart diseases diagnostic domain. It's one of the simplest non-invasive diagnostic methods for various heart diseases. Long-term recordings of the ECG signal are, for example, required for the clinical diagnosis of some disease conditions and for the evaluation of new drugs during phase-one studies by pharmaceutical groups [1], [2]. The analysis is usually performed off-line by physicians

One of the hardest tasks for automated ECG analysis is signal variability, even within ECG recordings of one patient only. Beside signal variability ECG signal is prone to many sources of noise that impact ("pollute") the ECG signal, such as power line interferences, muscular artifacts, poor electrode contacts and baseline wanderings due to respiration. These external factors can increase the number of errors in an analysis and doctors often have to compare an ECG recording with the patient's own, previous, individual record in order to make a reliable conclusion. In a similar manner, in the algorithm proposed in this paper, we used the patient's dominant heartbeat as one of the inputs to the heartbeat classifier.

Inter-patient heartbeat classification performance is addressed in [7] where, feature normalization has been achieved by dividing estimated features by the appropriate averaged features. However, this approach did not bring improvements in the heartbeat classification as the results are slightly worst than in the case when classification is done directly on estimated features, i.e. without any normalization. From mentioned algorithm results [7] it can be concluded that the most relevant features for arrhythmias detection are RR intervals. RR interval features usually contain RR time to next, previous heartbeat, some interval averaged or median Heart Rate Value (HRV). In [20], inter-patient adaptation is achieved in two steps. In the first step, a dominant heartbeat is estimated. In the second step, all heartbeats that are not similar to the dominant are considered as arrhythmic group beats. Arrhythmic group beats are not classified in heartbeat classes. Algorithm achieves high accuracy in separation between normal and arrhythmic heartbeats.

Offline ECG processing is often adopted in monitoring applications and systems. The main reason for such an approach, i.e. execution of the computing and processing tasks on the server side was a lack of the computing power in mobile health care devices like Holter devices used for long term ECG recording. However, modern mobile devices have significant processing power and can execute complex tasks, thus enabling implementation of real time monitoring systems with embedded ECG analysis algorithms at any place and at any time. In This paper, development and implementation of an algorithm for heartbeat classification in a mobile application of the mSens telemedicine system is described.

The key parts of the system are: an ECG device, a mobile and a server application. The ECG device offers 12 or 3/6 channels recording of ECG signal as well as acquisition of patients' physical activity using an embedded accelerometer. The ECG device transfers collected measurements to the mobile phone application using an XML based communication protocol [6] over a Bluetooth link. The mobile application runs on a mobile phone and is responsible for processing of the incoming data (ECG recordings) and its transfer to the server.

2. Method

2.1. ECG Modeling – state of the art

Several models have been proposed in the literature for modeling of the ECG signal. In [8], a nonlinear model based on the Gauss curve fitting for every wave (T wave asymmetry is achieved using two Gauss curve) is presented. This model is initially developed for generating synthetic electrocardiogram. The model parameters are estimated using nonlinear iterative numeric optimizations, also the ECG signal has to be sampled with frequency above 500Hz and as such is not suitable for implementation in mobile (portable) systems due to high computational demands. Several models based on the Hilbert transformation [9], Hermit polynomials [10], [7], Linear Discriminate Analysis (LDA) on delineated ECG [11], Auto Regressive (AR) modeling [12], and Wavelet [13], [14] have been proposed. Wavelet modeling is typically based on selecting mother wavelets similar to the QRS shape, like the Mexican hat wavelet and then monitoring coefficients on a specific scale. Wavelet can provide good temporal and spectral resolution, but authors often omit to comment the effects of using a discrete wavelet and dyadic scheme. Very little attention has been paid to the unevenly sampled nature of the RR interval time series which can lead to serious errors. Techniques for wavelet analysis of unevenly sampled data do exist [15], [16], but it is not clear how a discrete filter bank formulation with up-down sampling could avoid the inherent problems of re-sampling an unevenly sampled signal [3]. The

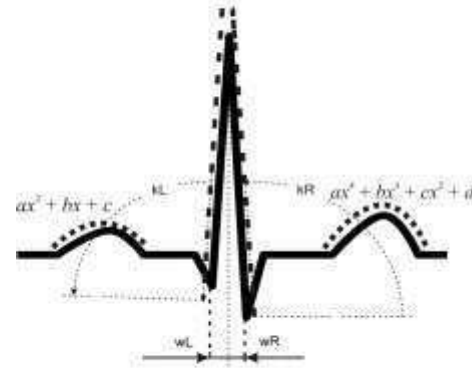

Fig. 1. QRS complex with model features.
kL and kR are the slopes of lines estimated from R peak
wL and wD are number of samples on which QRS is modeled on left and right sight from R peak

heartbeat classification algorithms benchmark testing is performed in [11], [7]. The best performing classifier is achieved using time-domain features. This is also found to be the simplest and fastest classifier to implement.

The most significant part of the existing heartbeat classification techniques involves significant amounts of computation and processing time for extraction of the features. The estimated model parameters are not suitable for direct classification and often need additional feature selection or processing like PCA [17] or ICA [18].

2.2. Modeling – approach used

In the system described in this paper, the ECG preprocessing filtering procedure defined in Chazal [11] has been used. Chazal describe procedure for baseline wandering cancellation in ECG signal. The power line and other high frequency artifacts are then removed from the baseline corrected signal with a linear phase Finite Impulse Response (FIR) filter.

In this work we used the MIT-BIH Arrhythmia database [23] for training and evaluating the classifier. The database contains two-lead ECG recordings of approximately 30 minutes and sampled at 360 Hz. The heartbeats are modeled using polynomial functions up to the fourth order. The first step in modeling is the R peak detection as the largest deflection away from the baseline. In our implementation, Pan and Tompkinson's QRS detection algorithm [19] is used. The QRS complex, the most notable transition in an ECG, is modeled using straight lines (Fig. 1). The QRS lines are estimated from the R peak on the left and right side, minimizing square of the difference between the ECG signal and the model. The QRS lines boundaries on the left and right side from the R peak point are the points of the major changes in the slope. The threshold values used to determine a major change of the slope are either 75% reduction of the initial slope kR and kL from the R peak or a change of the slope

Figure 2. ECG signls with appropriate model and difference.

sign. The QRS boundaries points represent the Q and S peaks. To avoid potential classification errors due to noise and jaggy peaks in the signal, the changes in the signal have to be above the threshold for six consecutive samples after the QRS lines boundary. The line slope is estimated over four samples. The selected number of samples (6 and 4) over which the thresholds were calculated were determined empirically as the values that provide the best accuracy in the presence of noise and artifacts in the ECG signal. The QRS model features are displayed on Fig. 1.

QRS modeling is followed by the first part of the T wave modeling, locating the T wave extreme point. Due to the T wave inversion, the T wave extreme point can be negative. The T wave is searched in the area of 250 ms [7] after the QRS complex. A square function estimated on a moving 110 ms window is used for T wave detection. The interval of 110 ms is chosen because it contains the most significant part of the T wave [2]. A wave is detected if the function extreme point is in the area of ±5 ms around the window center, otherwise the window moves to the right. A detected wave that covers the largest area of all detected waves is the T wave. The wave peak location and the area are calculated using the estimated parabola coefficients. The peak is located at the first derivate zero. The main advantage of this procedure is avoidance of the T wave onset detection and usage of heuristic ad-hoc variable threshold value for analyzing the ECG derivate. The T wave detection procedure proposed in this paper achieves better performance when applied on a noisy ECG signal.

Due to small amplitude, the P wave detection is one of the hardest tasks in ECG processing. The P wave can be absent, inverted or sharpen due to different arrhythmias. Often, a P wave absence occurs in supra SVT arrhythmias [1], [2]. In our modeling procedure, the P wave is modeled in a similar manner as the T wave, i.e. the P wave location is searched in the area after a preceding heartbeat T wave and next QRS complex. For the P wave detection, the moving window length is 80 ms. Some classification algorithms [7] use additional logical features for detection of a P wave presence. In our algorithm the P wave area is modeled with a square function and the square function coefficients only are sent to the classifier. Coefficients a and b from the square function $ax^2 + bx + c$, are used for classification because they carry the most significant part of the shape information. These features are used from the P and T wave models. Fig 2. presents several ECG heartbeats with one PVC and appropriate models.

2.3. Classification

For classification of ECG signals we used a feed-forward Artificial Neural Network (ANN) with one layer of hidden units and a soft-max output stage. The ANN has three outputs for heartbeat classes and 10 hidden neurons. Transfer functions are sigmoid. The Levenberg–Marquardt training algorithm was found to provide the best training results. ANN over fitting during training is reduced using early stopping procedure. Twenty percents of the test data is used for validation during training. Due to the extremely uneven heartbeat type ratio in the ECG signal dataset, ANN training could have lead to poor classification performance, even if the ANN output error is not high. To avoid poor classification performance and even up the heartbeat type ratio we introduced randomly repeating heartbeats with a smaller ratio in the dataset.

Several tests are performed to evaluate the ANN parameters decision. The tests are performed to evaluate decisions on the input to the classifier by selecting a model parameters subset. In the smallest input set, the QRS model features and RR intervals are considered only. The QRS model parameters are the slopes of linear functions fitted to the ECG signal and the number of samples on which ECG could be successfully modeled by a linear function. The RR interval parameters for QRS classification contain RR intervals to the preceding and the next heart beat averaged over RR intervals on ten preceding heart beats. The second data set contains dominant heartbeat QRS parameters as well as an additional input features. The dominant heartbeat has median parameters value of the last 60 beats [8]. In the third data set, the P wave model parameters are also included in the input classifier features set.

2.4. Mobile phone implementation

The MicroFloat - an IEEE-754 floating-point library [22] for small Java devices is used in J2ME environment. The CLDC 1.1 configuration brings floating point arithmetic in J2ME, but not with all functions from J2SE Math package. J2ME application is successful executed on several JAVA enabled cell phones, based on J2ME

Table 1. Classification Results

Group		N [%] Train	N [%] Test	S [%] Train	S [%] Test	V [%] Train	V [%] Test
T_1	Se	99.43	99.15	12.70	10.08	94.73	92.69
	Sp	81.20	79.50	97.21	96.41	97.21	93.79
	Acc	95.73	94.65	93.52	90.48	96.03	93.31
T_2	Se	99.43	99.31	85.02	83.95	96.01	93.61
	Sp	82.47	81.04	99.41	99.27	99.33	98.87
	Acc	96.01	94.82	98.38	98.25	98.72	98.19
T_3	Se	99.71	99.15	93.18	92.08	97.60	94.69
	Sp	94.78	97.50	97.54	96.41	99.72	95.66
	Acc	98.80	98.65	95.72	94.48	99.53	96.31

JAVA platforms JP6 and JP7.

3. Results

Evaluation of the proposed algorithm is performed using the MIT-BIH arrhythmias database subset. Table 1. summarizes the results of the heartbeat classifications. Group T_1 are the tests in which QRS and RR interval features only were provided to the classifier as the input. Group T_2 presents the classification test results when a dominant heartbeat feature has been added as an input in addition to the QRS and RR interval features. In the third group of tests, the P wave model is included to the T_2 group. The results show high accuracy for VEB heartbeats in all test groups. The SVEB heartbeats detection has the best accuracy in the third test group. This was expected due to a very similar morphology between the SVEB and the N heartbeats.

4. Conclusion

In this paper an efficient ECG heartbeat classification algorithm implemented in the mobile health monitoring system mSens is presented. The algorithm achieves high accuracy in classification and does not require significant computing resources. The proposed modeling and classification algorithm can be further extended for ECG delineation, other heartbeat tips as well as arrhythmia detection, especially life-treatments arrhythmias like ventricular flutters and tachycardia. Adding ST modeling could enable ischaemic heart disease analysis and detection.

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