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Adaptive learning based heartbeat classification

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Abstract. Cardiovascular diseases (CVD) are a leading cause of unnecessary hospital admissions as well as fatalities placing an immense burden on the healthcare industry. A process to provide timely intervention can reduce the morbidity rate as well as control rising costs. Patients with cardiovascular diseases require quick intervention. Towards that end, automated detection of abnormal heartbeats captured by electronic cardiogram (ECG) signals is vital. While cardiologists can identify different heartbeat morphologies quite accurately among different patients, the manual evaluation is tedious and time consuming. In this chapter, we propose new features from the time and frequency domains and furthermore, feature normalization techniques to reduce inter-patient and intra-patient variations in heartbeat cycles. Our results using the adaptive learning based classifier emulate those reported in existing literature and in most cases deliver improved performance, while eliminating the need for labeling of signals by domain experts.

Keywords: Cardiovascular, classifier, electrocardiogram, ventricular ectopic beats, supra ventricular ectopic beats

1. Introduction

Modern medical diagnostic techniques like radiology, histopathology and computerized tomography generate a lot of medical images that need to be indexed, archived and stored for future use. The medical image classification systems available today classify medical images based on modality, body part, disease or orientation. Classification of heartbeats is a fundamentally challenging problem. Cardiovascular diseases (CVD) are a leading cause of fatality representing 30% of all global deaths [1]. In 2008, an approximately 17.3 million persons died of cardiovascular diseases. Third world countries account for 80% of CVD related deaths. In 2010, CVD related illnesses cost the United States healthcare industry $316.4 billion. A large number of admissions to hospitals are unnecessary and avoidable. Due to inadequate preventive measures, CVD related fatalities continue to rise. It is imperative that we find a solution that reduces these fatalities. One way is to identify high risk patients is using simple and inexpensive tools. An automated system that can identify potential risks of patients can aid optimizing the usage of medical resources. Such systems must be able to identify patterns in cardiovascular activity that can pose

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a threat to the patients. Furthermore, in rural areas, where access to healthcare facilities is poor, early detection systems can be potentially lifesaving and cost effective.

Electrocardiogram (ECG) is a widely used device to monitor heart function irregularities. At present, an expert cardiologist analyzes ECG plots to detect abnormalities. However, such an analysis is over short durations of an ECG signal. Since certain kinds of heartbeat arrhythmias are time consuming to detect, the patient may require long term monitoring. Hu et al. [2] and Chazal et al. [3] proposed a set of time domain and ECG morphology features and evaluated the classification performance using Linear Discriminant Analysis. Both approaches require that in addition to the standard training set, a specified number of heartbeats of a new test patient is labeled by a domain expert and added to the training set, which may be difficult to obtain in practice. Basil et al. [4] proposed a four dimensional feature vector. The feature vector contains T-wave duration, Amplitude of R-Peak, Maximum Fourier coefficient of QRS complex and normalized Pre-RR Interval values and they use semi-parametric classifiers as opposed to restrictive parametric linear discriminant analysis and its variants used in conjunction with artificial neural networks. Wiens et al. [5] proposed an active learning technique to reduce the number of labeled heartbeats required for a new test patient. Other approaches, Alvarado et al. [6] focused on data compression without compromising on classification performance.

In this paper, we build on existing techniques and propose a technique to detect two types of heartbeat arrhythmias are Ventricular Ectopic Beats (VEB) and Supra Ventricular Ectopic Beats (SVEB). We propose new features from the time and frequency domains and furthermore, a data normalization technique to reduce inter-patient and intra-patient variations. Our results are comparable to those reported in existing literature and in most cases deliver improved performance. The paper is organized as follows, Section 2 describes the sources of data and feature extraction method. Section 3 describes the classification methodology and lastly, Section 4 describes the results and comparisons with the state of the art.

2. Data description

Heartbeat patterns in an ECG signal is identified by a cardiac cycle consisting of P-QRS-T waveforms. The P-QRS-T waveforms consist of 5 successive deflections in amplitude, known as P, Q, R, S and T waves as shown in Fig. 1. These patterns tend to vary within a patient recording resulting in intra-patient variations. In addition to intra-patient variations, these patterns exhibit inter-patient variations. This makes heartbeat classification a challenging problem. To effectively classify a heartbeat, a classifier must be able to take into account both inter-patient and intra-patient variations in ECG signal. Figure 1 shows the inter-patient variation of heartbeat pattern for patients 119 and 106. In order to compare our results with the existing literature, we used MIT/Beth Israel Hospital (BIH) Arrhythmia Database available in PhysioBank archives [7]. The database includes 48 Electrocardiogram (ECG) recordings obtained from 47 subjects. Each ECG recording is sampled at 360 Hz for a duration of half hour. ECG recording is susceptible to noise such as power line interference and baseline wander. Before the feature extraction, we preprocessed the ECG signal to reduce the baseline wander and 60 Hz power line interference. To remove baseline wander, we passed the signal through median filters of window sizes 200 ms and 600 ms. The first median filter removes P-waves and QRS complexes and second median filter removes the T-waves leaving behind the baseline wander. By subtracting the baseline wander from the original signal, we obtain the filtered signal. We removed power line interference using a notch filter centered at 60 Hz.

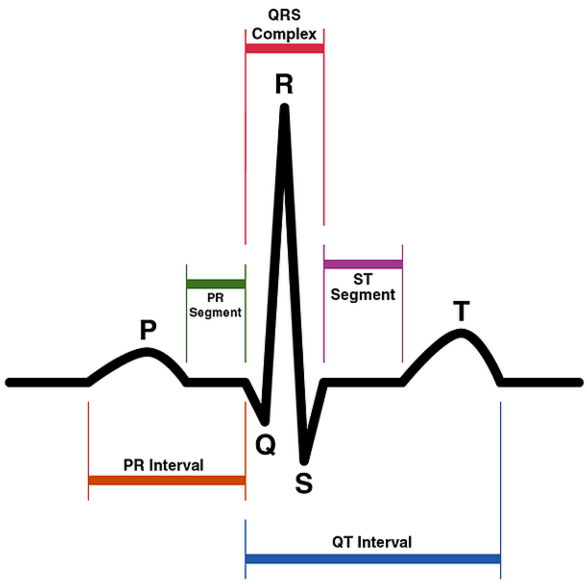

Fig. 1. Cardiac cycle of a typical heartbeat represented by the P-QRS-T wave form (Source Google). (Colors are visible in the online version of the article; http://dx.doi.org/10.3233/BME-151552.)

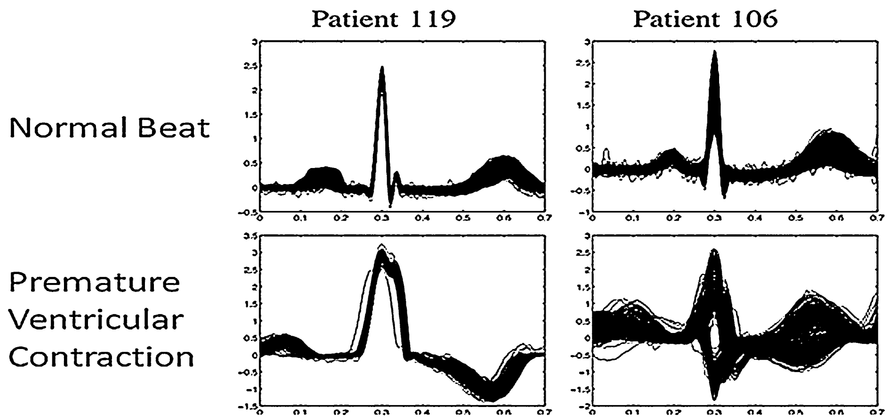

Fig. 2. Example of MIT-BIH data set heartbeat shapes. Each row represents the beats and each column represents a patient for that specific class. (Source Alvarado et al. [6].)

The database has annotations for 20 different types of heartbeats, with each heartbeat annotated by an expert cardiologist. The annotation includes the location of the R-Peak and the corresponding heartbeat label. The R-Peak is the peak of QRS complex as seen in Fig. 2. The heartbeat label indicate the type of heartbeat.

American Association of Medical Instrumentation (AAMI) protocol define five classes of heartbeat. In accordance with the AAMI protocol, we grouped together the 20 types of heartbeats available in MIT-BIH arrhythmia database into five classes. They are Normal and bundle branch block beats (N), Supra-Ventricular Ectopic Beats (SVEBs), Ventricular Ectopic Beats (VEBs), Fusion of normal and VEBs (F), and Unknown beats (Q). Although there exist 5 classes, our problem is a binary classification problem. For the detection of SVEB, a heartbeat is classified as either SVEB or not SVEB (N, VEB, F and Q). Similarly, for the detection of VEB, the heartbeat is classified as either VEB or not VEB (N, SVEB, F and Q). The data was divided into two disjoint sets of patients DS1 and DS2, containing 22 patients each. In accordance with the AAMI protocol [8], four patients with paced beats were not considered for the study. The training dataset was derived from dataset DS1 and testing dataset was derived from dataset DS2. In other words, training set DS1 is used to train the global classifier, which is then tested on testing set DS2 containing a new set of patients. Note that our approach do not require apriori knowledge of patient specific labeled beats from the testing set, unlike certain other techniques [3,5,6] in existing literature. DS1 and DS2 comprise of the following recordings: DS1 = {101, 106, 108, 109, 112, 114, 115, 116, 118, 119, 122, 124, 201, 203, 205, 207, 208, 209, 215, 220, 223, 230}, DS2 = {100, 103, 105, 111, 113, 117, 121, 123, 200, 202, 210, 212, 213, 214, 219, 221, 222, 228, 231, 232, 233, 234}, paced beats = {102, 104, 107, 217}. Note that paced beats are excluded from analysis.

2.1. Feature extraction

We extracted time domain features, ECG morphology features and frequency domain features from the ECG signal. Out of the 18 features extracted, 12 features are time domain features, 2 are ECG morphology and 3 are frequency domain features. The 18th feature is a flag indicating 0 or 1. Time domain features include RR Interval features, QRS duration, QR duration, RS duration and T wave duration, energy of QRS complex, energy of QR segment, energy of RS segment and energy of T wave. Energy of a signal is calculated as the sum of squares of magnitude of samples in that segment. The RR Interval features include the Pre-RR Interval, Post-RR Interval, Average RR-Interval and Local average RR Interval. Pre-RR interval is time interval between the current R-Peak and the preceding R-Peak and Post-RR interval is the time interval between the current R-Peak and the next R-Peak. Average RR Interval is the average of all the RR intervals in a recording. Local average RR Interval is calculated as the average of 10 RR intervals surrounding a heartbeat. QRS duration is the time interval between the QRS onset and QRS offset. QR duration is the time interval between the QRS onset and R-Peak. RS duration is the time interval between the R-Peak and QRS offset.

The ECG morphology features consist of fixed interval morphology features from the QRS complex and the T wave of a heartbeat cycle. In order to form the ECG morphology features, the ECG signal was down sampled to 120 Hz. Once down sampled, 2 samples to the left of R-Peak, the sample value at R-Peak and 2 samples to the right of R-Peak were extracted. In order to extract the T wave features, 9 samples representing the T wave were extracted. Linear interpolation was applied to extract the T wave samples [9].

The frequency domain features include maximum Fourier coefficients at QRS complex, QR segment of QRS complex and RS segment of QRS complex. In addition to time domain features, ECG morphology features and Frequency domain features, we also extracted the P wave flag, which is a binary flag representing the presence or absence of P wave associated with a beat. In total, we extracted 18 different types of features for Lead A. The features were extracted for every heartbeat in the 30 min recording of each patient. Feature selection involves the selection of the best subset of 18 features that maximize the classifier performance. We used three time domain (Pre-RR Interval, Local Average RR Interval and Energy of T wave), five ECG Morphology (R-Peak, 2 samples to the left of R-Peak at 120 Hz and 2 samples to the right of R-Peak at 120 Hz) and two Frequency Domain (Max. Fourier coefficient of QR Segment and Max. Fourier coefficient of RS segment) as feature vector.

3. Classification

In this chapter, we develop adaptive learning based classification technique for automatic classification of normal and abnormal heartbeats. We designed the classifier for use in a clinical setting, where physicians have little time to label beats, let alone tune classifier parameters. Then, correctly classified results are merged with original training dataset to form a new training dataset. The updated training data and the original test data sets are again given as input to classifier to classify medical database. This process is repeat until results are convergence.

Adaptive learning based classification approach improves the classification accuracy, then compared with single time classification approach.

4. Experimental results

A variety of metrics are used in the realm of classification. Adhering to common practice in heartbeat classification, we used the metrics listed below. The classification results are reported in terms of accuracy (Acc). Accuracy defined as follows:

$$Accuracy = \frac{(TP + TN)}{(TP + TN + FN + FP)}, \quad (1)$$

where TP = true positive, TN = true negative, FN = false negative and FP = false positive.

In this experiments training data consists of 45,833 normal heart beat samples, 942 SVEB samples and 3785 VEB samples and test data consists of 44,228 normal heart beat samples, 1836 SVEB samples and 3219 VEB samples. Two different ways of experiments conduct on this training and testing datasets. First one is classify the normal, SVB and VEB heart beats using various classifiers with and with out adaptive learning mechanism. Table 1 reports the classification results using single time classification approach. Classification performance is measured in terms of accuracy. The results of single classification techniques such as Linear Discriminative Analysis (LDA), Quadratic Discriminant Analysis (QDA), Dictionary learning (DL), Neural Network (NN), K-Nearest Neighbor (KNN) and Bayes Classifier (BC) are shown in Table 1. Columns in Table 1 represents the classifiers accuracy results.

Table 2 reports the gross classification performance using adaptive learning based classification approach. Proposed approach produces improved performance results compared with the individual classifiers results.

Second, classify only SVEB and VEB heart beats using various classifiers with and with out adaptive learning mechanism. Table 3 reports the classification results using single time classification approach. Table 4 reports the gross classification performance using adaptive learning based classification approach. Among these, proposed approach produces improved performance relative to sensitivity and positive predictive value. The proposed method is optimized at detecting only two types of anomalies,

Table 1
Comparison of accuracy results using individual classifiers without adaptive learning

Classes/Classifiers	QDA	LDA	KNN	NN	DL
Normal	95.6	99.1	91.9	99.4	84.3
SVEB	91.6	77.8	48.2	87	56.4
VEB	92.8	85.8	69	91.9	78.2

Table 2
Comparison of accuracy results using individual classifiers with adaptive learning

Classes/Classifiers	QDA	LDA	KNN	NN	DL
Normal	97.3	99.2	99.6	99.6	86.4
SVEB	93.6	94.2	68.8	89.5	68.2
VEB	96.4	97.8	83.6	92.6	84.8

Table 3
Comparison of accuracy results using individual classifiers without adaptive learning

Classes/Classifiers	QDA	LDA	KNN	NN	DL
SVEB	93.2	84.5	78.1	94.7	78.4
VEB	94.6	98.3	95.2	97.4	88.2

Table 4
Comparison of accuracy results using individual classifiers with adaptive learning

Classes/Classifiers	QDA	LDA	KNN	NN	DL
SVEB	95.5	93.6	96	97.4	89.2
VEB	97.6	97.3	97.1	98.6	91.3

ventricular ectopoic beats and supraventricular ectopic beats. To demonstrate the utility of the proposed scheme we relied on the annotations of the PhysioNet database. Where, two cardiologist worked independently to added additional beat labels where the detector missed beats, deleted false detections as necessary, and changed the labels for all abnormal beats. They also added rhythm labels, signal quality labels, and comments. Though the experiment is not evaluated through a thorough clinical trial, we use experts annotation from abundant databases of PhysioNet.

5. Conclusion

We have shown that by addressing the problems related to inter-patient and intra-patient variations, classification performance can be improved significantly. We proposed a set of new features in the time domain and frequency domain, and demonstrated the significance of Pre-RR Interval. Furthermore, our technique is fully automated and eliminates the requirement for patient specific labeled data.

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