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Automated detection of atrial fibrillation using Bayesian paradigm

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ABSTRACT

Electrocardiogram (ECG) is widely used as a diagnostic tool to identify atrial tachyarrhythmias such as atrial fibrillation. The ECG signal is a P-QRS-T wave representing the cardiac function. The minute variations in the durations and amplitude of these waves cannot be easily deciphered by the naked eye. Hence, there is a need for computer aided diagnosis (CAD) of cardiac healthcare. The current paper presents a methodology for ECG based pattern analysis of normal sinus rhythm and atrial fibrillation (AF) beats. The denoised and registered ECG beats were subjected to independent component analysis (ICA) for data reduction. The weights of ICA were used as features for classification using Naive Bayes and Gaussian mixture model (GMM) classifiers. The performance and the upper bound on probability of error in classification were analyzed using Chernoff and Bhattacharyya bounds. The Naive Bayes classifier provided an average sensitivity of 99.32%, specificity of 99.33% and accuracy of 99.33%, while the GMM provided an average sensitivity of 100%, specificity of 99% and accuracy of 99.42%. The probability of error during classification was less for GMM compared to Naive Bayes classifier (NBC) as GMM provided higher performance than the NBC.

1. Introduction

Atrial fibrillation (AF) is the most common sustained arrhythmia observed in the clinical practice. Electrocardiogram (ECG) is commonly used as a diagnostic tool to discriminate different kinds of atrial tachyarrhythmias. The ECG signal is the electrical activity of the heart. A typical normal ECG cycle consists of a *P* wave, QRS complex and *T* wave. AF is characterized by lack of organized atrial activity without clear *P* waves before each QRS complex. It is very difficult to quantify very small variations in the ECG beats. Development of an automated diagnosis of AF is one of the challenges in the cardiac rhythm disorder domain. The incidence of AF increases with the age of the patient. Approximately 1% among those aged above 60 years of age, 5% among those aged above 70 years of age and 8% among those aged above 80 years of age suffer from AF. AF accounts for 1/3rd of all hospital admission with arrhythmia as principal diagnosis. The rate of hospital admission for AF has risen in recent years. The common causes for AF are hypertension, cardiomyopathy, ischemic heart disease and rheumatic heart disease [1].

The atrial rate is usually 300–600 beats per minute (bpm), while the ventricular rate can be 170 bpm or more. In addition, the rhythm is irregular. AF is a growing public health problem due to its association with increased risk of embolic stroke, heart failure, cognitive dysfunction, mortality and economic burden [1]. Accurate detection of AF is necessary, at least for patients with high risk, anticoagulation should be established and maintained indefinitely. The cardiac arrhythmia detection using computer software play a significant role in the management of cardiovascular diseases. A recent prospective, blinded and multicenter study suggested that the use of computer based algorithms helped to discriminate atrial tachyarrhythmias with improved diagnostic accuracy [2]. Therefore there is a need to improve the diagnostic accuracy in detection of AF.

In the literature various methods were proposed for detection of AF. Recently AF was detected using an iPhone 4S device and by the use of nonlinear features such as Shannon entropy and sample entropy [3]. Martis et al. classified AF and atrial flutter ECG segments using fractal dimension of continuous wavelet transform and reported 100% of diagnostic accuracy with a few segments of training and testing sets [4]. However there is a need to have similar diagnostic accuracy when the sample size was increased. The principal components of ECG beats were used for the classification of five types of beats in arrhythmia and obtained accuracy of 98.11% over large number of samples (34,989 ECG beats) [5]. The principal components of bispectrum (3rd order poly-spectra) were used for the classification of 5 types of beats in arrhythmia using least square support vector machine (LS-SVM) with 93.48% of accuracy [6]. Moreover these ECG beats provided class specific unique

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3-dimensional bispectrum plots which would help in classifying the ECG beats [6]. The principal components of 3rd order cumulant of the ECG beats were classified using neural network and reported an accuracy of 94.52% for five classes [7]. Moreover these cumulant plots of ECG beats provided class specific unique representation which was helpful in classifying the ECG beats [7]. The independent components of discrete wavelet transform (DWT) coefficients have provided 99.28% of accuracy for five class classification problem with probabilistic neural network (PNN) [8].

All these methods are tested on large number of ECG beats, the abnormalities under consideration do not have life threatening complications. These methods have classified normal and abnormal class classification. However the similar methods need to be tested on similar databases for the life threatening malignant atrial and ventricular tachy arrhythmias such as ventricular fibrillation and ventricular flutter and also the abnormalities which have life threatening complications such as AF and AFL. Complex fractioned atrial electrograms were used to diagnose atrial fibrillation [30–32].

The conventional standard to assess the performance of the methods during classification, are sensitivity, specificity, positive predictive value and accuracy. There are less works on the use of error probabilities as performance measures of methods during classification. ECG from two abnormalities (arrhythmia and ischemia) were classified using Gaussian mixture model (GMM) and reported 94.29% of accuracy with minimum attainable probability of error during classification using Chernoff and Bhattacharyya bounds [9].

In the current study the 1200 normal sinus rhythm beats and 887 AF beats were used. These beats were subjected to a nonlinear dimensionality reduction method using ICA. These reduced number of features were subjected to classification using Naive Bayes and Gaussian mixture model (GMM) classifiers. Both of these classifiers are probabilistic Bayesian classifiers. The classification performance analysis was evaluated using sensitivity, specificity, positive predictive value and accuracy. Also the upper bound on the classification error was computed using Chernoff and Bhattacharyya bounds which is a new tool to measure the performance of a classifier. These bounds provide probability of error in classification.

Section 2 provides materials used, Section 3 explains the methods used, Section 4 presents the results obtained. Section 4 discusses the results obtained and finally, the paper concludes in Section 5.

2. Materials

In the present study two open source databases, MIT BIH arrhythmia database and MIT BIH atrial fibrillation database were used and are explained in the following section.

2.1. MIT BIH arrhythmia database

The database consists of 48 files, each file having two channel ECG of 30 min duration extracted from 47 subjects [10,11]. The data is sampled at 360 samples per second per channel with 11-bit resolution over a 10 mV range.

2.2. MIT BIH atrial fibrillation database

The database consists of 25 long term ECG recordings of human subjects with atrial fibrillation (mostly paroxysmal) [10,12]. Each recording is 10 h duration, and contain two leads of ECG signals sampled at 250 samples per second with 12 bit resolution over a range of ±10 mV.

In total, 1200 normal ECG beats in MIT BIH arrhythmia database were chosen based on reference annotations. Similarly the atrial fibrillation segments were chosen from both MIT BIH arrhythmia database and MIT BIH atrial fibrillation database using reference annotations and cross verified with an expert cardiologist. Also, 887 AF beats were used in this study. These segments were subjected to Pan Tompkins QRS complex detection algorithm for selection of individual beats. All the beats in this study were subjected to discrete wavelet transform (DWT) denoising to remove noise, artifacts and baseline wander.

3. Methodology

Fig. 1 depicts the proposed methodology which consists of preprocessing, QRS complex detection, independent component analysis and pattern classification. Each block is explained clearly in the following section.

3.1. Preprocessing

The ECG segments were sampled at different sampling frequency. The sampling frequency of MIT BIH arrhythmia database is 360 HZ and that of MIT BIH atrial fibrillation is 250 Hz. Therefore a common sampling frequency of 250 Hz is chosen and all the signal segments from MIT BIH arrhythmia database are re-sampled at 250 Hz [9,13]. The re-sampled signals are subjected to QRS complex detection using Pan Tompkins algorithm [14], involving estimation of derivatives, squaring and thresholding. The threshold operation provides a pulse train, whose rise point coincides exactly with the QRS middle point. After QRS complex detection, 74 samples before QRS middle point, 75 samples after QRS middle point and the QRS middle point are considered as a beat which was a segment of 150 samples. In each segment of the ECG beat, the 75th sample is the QRS middle point, by this process all the beats are registered. The ECG beats are denoised using discrete wavelet transform decomposition with Daubechies D6 ('db6') wavelet basis function [5,6]. The ECG beats may contain baseline wander, muscle and movement artifacts, etc. which may not be part of the signal and need to be eliminated. Using DWT denoising these unwanted parts in the signals were removed. The signals sampled at 250 Hz were decomposed up to eight levels in time-frequency domain using DWT. The first level detail sub band contain frequency components 62.5–125 Hz. Since the ECG signal does not contain these range of frequencies, this sub band can be discarded. The eighth level approximation (0–0.488 Hz) contain exactly the baseline wander and it can be discarded. The useful sub bands are 2nd, 3rd, 4th, 5th, 6th and 7th level detail contain the frequency range 0.488–62.5 Hz. These sub bands are used to compute inverse DWT and the denoised ECG may be obtained.

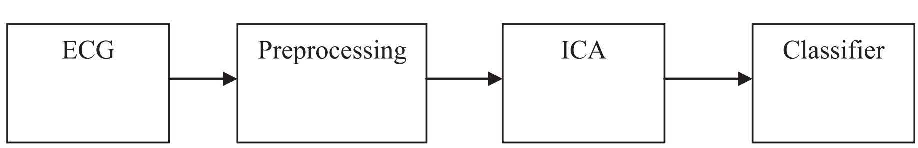

Fig. 1. The proposed system.