Biomedical Signal Processing and Control 13 (2014) 295–305

Contents lists available at ScienceDirect

Biomedical Signal Processing and Control

journal homepage: www.elsevier.com/locate/bspc

Computer aided diagnosis of atrial arrhythmia using dimensionality reduction methods on transform domain representation

Roshan Joy Martis [a,*], U. Rajendra Acharya [a,b], Hojjat Adeli [d], Hari Prasad [e], Jen Hong Tan [a], Kuang Chua Chua [a], Chea Loon Too [c], Sharon Wan Jie Yeo [c], Louis Tong [c,f,g,h]

[a] Department of Electronics and Computer Engineering, Ngee Ann Polytechnic, Singapore 599489, Singapore
[b] Department of Biomedical Engineering, Faculty of Engineering, University of Malaya, Malaysia
[c] Singapore Eye Research Institute, Singapore 168751, Singapore
[d] Departments of Biomedical Engineering, Biomedical Informatics, Civil and Environmental Engineering and Geodetic Science, Electrical and Computer Engineering and Neuroscience, The Ohio State University, 470 Hitchcock Hall, 2070 Neil Avenue, Columbus, OH 43210, United States
[e] Department of Physiology, Johns Hopkins University School of Medicine, Baltimore, MD 21205, United States
[f] Singapore National Eye Center
[g] Duke-NUS Graduate Medical School
[h] Yong Loo Lin School of Medicine, National University of Singapore

ARTICLE INFO

Article history:
Received 7 January 2014
Received in revised form 24 March 2014
Accepted 4 April 2014
Available online 8 July 2014

Keywords:
Electrocardiogram
Atrial fibrillation
Atrial flutter
Discrete wavelet transform
Discrete cosine transform
Principal component analysis
Independent component analysis
K-Nearest neighbor

ABSTRACT

Electrocardiogram (ECG) is a P-QRS-T wave, representing the depolarization and repolarization mechanism of the heart. Among different cardiac abnormalities, the atrial fibrillation (AF) and atrial flutter (AFL) are frequently encountered medical emergencies with life threatening complications. The clinical features of ECG, the amplitude and intervals of different peaks depict the functioning of the heart. The changes in the morphological features during various pathological conditions help the physician to diagnose the abnormality. These changes, however, are very subtle and difficult to correlate with the abnormalities and demand a lot of clinical acumen. Hence a computer aided diagnosis (CAD) tool can help physicians significantly. In this paper, a general methodology is presented for automatic detection of the normal, AF and AFL beats of ECG. Four different methods are investigated for feature extraction: (1) the principal components (PCs) of discrete wavelet transform (DWT) coefficients, (2) the independent components (ICs) of DWT coefficients, (3) the PCs of discrete cosine transform (DCT) coefficients, and (4) the ICs of DCT coefficients. Three different classification techniques are explored: (1) *K*-nearest neighbor (*K*NN), (2) decision tree (DT), and (3) artificial neural network (ANN). The methodology is tested using data from MIT BIH arrhythmia and atrial fibrillation databases. DCT coupled with ICA and *K*NN yielded the highest average sensitivity of 99.61%, average specificity of 100%, and classification accuracy of 99.45% using ten fold cross validation. Thus, the proposed automated diagnosis system provides high reliability to be used by clinicians. The method can be extended for detection of other abnormalities of heart and to other physiological signals.

1. Introduction

Atrial fibrillation (AF) and atrial flutter (AFL) are the two most often reported arrhythmia in the day to day healthcare management. It is still a challenge to develop automated diagnosis systems for accurate classification and diagnosis of these abnormalities. Approximately 1% of people older than 60 years, 5% of people older than 70 years and 8% of people older than 80 years suffer from AF [1–4]. The prevalence rate of AF in the United States alone was in the range of 2.7 million to 6.1 million in 2010. This rate is expected to rise into the range of 5.6 million to 12 million by the year 2050 [52]. In the United States population, the incidence rate of AF in men (women) is 20.6 (6.6) per 100,000 people per year for the age group between 15 and 44 years. It is 1077.4 (1203.7) per 100,000 people per year for the group above 85 years [52]. Electrocardiogram (ECG) is used often to distinguish and detect different arrhythmia such as AF and AFL. The ECG is a trans-thoracic representation of electrical activity of the heart with respect to time.

Accurate classification of both abnormalities (AF and AFL) is important because the mechanism of generation of the disease is different for the different abnormalities. One of the main reason

* Corresponding author. Tel.: +65 6460 8393.
E-mail addresses: roshaniitsmst@gmail.com (R.J. Martis), aru@np.edu.sg (U.R. Acharya), adeli.1@osu.edu (H. Adeli).

http://dx.doi.org/10.1016/j.bspc.2014.04.001
1746-8094/

for the failure of diagnosis is misclassification of AF as AFL. The ECG is a variation of depolarization and repolarization potentials with respect to time. These variations are very subtle and minute and difficult to decipher by the naked eye. Manual screening of the abnormalities is also time consuming, tedious and prone to inter-observer variability. The computer assisted diagnosis (CAD) of heart diseases can overcome these limitations and provide mass screening of populations in real time at a low cost. Recently, Sankari and Adeli [55] invented Heart saver, a low-cost mobile medical device for real time monitoring of cardiac health, capable of detecting atrial fibrillation, myocardial infarction and atrio-ventricular block and proposed it for mass screening of cardiac health.

Recently, Martis et al. [56] presented a state-of-the-art review of various computer aided cardiac diagnosis (CACD) systems and analysis methods including time domain, frequency transform domain, time–frequency domain, and nonlinear methods. Various methods are reported in the literature for classification to provide discrimination between AF and AFL signals. The fundamental frequency of the fibrillatory waves is tracked using the Wigner Ville distribution and an analysis of the V1, V2 and V3 leads of the ECG is performed [7]. Mehra et al. used P-P, P-R and R-R intervals for the detection of atrial tachyarrhythmias so that these methods are useful in therapeutic devices such as cardiac defibrillators and pacemakers [8]. Stridh et al. present a survey on the existing methods of AF detection and detected AF using time–frequency analysis [6,9]. The dominant frequency of AF is tracked using hidden Markov model [10]. By adding simulated noise to ECG signals, they show the advantage of their method using root mean square error associated with frequency tracking [10]. Optimal number of leads of ECG necessary to reconstruct the surface ECG potentials is studied [11]. They proved experimentally that it is necessary to have a minimum of 23 leads to accurately reconstruct the ECG with a similar accuracy as that of sinus rhythm detection in normal ECG [11]. Recently nonlinear features like Shannon entropy and sample entropy are used for detection of AF on a iPhone 4S device [12]. Martis et al. classified the ECG from two abnormalities (arrhythmia and ischemia) with detailed classification error bound analysis with Chernoff and Bhattacharyya bounds [13]. They performed classification with 94.29% of diagnostic accuracy using the principal components (PCs) of linear predictive model output. However, the data sets considered in all these studies are not large enough and there is a possibility to obtain a high performance by overfitting the model to the small dataset. The same authors (Martis et al.) have performed a few studies to show the performance with a large dataset and multiclass problems like many abnormalities. The five types of ECG beats (normal (N), left bundle branch lock (LBBB), right bundle branch block (RBBB), atrial premature contraction (APC) and premature ventricular contraction (VPC)) are classified using the PCs of time domain features to report 98.11% of diagnostic accuracy using 35,989 ECG beats [14]. Martis et al., used bispectrum, which is a third order spectrum of the signal, the extracted features provided an accuracy of 93.48% [15]. The independent components of discrete wavelet transform (DWT) representation of ECG signals have provided an accuracy of 99.28% using probabilistic neural network (PNN) for five classes (non-ectopic beats, supra-ventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable and paced beats) of ECG [17,60–62]. The same authors in their further studies have classified PCs of discrete cosine transform (DCT) of ECG beats into five classes (non-ectopic beats, supra-ventricular ectopic beats, ventricular ectopic beats, fusion beats and unclassifiable and paced beats) and achieved a diagnostic accuracy of 99.52% using PNN [18]. The same group also shown the PCs of cumulants of ECG beats can provide a diagnostic accuracy of 94.52% using error back propagation neural network for five classes (N, LBBB,RBBB,APC and VPC) [16].

However, the research summarized in the previous paragraphs deals with classification of a few arrhythmia beat types which are not clinically very important. These arrhythmia beats such as LBBB, RBBB, APC and VPC do not have life threatening complications even though they are abnormalities. In a clinical setting, it is necessary to detect and diagnose the severe arrhythmia beats which are life threatening or have life threatening complications. The arrhythmias like ventricular fibrillation and ventricular flutter are threatening arrhythmias and require immediate defibrillation. Also, there are, few arrhythmia such as AF and AFL which have life threatening complications. Even though they are not fatal, they require proper detection and management. The misclassification cost is high and upon correct classification into AF or AFL they require anticoagulation therapy. In this direction a few studies have been reported to detect and classify the two abnormalities (AF and AFL). The fractal dimension of continuous wavelet transform coefficients and along with other nonlinear features provided classification accuracy of 100% in classifying AF and AFL [19,63,67–69]. Using the ICs of bispectrum, normal, AF and AFL beats of ECG are classified with 97.65% of diagnostic accuracy [20,63–66]. The sample size used in these studies is very small. It is necessary to show the similar performance with an improved and large database having large samples.

In the present work, a general methodology is presented for automatic detection of normal, AF and AFL beats of ECG. Four different methods are investigated for classification: (i) the PCs of DWT coefficients, (ii) the ICs of DWT coefficients, (iii) the PCs of DCT coefficients, and (iv) the ICs of DCT coefficients. The performances of these four methodologies are compared.

Section 2 explains the data set used for the analysis. Section 3 describes the general methodology used along with brief description of different methods used. Section 4 provides the experimental results followed by a discussion of the results in Section 5, the paper ends with a conclusion in Section 6.

2. Data set used

In this research, two publicly available databases are used namely, MIT BIH arrhythmia database [21–23] and MIT BIH atrial fibrillation database [21–23]. From these databases, the prominent episodes of AF and AFL are selected based on the rhythm annotations provided in the database. As per the reference annotations given in the database, 1200 normal ECG beats are chosen from MIT BIH arrhythmia database. The atrial fibrillation and atrial flutter beats are chosen from both MIT BIH arrhythmia database and MIT BIH atrial fibrillation database. In total 887 atrial fibrillation beats and 855 atrial flutter beats are used in the current study. All these beats are first denoised using a DWT based denoising explained in Section 3.1, then the R peak is detected and beats are segmented. These episodes are also verified by a medical expert.

3. Methodology

Fig. 1 shows the proposed methodology. It consists of transform computations DWT, DCT and dimensionality reduction methods PCA and ICA.

3.1. Preprocessing

The ECG signals from the two different databases have different sampling frequency. The signals in MIT BIH arrhythmia database are at 360 samples per second, whereas in atrial fibrillation database are at 250 samples per second. A common frequency of 250 samples per second is chosen for sampling and the signals from MIT BIH arrhythmia database are re-sampled at 250 samples per second.