Automated Detection of Atrial Fibrillation using Fourier-Bessel Expansion and Teager Energy Operator from Electrocardiogram Signals

Shivnarayan Patidar [1], Ashish Sharma[1], Niranjan Garg[2]

[1] National Institute of Technology Goa, Ponda, India
[2] Nakshatra Heart and Multispeciality Hospital, Pipliyana Square, Indore, M.P., India

Abstract

This work presents a new method for detection of atrial fibrillation using predictors derived from Fourier-Bessel (FB) expansion and Teager energy operator (TEO) which are applied strategically on electrocardiogram (ECG) signals. The proposed method begins by extracting a set of direct and indirect predictors. The direct predictors are computed from pre-processed ECG signals themselves. A part of indirect predictors are computed from (a) RR-interval and heart rate (HR) signals, and (b) FB expansion along with its spectrum applied on RR and HR signals. The rationale of using FB expansion is that the clinical information is found to be more evident in the FB coefficients (FBC) and their spectrum than that of RR and HR signals themselves. In the same line of thought, TEO is applied on pre-processed ECG, RR-interval, HR signals, said FBC and their spectrum to obtain the other part of predictors. In all, 47 predictors are computed and subsequently they are fed to an ensemble system of bagged decision trees for classifying the ECG recordings. When evaluated with 2017 PhysioNet/CinC Challenge dataset (Phase II subset), the experimental outcomes demonstrate the F_1 scores of Normal, AF and other classes as: 90.89 %, 80.07%, 72.24% respectively with overall F_1 score of 81% for the hidden test data.

1. Introduction

Atrial fibrillation (AF) is the most common cardiovascular disorder encountered in clinical practice [1]. Early and accurate diagnosis of AF can save many human lives. Conventionally, echocardiography and ECG tests in various forms are widely used to detect AF[2]. Echocardiography is quite expensive and needs experts in the field therefore its availability is limited to health care centers in urban areas. On the contrary, the ECG machine has shown to have huge clinical potential for affordable diagnosis of AF. However, manual interpretations of ECG recordings for detecting AF is not quite reliable [3]. Fortunately, the recent efforts in the field of signal processing, high performance computing and data mining techniques have paved the way for the emergence of automated diagnosis.

Currently, a wide variety of algorithms have been proposed for automatic detection of AF. These algorithms are mostly based on atrial activity and ventricular response analysis. The atrial activity analysis is based on the TQ interval of the ECG waveform. In presence of AF, the P wave are replaced by time varying fibrillatory f-waves. [4]. Popular atrial activity analysis based method to detect AF includes echo state neural network [5], Gaussian mixture model [4], average number of f-waves in a TQ interval [6], wavelet transform [7]. Most of these methods are prone to noise and therefore require high resolution ECG signals with lower noise contamination for accurate detection of AF [8].

On the other hand, detection of AF using ventricular response analysis is found to be more reliable and suitable for automatic, real-time AF detection [9]. Irregular and uncorrelated ventricular response in AF patients generate the irregular RR-intervals which serves as noise resistant measure for AF detection system. The popular ventricular response based methods include the use of Poincare plot [10] and Lorenz plot [11] to detect AF. Other methods use histograms [12, 13], sample entropy, normalized fuzzy entropy, symbolic dynamics and Shannon entropy to detect AF [14–17].

2. Methodology

The proposed methodology for diagnosis of AF using ECG signals is presented in Figure 1. The details of main subsections are described as follows.

2.1. Pre-processing

In this work, one state-of-the-art is used to pre-process and detect the R peaks in ECG signals to obtain the RR-interval and HR signals [18].

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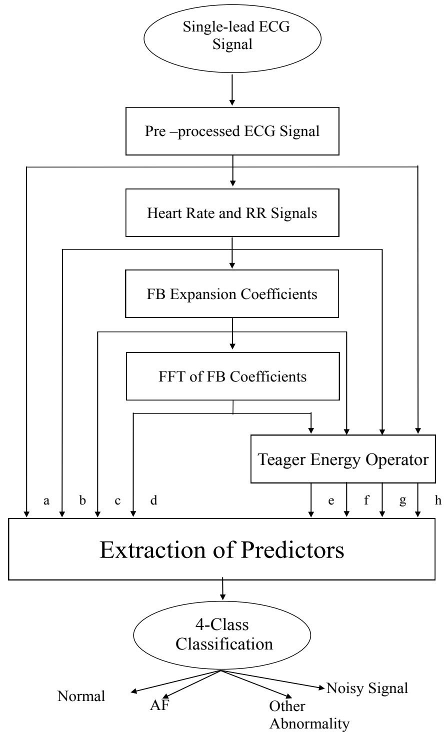

Figure 1. The proposed system.

2.2. Applied Transform and Operation

In context to signal processing, transforms and operators are commonly used for mapping the raw data from one domain to other which can be more informative. We have used FB expansion and TEO in this work which are described as follows:

2.2.1. Fourier-Bessel Expansion

A continuous-time signal $f(t)$, in the interval $(0, 1)$, in terms of Bessel functions of first kind as basis functions can be expressed as follows [19]:

$$f(t) = \sum_{i=1}^{M} A_i J_0(\lambda_i t) \tag{1}$$

where, A_i are the FB coefficients (FBC) which can be computed by using following equation:

$$A_i = \frac{2\int_0^1 t f(t) J_0(\lambda_i t) dt}{[J_1(\lambda_i)]^2} \tag{2}$$

where, $J_0(\cdot)$ and $J_1(\cdot)$ are the zero-order and first-order Bessel functions of first kind respectively. For $i = 1, 2, ..., M$, the values of λ_i are M ascending order positive roots of $J_0(\lambda) = 0$. The FBC A_i are unique for a given signal.

2.2.2. Teager Energy Operator

TEO is a nonlinear function which is popularly used in the area of signal processing [20]. As against the conventional notion of energy that measure the sum of squared signal elements, TEO measures the energy of the system that generates it. The TEO for discrete-time signal $x[n]$ can be expressed as follows [20]:

$$TEO\{x[n]\} = x^2[n] - x[n-1]x[n+1] \tag{3}$$

2.3. Diagnostic Predictors

In order to detect AF, a set of useful predictors are derived from ECG signals, segmented ECG signals and the signals obtained after applying FB expansion and TEO. In this work, we have used the predictors as listed in Table 1 and 2. Some of these are: (a) Shannon entropy [21] (b) Sample Entropy [22] (c) Spectral Entropy [21] (d) Robust Permutation Entropy (RePE) [23] and (e) Morphological predictor: Inverse of normalized weighted difference of P and T peaks.

2.4. Classification using an Ensemble System of Bagged Decision Trees

Ensemble classification [24] strategically generates a set of classifiers and combines them to get better performance than every one of them to address a particular machine learning problem. In an ensemble system of bagged decision tree, decision trees are used as the classification models and their decisions are combined by bootstrap aggregation [25]. For bagging with training set of size N, the decision trees are developed on the bootstrap replicas of the training dataset which are formed by randomly choosing M observations out of N with replacement, where N is the training set size. The predictions of the individual classifiers are then combined using majority vote to cast the final decision.

3. Results and Discussion

The proposed work has been evaluated using 2017 PhysioNet/CinC Challenge dataset [18]. The training set contains 8,528 signals lasting from 9 to 61 seconds and the test set contains 3,658 signals of similar lengths (and class distributions). After adequate pre-processing, predictors are derived from FB expansion and TEO which in turn are applied strategically on ECG signals. Figure 1 shows the predictor extraction workflow. A set of carefully chosen direct and indirect predictors as listed in Tables are extracted. Where in the Table 2, Md, Mo, Ku, and Sk represent median, mode,kurtosis and skewness respectively. The direct predictors are computed from pre-processed ECG signals as depicted in the Figure 1 with arrow marked by (a). A part of the indirect predictors are computed from (i) RR and HR signals, (ii) FB expansion along with its spectrum as marked by (b), (c) and (d) respectively . In order to obtain the other part of predictors, we have applied TEO on the above set of signals obtained at different levels of proposed framework as marked by (e)-(h). We have found 47 clinically significant predictors as listed in Tables that ultimately yielded robust 10-cross validation based results.

Table 1. List of predictors used for classification

S. No.	Predictors	Input Signals		
		ECG	HR/RR	FBC-HR/FBC-RR
1	Sample Entropy	34,35	10/11	/12
2	Spectral entropy	21	19	
3	RePE	5	/6,7	8,9
4	Shannon entropy	22		/1
5	Shannon entropy of TEO		/2,3,4	
6	Energy of TEO		13	

Table 2. List of predictors used for classification

S. No.	Input Parameters	Predictors						
		μ	Md	Mo	σ	σ^2	Ku	Sk
1	HR/RR Signals	27	28/ 23	29/ 24		30	/ 25	/ 26
2	FBC of HR			20				
3	TEO of HR				18		14	
4	TEO of ECG						15	
5	TEO of FBC of HR				17			16
6	Kurtosis of ECG		31					32
7	Median of ECG		33					
8	Widths of R peaks			37	39	41		
9	Widths of S peaks			38		42		
10	Prominences of R peaks				40			
11	Ratios of widths of R & S peaks	36						
12	Diff. of R & S peaks	43	45					
13	Diff. of widths of R & S peaks	44						
14	Diff. of locations of R & S peaks						46	

Using the auto-search engine in Matlab, an optimal ensemble classifier model based on the bootstrap aggregation is generated for classifying the ECG recordings into following classes: normal, AF, others and noisy.

A graph to illustrate the importance of each predictors used in decision making for the ensemble classifier is shown in Figure 2. It indicates the relative relevance of a set of 47 predictors. The out-of-bag (OOB) classification error as a function of the number of decision trees were used to construct the ensemble as illustrated in Figure 3. The optimal ensemble classifier was constructed by using 477 weak learners that are decision trees with minimum leaf size of 2 and with training instances of 8528.

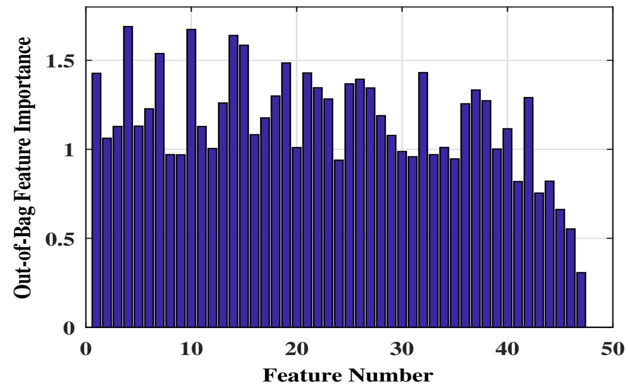

Figure 2. The predictor's importance.

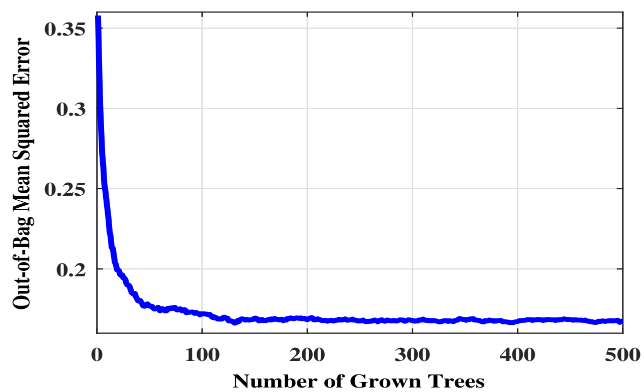

Figure 3. OOB classification error versus weak learners.

We have obtained the average F_1 scores for normal rhythm, AF, other rhythm and noisy as follows: 90%, 77%, 73%, 61% with overall average F_1 score of 80% for first three classes with training data applying 10-cross validation. The average accuracy of 84% is obtained. The test F_1 scores of Normal, AF, other classes and noisy recordings using hidden data from PhysioNet (Phase II subset) are as follows: 90.89 %, 80.07%, 72.24% and 50.07% respectively with overall F_1 score of 81% for the first three classes .This work reveals that the predictors derived using FB expansion and TEO are quite promising for better characterization of different ECG signals to detect and identify AF and other cardiovascular disorder (CVDs).

4. Conclusion

In this work, we have explored the strength and applicability of FB expansion and TEO based algorithm for automated diagnosis of AF. Our method has shown significant performance on a large and diverse dataset with noisy records. This work has clinical potential to be realized into an automatic real-time system for detection of AF and other CVDs.

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Address for correspondence:

Dr Shivnarayan Patidar
Department of Electronics and Communication Engineering
National Institute of Technology Goa, Ponda
India, 403401
shivnarayan.patidar@nitgoa.ac.in