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A Fast and Accurate Method for Arrhythmia Detection

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***Abstact*- Electrocardiography is the method of choice for cardiac electrophysiological evaluation. Arrhythmia is one of the most crucial problems in cardiology. So far, many methods have been developed for arrhythmia detection, recognition and classification. A popular method is ECG modeling using a basis function (such as wavelet, hermite or RBF) and classifying the coefficients of the basis functions. We present a new method based on non-uniform sampling (selecting 7 samples) of ECG signal. It is shown that Left and Right Bundle Branch block arrhythmia as well as normal signals can be better analyzed using a newly introduced method called Finite Rate of Innovation (FRI) and other types of arrhythmia can be better analyzed based on spline modeling. Therefore, a multi-stage algorithm is proposed for diagnosing and compression of ECG signal which is faster and yet accurate.**

I. INTRODUCTION

A. EKG preliminaries

Electrocardiography or EKG is the main diagnostic approach for cardiac rhythm evaluation. Arrhythmia is any disturbance in the rhythm of the EKG signal. There are various kinds of arrhythmia of which only 5 to 6 are important. The vital and weight bearing types of arrhythmia are ventricular tachycardia ventricular fibrillation, premature ventricular contracture (PVC), right bundle branch block (R or RBBB) and left bundle branch block (L or LBBB).

B. Literature Review

So far there have been many methods for diagnosing different types of arrhythmia. Primary methods were based on time and frequency domain analysis of EKG signal [5,6]. For example a simple method has been extracting amplitudes and duration of each wave [5].

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Newer approaches use wavelet domain analysis of signals or modeling the EKG data using hermitian, Gaussian RBF [6,7,8] or spline basis functions and classifying coefficients for each one. Support vector machine [7,8], fuzzy, neurofuzzy, neural network (MLP, etc) and many other classifiers were used to classify the coefficients [9, 10, 11, 12]. Instead of directly modeling the EKG, some papers have used hermitian modeling of higher order statistics of the EKG signal to achieve robustness to failures in QRS detection. In another paper, an optimized hermitian modeling based on genetic algorithm has been performed. Improvements have been done using piecewise hermitien modeling and coefficient selection of EKG waveform [6, 7, 8].

II. METHODS AND MATERIALS

Here in this paper, a multi-stage algorithm for arrhythmia analysis is proposed that classifies each arrhythmia using a specified method. Contrary to previous papers, different methods are used for modeling different types of arrhythmia.

A. Multi-stage Potential to Classify different types of arrhythmia

In the classical EKG modeling, as is in hermite decomposition or RBF, the EKG signal is decomposed blindly. On the other side, in knowledge based analysis, there is no place for mathematical dexterity and every thing is viewed as it is observed by an expert clinician. A combination of these two methods can detect EKG arrhythmia more accurately.

B. Non-Uniform Sampling

Non-uniform sampling greatly reduces the rate of calculation and computation which is necessary to model or classify a signal. FRI as will be discussed in section 2.5 dramatically reduces the number of input samples which is theoretically needed to fully reconstruct a signal using its degree of freedom instead of the traditional Nyquist frequency.

C. FRI (Finite Rate of Innovation)

Finite Rate of Innovation is a brand new method for performing perfect reconstruction of non-band limited signals using their rate of innovation, irrespective of their Nyquist frequency. Previous approaches in non-uniform

sampling satisfy Nyquist theorem (for example iterative methods) but in FRI sampling each signal is thought as a summation of some unknown basis functions from which the primary signal can be obtained.
Consider classes of signals which have a finite number of degrees of freedom per unit of time, and call this number the rate of innovation Such as of signals with a finite rate of innovation include streams of Diracs, nonuniform splines and piecewise polynomials. Although these signals are not band-limited, it is shown in [12], [13] that they can be sampled uniformly at (or above) their rate of innovation (which can be lower than their Nyquist frequency) using an appropriate kernel, and then can be perfectly reconstructed. Now considering the linearity which is present in some types of arrhythmia (LBBB, RBBB and normal signals), it is noteworthy that FRI can be a good method of sampling of these types of signals [12, 1].

D. Hermite Modeling

Hermite basis functions, HBF, are a set of orthogonal basis functions famous for their power in modeling curvature of splines and polynomial and any other structure such as EKG signal. The mathematical background of Hermitian functions is beyond the scope of this paper.

E. FRI versus Spline Interpolation

In this paper we show a comparison between FRI, spline, Gaussian RBF and hermitian basis function modeling. It is a knowledge based fact that normal, RBBB and LBBB signals are almost linear and therefore they can have a Finite Rate of innovation. On the other side, Ventricular Tachycardia (VT), Ventricular Fibrillation and Premature Ventricular Contraction (PVC) are morphological curves and seem to be better modeled using spline, hermitian or RBF modeling.

F. Linearity Assessment of EKG Signal

As was discussed, those types of arrhythmia which are more linear (RBBB and LBBB) than the other parts can be modeled using FRI. Therefore, we set a thresholding (level set) step to the linearity of the signal.

G. Multi-stage Method Description

The multi-stage flowchart is depicted in figure 1.
First step: The EKG signal enters in a Butterworth band-pass filter to remove the low pass and high pass noises. Low pass cut-off is 0.01 Hz and high-pass one is 100 Hz. Seven samples of the primary signal are picked up according to its peak location and zero crossing locations and the other samples are read from the vicinity of EKG peak.
Second step: Each EKG signal is derived twice; hence linear pieces of the signal are converted to a Dirac (positive or negative).
Third step (level set step): In this section linearity of EKG signal is assessed through statistical formulation (density of the second derivation is determined which indicates their similarity to Dirac). The final signal extracted from the windowing step will be filtered using a level set in which only the high amplitude parts of the signal will remain after two times of derivation.

Fourth step: Q, R and S waves are detected in combination with their duration and point of origin.
Step five(yes step): FRI coefficients of normal, right bundle branch block and left bundle branch block beats are obtained and fed into the diagnostic and compression system. These signals have high degree of linearity which means a degree of freedom of two (according to FRI theory).

Step six (no step): we designed a hermitian , Gaussian RBF or spline modeling system for non-linear waveforms (usually ventricular tachycardia, ventricular fibrillation and premature ventricular contraction (PVC)).
In the next step, these coefficients are fed into a kNN (k=3) classifier and EKG signals is classified into VT, VF or PVC. Primary data were divided into two groups, one for training and the other one for testing. The method of training was hold-out. Data was obtained from MITBIH arrhythmia and EKG database www.physionet.org. It is considerable that results of these types of modeling can be used to compress EKG data.

III. RESULTS

Result of each step in QRS detection and classification was obtained separately. During each step, specificity, sensitivity, error rate and gain of that stage were calculated.
(1) Derivation, windowing and level set step: The goal of these steps has been determining the linearity of the EKG signal and therefore classifying RBBB, LBBB and normal EKG. The system was 97% sensitive and 98% specific.
(2) FRI coefficient detection and compression:
Detection method of L, R and normal using FRI techniques has been 99% sensitive and 99% specific. Compression ratio has been between 65 to 100 depending on the type and shape of QRS wave.
(3) Hermitian, Gaussian RBF and Spline modeling results which were performed on VT and VF achieved an error rate of 0.2 , 0.24 and 0.15 of the original signal using 7 samples which were extremum points, zero-crossing and symmetric points around the peak point (usually in vicinity of 20 samples). Figure 2 shows

different types of arrhythmia overlapping on each other. Figure 3 illustrates the ability of the hermitian basis functions for modeling different types of EKG with considerable accuracy.

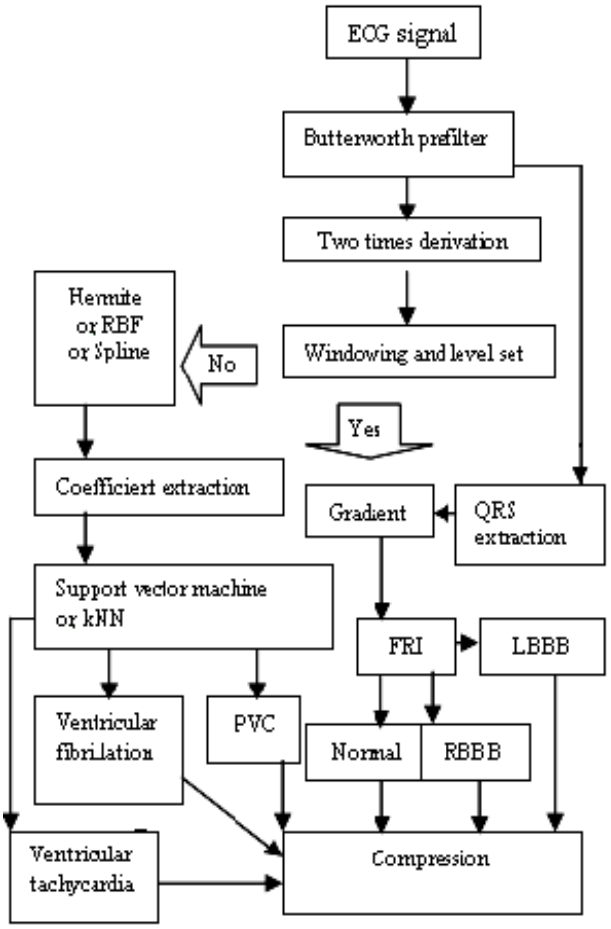


Fig. 1. Flow-chart of the decision tree.

A. Classification Results

Data were divided into two groups based on hold-out method, one group for testing and the other one for training. Table 1 shows the number of the total data, the training and the testing groups. Table 2 illustrates the results of the sensitivity and specificity of Gaussian RBF, hermitian, spline and FRI diagnosis of different types of arrhythmia using kNN (K=5). Notice that the linear kernel is not congruent with the non-linear types of arrhythmia and are not included in the table. All the models were based on 7 samples (peak, zero crossing, and two samples in the vicinity of the peak with a distance of 20 samples usually). The results obviously indicate that FRI is more powerful for diagnosing the linear types of arrhythmia (LBBB, RBBB and normal) while the other types of arrhythmia are better classified using spline models. Gaussian RBF seems to be the weakest due to its lower potential for curve fitting with respect to hermite models.

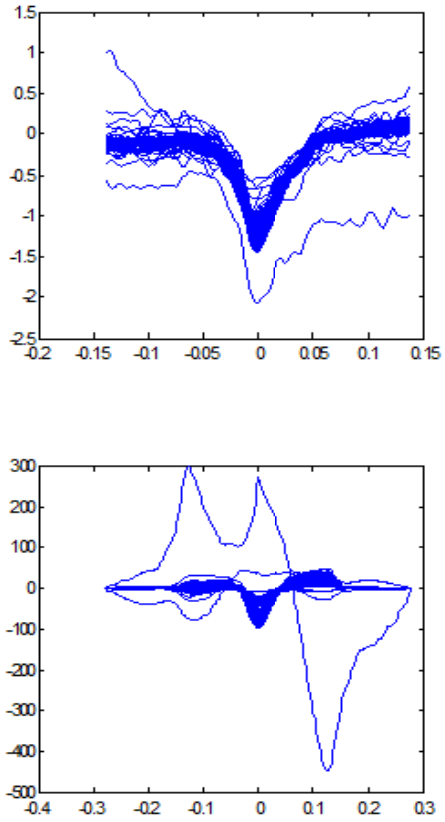
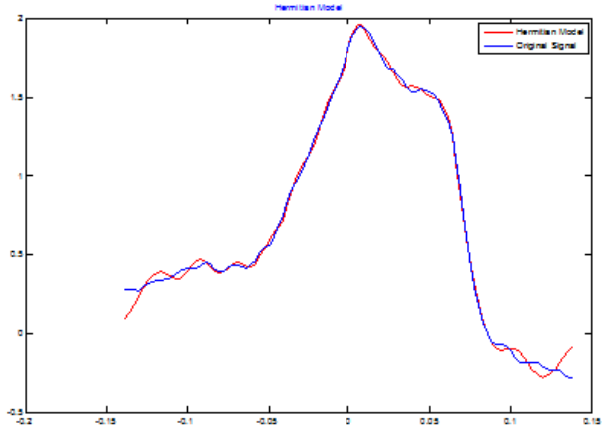


Fig.2. several types of arrhythmia depicted in an overlapping view.



Figures 3. Hermitian model of ventricular tachyarrhythmia using 7 samples (peak zero, crossing and near the peak samples). Blue line is the primary EKG and red one in the model results.

IV. CONCLUSION and DISCUSSION

In this paper, we presented a Multi-stage method for arrhythmia classification based on FRI feature extraction.

Our results outperformed the previous arrhythmia classification methods due to the division of different types of arrhythmia into linear and non-linear groups.

FRI demonstrated great ability to model linear EKG structures using only 7 samples of each beat and outperformed Gaussian RBF and hermitian modeling. Spline modeling proved its relative superiority in comparison with the other methods. The other important feature in this article is the non-uniform sampling based approach that considerably decreases the computational burden without losing the accuracy. Therefore a valuable future work can be implementation of this method on hardware to achieve fast and accurate results on DSP chips. On the other side this article yields a good evaluation for EKG modeling using different basis functions (Spline, Hermite and RBF).

TABLE 1.
DIVISION OF EKG DATA INTO TRAINING AND TESTING GROUPS

Type of arrhythmia	Total number of data	Training data	Testing data
Normal	2000	1200	800
PVC (V)	2888	1735	1153
RBBB(R)	2252	1350	902
LBBB(L)	1557	875	582

TABLE 2.
RESULTS OF NON-UNIFORM 7-SAMPLE CLASSIFICATION BASED ON KNN (K=5)

Type of arrhythmia	Specificity for spline	Sensitivity for spline	Specificity for RBF	Sensitivity for RBF
Normal	84.1	83.4	81.9	79.4
PVC (V)	83.3	82.2	82.1	82.2
RBBB(R)	84.0	85.4	82.1	85.4
LBBB(L)	80.0	81.0	79.6	81.0
VT	79.9	74.2	79.1	74.2
VF	82.8	86.6	85.8	86.5

Type of arrhythmia	Specificity for hermite	Sensitivity for hermite	Specificity for FRI	Sensitivity for FRI
Normal	82.3	75.4	95.7	98.2
PVC(V)	83.9	84.9		
RBBB(R)	77.1	84.7	92.2	95.3
LBBB(L)	80.0	80.9	91.2	94.2
VT	78.1	78.2		
VF	87.8	83.0		

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