Classification of Cardiac Arrhythmia Using WT, HRV, and Fuzzy C-Means Clustering

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Abstract

The classification of the electrocardiogram registration into different pathologies disease devises is a complex pattern recognition task. In this paper, we propose a generic feature extraction for classification of ECG arrhythmias using a fuzzy c-means (FCM) clustering and Heart Rate variability (HRV). The traditional methods of diagnosis and classification present some inconveniences; seen that the precision of credit note one diagnosis exact depends on the cardiologist experience and the rate concentration. Due to the high mortality rate of heart diseases, early detection and precise discrimination of ECG arrhythmia is essential for the treatment of patients. During the recording of ECG signal, different forms of noise can be superimposed in the useful signal. The pre-treatment of ECG imposes the suppression of these perturbation signals. The row date is preprocessed, normalized and then data points are clustered using FCM technique.

In this work, four different structures, FCM-HRV, PCM-HRV, FCMC-HRV and FPCM-HRV are formed by using heart rate variability technique and fuzzy c-means clustering. In addition, FCM-HRV is the new method proposed for classification of ECG.

This paper presents a comparative study of the classification accuracy of ECG signals by using these four structures for computationally efficient diagnosis. The ECG signals taken from MIT-BIH ECG database are used in training to classify 4 different arrhythmias (Atrial Fibrillation Termination).

All of the structures are tested by using the same ECG records. The test results suggest that FCMC-HRV structure can generalize better and is faster than the other structures.

Keywords: Fuzzy C-Means Clustering, WT, HRV, Arrhythmia, MCN, Classification.

1. INTRODUCTION

Electrocardiography deals with the electrical activity of the central of the blood circulatory system, i. e. the heart. Monitored by placing sensors at the limb extremities of the subject, electrocardiogram (ECG) is a record of the origin and the propagation of the electrical potential through cardiac muscles [1]. Thus, ECG is an important non – invasive clinical tool for the diagnosis of heart diseases [2].

The state of cardiac heart is generally reflected in the shape of ECG waveform and heart rate. It may contain important pointers to the nature of diseases afflicting the heart. Early and quick detection and classification of ECG arrhythmia are important, especially for the treatment of patients in the intensive care unit. In recent years, computer assisted ECG interpretation and automatic classification has received great attention from the biomedical engineering community.

This is mainly due to the fact that ECG signal provides cardiologists with useful and important information concerning the dysfunctions and physical condition of human heart. In designing of CAI system, the most important is the integration of suitable features extractor and pattern classifier such that they can operate in coordination to make an effective and efficient system [2].
Several algorithms have been developed in the literature for detection and classification of ECG records. One of the methods of ECG beat recognition is neural network classification method (dallali ssd'03; engine & demirag 2003; foo, stuart & meyer – baese 2002).
The hybrid system of neural network and fuzzy logic has been widely accepted for pattern recognition tasks (Mean et al2 2006; ozbay, ceylam, & karlik 2006). Yu et al. have implemented the integration of independent component analysis and neural network classifier (ICA – NN) along with R-R intervals to discriminate eight types of ECG beats [3].
In [3, 4], Ozbay et al. had combined principal component analysis with neural network (PCA –NN) and compared with wavelet transform technique for ECG signal classification. In [5], T.M. Nazmy had combined ICA and hybrid system (ICA –ANFIS) for ECG signal classification. In this paper, we evaluate the integration of WT-FCM to discriminate four types of ECG beats. The proposed structure is composed of three sub - systems: the filtrate, wavelet transform to extract the parameters, and classification by FCM technique.

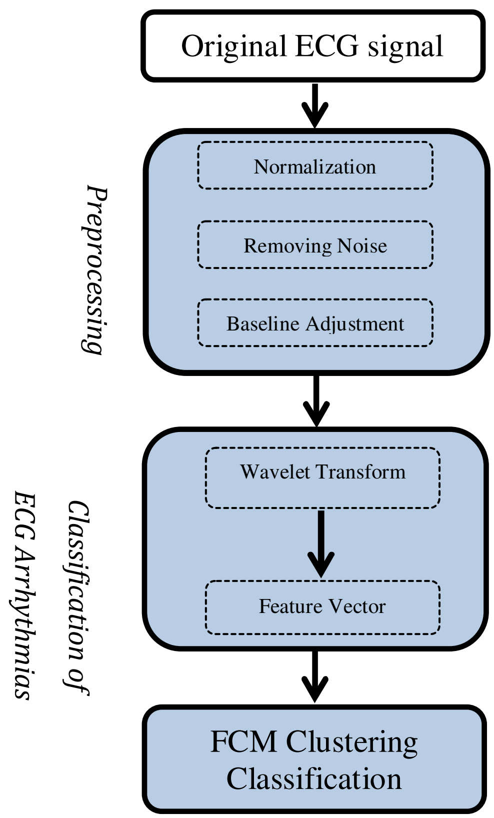

FIGURE 1: Block diagram of proposed arrhythmia classifier

Figure 1 summarizes the classification steps of the signals. One distinguishes the stage of data Conditioning (sampling and filtering), the stage of extraction of the characteristics and the stage of FCM algorithm (training of the data and validation of the test data).

All the samples must be normalized in order to have the features at the same level. ECG signals can be contaminated with several kinds of noise, such as power line interference (A/C), baseline wandering (BW), and electromyography noise (EMG), which can affect the extraction of parameters used for classification, so we want to filter the signal. The unwanted noise of the signal must be removed. ECG were filtered using Low pass filter, high pass filter. The pre-treatment of ECG signals imposes the suppression of each perturbation signals, the noise high frequency electromyography and the low frequency drift. After that, the signal baseline may be shifted from zero line. The baseline of the ECG signal was adjusted at zero line by subtracting the median of the ECG signal [8, 9].

2. CHARACTERISTICS OF THE ECG

The ECG represents the wave's electrical propagation through the respective regions of the heart (SA. node, Arial Muscle, AV node, Atria ventricular Bundle, Left and Right Bundle Branches). These waves are the major evident observable of the human heart and have been used to intensive diagnosis since of their significance in the context of pathologies [11].
Usually, the listing of the electrical wave's variations on the papers constitutes the ECG signal. Figure 1 shows the temporal characteristics of normal ECG.

Mechanical actions	**associated Wave**	**Duration (sec)**	**Amplitude (mV)**	**wave Frequency (Hz)**	**Axe**
Auricular depolarization	P wave	<0.12	≤ 0.3	10	20° à 80°
Depolarization of the ventricle	QRS Complex	0.08 à 0.12	Q<0 - S>0 R (0.5-2) DI + DII+ DIII > 15	20 - 50	-30° à +110° < -30° axe gauche > 110° axe droit
Repolarization of the ventricles	T wave	0.2	0.2	5	
Repolarization of the auricles		Hidden wave			

TABLE 1: ECG properties

3. REVIEW OF LITERATURE

CUIWEI Li et al., (1995) showed that it is easy with multi scale information / decomposition in wavelets transformation to characterize the ECG waves. KHADRA et al. (1997) proposed a classification of life threatening cardiac arrhythmias using wavelet transforms. MG Tsipouras and al (2004) used time frequency analysis for classification of atrial tachyarrhythmia. Mei Jiang Kong and al. (2005) used block-based neural networks to classify ECG Signals. Srinivasca K G, Amrinder Singh, A O Thomas, Venugopal K R and L M Patnaik, (2005) used Fuzzy C – Means Clustering for classification of generic feature extraction. (2007), Ceylan, R. & Ozbay, Y. proposed a classification of ECG arrhythmias using neural network method based in techniques of FCM, PCA and WT.

4. MATERIALS AND METHODS

In many pattern recognition applications, the task of partitioning a pattern set can be considered to be the result of clustering algorithms in which the cluster prototypes are estimated from the information of the pattern set. In many cases, it may be impossible to obtain exact knowledge from a given pattern set. For recognition of the ECG arrhythmias, different methods were presented in the literature, such as the MLP approach, LVQ. In this paper, we present the combination of different forms of fuzzy c-means clustering, and wavelet transform; named as
WT – FCM or HRV – FCM and then compare this technique with the other models of FCM.

4.1 Wavelet Transform

The ECG signals are considered as representative signals of cardiac physiology, which are useful in diagnosing cardiac disorders. The WT provides very general and power full techniques, which can be applied to many tasks in signal processing. The most important application is the ability to compute and manipulate data in compressed parameters. Thus, the ECG records can be compressed into a few useful parameters. These parameters can be used for recognition and diagnosis. Selection of appropriate wavelet and the level of decomposition is very important in treatment of signals using WT. the smoothing feature of the Daubechies wavelet of order 3 made it more suitable to detect variation on the ECG signals [8]. Therefore, the wavelet coefficients were computed using the Daubechies wavelet of level 3 in the present work.

4.2 The fuzzy C-means Clustering

The FCM algorithm has successfully been applied to a wide variety of clustering problems. The FCM algorithm attempts to partition a finite collection of elements X = {x_1, x_2, …, x_N} ⊂ R^h where N represents the number of data vectors and h the dimension of each data vector, into a collection of C fuzzy clusters. C – Partition of X constitutes sets of (c.N) {uij} member ship values can be conveniently arranged as a (c.N) matrix u = [uij]. The objective of fuzzy clustering is to find the optimum member ship matrix U. the most widely used objective function for fuzzy clustering is the weight within – groups sum of squared errors Jm, which is used to define the following constrained optimization problem [13].

$$J_m = \sum_{i=1}^{N} \sum_{j=1}^{c} u_{ij}^{m} \|x_i - c_i\| \tag{1}$$

Where 1≤m≤∞.., i. e. m is any real number greater than 1, uij is the degree of member ship of xi in the cluster j, xi is the ith component of d-dimensional measured data, cj is the d – dimension center of the cluster, and $\| \quad \|$ is any norm expressing the similarity between any measured data and the center. Fuzzy partition is carried out through an iterative optimization of the objective function shown above, with the update of member ship uij.

$$u_{ij} = \frac{1}{\sum_{k=1}^{c} \left(\left\| \frac{x_i - c_{ij}}{x_i - c_{jk}} \right\| \right)^{\frac{2}{m-1}}} \tag{2}$$

and the cluster cj by:

$$c_j = \frac{\sum_{i=1}^{N} u_{ij}^{m} . x_i}{\sum_{i=1}^{N} u_{ij}^{m}} \tag{3}$$

This iteration will stop when error $\{\|u_{ij}^{k+1} - u_{ij}^{k}\|\} \leq \varepsilon$, where ε is a termination criterion between 0 and 1; whereas k are the iteration steps. This procedure converges to a local minimum or a saddle point of Jm. The algorithm is composed of the following steps:

The steps are as follows:

i- Initialize the number of clusters (c), weighting exponent (m), iteration limit, termination criterion (ε > 0) and U=[uij] matrix, U(0).

ii- Guess initial position of cluster centers.

iii- At k step calculate the center vectors $c^k = [c_j]$

$$c_j = \frac{\sum_{i=2}^{N} u_{ij}^{m} x}{\sum_{i=2}^{N} u_{ij}^{m}}$$

iv- Update U(k)to U(k +1)

$$u_{ij} \frac{1}{\sum_{k=1}^{c} \left(\frac{\|x_i - c_j\|}{\|x_i - c_j\|} \right)^{\frac{2}{m-1}}}$$

If $\|U^{(k+1)} - U^{(k)}\| \leq \varepsilon$ then stop; otherwise to step (i)

5. PROPOSED METHOD

The method is divided into four steps: (i) ECG sampling and processing, (ii) data reduction, (iii) extraction of feature vector, and (iv) classification using FCM clustering. The validation of the proposed algorithm for the HRV extraction is done using 80 original ECG record of ECG data base [17]. The ECG signals used in this work are obtained from MIT – BIH arrhythmia database. The sampling frequency is 360 Hz in different classes. A total of 152 samples HRV attributing to four ECG beat types are summarized in table 1, in which half of the ECG beats are selected for training and the other half for testing the classification

Type	MIT – BIH data base	Training file	Testing file
1	n01, n02, n03, n04	20	18
2	S01, s02, s03, s04	20	18
3	A01, a02, a03, a04	20	18
4	B01, b02, b03, b04	20	18
Total		80	72

TABLE 2: ECG samples used in this study

The associated RR interval is calculated from the location of the R points documented in the annotation files of the MIT – BIH database

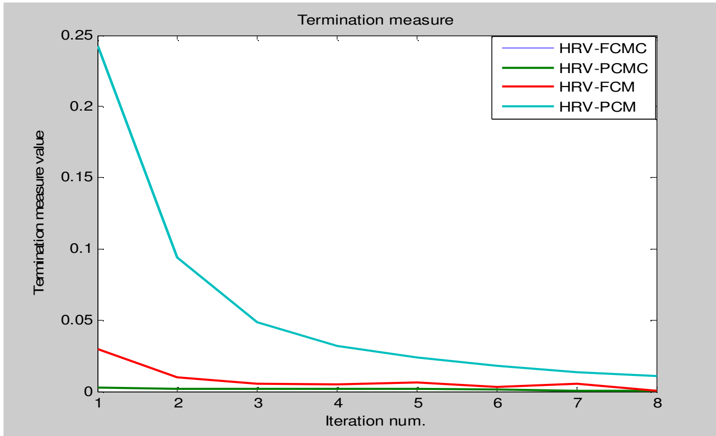

FIGURE 2: Convergence performance of different structure of FCM

Figure 2 shown that FCMC and PCMC have the same graph. PCMC is applied to noisy signals. So, FCMC is widely applied in this work as the signals are filtered before use.

Arrhythmia types of test pattern	Number of beats	FCMC		FCM		PCM		PCMC	
		MCN	RMC (%)	MCN	RMC (%)	MCN	RMC (%)	MCN	RMC (%)
1	20	0	0	1	5	0	0	0	0
2	20	0	0	0	0	0	0	1	5
3	20	0	0	2	10	2	10	0	0
4	20	1	5	0	0	2	10	0	0
Total	80	1	1.25	3	3.75	4	5	1	1.25
Average test error (%)		0.0118		0.0126		3.026		0.0118	

TABLE 3: pre – classification results for each arrhythmia in test

6. TEST RESULTS

Table 3 describes the test errors for each arrhythmia obtained with FCM and the other three structures. Misclassification Number (MCN) noted in table 3 represents number of misclassification ECG in testing. Rate of misclassification (RMC) is calculated using:

$$\text{RMC}\ (\%) = \left(\frac{\text{Number of misclafication beat}}{\text{Number of total beat}}\right) \qquad (4)$$

The performance of FCMC – HRV technique is depicted as shown in figure 1. It is observed that the % of error in case of WT – FCMC allows us to make a comparison to others structures keeping the number of the same iteration

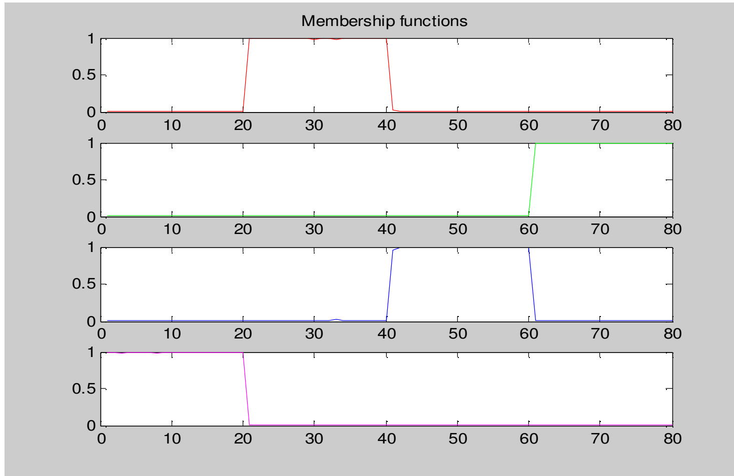

FIGURE 3: Classification results for different classes

Figure 3 shows the output of the FCM classifier. All the ECG arrhythmias detected from the ECG records are classified correctly. As noted, recognition rates vary between 98.5 and 99.6 with average accuracy 99.05

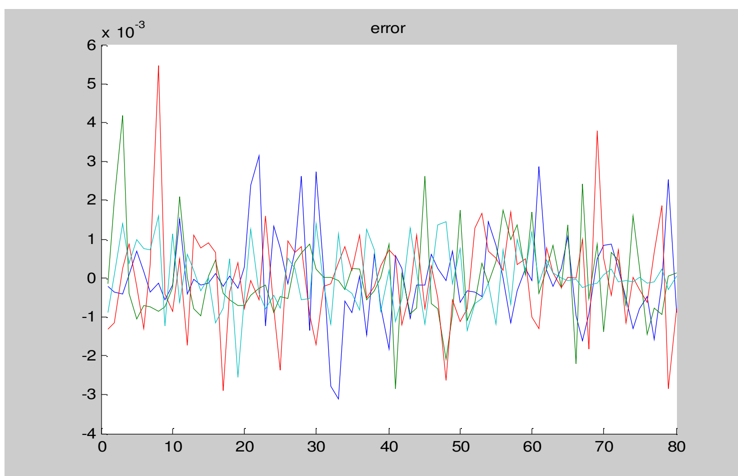

FIGURE 4: Error of classification for different classes

The error curve (figure 4), illustrates the smallest values obtained for the classification of different arrhythmias (less than 0.6 %).

7. CONCLUSION

For the conventional FCMC, all patterns in the pattern space are assigned membership values, which are based on the Encludean distance between the patterns to each cluster.

This paper represents new method for the classification of ECG arrhythmia signal using Fuzzy C-Means algorithm. The method has been comprehensively tested using the ECG database covering wide variety of ECG arrhythmias. In this paper, the WT – FCMC has been developed and presented to classify electrocardiography signals. In doing so, a comparative assessment of the performance of FCM shows that more reliable results are obtained with the FCMC in shorter time for the classification of ECG signals. The aim in developing WT – FCM was to achieve more optimum cluster centers locations and to reduce the time of training of the structure. We hope that

the performance of the method will be better if we use a neural network to classify the output of the FCM clusters (WT-FCM-NN).
This technique is obtained by incorporating the technique preprocessing different ECG signal, fuzzy c-means clustering method for classification of ECG arrhythmias. So, it can be said that the structure, which is a widely beneficial structure than conventional WT – NN to recognize and classify ECG signals, is obtained.

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