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Diagnostic of ECG Arrhythmia using Wavelet Analysis and K-Nearest Neighbor Algorithm

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***Abstract*—The automatic electrocardiogram (ECG) beat classification is a very useful tool to timely diagnosis of dangerous heart conditions. In this paper, we have implemented an automatic ECG heartbeats classifier based on the K Nearest Neighbor algorithm (KNN). The segmentation of ECG signals has been performed by Discrete Wavelet Transform (DWT).The considered categories of beats are: Normal (N), Premature Ventricular Contraction (PVC), Atrial Premature Contraction (APC), Right Bundle Branch Block (RBBB) and Left Bundle Branch Block (LBBB). The validation of the presented KNN based classifier has been achieved using ECG data from MIT-BIH arrhythmia database. We have obtained the good classification performances, in terms of the calculated values of the specificity and the sensitivity of the classifier for several pathological heartbeats and the global classification rate, which is equal to 98,71%.**

Keywords—ECG beats classification, Segmentation, K Nearest Neighbor algorithm, and classification performances.

I. Introduction

Classification of electrocardiogram signals (ECG) into several disease categories represents a composite pattern recognition task. The variation in the heart electrical activity is used in order to diagnose heart diseases. However, manual analysis of long ECG signals takes a long consuming time and isn't practical when using the visual inspection of cardiologists. Therefore, the development of computer based analysis systems becomes a dynamic research study subject, because it makes this analysis automated and easier [1-6].

Classification is achieved by detecting the ECG components shapes that provide an accurate discrimination between the required disease Categories. Conventionally, a typical heart beat of the ECG signal is characterized using measurements such as magnitude, duration and area of different constitutive waves. The most amounts of cardiac arrhythmia classification works published in the literature are based on the artificial intelligent approaches, such as: Bayesian and Heuristic approach [7], Hidden Markov Models [8-9], Adaptive Resonant Theory (ART) [10], Support Vector Machines (SVM) [11] and Artificial Neural Networks (ANN) [12].

The selection of the pertinent feature parameters is an important step for the accurate discrimination between different categories of ECG beats. Javadi et al[6] have proposed a new combination method for classifying different types of ECG beats (Normal, PVC and other ones) based on a suitable set of morphological and temporal features for including both shaping and timing information in ECG signals.

In this paper, we have presented an automatic classification system based on the K Nearest Neighbor algorithm (KNN). The classifier has been implemented and evaluated using the MIT-BIH arrhythmia database.

II. Materials and Method

Fig.1 illustrates the block diagram of the proposed method for the automatic recognition and classification of normal and abnormal ECG beats.

A. ECG Data Collection

The MIT-BIH arrhythmia database [13] is considered as the standard database in the arrhythmia detection and classification and it has been extensively used for algorithms validation. In this work, ECG data from this database are too used for the evaluation and the test of the classification approach, allowing us to directly compare the obtained results with those of the literature.

The database consists of 48 half-hour ambulatory ECG signals with a sampling frequency equal to 360Hz. Each record of this database is associated with an annotation file,

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providing the reference annotations for each heartbeat. The manual annotations associated with the selected ECG data are exploited respectively in the training step of the proposed classifier and the evaluation of the classification performance during the testing step.

Five predominant classes of ECG heartbeats of MIT-BIH database have been taken in our study. Fig. 2 shows the various considered categories of ECG beats: Normal beat (N), Premature Ventricular Contraction (PVC), Atrial Premature Contraction (APC), Right Bundle Branch Block (RBBB) and Left Bundle Brunch Block (LBBB).

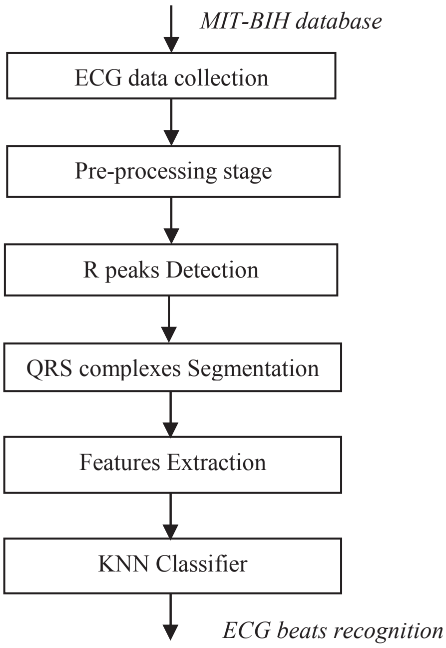

Fig. 1. Block diagram of the proposed method for the automatic heartbeats classification.

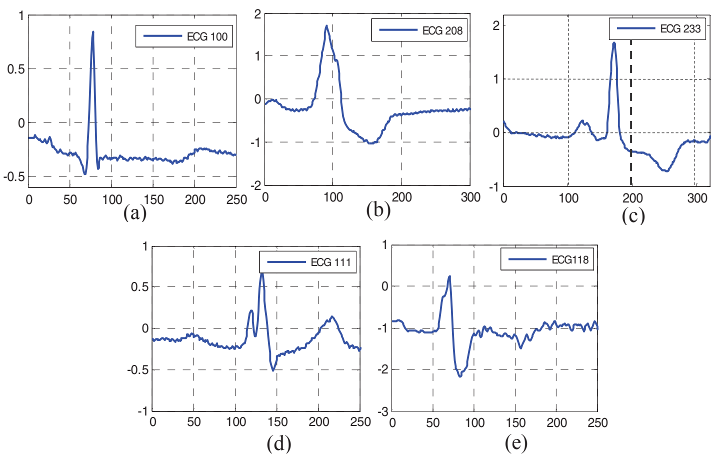

Fig. 2. Different considered categories of ECG beats: (a) Normal beat (N), (b) PVC beat, (c) APC beat, (d) LBBB beat and (e) RBBB beat.

Table I presents the ECG data from MIT-BIH database that are used in this study and also the number of beats for each considered classes.

B. ECG Signals Preprocessing

Since the ECG data capturing and recording are done by using skin electrodes, they are prone to corruption by various kinds of noise and artifacts. There are two different kinds of artifacts: low frequency noise (baseline wander) and high frequency noise (power line interference, electromyogram…).

The ECG signals enhancement from several last mentioned kinds of noise is a perquisite for the right extraction and detection of their various components. In [14], we have achieved the multiresolution wavelet analysis of the original ECG signals for identifying frequency ranges of different kinds of low and high frequency noise and so removing corresponding detail coefficients. After the preprocessing stage, we have obtained a free noise signal '*ECG_deno'* with a frequency band situated in the range of '0- 45 Hz'.

TABLE I. MIT-BIH DATA USED FOR THE CLASSIFICATION OF THE FIVE CONSIDERED ECG BEATS.

Type of beat	ECG data	Number of beats	Total number of beats
N	119	1543	**8860**
	200	1743	
	209	2620	
	212	923	
	221	2031	
PVC	119	444	**2750**
	200	823	
	214	256	
	221	396	
	233	831	
APC	118	96	**1890**
	200	30	
	209	383	
	232	1383	
RBBB	118	2163	**7170**
	124	1531	
	212	1825	
	231	1254	
	232	397	
LBBB	109	2492	**6610**
	111	2123	
	214	2003	

C. R peaks Detection

In order to detect the R peaks positions, we have focused on our previously published R wave detection algorithm [14]. This approach has been based on the conjoint use of the multiresolution discrete wavelet transform and the power spectrum of the resulting decomposition signals. In this stage, we had first introduced and proposed a new mathematical function. Next, the R wave positions are extracted as the points with maximum amplitude values of the signal in each position of a sliding window with a width equal to the maximal interval of the QRS complex (160 ms) [15].

The evaluation of our R peaks detection algorithm was performed using the whole MIT-BIH arrhythmia database. It gave significant ability in cases of low signal to noise ratio, high baseline drift and irregular morphologies of ECG signals. The very good detection performances had been computed; we had obtained a global sensitivity of 99.87%, a positive predectivity of 99.79% and a percentage error equal to 0.34%.

D. QRS Complexes Segmentation

The QRS complex segmentation is introduced by extracting the positions of Q and S waves, then the detection of *QRS_on* and *QRS_off* points.

The Q and S points represent the two inflection point on either side of the R peak. Hence, the first two points on each side of the R peak (left and right) that check sign inversion of the free-noise signal (*ECG_deno*) slope signify respectively the positions of the Q and S wave. The search of the Q point is initiated from an R peak towards left within a window of [*R_Position: R_position- 80 ms*]. The same way is used for extracting the S point, but the window is defined at the right of the R peak [*R_Position*: *R_Position+ 80 ms*].

For every point of *ECG_deno* array, we have computed the slope using the five point differentiation method as follow:

$$f'(x) \approx \frac{-f(x+2h)+f(x-2h)+8f(x+h)-8f(x-h)}{12h} \tag{1}$$

Where: h is the time division and f represents the free-noise signal '*ECG_deno*'.

The extracted Q peaks and S peaks are taken in two arrays, which are noted *Q_Position* and *S_Position*, respectively.

The onset (offset) of the QRS complex is identified from the position of Q peak (S peak) within a window of 40 ms towards the upside (downside) along the *ECG_deno* array [16]. The positions of the points corresponding to the minimum of the slope in the region of [*Q_Position*:*Q_Position*-40 ms] ([*S_Position*: *S_Position* + 40 ms]) are extracted and taken as QRS onset (QRS Offset).

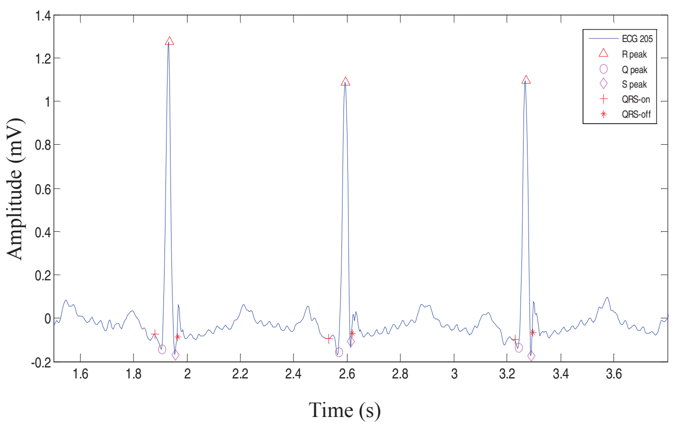

Fig. 3. Fiducial points detection in the record '205' from MIT-BIH database.

E. ECG Features Extraction

An efficient automatic algorithm of classification focuses on the use of the relevant features to the studied kinds of heartbeats. In this work, we have based on the same features to those employed by the cardiologist in order to establish the diagnostic and the recognition of the five considered types of beats. So, we have created *n* vectors containing five significant parameters, which are using to characterize each ECG data of *n* beats. These significant features are defined respectively:

- *R_ampli*: represents the R waves amplitudes;
- *QRS_width*: is the QRS complex duration;
- RR_p : measures the distance between the current and the previous R peak;
- RR_f : measures the distance between the current and the following R peak;
- RR_p/RR_f : represents the ratio between the two previously mentioned RR intervals.

F. K-Nearest Neighbor (KNN) Classification Algorithm

The K Nearest neighbor (KNN) method is one of potential statistical algorithms using for classification. It is a lazy learning method that is based on storing all available data points and then classifying new data points using similarity measures. The KNN algorithm is achieved by two phases, namely training phase and classification phase. During the training phase, no actual model of learning is performed, although a training dataset is required. In this phase, the features vectors of training samples (examples) are stored with their own labels in the memory. In [17], The KNN approach was primarily employed for automated ECG analysis and it gave an accurate delineation of QRS complexes. In our work, the delineation step is achieved using wavelet analysis and the classification step will be made with the KNN algorithm.

In the classification phase, a test point is classified by assigning a label, which represents the most recurrent among the k training samples nearest to this test point. So, K represents the number of all adjacent neighbors in term of a distance measure between training samples and test samples.

The KNN approach based classifier needs only two principal parameters: the number of nearest neighbors and the distance metric. However, the best choice of these parameters becomes a critical task.

1. The distance parameter

In order to find the nearest neighbors, we can exploit one of the following distance measures [18]:

• ***The Euclidean distance***: it represents the most usual way to compute the distance between two objects by examining the root of square difference between coordinates of an objects pair. That distance is defined by the following equation:

$$d(x_i, x_j) = \sqrt{\sum_{s=1}^{p} (x_{is} - x_{js})^2} \tag{2}$$

• ***The Minkowski distance***: it is first considered by Hermann Minkowski. In this case, the distance between two points is calculated as the sum of the absolute differences of their coordinates, as illustrated by the equation:

$$d(x_i, x_j) = (\sum_{s=1}^{p} \left| x_{is} - x_{js} \right|^{p})^{1/p} \tag{3}$$

• ***The Correlation distance***: this type of distance is defined as follows:

$$d(x_i, x_j) = 1 - \frac{(x_i - \overline{x_i})(x_j - \overline{x_j})'}{\sqrt{(x_i - \overline{x_i})(x_i - \overline{x_i})'}\sqrt{(x_j - \overline{x_j})(x_j - \overline{x_j})'}} \tag{4}$$

where :

$$\overline{x_i} = \frac{1}{p}\sum_{s=1}^{p} x_{is} \tag{5}$$

$$\overline{x_j} = \frac{1}{p}\sum_{s=1}^{p} x_{js} \tag{6}$$

2. The K parameter

Generally, the value of the *K* parameter is chosen in such a way that it gives the maximum accurate classification rate [19]. It is found that the larger values of the *K* parameter increase the classification error, because the boundaries between classes become less distinct. Furthermore, it is helpful to select *K* to be an odd number as it avoids tied votes in the case of problems of binary classification.

In our work, we have tested the classification algorithm using various values of the neighbors number (*K*=1, 3, 5, 7) and different types of distance. Hence, we have found that the choice of *K* equal to 3 with the Euclidean distance has provided the best classification rate for each class in comparison to other choices.

As stated before, the KNN based classifier necessitates two steps of training and testing. So, we have taken the half of the total number of beats in each class for training the algorithm and the residual beats have been used for testing the classification performance.

III. Results and Discussion

A. Confusion Matrix

Table II shows the obtained results of classification as a confusion matrix. Where, each row characterizes the instances in a predicted class and each column signifies the instances in an actual class. The confusion matrix is a significant representation, because the misperception of the classifier between different classes becomes more evident.

From Table 2, it is clear that the majority of misclassified normal beats (N) are those classified as APC (32 beats). Identically, most misclassified APC beats are those classified as normal (30 beats). This is mainly due to the morphological similarity between normal and premature auricular contraction beats.

TABLE II. *Results of Classification as a Confusion Matrix.*

Confusion Matrix	N	PVC	APC	RBBB	LBBB
N	4385	13	32	0	0
PVC	68	1307	0	0	0
APC	30	15	900	0	0
RBBB	0	10	0	3575	0
LBBB	0	8	0	0	3297

Note also that there is no APC beat classified as RBBB or LBBB. Similarly, there is no PVC, RBBB or LBBB beat that is classified as APC. This is due to the large dissimilarity between beats with auricular origin (APC) and those with ventricular origin (PVC, LBBB, RBBB). Moreover, despite the morphological similarity between beats having ventricular origin (PVC, RBBB or LBBB), we have obtained low numbers of RBBB and LBBB beats that are classified as PVC beats and also no PVC beat is classified as RBBB or LBBB patterns.

These all obtained results highlight the relevance of the five descriptive features that we have used for ECG beats characterization and demonstrate the aptitude of the proposed and implemented classifier based on the KNN algorithm, principally in discriminating patterns with comparable morphologies (i.e. Normal and APC beats or PVC, LBBB and RBBB).

B. Validation of the Classifier

As shown in Table I, about 13640 ECG beats of five categories (N, PVC, APC, RBBB and LBBB) are employed for analyzing and testing the performance of the proposed K nearest neighbor classifier.

In order to test and evaluate the performance of the classifier, all classified heartbeats will be compared with annotations that are associated with each record in the MIT-BIH database for controlling the classification error. For this reason, we have calculated three statistical parameters: specificity (*Sp*), sensitivity (*Se*) for each type of pathological beats (PVC, APC, RBBB and LBBB) and the classification rate (*Rc*). These parameters are defined respectively as follow:

$$Sp(\%) = \frac{TN}{TN + FP}.100\% \quad (7)$$

$$Se\,(\%) = \frac{TP}{TP + FN}.100\% \quad (8)$$

$$Rc(\%) = \frac{TP + TN}{TP + FN + TN + FP}.100\% \quad (9)$$

Where:
TP (*True Positive*): number of pathological heart beats (PVC, APC, RBBB or LBBB) that are classified correctly.
TN (*True Negative*): number of normal heartbeats (N) that are classified correctly.

FP (False Positive): number of normal heartbeats that are classified as pathological.

FN (False Negative): number of pathological beats that are not classified correctly.

The evaluation results of the proposed heartbeats classifier based on the KNN algorithm are summarized in Table III. It is clear that the overall number of beats that are wrongly classified is lower to the number of correctly recognized beats for each considered category. Furthermore, the proposed method presents high ability of classification and discrimination between all classes, because it achieves an overall classification rate of *98.71%*.

TABLE III. VALIDATION RESULTS FOR DIFFERENT TYPES OF BEATS.

Performance parameter	Type of beat	Number of well classified beats	Number of misclassified beats	Value of parameter (%)
Spécificity (Sp%)	N	4385	45	98.98
Sensitivity (Se%)	PVC	1307	68	95.06
	APC	900	45	95.24
	RBBB	3575	10	99.72
	LBBB	3297	8	99.76
Classification rate (Rc%)	Total	**13464**	**176**	**98.71**

C. Comparison with Other Classifiers

In order to assess our KNN based classification algorithm performance, a comparative study is done versus a set of last published algorithms carried out on the MIT-BIH database. Table IV summarizes the comparison of the proposed method with other ones of the literature.

It is evident that the classification rate (R_c) obtained by the validation of the proposed method is satisfier compared to the classification rate computed by other methods based on several neural networks structures, such as: Modulator Neural Network [6], Self-Organizing Cerebellar Model Articulation Controller Network (SOCMAC) [22], Multi-Layer Perceptron (MLP) [20,21], Self-Organization Map (SOM) [24], Multichannel Adaptive Resonance Theory Neural Network (MART) [26], combined neural network for ECG beat classification [23, 25], Adaptive neuro fuzzy inference network with lyapunov exponent (LEANFIS) [4] and Hybrid Fuzzy Neural Network (HFNN) [1].

It should be noted that in these precedent mentioned works, the ECG data are taken from the MIT/BIH arrhythmia database. However, each method has considered different categories of beats, various amounts of data, different segmentation methods and different methods of feature extraction. All these differences between classifiers have a high influence on the classification results.

TABLE IV. COMPARISON OF THE PROPOSED METHOD WITH OTHER REPORTED METHODS OF CLASSIFICATION.

Classifier	Method of classification	*Rc* (%)
Proposed classifier	K Nearest neighbor Classifier (KNN)	**98.71**
Javadi et al[6]	Modular Neural Network	96.02
Benali et al[5]	Wavelet Neural Network (WNN)	98.78
Ubeyli et al[4]	Lyapunov Exponent with Adaptive Neuro Fuzzy Inference Network (LE-ANFIS)	96.39
Güler et al[20]	Tow Multi Layer Perceptron (MLP)	96.94
Osowski et al[1]	Hybrid Fuzzy Neural Network (HFNN)	96.06
Minami et al[21]	Fourier transform (FT) with Multi Layer Perceptron (MLP)	98
Wen et al[22]	Self-Organizing Cerebellar Model Articulation Controller Network (SOCMAC)	98.21
Vargas et al[23]	Principal Component Analysis (PCA) with Multi Layer Perceptron (MLP)	94.09
Lagerholm et al[24]	Hermite functions and self-organizing maps (SOM)	98.49
Linh et al[25]	Fuzzy C-Mean with Multi-Layer Perceptron (FCM +MLP)	93.5
Delgado et al[26]	Multichannel Adaptive Resonance Theory Neural Network (MART)	96.6

This comparison study proves that the proposed KNN based classifier can be used as an important and significant tool for the ECG heartbeats recognition and the cardiac arrhythmia classification.

IV. CONCLUSION

This paper deals with the presentation and the implementation of an automatic classifier of five types of heartbeat based on the K nearest neighbor algorithm (KNN). The best choice of significant parameters for characterizing some ECG beats is necessary for an effective recognition and discrimination between classes. The obtained results show a good discrimination between different studied categories of ECG beats because of the relevance of the feature parameters. Also, the comparative study of the proposed approach and other approaches reported in the literature shows that the classification rate is satisfactory and in most cases relatively good as those obtained by other studies using neural networks.

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