RP102 FINAL PAPER

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ABSTRACT

In this paper, we present an .... to do!

***Index Terms*—** ECG, arrhythmias classification, preprocessing, segmentation, and feature extraction.

1. INTRODUCTION

The electrocardiogram (ECG) is the non-invasive technique most used in heart disease diagnoses. It could be described as a record of the electrical phenomena originated from the cardiac activity. Fig. 1 shows such record of a normal heart beat. The ECG is frequently used to detect cardiac rhythm abnormalities, a.w.a. arrhythmia, and the utilization of pattern recognition techniques can help the physician to improve this detection and consequently make a more accurate diagnoses.

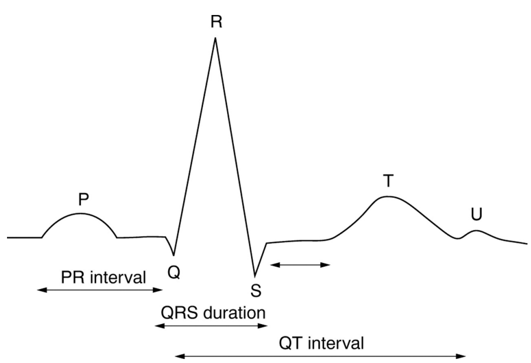

Fig. 1. A normal heart beat ECG signal

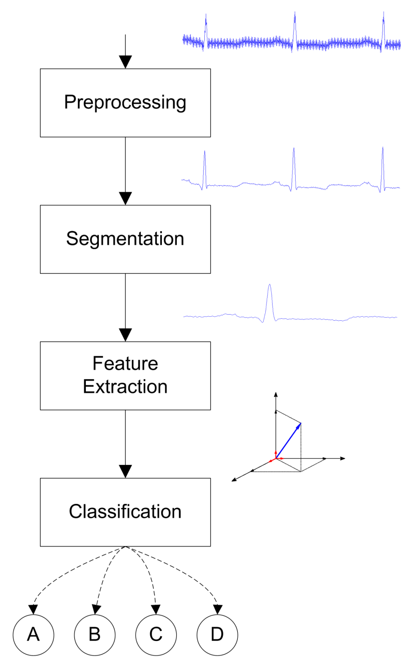

Fig. 2. A diagram of a classification system of arrhythmias in ECG signals

The complete pattern recognition process for the case in analysis, classification of an arrhythmia type, can be divided into four subsequent steps (as shown in Fig. 2): preprocessing , segmentation , feature extraction , and classification.

The preprocessing consists mainly in detecting and attenuating frequencies of the ECG signal related to noise or artifacts. These artifacts can be originated from a biological source, such as muscular activity and the noise can be originated from an external source, such as 50/60Hz from electrical network. It is also desired, in the preprocessing, to perform a signal normalization.

Many methods has been proposed to reduce noise or artifacts in ECG signals. The most simple and fairly used is the implementation of digital filters [1]. For this paper a bandpass digital filter was implemented by the use of two cascaded filters to achieve a 3dB passband from approximately 5-12Hz [2].

The segmentation consists in delimitating the most interesting part of the signal, *i.e.*, the QRS complex, since it reflects the electrical activity of the heart (see Fig. 1). Once the segmentation of QRS complex is done one can obtain many physiological information, such as the cardiac frequency, and so the techniques to extract features from the signal can be applied. In this paper, the same database was used for training, test, and validation, *i.e.* the MIT-BIH arrhythmia database [3]. The MIT-BIH arrhythmia database provide 48 records, each one of them containing about 30 minutes of ECG wave data for two different leads, and an annotation file containing all the events labeled. Thus, eliminating the need to use segmentation methods, seeing that they are out of scope of this paper.

All 48 records of the MIT-BIH arrhythmia database was used to classify six types of arrhythmias of vital importance according to [4], and those six types of arrhythmias belong to the groups of important arrhythmias to be detected, recommended by Association of Medical Instrumentation (AAMI) (see Fig 3). These types are normal sinus rhythm (N), premature ventricular contraction (V), atrial premature contraction (A), right bundle branch block (R), ventricular fusion (F) and fusion (f). Almost all beats of the database are used, except the first pair and the last beat of each record. There is four well defined steps in the problem of classification arrhythmias on the ECG signal (see Fig 2) but there is another factor that influences the classificator final result. The dataset selected for training. AAMI provide standard and procedures to evaluate the performance of methods, however few works have done that [5]. Several methods on the literature are favoured by biased dataset [6, 7, 8, 4, 9, 10, 11, 12], which makes a fair comparison between methods difficult.

The aiming of these paper is to analyze the results of two widely used classification methods, the multi layer perception (MLP) and support vector machine (SVM) with 3 different datasets. Each dataset are composed by two groups - training and test. In the first dataset, the data (harbeats) from one patient record appears only for training or test, never for both groups. In the other two datasets, data from one patient are forced to belong to both training and test groups. Details of feature extraction are show in Section 2, and how the dataset are created in Section 3.

Experimental results (Section 5), conclusions and open problems (Section 6) are presented as well.

2. FEATURE EXTRACTION

Features are extracted according to method proposed by [13]. In order to extract the features, a window of 144 samples around the R peak are selected, *i.e.* 72 samples before the R peak and 72 samples after the R peak. Those 144 samples segment are used to extract features for the morphology information. To extract features to represent the rhythm, the interval between R peaks of adjacent beats are computed according to:

$$valor = \begin{cases} 1 & \frac{K}{RR_i} \\ 2 & \frac{K}{RR_{i+1}} \end{cases} \quad (1)$$

The other 19 features are extracted from the morphology, *i.e.* level 4, 5, 6 and 7 of discreet wavelet transformation detail coefficients of the segment, considering the wavelet deubechie 1 as the wavelet mother. This feature extraction method is choosen due to its simplicity and to its remarkable results reported by the authors.

3. DATASETS

In this paper, 3 datasets are used in order to test 2 distinct situations : heartbeats from one patient present for both training and test group, *i.e.* highly related beats for training and test - Dataset 2 (D2) and Dataset 3 (D3). Heartbeats from one patient exclusively belong to only one group, training or test - Dataset 1 (D1).

3.1. Dataset 1

The first dataset are formed by 3 partitions (see Fig 4). Each partition is constructed by the following algorithm :

1. consider bp = f,R,F,A,N,V the patient beats type list , sorted in an ascendent mode
2. consider lp = 100,101,...234 the MIT-BIH patient records list.
3. for t = 1 to 6 do
4. sort lp acording to number of beats of class bp(t)
5. while number of beats of class bp(t) is greater than zero, do
6. remove from lp list the patient record with more beats of type bp(t)
7. insert the last patient record removed from the list and in the partition with fewer beats of type bp(t)
8. end while
9. end for

This algorithm assure that the beats from one record belongs only to one partition. The two groups (training and test) are formed by the combination of the tree partitions using the leave-one-out cross-validation method. Thus, always one group is left for test, and this group contain unknow beats to the classifiers (see Fig 5).

3.2. Dataset 2

To build the second dataset, all beats from all records are read and 6 matrix created. Each matrix having data from one class of heartbeat, *i.e.* N, R, A, V, F or f. This n x m size matrix are randomically sorted by n, where n is the number os beats and m the number of features extracted. After the sorting, a percent of beats (some lines of matrix) are used to construct the groups of training and test, following the rule proposed in [6]:

- Type N : 13% of beats to training group and 87% to test group

AAMI heartbeat class	N	S	V	F	Q
Description	Any heartbeat not in the S, V, F or Q classes	Supraventricular ectopic beat	Ventricular ectopic beat	Fusion beat	Unknown beat
MIT-BIH heartbeat types	normal beat (NOR) left bundle branch block beat (LBBB) right bundle branch block beat (RBBB) atrial escape beats (AE) nodal (junctional) escape beat (NE)	atrial premature beat (AP) aberrated atrial premature beat (aAP) nodal (junctional) premature beat (NP) supraventricular premature beat (SP)	premature ventricular contraction (PVC) ventricular escape beat (VE)	fusion of ventricular and normal beat (fVN)	paced beat (P) fusion of paced and normal beat (fPN) unclassified beat (U)

Fig. 3. Mapping the MIT-BIH Arrhythmia types to the AAMI Classes

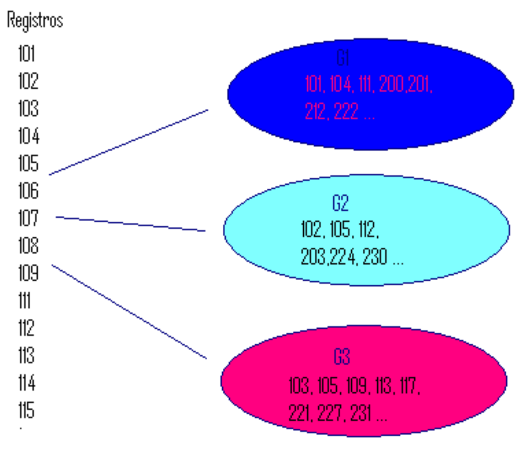

Fig. 4. Records are divided in tree partitions

- Type R : 40% of beats to training group and 60% to test group
- Type A : 40% of beats to training group and 60% to test group
- Type V : 40% of beats to training group and 60% to test group
- Type F : 50% of beats to training group and 50% to test group
- Type f : 50% of beats to training group and 50% to test group

3.3. Dataset 3

To build the third dataset, all beats from one record are read, and then the same rule applied above are used to separate the

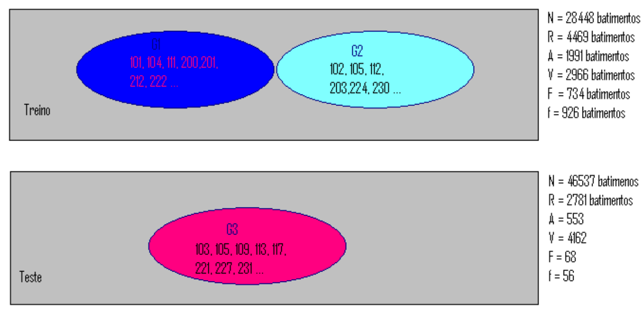

Fig. 5. Example of training set : G1 and G2 for training, G3 for test.

beats into two groups : training and test. The beats are chosen randomically and the process is done to all records of MIT-BIH arrhythmia database. The number of beats for training and test groups are exactly the same for D2 and D3.

4. CLASSIFICATORS

Classify the patterns is a critical step in ECG recognition system. The classifier receives the data set entry (the features) for training and generate a space of decision. Usually in ECG systems, the classifiers are supervised [14]. Two of most common classifiers used for arrythmia recognition are: Multi Layer Perceptron Neural Network (MLPNN) and Support Vector Machine (SVM).

4.1. Multi Layer Perceptron Neural Network (MLPNN)

In the MLPNN, each neuron j in the hidden layer sums its input signals x_i after multiplying them by the strengths of the respective connection weights w_{ji} and computes its output y_j as a function of the sum:

$$y_j = f\left(\sum w_{ji} x_i\right) \tag{2}$$

where f is activation function that is necessary to transform the weighted sum of all signals impinging onto a neuron. The activation function (f) can be a simple threshold function, a sigmoidal, hyperbolic tangent, or radial basis function.

The sum of squared differences between the desired and actual values of the output neurons E is defined as:

$$E = \frac{1}{2}\sum_j (y_{dj} - y_j)^2 \tag{3}$$

where y_{dj} is the desired value of output neuron j and y_j is the actual output of that neuron. Each weight w_{ji} is adjusted to reduce E as rapidly as possible. How w_{ji} is adjusted depends on the training algorithm adopted [7] Backpropagation, or propagation of error, is a common method of teaching artificial neural networks how to perform a given task. The Backpropagation learning process works in small iterative steps: one of the example cases is applied to the network, and the network produces some output based on the current state of it is synaptic weights (initially, the output will be random). This output is compared to the known-good output, and a mean-squared error signal is calculated (Eq3). The error value is then propagated backwards through the network, and small changes are made to the weights in each layer. The weight changes are calculated to reduce the error signal for the case in question. The whole process is repeated for each of the example cases, then back to the first case again, and so on. The cycle is repeated until the overall error value drops below some pre-determined threshold. At this point we say that the network has learned the problem "well enough" - the network will never exactly learn the ideal function, but rather it will asymptotically approach the ideal function [15].

For this paper, a Matlab Neural Network Pattern Recognition Tool was used for MLP implementation of a two layer feed-forward network, with sigmoidal activation function and 20 neurons on the hidden layer.

4.2. Support Vector Machine (SVM)

A SVM performs classification by constructing an N-dimensional hyperplane that optimally separates the data into two categories. SVM models are closely related to neural networks. In fact, a SVM model using a sigmoid kernel function is equivalent to a two-layer, perceptron neural network. Other kernel functions are also available, such as linear, polynomial and radial basis function.

A SVM classifier with radial basis function (RBF) kernel was chosen for the classification task. The SVM with RBF kernel is a very powerful tool and it can handle non linear separable data. There are two parameters for RBF kernel, C and gamma, and several tests were evaluated in order to achieve the best values. The cross-validation technique as well as grid-search was employed, and the optimal values of C and gamma was respectively 10 and 0.02380. The LIBSVM [16] was used for SVM implementation.

5. EXPERIMENTAL RESULTS

In order to determine the classification performance, tree metrics are used, accuracy (4), specificity (5) and sensitivity (6). Accuracy is the percent of total beats correctly classified for all classes of beats, while the other metrics are specific for each class. Specificity is the ratio of correctly classified beats among all beats of an specific class and sensitivity is the ratio of correctly classified beats of one class to total of beats classified as that class, including the miss classification beats. Specificity and sensitivity are the most important metrics for the problem in question, *i.e.* arrhythmia classification, since the number of beats for each class are non-balanced and one class alone could represent most of the total accuracy.

$$accuracy = \frac{beatscorrectlyclassified}{numberoftotalbeats} * 100 \tag{4}$$

$$specificity = \frac{truepositives}{truepositives + falsenegatives} * 100 \tag{5}$$

$$sensitivity = \frac{truenegatives}{truenegatives + falsepositives} * 100 \tag{6}$$

5.1. Results for dataset 1

To evaluate the classification performance with dataset 1, a leave-one-out cross-validation technique was employed. First, a training group was created by the union of partition 1 and partition 2, thus partition 3 was used as the test group. Second, the training group was formed by partition 1 and partition 3, and the test group by partition 2. Finally, the last training group was formed by partition 2 and partition 3, and the test by partition 1. Those tree configuration are then applied to train and test the SVM and MLP classificators. (See Tables 1 and 2)

5.2. Results for dataset 2 and dataset 3

Dataset 2 and 3 are already divided into two groups - training and test. As the beats selected for the groups are randomically picked, all the process was executed 5 times. Mean values and standard deviation was then calculated. (See Tables 1 and 2)

6. CONCLUSIONS AND OPEN PROBLEMS

The challenges to proper classify arrhythmias on ECG signal are many. Researches are working for improvements, and

Table 1. MLP - 20 neurons on hiden layer

Class	Specificity/Sensitivity (%)				
	D2 (std)	D3 (std)	D1 - G1	D1 - G2	D3 - G3
N	98.44/97.20 (0.35/0.57)	98.32/97.30 (0.72/0.33)	83.20/99.40	76.0/100	94.30/80.30
R	94.22/98.54 (1.57/0.60)	94.38/98.70 (0.82/0.36)	27.60/1.80	0.00/0.00	82.00/39.04
A	62.20/64.96 (6.35/8.74)	47.58/55.10 (26.66/31.62)	0.00/0.00	0.00/0.0	7.70/22.4
V	79.57/94.66 (6.01/0.62)	80.88/94.76 (3.93/0.84)	5.80/9.20	92.60/22.4	37.90/80.70
F	45.88/30.10 (8.72/8.43)	36.32/33.22 (12.68/12.66)	0.00/0.00	0.00/0.oo	0.50/20.60
f	59.14/39.94 (6.83/11.04)	56.48/39.76 (7.44/12.50)	0.00/0.00	100/5.00	0.00/0.00

Table 2. SVM - kernel RBF, C = 10 and gamma = 0.023810 (1/2*num features)

Class	Specificity/Sensitivity (%)				
	D2 (std)	D3 (std)	D1 - G1	D1 - G2	D1 - G3
N	99.81/99.45 (0.00/0.00)	98.41/99.40 (0.00/0.00)	95.78/91.67	99.98/77.76	79.36/93.62
R	99.45/99.05 (0.00/0.00)	99.30/99.01 (0.00/0.00)	0.00/0.00	0.00/0.00	33.62/74.62
A	87.83/82.83 (0.00;0.01)	86.89/84.47 (0.00/0.01)	22.56/55.46	0.49/22.58	10.66/8.70
V	97.26/91.40 (0.00/0.00)	97.19/91.50 (0.00/0.00)	89.40/35.49	87.21/88.85	75.27/37.21
F	76.89/74.33 (0.01/0.00)	75.56/75.44 (0.01/0.02)	0.26/0.23	0.27/3.03	8.82/0.50
f	87.31/84.57 (0.01/0.01)	86.38/86.27 (0.01/0.00)	16.51/94.82	47.07/100.0	58.92/1.04

Table 3. Total accuracy

Classifier	Total Accuracy (%)				
	D2 (std)	D3 (std)	D1 - G1	D1 - G2	D1 - G3
SVM	98.35 (0.02)	98.39 (0.02)	77.60	78.38	75.89
MLP	95.78 (0.74)	95.72 (0.60)	72.6	76.9	77.5

many of them have shown remarkable results but few authors have considered the impact of the dataset selected for training and test on their results.

The results presented in Tables 1,2 and 3 show that the performance of classifiers on dataset 2 and dataset 3 are significant higher than results obtained by the same classifiers on dataset 1. The same rules to extract features were applied to all tree datasets and the same pre-processing in ECG sinal as well.

This paper shows that use beats from same patients for training and test, favor the classifiers results. Unbiased dataset, such as proposed by [17] and this work, should be used for arrhythmia classification methods in order to obtain more reliable results, since once this methods are used by physicians, the classificators will deal with new beats, *i.e.* unknown beats.

Several methods can be re-implement and re-tested on unbiased datasets, and the new results provided can be used for a more realistic prediction of the methods in a real environment.

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