NEURO-FUZZY CLASSIFIER FOR CARDIAC ARRYTHMIAS RECOGNITION

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ABSTRACT

The premature ventricular contraction (PVC) and the premature atrial contraction (PAC) are cardiac arrhythmias which are widely encountered in the cardiologic field. They can be detected using the electrocardiogram signal parameters. We use in this work a Neuro-fuzzy approach to identify these abnormal beats. To achieve this objective we have developed a Neuro-Fuzzy Classifier (NFCL), its performances were evaluated by computing the percentages of sensitivity (Se), specificity (Sp) and correct classification (CC). This classifier allows extraction of rules (knowledge base) to clarify the results obtained. We use the medical database (MIT-BIH) to validate our results.

Keywords : *ECG, neuro-fuzzy, fuzzy logic, PVC, PAC, explicit classification, MIT-BIH data base.*

1. INTRODUCTION

The Holter exam which is widely used in cardiology is a tool of recording electrocardiogram (ECG) of long duration. It facilitates the diagnosis of cardiac arrhythmias.
Due to large number of patients in intensive care units and the need for continuous observation of such condition, several methods and techniques for automated ECG beats recognition have been developed in the past ten years to look for solutions to this problem (**[1] [2] [3]).**

The electrocardiogram ECG is a physiological signal that represents the mechanical heart (contraction and relaxation). Figure (1) shows an ECG pattern for healthy subjects.

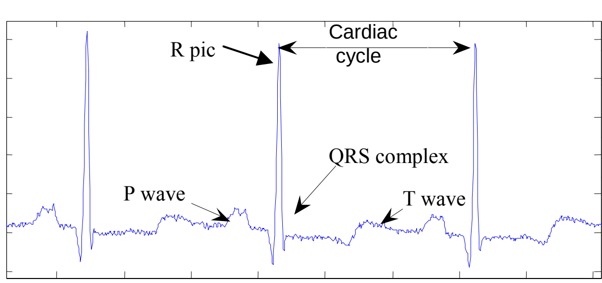

Fig1: ECG of a health person

We can see different waves in an ECG signal:

- P wave: is the contraction of the atria.
- QRS Complex: equivalent to a contraction of the ventricles.
- T wave: is the relaxation of ventricles.

The PVC and PAC premature beats are appearing with Normal beats (N) on the ECG signal (Figure 2 and 3)

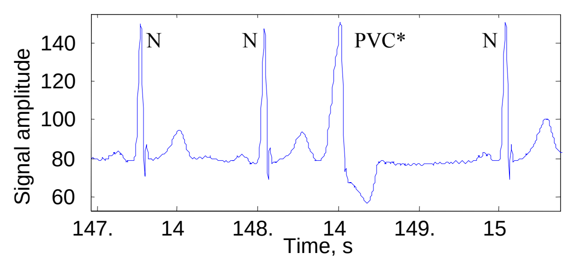

Fig.2 The premature ventricular contraction (PVC)

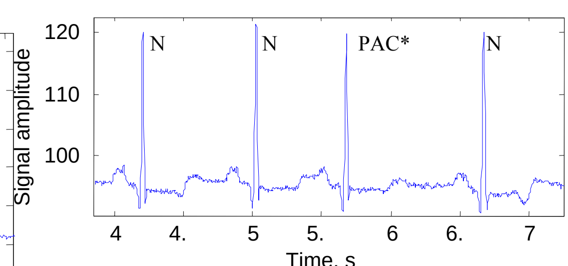

Fig.3 The premature atrial contraction *(PAC).*

Both neural networks and fuzzy logic are universal estimators. They can approximate any function to any prescribed accuracy, provided that sufficient hidden neurons and fuzzy rules are available.

Neural networks have been the subject of biomedical research interest during the past decade **([4] [2] [3] [1]).** But this technique is considered as a black box because it can't justify its results. However, fuzzy set theory plays an important role in dealing with uncertainly like making decisions in medical applications **([5] [6]).** The fuzzy inference systems can interpret their results through their knowledge base (basic rules) [7].

Recent results show that the fusion procedure of these two approaches (neuronal and fuzzy approach) seems to be very effective for the pattern recognition.

2. PRESENTATION OF THE NEURO-FUZZY APPROCH

Neuro-fuzzy systems are fuzzy systems which use neural networks theory in order to determine their properties (fuzzy sets and fuzzy rules) by processing data samples. Neuro-fuzzy systems harness the power of the two paradigms: fuzzy logic and neural networks, by utilizing the mathematical properties of neural networks in tuning rule-based fuzzy systems that approximate the way man processes information **[1]**.

Successful implementation of neuro-fzzy systems have been introduced by several authors, as (**[10] [8] [9]).**

In this work we present the ANFIS approach (adaptive neuro fuzzy inference system) which is a neuro-fuzzy hybrid method proposed by Jang **[12] [11],** and it is the most widely used of neuro-fuzzy techniques and the best one to solve problems of classification and Pattern Recognition.

2.1. ANFIS structure's

The ANFIS is a fuzzy inference system based on the model of Takagi-Sugeno **[11]** and uses five layers.
For reasons of representation, we will consider a system with two inputs and one output and also consider a model of the 1st order using two rules:

If x1 is A1 and x2 is B1 then y1=f1(x1,x2) = a1x1 + b1x2 + c1.

If x1 is A2 and x2 is B2 then y2=f2(x1,x2) = a2x1 + b2x2 + c2.

The ANFIS architecture that allows representing the basic rules is carried out by an adaptive network that contains fixed nodes (circular) and adaptive nodes (square) as illustrated in figure.4.

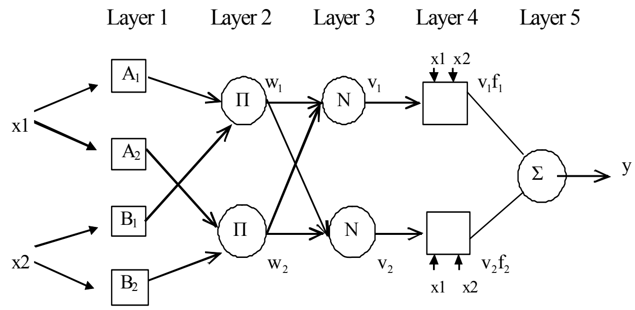

Fig.4. ANFIS Architecture

Each node square or circular applies a function on its input signals and for a given layer nodes have the same type of function. The output O_i^k of a node i of the k layer (called node (i, k)) depends on the signals from the layer k-1 and parameters of the node (i, k).

$$O_i^k = f\left(O_1^{k-1} \dots O_{n_{k-1}}^{k-1}, a, b, c, \dots\right) \quad (1)$$

n_{k-1} is the number of nodes in the (k-1)layer, and a, b, c are the parameters of the (i,k) node.

It should be noted that a circular node has no parameters.

Layer 1:
Nodes of this layer are all adaptive nodes. This layer performs fuzzification of the inputs; it determines the membership of each input:

$$O_i^1 = \mu_{Ai}(x) \quad (2)$$

x input of i node,
A_i : linguistic variable & O_i^1: degree of membership of x to A_i.
The parameters of a node in this layer are those of the corresponding membership function, these are the premise parameters.

Layer2:
The nodes of this layer are fixed nodes. They receive the output signals from the previous layer and send their product output

$$w_i = \mu_{Ai}(x_1).\mu_{Bi}(x_2) \qquad i = 1,2 \quad (3)$$

w_i The degree of truth of the rule i.

Layer 3:
Each neuron in this layer calculates the normalized degree of truth of the fuzzy rule.

$$v_i = \frac{w_i}{w_1 + w_2} \qquad (4)$$

The result out of each node represents the contribution of this rule on the final result.

Layer 4:
The nodes in this layer are adaptive and perform the consequent of the rules. The output of a node *i* is given by:

$$O_i^4 = v_i . f_i = v_i (a_i x_1 + b_i x_2 + c_i) \qquad i = 1,2$$
(5)

The parameters in this layer (a_i, b_i, c_i) are to be determined and are referred to as the consequent parameters.

Layer 5:
This layer consists of a single neuron circular makes the sum of signals from the previous layer to give the final output of the network:

$$O_1^5 = y = \sum_i v_i . f_i$$
(6)

The generalization of the system to a system with multiple inputs does not pose any problem. The number of nodes in the first layer is always equal to the total number of linguistic terms defined.

2.2. ANFIS learning's:

There are several learning algorithms for a neuro-fuzzy model **[13]**. Jang proposed a learning method called "hybrid algorithm". This algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. Once the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS **[12] [11].**

3. RESULT AND DISCUSSION

In this work, we classify the cardiac arrhythmias by a neuro-fuzzy approach using ANFIS.

The ECG signals used in this work are recordings collected between 1975 and 1979 by the laboratory of BIH arrhythmia (Beth Israel Hospital) in Boston in the United States, which is known as the MIT-BIH data base **[14]**. The ECG signals are sampled at a frequency of 360 Hz. Two or more cardiologists have made the diagnosis for these various records and they have annotated each cardiac cycle. These annotations will be useful for learning and assessment of the classification.

The choice of target diseases is dictated by the nature of work itself. Indeed, a review Holter is requested by a cardiologist to detect sporadic events that not appears on the ECG 12 D (12 leads) and especially transient arrhythmias (PVC, PAC).

PVC: The premature ventricular contraction

PAC: The premature atrial contraction

The choice of descriptive parameters which are the input vector is dictated by the nature of the pathology targeted [**16] [15]**.

For describing the heartbeat, we have chosen:

- RRp : the distance between the current R-wave and the previous R-wave (see Figure 8).
- RRs : the distance between the current R-wave and the following R-wave (see Figure 8).
- RRs / RRp : the ratio between the distance RR following the previous one (see Figure 8).
- QRS : the duration of the QRS complex (see Figure 8)

The parameters used were calculated using an algorithm developed and implemented in the LISI laboratory at the University of Rennes 1. This algorithm is based on the technique introduced by Pan J. and Tompkins W.J **[17]**.

The database built is used for learning and testing the classifier. Patients selected to build the database are patients who have diseases targeted (PVC, PAC) and are presented in the following table (Tab.1):

Table.1 Number of beats for each record

records	N	PVC	PAC
100	2225	1	30
116	2175	108	1
200	1726	815	30
201	1325	176	122
209	1850	1	380
210	2100	181	19
223	1986	449	73
233	1029	813	7
234	1700	3	43
Nombre total	**16116**	**2548**	**705**

Given the large number of normal beats compared to other types of beats, and to avoid specialization. We choose 500 beats for each of 3 classes (normal, PAC and PVC) (1500 total to form the learning base).

From this database, we generate an initial fuzzy inference system (FIS) of Sugeno type zero order (see figure.5) with the initial choices includes:

1. Membership function type : "Trapezoidal"
2. Number of membership function for each variable.
   -RRp: 2 functions
   -RRs/RRp: 3 functions
   - QRS: 2 functions
3. Manual initialization of modal points, based on knowledge of the expert (doctor).

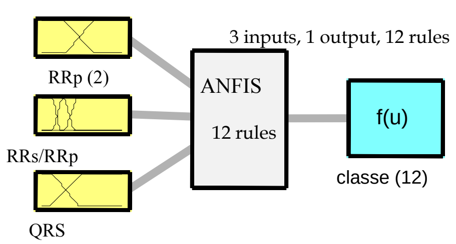

Fig.5. initial neuro-fuzzy model

At the end of the learning, parameters of the initial membership functions (figure.6) will be modified as shown on figure.7.

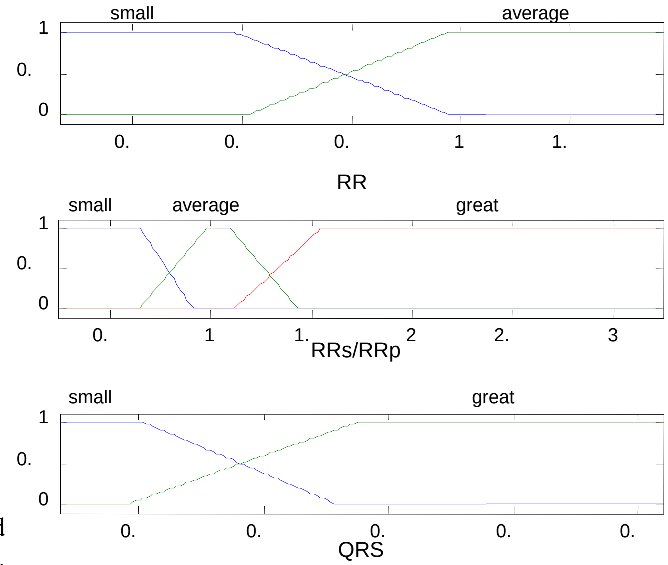

Fig.6. : initial membership functions

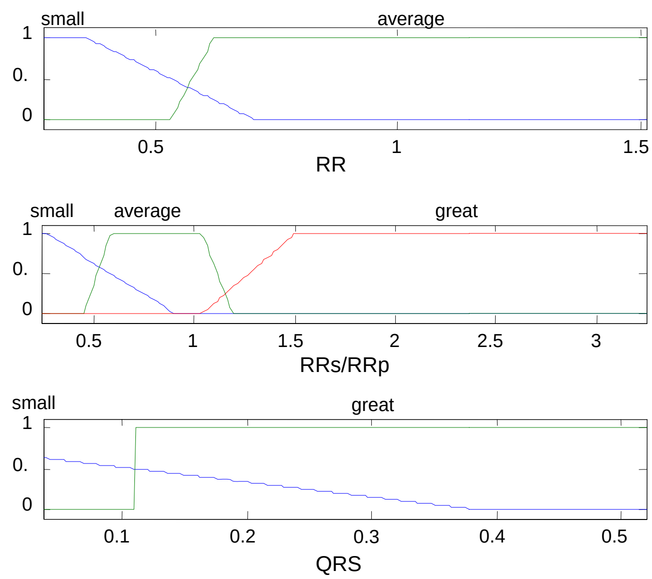

Fig.7: final membership functions (after learning)

4. RESULTS ANALYSIS

The performance of the neural classifiers was evaluated by computing the percentages of sensitivity (SE), specificity (SP) and correct classification (CC), the respective definitions are as follows:

• *Sensitivity (Se %):* [Se = 100×TP/(TP+FN)] is the fraction of real events that are correctly detected among all real events.

• *Specificity (Sp %):* [Sp = 100×TN/(TN+FP)] is the fraction of nonevents that has been correctly rejected.

• *Correct classification (CC %):*
[CC=100×(TP+TN)/(TN+TP+FN+FP)] is the classification rate.
In these formulas TP was the number of true positives, TN was the number of true negatives, FN was the number of false negatives, and FP was the number of false positives.
Since we are interested in estimating the performance of the classifier based on the recognition of PVC beats and PAC beats, the true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN) are defined appropriately as shown below:
− TP: classifies PVC as PVC (or PAC as PAC)
− FP: classifies normal as PVC or PAC;
− TN: classifies normal as normal;
− FN: classifies PVC or PAC as normal.

Note that
Se1 (%): is the sensitivity for detecting PVC beats.
Se2 (%): is the sensitivity for detecting PAC beats.

The results of the evaluation of the neuro-fuzzy classifier in terms of correct classification, sensitivity and specificity are summarized in table 2

Table .2. Performances of the neuro-fuzzy classifier (%).

records	Sp (%)	Se_1 (%)	Se_2 (%)	CC (%)
100	96,15	100,00	95,75	97,30
116	95,26	96,74	100,00	97,33
200	89,36	97,62	93,33	93,44
201	93,25	96,82	95,40	95,16
209	97,23	100,00	95,09	97,44
210	97,01	97,31	96,27	96,86
223	95,11	96,48	97,15	96,25
233	94,59	96,29	90,71	93,86
234	92,75	100,00	93,87	95,54
Average (%)	**94,52**	**97,92**	**95,29**	**95,91**

The average correct classification is 95.91%.
We notice from the results obtained in the table 2 that the neuro-fuzzy classifier NFCL gave satisfactory results (95.91%) and very similar to neural classifier cited in the literature [Chi'05] [Cha'04].
However, the results obtained by our classifier NFCL are explicit and interpretable, which is not the case for neural classifiers (black box type).

Our method generates automatically a knowledge base (12 rules) to justify the classification.

The rule base generated by the NFCL is :
1. If (RRP is small) and (RRS / RRP is small) and (QRS is small) then (class C1)
2. If (RRP is small) and (RRS / RRP is small) and (QRS is great) then (class is C2)
3. If (RRP is small) and (RRS / RRP is average) and (QRS is small) then (class C3)
4. If (RRP is small) and (RRS / RRP is average) and (QRS is great) then (class is C4)
5. If (RRP is small) and (RRS / RRP is high) and (QRS is small) then (class is C5)
6. If (RRP is small) and (RRS / RRP is high) and (QRS is great) then (class is C6)
7. If (RRP is average) and (RRS / RRP is small) and (QRS is small) then (class is C7)
8. If (RRP is average) and (RRS / RRP is small) and (QRS is great) then (class is C8)
9. If (RRP is average) and (RRS / RRP is average) and (QRS is small) then (class is C9)
10. If (RRP is average) and (RRS / RRP is average) and (QRS is great) then (class is C10)
11. If (RRP is average) and (RRS / RRP is high) and (QRS is small) then (class is C11)
12. If (RRP is average) and (RRS / RRP is high) and (QRS is great) then (class is C12)

To clarify our work, we take for example the 260th beat of recording 100

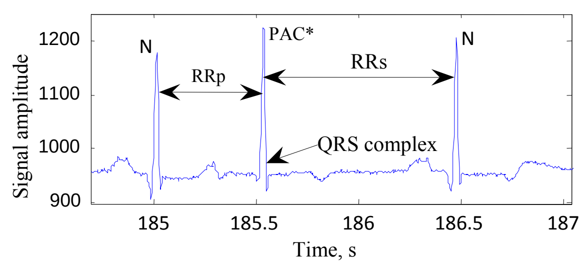

Fig.8 The 260 cycle of record 100, « PAC* »

Characterizing beat
RRp = 0.53 sec
RRs/RRp = 1.61
QRS = 0.053 sec

RRp: 48.18 % small
23.52 % average

RRs/RRp : 0 % small
0 % average
100 % great

QRS: 50.34 % small
0 % great

The real output is 1.99 ≈ 2 (Class PAC).

The rules that contribute to this output are shown in the figure below:

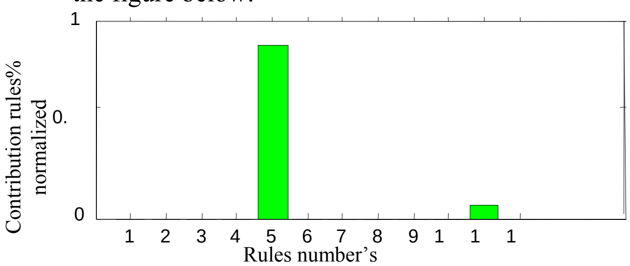

Fig.9. Contribution des règles

Rule 11 : active 5.83 %

11. If (RRp is average) and (RRs / RRp is great) and (QRS is small) then (class is C11)

Rule 5 : active **94.17 %**

5. If (RRp is small) and (RRs / RRp is great) and (QRS is small) then (class is C5)

With

C5 = 1.87

C11 = 0.12

The actual output is the sum of two outputs active:

S = C11+ C5 = 1.997 ≈ 2 (class PAC)

The rule "5" has more weight in the final decision, and it is very close to the reasoning of the human expert (cardiologist). For any beat, we find the most activated rules, which contribute and justify the final decision taken by the neuro-fuzzy classifier NFCL.

5. CONCLUSION

This work presents a knowledge extraction and classification of cardiac arrhythmias (PVC, PAC) using a hybrid approach called neuro-fuzzy that combines neural networks with fuzzy logic.

This approach has given very good results with an average correct classification rate of 95.91%, in addition to the justification of decisions taken in the NFCL classifier using its rule base (12 rules). These rules are very consistent and closer to the cardiologist reasoning.

These obtained results are very promising and encourage us to extend this study to other types of cardiac arrhythmias. Such neuro-fuzzy classifier can be easily hardware implemented (real time response) and used in intensive care units.

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