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ECG arrhythmia Detection using a Linguistic Hedges based Neuro-Fuzzy Classifier

O. Arellano Cardenas[1], L. M. Flores Nava[1], F. Gomez Castañeda[2], J. A. Moreno Cadenas[2]

Research Assistant, Dept. of EE, CINVESTAV-IPN, Mexico City, Mexico[1]

Professor [VLSI], Dept. of EE, CINVESTAV-IPN, Mexico City, Mexico [2]

ABSTRACT: The process of determining the disease or condition by seeing the patient's symptoms and signs is called Medical Diagnosis. The methods or procedures used to diagnose a particular disease are known as Diagnostic Methods. The heart produces electrical signals whose performance can be assessed in the Electrocardiogram (ECG) signal for identifying heart problems. This work proposes a method for classification of cardiac arrhythmias by using an adaptive neuro-fuzzy classifier based on linguistic hedges (LHs) as a tool to aid the physician to diagnose the patient condition more efficiently. First a QRS complex detection algorithm is used.From each QRS complex, two linear prediction coefficients (LPC) are extracted, which, together with the mean square value, generate a data set that can be utilized to train the classifier.The ECG signals to generate the data set are from the MIT-BIH arrhythmia database, which present annotated ventricular ectopic beats. In this paper the method has been focused on classifying premature ventricular contraction (PVC) and normal beats, but indeed the proposed procedure can be extended for detecting other cardiopathies.

KEYWORDS: Neuro-Fuzzy Classifier, ECG Diagnosis, Arrhythmia Detection, Linguistic Hedges.

I.INTRODUCTION

When talking about electrocardiography, pattern recognition has promissory potential for the diagnosis of heart conditions. ECG recognition of reference points and the calculation of parameters is a tedious routine for the physician; every day thousands of cardiac cycles are recorded per patient with Holter device [1]. The specialist must interpret this large amount of ECG data to look for only a few abnormal cardiac cycles. Since it would be extremely time demanding to peruse through such a long record, there is an integrated automatic analysis process in the software of each Holter device which commonly provides the physician with information about heart beat morphology, beat interval measurement, heart rate variability, rhythm overview and patient diary (moments when the patient feels an unusual symptom and presses the patient button). Advanced systems also perform spectral analysis, ischemic burden evaluation, graph of patient's activity or PQ segment analysis, but they are unable of interpreting ECG signals and some abnormal cycles can be overlooked. This can be prevented by comparing the physician's interpretation with the interpretation of an automatic ECG interpretation system. A number of systems has been developed [2][3][4] capable of determine the presence of heart diseases using a set of extracted parameters or other strategies.

The main disadvantage of those methods is the lack of interpretability of the resulting system and the fact that it is not possible to incorporate previous knowledge during the training stage. In this sense, fuzzy and neuro-fuzzy systems are more appropriated for dealing with these issues. Fuzzy systems need the knowledge of an expert for establishing the fuzzy rules and fine tuning all the parameters; neuro-fuzzy systems can learn and optimize their parameters by means of a training set, so they can achieve an optimal performance even if there is not previous knowledge; additionally, if such knowledge is available, it can be taken as start point to facilitate and reduce the time consumed by the training phase. There are sundry neuro-fuzzy architectures used for classification problems; a system that is extensively used for this matter is ANFIS (Adaptive-Network-Based Fuzzy Inference System) [5]. ANFIS has been used as classifier for several health conditions [6], [7], [8] with very good results.

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The difficulty that arises when using ANFIS as a classifier is due that, in fact, it is a Function Approximator with one unique output, and in order to use it for other applications (e.g. prediction, classification, control, etc.) requires certain subterfuges [9]. In [10], they have to use five ANFIS systems, four of them trained with the back propagation gradient descent method in combination with the least squares method. In reference [11] it is proposed a Multiple Instance ANFIS for realizing the described applications. In [12] it is used the same 5-ANFIS technique as in [10]. In reference [13] the method employed is based on Independent Component Analysis (ICA), Power Spectrum and ANFIS; finally, in [14], the structure developed consists of six binary ANFIS classifiers.

In this work it is proposed the use of a neuro-fuzzy system specifically conceived as classifier, for detecting arrhythmias in ECG signals; the system is an Adaptive Neuro-Fuzzy Classifier (ANFC) that uses Linguistic Hedges (LHs) [15]. This ANFC was tested for identifying premature ventricular contractions (PVC), which are extra, abnormal heartbeats that begin in the ventricles, or lower pumping chambers, and disrupt the regular heart rhythm. In people with healthy hearts, occasional PVCs are harmless and usually resolve on their own without treatment. In patients with heart problems such as heart failure or heart disease, however, PVCs may be a sign of a more dangerous heart rhythm to come.

II. SYSTEM ARCHITECTURE

ANFC is based on Linguistic Hedges which are special modifiers of other linguistic terms. An LH is any operation that changes the meaning of any linguistic term, for example "very", "some", "more or less", "quite". Let A be a continuous linguistic term for input variable x with membership function (MF) $\mu_A(x)$. Then A^S is assumed to be the modified version of the original linguistic term, denoted as:

$$A^S := \{(x, (\mu_A(x))^p) | x \in X\}$$

where p denotes the linguistic hedge value of the linguistic term A. The most common modifier operations are *concentration* and *dilation* [9], defined respectively as follows:

$$\mathrm{CON}(A) := A^2 \text{ and } \mathrm{DIL}(A) := A^{0.5}$$

Usually, CON(A) is the result of applying hedge "very" to the linguistic term A while DIL(A) corresponds to hedge "more or less". Some LH defined in literature are "very very" (p=4), "quite" (p=1.25), "a little less" (p=0.75). In Fig. 1 is shown linguistic term A (gaussian function) modified by LHs corresponding to p=2 and p=0.5.

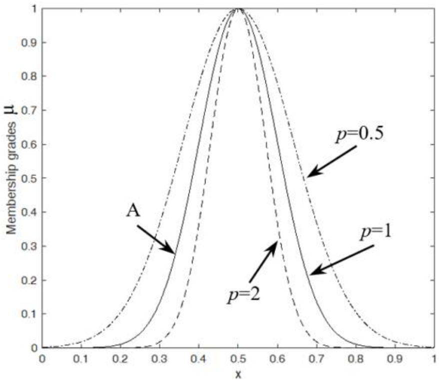

Fig. 1. Representation of modified linguistic terms of set A for different p values.

An ordinary fuzzy rule with two inputs $\{x_1, x_2\}$ and one output y has the form: If x_1 is A_1 AND x_2 is A_2 THEN y is B. If the fuzzy rule is modified with LHs, it takes the following form: If x_1 is A_1 with p_1 hedge AND x_2 is A_2 with p_2 hedge THEN y is B.

The ANFC with LHs is based on fuzzy rules. In this case, a fuzzy classification rule with two inputs $\{x_1, x_2\}$ and one output y is described as: If x_1 is A_1 with p_1 hedge AND x_2 is A_2 with p_2 hedge THEN y is C_1 class, where A_1 and A_2

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denote linguistic terms defined on X_1 and X_2 feature space; p_1 and p_2 designate linguistic hedges; C_1 represents the class label of output y.

Fig. 2 shows a 2-inputs $\{x_1, x_2\}$ ANFC-LH architecture with feature space partitioned into three classes $\{C_1, C_2, C_3\}$. It is based on a zero-order Sugeno fuzzy model whose crisp outputs are determined by weighted average operator [9].

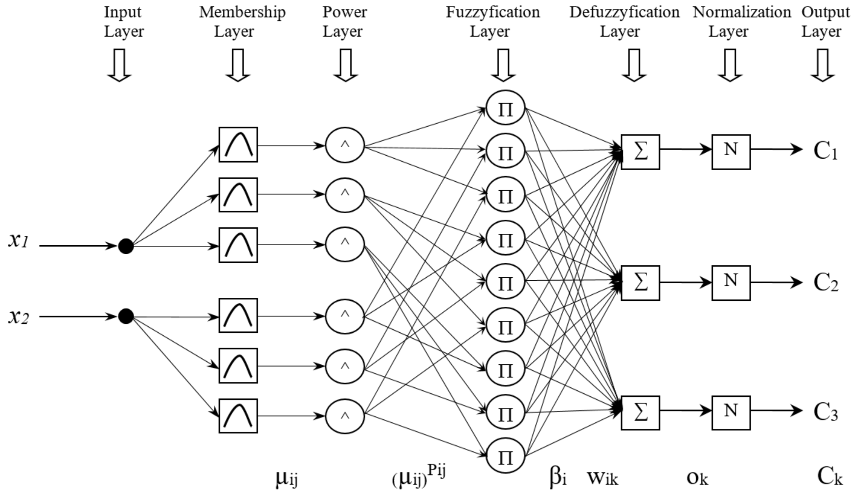

Fig. 2. Architecture of Adaptive Neuro-Fuzzy Classifier with LHs.

In this architecture, nodes in the same layer have the same type of node function. The layers are described below.

Input Layer. Indicates the input variables.

Layer 1 (Membership). Every node in this layer is defined by a membership function (MF). Gaussian function is employed due to smooth partial derivatives of its parameters, and has few parameters. Gaussian MF is given as:

$$\mu_{ij}(x_{sj}) = exp\left(-0.5\frac{(x_{sj} - c_{ij})^2}{\sigma_{ij}^2}\right),$$

where $\mu_{ij}(x_{sj})$ represents the membership grade of the *ith* rule and the *jth* feature; x_{sj} denotes the *sth* sample and the *jth* feature of input matrix $\mathbf{X}\{\mathbf{X}\epsilon\Re^{N\times D}\}$; c_{ij} and σ_{ij} are the center and the width of Gaussian function, respectively. This layer effects the fuzzyfication of input variables.

Layer 2 (Power). Each node in this layer calculates the modified fuzzy sets according to their respective LHs, defined as: $\alpha_{ijs} = [\mu_{ij}(x_{sj})]^{Pij}$, where α_{ijs} denotes the modified membership grades of $\mu_{ij}(x_{sj})$; p_{ij} denotes the LH value of the *i*th rule and the *j*th feature.

Layer 3 (Fuzzyfication). In this layer the *firing strength* (β_{is}) of each rule is calculated. It represents the degree of fulfillment of the fuzzy rule for x_s sample. The firing strength is defined as:

$$\beta_{is} = \prod_{j=1}^{D} \alpha_{ijs},$$

where *D* represents the number of features.

Layer 4 (Defuzzyfication). Here every rule can affect each class according to their weights and weighted outputs are calculated. If a rule dominates a specific class region, the weight between this rule output and the specific class will be superior to the other class weights. Else, the class weights are firmly small. The outputs of this layer are calculated as:

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$$O_{sk} = \sum_{i=1}^{U} \beta_{is} w_{ik},$$

where w_{ik} represents the degree of belonging to the kth class controlled by the ith rule; O_{sk} denotes the weighted output for the sth sample that belongs to the kth class; U is the number of rules.

Layer 5 (Normalization). The outputs of the network are normalized to prevent the case that the sum of weights be larger than 1.

$$h_{sk} = \frac{O_{sk}}{\sum_{l=1}^{K} O_{sl}} = \frac{O_{sk}}{\delta_s}, \qquad \delta_s = \sum_{l=1}^{K} O_{sl},$$

where h_{sk} represents the normalized degree of the sth sample that belongs to the kth class; K is the number of classes. The maximum h_{sk} value determines the class label of the sth sample as:

$$C_s = \max_{k=1,2,\ldots,K}\{h_{sk}\},$$

where C_s is the class label.

Output Layer. This layer indicates the corresponding labels of each class for the respective normalized output.

The antecedent parameters of the network {c, σ, p} are adapted by scaled conjugate gradient (SCG) method. The SCG is a second-order supervised training and derivative-based method. It determines the second-order derivatives of parameters from their first-order derivatives. This calculation method is decreased by the number of operation in each iteration. The SCG has a super linear convergence rate, which is two times faster than that of the back-propagation. Parameter w_{ik} is determined from the ratio of the number of *kth* class samples in the *ith* fuzzy rule region respect to the total number of *kth* class samples [15].

III. METHODS AND MATERIALS

ECG signals that present PVC beats were taken from the MIT-BIH arrhythmia database [16]. All the implementations were carried out in Matlab, and in order to use ANFC for arrhythmia classification, a QRS complex detection algorithm based on [17]**Error! Reference source not found.** was used.

Linear prediction models each successive sample of a signal as a linear combination of previous samples. This process is given by the following relationship: $x(k) = -a(2)x(k-1) - a(3)x(k-2) - \ldots - a(n+1)x(k-n-1)$, where x is the time series of the real input and n is the order of the polynomial denominator a(z), that is, a = [1, a (2), ..., a (n + 1)]. The Mean Square value (MS) is defined by $\overline{x^2} = E[x^2]$, where E is the expectation operator, and x are the values of the samples in each segment.

Subsequently, for each QRS segment, two linear prediction coefficients (LPC) (a_1 and a_2) as well as MS value were calculated, in order to produce the set of data to train and test the ANFC system. The method to obtain LPC coefficients is described in [18]. Fig. 3 shows the plots of coefficients a_2 vs a_1 and MS vs a_1 for normal and PVC beats.

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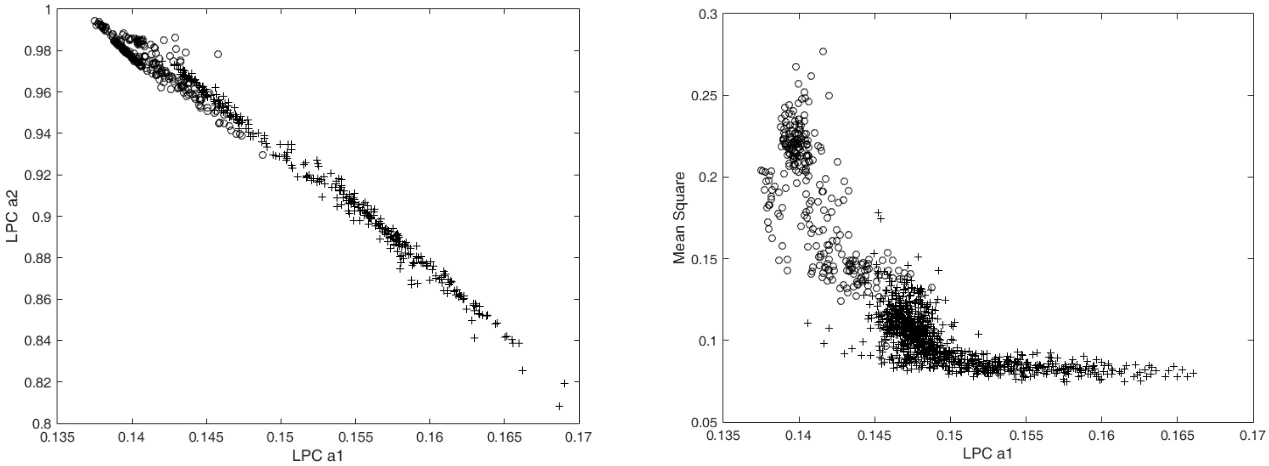

Fig. 3. a_2 vs a_1 and MS vs a_1 (+ = Normal; o = PVC)

The total training set created includes 3520 beats from several patients that present PVC condition; from that, 2040 are normal, and the rest are PVC. From the set, half of beats were taken to train the system, and the other half to test it.

IV. RESULTS AND EVALUATION

In ANFC-LH architecture the values of LHs can be a measure of the importance degree of fuzzy sets [19]. For classification problems where every class is defined by a fuzzy rule, LHs indicate the importance degree of input features. When LHs values vary by concentration operation, these features become more significant, and should be selected; if the LHs values vary by dilation operation, these features are little significant, and can be eliminated. The LH-based FS algorithm proposed in [19] was the used in this work. The system started with a 3-input, 2-output architecture with 2 fuzzy sets per input; after training, and considering the importance of input features, the resulting architecture was a 2-input, 2-output system with 4 fuzzy sets per input.

For evaluating the system performance, two scenarios were proved: 1) Classification taking the training data as input (1020 normal and 740 PVC; 2) Classification using the rest of vectors, corresponding to test data (1020 normal and 740 PVC). The measurements of the two scenarios are summarized in Table 1, where the results obtained for each type of beat (normal or PVC) are shown. The first column shows the two cases and the beats considered for each type. The second column indicates the number of normal beats detected correctly (ND), and normal beats that were classified as PVC (false positives - NV). The third column represents the number of PVC beats correctly identified (VD) and PVC identified as normal (false negatives - VN).

Scenario	Normal ND / NV	PVC VD / VN
1) Training vectors (N=1020, V=740)	1013 / 7	732 / 8
2) Test vectors (N=1020, V=740)	1011 / 9	729 / 11

Table 1. Results of classification (N- Normal, V-PVC, ND-Normal detected, VD-PVC detected, NV-False positive, VN-False negative.

In order to evaluate the results of table 1, the global error of the system, as well as some other characteristics that quantify its performance for this particular problem, are calculated. Considering the same literals defined in table 1, the expressions are the following:

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Accuracy (%):

$$Acc = \frac{ND + VD}{N + V} \times 100$$

Sensitivity (%):

$$Sn = \frac{VD}{VD + VN} \times 100$$

Specificity (%):

$$Sp = \frac{ND}{ND + NV} \times 100$$

With the results of table 1, and using the previous expressions, is elaborated table 2, where evaluations for each scenario are presented.

Test Case	Acc	Sn	Sp
Scenario 1	99.15	98.92	99.31
Scenario 2	98.86	98.51	99.12

Table 2. Assessment of the system performance for ECG classification.

V. CONCLUSIONS

Traditional methods to do classification of arrhythmias are performed by means of statistical methodologies, using purely neural or fuzzy methods. ANFIS is a neuro-fuzzy system that has been widely used for classification tasks, including ECG arrhythmias, however ANFIS architecture was conceived to perform function approximation so, in order to realize classification, it needs some artifices that can make its implementation more complex. On the other hand, the proposed ANFC-LH architecture in fact was developed as a classifier, and the use of linguistic hedges allows to improve the meaning of the classical fuzzy rules and simplifies the distinguishability of overlapping classes. In some cases, the adaptive linguistic hedges can increase the classification accuracy rates.

The ECG arrhythmia classification problem presented in this work shows that ANFC-LH system has a remarkable throughput and it can be a good option for this kind of applications. Here, two types of ECG beats (normal sinus rhythm and premature ventricular contraction) were classified and collected from MIT-BIH data base and these sample signals were extracted by using linear prediction coefficients and the mean square value, but ANFC-LH system can be applied for problems with more classes and using other extracting techniques. Finally, the system was implemented in Matlab, but for a more versatile universe of uses, in a future work it would be built a hardware version in FPGAs.

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