2019 16th International Conference on Electrical Engineering, Computing Science and Automatic Control (CCE) Mexico City, Mexico.
September 11-13, 2019

ECG Arrhythmia Classification based on Fuzzy Cognitive Maps

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Abstract— **Medical Diagnosis is the process of determining the disease or condition of a patient by seeing his symptoms. Diagnostic Methods are the procedures used to diagnose a particular disease usually following the report of symptoms, or based on other medical test results. Electrical signals produced by the heart can be assessed in the Electrocardiogram (ECG) signal for identifying heart problems and carry out a diagnosis. In this work, we propose a method for classifying cardiac arrhythmias by using a Fuzzy Cognitive Maps (FCMs) approach as a tool to assist the physician to diagnose more efficiently the patient condition. First, a QRS complex detection algorithm is used. From each QRS complex, two linear prediction coefficients (LPC) are calculated as well as the mean square value, which altogether generate the data set utilized for training the FCM classifier. The ECG signals used to generate the training data set were obtained from the MIT-BIH arrhythmia database. 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 as well.**

Keywords— Fuzzy Cognitive Maps, Neuro-Fuzzy Classifier, ECG Diagnosis, Arrhythmia Detection.

I. Introduction

Pattern recognition has promissory potential for the diagnosis of heart conditions based on electrocardiography interpretation. For the physician ECG recognition of reference points and the calculation of parameters is a tedious routine; every day a Holter device can record thousands of cardiac cycles per patient [1]. The specialist has to interpret this large amount of ECG data to look for only few abnormal cycles. The task of perusing through such a lengthy record would be extremely time consuming, therefore Holter devices normally include software to perform an automatic analysis process to inform the physician about heart beat morphology, beat period, heart rate irregularity, rhythm summary and a special register button (used when the patient feels an unusual symptom and presses the patient button to mark it). Systems more sophisticated also can perform other advanced processes, but they are unable to interpret ECG signals and abnormal cycles can be overlooked. This can be prevented by comparing the physician's interpretation with the interpretation of an automatic ECG interpretation system. Several systems have 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 these 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, FCMs are a symbolic representation for the description and modeling of complex systems [5]. FCMs consist of nodes called concepts that represent diverse features in the conduct of the system, and the interaction among these nodes shows its dynamics. FCMs use graphs to shape the system, displaying the cause and effect between concepts, and it is a symbolic way for describing its behavior in a simple way. The development of FCMs can integrate human knowledge and experience collected from their operation of complex systems through the years.

There are diverse neuro-fuzzy architectures used for classification problems; a system that is broadly used for this matter is ANFIS (Adaptive-Network-Based Fuzzy Inference System) [6]. ANFIS has been used as classifier for several health conditions [7], [8], [9] with very good results. The difficulty that arises when using ANFIS as 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 [10]. In [11], 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 [12] it is proposed a Multiple Instance ANFIS for realizing the described applications. In [13] it is used the same 5-ANFIS technique as in [11]. In [14] the method employed is based on Independent Component Analysis (ICA), Power Spectrum and ANFIS; finally, in [15], the structure developed consists of six binary ANFIS classifiers.

In this work it is proposed the use of Fuzzy Cognitive Maps for detecting arrhythmias in ECG signals. FCM architecture can be constructed specifically for classification tasks, so it does not need any extra artifice; the system is built and trained with the aid of FCM-Expert software [16]. The cardiopathy to be detected is premature ventricular contraction (PVC). PVCs are extra, atypical heartbeats originated in the ventricles, and disturb the normal heart pulse. For people with hearts in good physical shape, sporadic PVCs are innocuous and generally resolve without any treatment. However, the presence of PVCs may be a warning for more risky heart disorders to come if the patient has heart problems antecedents.

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II. FCM ARCHITECTURE

FCMs consist of concept nodes and signed weighted arcs connecting them. These arcs symbolize the causal correlation existing among concepts. This graphical representation displays accurately how each concept influence other concepts and their influence degree. If there exist previous knowledge about the system dynamics, it can be embedded in the structure of concepts and weighted arcs of the map.

Fig. 1 shows an FCM consisting of five (5) concepts and eleven (11) weighted arcs. Nodes C1 to C5 represent concept variables. A number A_i characterizes each concept, which defines a fuzzyfied value of the real value of the system's variable, standing in the interval [0, 1]. Weights of the arcs have three possible values: a) positive causality ($W_{ij} > 0$), b) negative causality ($W_{ij} < 0$), and c) no correlation ($W_{ij} = 0$). The value of W_{ij} specifies how strongly concept C_i affects concept C_j, and its sign specifies if relationship is direct or inverse. The direction of the arc states if concept C_i causes concept C_j, or vice versa. Thus, causality between concepts can range in the interval [-1,1]. In general, the numbers A_i for each concept represent the outputs of the FCM; however, for a classification architecture, there are concepts specifically appointed to be outputs.

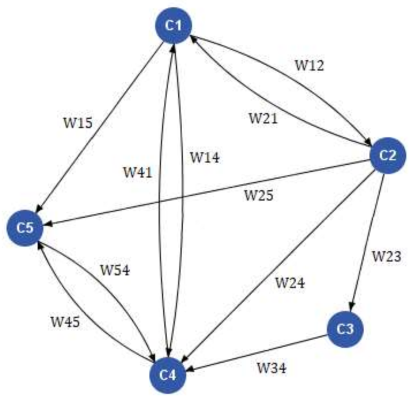

Fig. 1. Simple representation of an FCM

The aim of learning an FCM is to generate a weight matrix capable of making good approximations and offer consistent outcomes according with the outlines and problem restrains. There exist three principal methods to train an FCM: adaptive techniques (generally based on the Hebbian law), population-based techniques and hybrid approaches, that include both methods [17].

Equation (1) formalizes Kosko's activation rule, with $A^{(0)}$ as the initial state. A new activation vector is calculated at each step t, and after a defined number of iterations, the FCM will arrive at one of three situations: a) equilibrium point, b) limited cycle or c) chaotic behavior. Convergence of the FCM is reached if it achieves a fixed-point attractor, otherwise if a determined number of iterations T is hit, the updating process concludes.

$$A_i^{(t+1)} = f\left(\sum_{\substack{j=1 \\ i\neq j}}^{M} w_{ji} A_j^{(t)}\right) \quad (1)$$

Where $f(\text{-})$ denotes a monotonically non-decreasing function that limits the activation value of each concept to the allowed interval, typical functions used are bivalent, saturation, trivalent, sigmoid and hyperbolic functions. M is the total number of concept nodes. A_i is the new value of the state calculated from the current state A_j.

An FCM model construction consists of three main stages: a) election of quantity and class of model concepts, b) designation of relationships amid concepts and their interaction, as well as the starting model weight, and c) training weight with learning algorithms. The first two steps can embed the previous knowledge if there is some expert to define the model.

FCM-Expert is a software tool that supports implementation and training of FCMs. It surpasses currently existing software developed for this topic in many aspects [18], and this is the main reason to use it in our research. One advantage of using FCM-Expert software is that it is possible modeling an FCM from scratch without any previous knowledge. If there is available a data set, FCM-Expert can build a generic structure from the parameters and targets defined in the data (supervised pattern classification problem). The number of parameters defines the number of concepts, and the number of targets states the quantity of outputs (classes). Initially it can be defined a 100% connected net and apply one of several optimization processes. The learning process generates a weight matrix that minimizes the dissimilarity between the expected outputs and the predicted ones, as well as a custom transfer function for each concept, hoping to increase the overall prediction rates.

III. METHODS AND MATERIALS

ECG signals that present PVC beats were obtained from the MIT-BIH arrhythmia database [19]. Fig. 2 shows the aspect of an ECG signal of this database. QRS complexes are well defined in ECG literature and are the part of the signal that serves to our approach. The processing of ECG signals was carried out in Matlab, it involves a QRS complex detection algorithm based on [20], the calculus of two linear prediction coefficients (LPC) (a_1 and a_2) and the mean square value (MS) for each complex in order to produce the set of data to train and test the FCM system. The method to obtain LPC coefficients is described in [21].

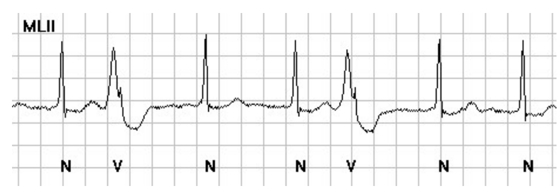

Fig. 2. Example of ECG signal showing PVC beats

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) – ... – 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)], so a(2) is the first coefficient (a1), a(3) the second (a2), etc. The Mean Square value (MS, called MED in the architecture implementation) 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.

Fig. 3 shows the plot of coefficients a_1, a_2 and MS for normal and PVC beats. The total training set created includes 3520 beats from several patients that present PVC condition; from that, 3040 are normal, and 480 are PVC. Half of the data were taken to train the system, and the rest to test it.

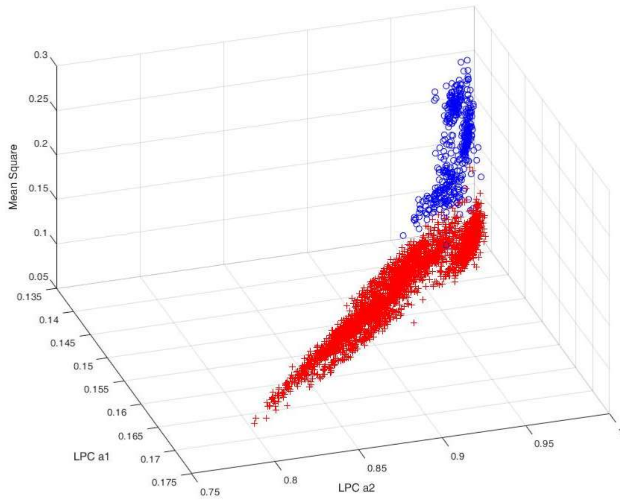

Fig. 3. MS vs a_1 vs a_2 (+ = Normal; o = PVC)

IV. IMPLEMENTATION AND EVALUATION

The format of the data set contains three input parameters for each QRS complex (denoted as a_1, a_2 and MED) and two target outputs (LN and LP) for normal and PVC beats respectively. With this data set, FCM-Expert can generate the FCM architecture to build the classifier, and it consist of three generic input concepts and two decision concepts, as shown in Fig. 4. Initially, due to the lack of previous knowledge, causal connections among concepts are randomly generated with a 100% connection schema and initial relationship of 0.5 among them. The elected learning approach in FCM-Expert is supervised learning with *Global-best Particle Swarm Optimization* and for the learning goal *Optimize the weights, slope and offsets*. For General and Custom settings, the default values performed well.

After 10,000 training epochs, we got the weight values shown in Fig. 4 and the summary reported in Fig. 5. It can be noted that the weight from concept MED to A1 seems quite small, so it could be removed, however when doing so, there is a light improvement detecting normal beats (1507 instead of 1505), but PVC beats detection has also a slight decay (232 instead of 234). Therefore, the overall performance remains similar, but as the main objective is PVC beats detection, we chose to let that weight untouched.

For evaluating the system performance, two scenarios were proved: 1) Classification taking the training data as input (1520 normal and 240 PVC; 2) Classification using the rest of vectors, corresponding to test data (1520 normal and 240 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).

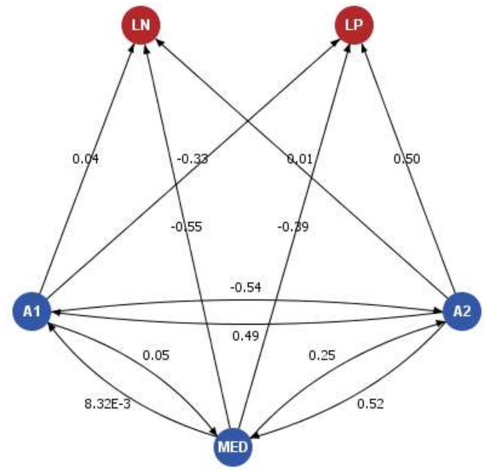

Fig. 4. Trained FCM for ECG classification

Performance summary

Correctly Classified Instances	1739	98.81%
Incorrectly Classified Instances	21	1.19%
Total Number of Instances	1760	
Cohen's Kappa Coefficient		0.95

=== Detailed Accuracy By Class ===

TP Rate	FP Rate	Precision	Recall	F-Measure	MCC	Class
0.99	0.03	1.0	0.99	0.99	0.95	LN
0.97	0.01	0.94	0.97	0.96	0.95	LP

=== Confusion Matrix ===

	LN	LP
LN |	1505	15
LP |	6	234

Fig. 5. Summary after training process in FCM-Expert

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

Scenario	Normal ND / NV	PVC VD / VN
1) Training vectors (N=1520, V=240)	1505 / 15	234 / 6
2) Test vectors (N=1520, V=240)	1491 / 29	229 / 11

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:

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.

TABLE 2. System performance of FCM-based ECG classifier.

Test Case	Acc	Sn	Sp
Scenario 1	98.81	97.5	99.01
Scenario 2	97.73	95.42	98.10

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 originally 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 FCM architecture in fact is developed as a classifier, and the use of FCM-Expert software simplifies its implementation and training by counting solely with a data set. Additionally, it is not necessary any previous knowledge.

The ECG arrhythmia classification problem presented in this work shows that the system based on FCM 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 database and the parameters set was generated by using linear prediction coefficients and the mean square value, but this FCM methodology can be applied for problems with more classes and using other extracting techniques. Finally, the system was implemented in software, 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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