Automatic Fuzzy rules-base generation using Modified Particle Swarm Optimization

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***Abstract*—Interpretability represents the most important driving force behind the implementation of fuzzy-based classifiers for medical application problems. The expert should be able to understand the classifier and to evaluate its results. The use of Particle Swarm Optimization (PSO) is a new attempt to effectively explore the large search space. It is usually associated with fuzzy classification system in order to find the optimal set of rules. This paper presents a Modified PSO as a new tool to build and obtain an optimal fuzzy rule-base, named Mutation PSO (MPSO). Experiments are performed on two well-known medical database breast cancer and diabetes available in UCI machine learning repository. The obtained classification accuracies of our proposed system for breast cancer and diabetes are respectively 98.26% and 82.17% using 10-folds Cross Validation method. The results indicate that the proposed method generated a compact fuzzy rule based and can work efficiently for medical diagnosis problems**

Keywords-Particle swarm optimization; interpretable classification; fuzzy rules; UCI Machine Learning Database.

I. INTRODUCTION

Machine learning algorithms have been applied to the medical diagnosis process with all success. Even if the decision of the expert is the most significant factor during the medical diagnostic, intelligent techniques provide an important and substantial help because they reduce the errors due to expert tiredness and to the time needed for the medical diagnostic. Early diagnostic requires an accurate and reliable detection procedure in order to allow the physicians to distinguish the patient who is affected by the disease in reality and the patient who is not having the disease in reality. Therefore, with regard to the importance of this problem (life application) and to ensure making fast, accurate and meaningful decision, classification systems could be used. This paper specifically focuses on the use of fuzzy modeling method to detect medical problems because of their advantage in discovering human comprehensible knowledge.

Fuzzy Rule Base Classification System (FRBCS) is known for their transparency and ability of accounting for uncertainty. An FRBCS presents two main components: the inference system and the Knowledge Base (KB). The KB is composed of the Rule Base (RB) constituted by the collection of fuzzy rules, and of the data base, containing the membership function of the fuzzy partitions associated to the linguistic variables. The composition of the KB of an FRBCS directly depends on the problem being solved. Traditionally, fuzzy rules are generated from human expert knowledge, which brings about good high-level semantic generalization capability. If there is no expert information about the problem under solving, an automatic learning process must be used to build the KB from experimental data. Many methods have been proposed to construct the rule base from numerical data. These include heuristic approaches [1], genetic algorithms [2, 3, 4, 5, 6] and data mining techniques [7] etc. More recently a hybrid learning algorithm is proposed to utilize Particle Swarm Optimization (PSO) for classification task. In [8] Sousa and al. proposes a first application of PSO as a new tool for data mining, they used PSO for classification rule discovery. From their results, PSO proved to be a suitable candidate for classification tasks. Holden and Freitas [9] used a hybrid Particle Swarm Optimization /Ant Colony Optimization (PSO/ACO) algorithm for discovering classification rules in data mining. In [10] the same authors extended and improved a first version by new algorithm called PSO/ACO2. Rani and Deepa [11] proposed a particle swarm optimization approach for optimal design of fuzzy classifier and named it PSOFLC. Experiments are conducted on IRIS dataset, where the proposed technique is compared to two popular classification techniques, including Genetic Fuzzy Classifier and Gaussian Fuzzy Classifier.

In our work, some modifications to standard Particle swarm optimization are introduced. The modified PSO differs from the original version in two ways; firstly we have changed the random initialization by the opposition based initialization method and secondly we have blended the PSO with mutation operator of Genetic algorithm, in order to improve the diversity of PSO, without compromising with the solution quality. Furthermore, the MPSO is responsible for rules base discovering, and then the fuzzy classifier system focuses on identifying the different diseases patterns promptly and accurately. The results of this paper show that the proposed technique outperforms others methods and produce a compact fuzzy rules base and can work effectively for medical diagnosis problems.

The paper is structured as follows: Section 2 introduces the used methods: Fuzzy Logic principles and Particle Swarm

Optimization. In section 3 the MPSO Fuzzy classifier learning is described. The results are presented and discussed in Section 4, and in Section 5, we conclude the paper.

II. THEORY

A. Fuzzy Classifier Architecture

During the last two decades, FUZZY LOGIC [12] has been a dominant topic in intelligent systems research. Which have been successfully applied in many fields and can solve different kinds of problems in various application domains such as modeling, control and classification. The classification problem can be easily solved with interpretable “if-then” rules and membership function. In this study the fuzzy “if-then” rules can be expressed as follows:

$$R_j : if\ x_{p1}\ is\ A_{j1}\ and\ x_{p2}\ is\ A_{j2}\ and \ldots and\ x_{pn}\ is A_{jn}$$
$$THEN\ x_p\left(x_{p1}, \ldots, x_{pn}\right) belongs\ to\ class\ C$$
$$j = 1, \ldots, N \quad \textbf{(1)}$$

Here $x_p(x_{p1},\ldots,x_{pn})(p=1,2,\ldots,m)$ is the input vector, R_j is the label of the j^{th} fuzzy “if-then” rule $A_{j1},\ldots,A_{jn}$ are fuzzy sets defined in the antecedent space by membership functions $\mu_{Aji}(x_i)$, the degree of membership in a set is expressed by a number between 0 and 1. $\mu_A(x) = 0$ means not in the set $\mu_A(x) = 1$ means completely in the set, and a number in between means partially in the set. $C \in \{C1, C2 \ldots CM\}$ is the consequent class output of the j^{th} fuzzy rule. This paper uses the trapezoidal membership function as in figure 1 defined by a lower limit ***a***, an upper limit ***d***, a lower supper limit ***b*** and an upper support limit ***c***.

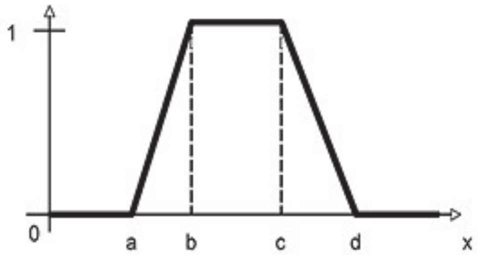

Figure1. Trapezoidal membership function

A winning rule is used to make a decision. Thus, given a rule-base consisting of N rules, an input pattern is classified according to consequent class of the winner rule R_w. With the rules of form (1), the winner rule has the maximum product of the compatibility grade, which is specified as:

$$w = argmax\left\{\mu_j\left(x_p\right) \middle| j = 1, 2, \ldots, N\right\} \quad \textbf{(2)}$$

We note that classification of a pattern not covered by any rules in the rule base is rejected.

B. Particle Swarm Optimization

Particle Swarm Optimization (PSO) is one of the evolutionary computation techniques introduced by Kennedy and Eberhart [13, 14] in 1995. Which used group intelligence generated by cooperation and competition between group particles to guide the optimization search. PSO has been successfully applied in several areas, such as clustering problem [15], image processing [16], function optimization [17] etc. compared with others algorithms like GA, the main advantage of PSO is that it has no evolution operators such as crossover and mutation and moreover, PSO has less parameters to adjust. Similar to the evolutionary algorithms, in PSO a set of solution of the problem be solved is used to probe the search space. The concept of PSO can be described as follows: each potential solution called particle, this particle has a position, an adaptable velocity according to which it moves in the search space and it has a memory to remember the best position of the search space that has ever visited. Thus its movement is an aggregated acceleration towards its best previous position visited and towards the best individual in the swarm [18]. Particles update their velocity and position by Equation (3) and Equation (4) respectively, through tracing two kinds of “best” value. One it is personal best called P_{best} which is the location of its highest fitness value. The other one is the global best value called P_{Gbest}, which is the location of overall best value found so far by all particles. All of the best values are based on fitness function.

$$V_i^{k+1} = \underbrace{\gamma v_i^K}_{1} + \underbrace{c_1 r_1\left(p_{besti}^k - x_i^k\right)}_{2} + \underbrace{c_2 r_2\left(p_{Gbesti}^k - x_i^k\right)}_{3} \quad \textbf{(3)}$$

$$X_i^{k+1} = X_i^k + V_i^{k+1} \quad \textbf{(4)}$$

Here:

V_i^k is the velocity of the particle i in the k^{th} iteration and X_i^k is the corresponding position. C_1 And C_2 are two positive acceleration constants; they keep balance between the particle’s individual and social behavior when they are set to be equal. r_1 And r_2 are two randomly generated numbers with a range of (0, 1) added in the model to introduce stochastic nature to the particles’ movement. P_{besti} is the best position particle i achieved based on its own experience in the k^{th} iteration. P_{Gbesti} is the best particle position based on overall swarm’s experience in the k^{th} iteration. γ is the inertia weight, which is chosen beforehand to control the balance between the local and global search abilities [19]. The structure of algorithm has been shown in figure2:

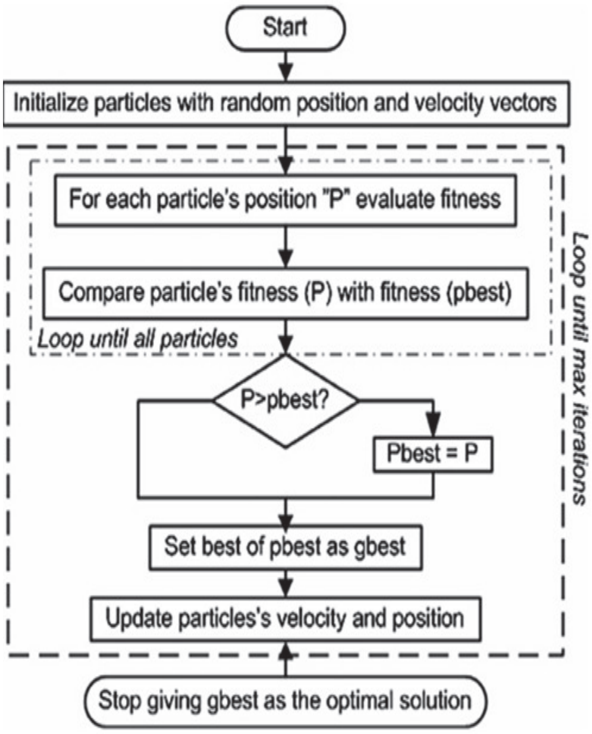

Figure2. PSO Algorithm

III. MPSO FUZZY CLASSIFIER LEARNING

This section is divided into five subsections namely, modified PSO, individual representation, initial population, fitness function and algorithm.

A. Modified PSO:

In basic version of PSO, velocity and position updating are the two major operations to produce a new candidate solution, so if there is no improvement in fitness of an individual, then it is a sign that the converged fitness is not the optimal one. This is because the mechanism of updating solution is limited in providing a variety of solution. To overcome this shortcoming we included a blended crossover (BLX-α) operator of genetic algorithm to induce diversity in the population. This proposed version MPSO differs from other versions in the sense that if there is no improvement in fitness function, the particles are mutated according to the following rules:

1) Choose two positions x_1, x_2 randomly from the population
2) A value of new position Y is generated by equation (5):

$$Y = \begin{cases} a + r*(b-a) & : if\ x_{\min} \le Y \le x_{\max} \\ repeat\ generating & :otherwise \end{cases} \qquad (5)$$

Where:

$$a = x_1 - \alpha\left(x_2 - x_1\right)$$
$$b = x_2 - \alpha\left(x_2 - x_1\right)$$
$$r : random\ number\ in \left[0,1\right]$$

$x_{\min}, x_{\max}$ represent the variable's lower and upper bounds respectively and α is a positive parameter

B. Individual representation:

In this work we used two fuzzy sets (Low (L) and High (H)) for each attribute with trapezoidal membership function. These fuzzy sets are defined by six real-valued P0, P1, P2, P3, P4, and P5. Where P0 and P5 are fixed and represent the minimum and the maximum value of the input variable. The others values are used for the creation of the membership functions and each one of them has their own limits such that P1 has {P0, P5}, P2 has {P0, P1}, P3 has {P1, P5}, and P4 has {P2, P5}. However, each particle represents a Rules Base (RB) and each rule in the RB is characterized by the premise parameters and the labels for the selection of rules, in order to create and obtain an optimal fuzzy rule base classifier. Shown as Fig3, the particle i is represented by a vector which includes the premise parameters $\left[mf_{j1}^{i}, p_{j1}^{i}, mf_{j2}^{i}, p_{j2}^{i}, ..., mf_{jk}^{i}, p_{jk}^{i}, ..., mf_{jn}^{i}, p_{jn}^{i}\right]$ and label l_j, where $p_{jk}^{i} = \left[p_{jk,1}^{i}, p_{jk,2}^{i}, p_{jk,3}^{i}, p_{jk,4}^{i}\right]$ encode four real-valued parameters and mf_{jk}^{i} is assigned a value in the set {1, 2} specifying the type of membership function {Low, high}, respectively. The label l_j is represented by one bit set to 0/1 means that if $l_j=0$, the rule is excluded from the rules base; otherwise, the rule is included. After the antecedents have been created by the particles, we select for each antecedent a suitable consequent by the following procedure [1]:

- Step1: calculate the compatibility of each training pattern $x_p(x_{p1},...,x_{pn})$ for the j^{th} fuzzy rule as:

$$\mu_j\left(x_p\right) = \mu_{j1}\left(x_{p1}\right) * \mu_{j2}\left(x_p 2\right) * .... * \mu_{jn}\left(x_{pn}\right) \quad \mathbf{(6)}$$
$$p = 1, 2, ..., m$$

- Step2: for each class C $(C=1...M)$ calculate the relative sum of the compatibility grades for the j^{th} rule

$$\alpha_{\text{class c}}\left(R_{\text{j}}\right) = \sum_{x_p \in class\ c} \mu_j\left(x_p\right) \mathbf{(7)}$$

- Step3: find class C for the j^{th} rule with the maximum value of $\alpha_{class\ c}$

$$\alpha_{\text{class c}}\left(R_{\text{j}}\right) = argmax\left\{\alpha_{\text{class i}}\left(R_{\text{j}}\right) | i = 1, 2, \ldots, M\right\} \mathbf{(8)}$$

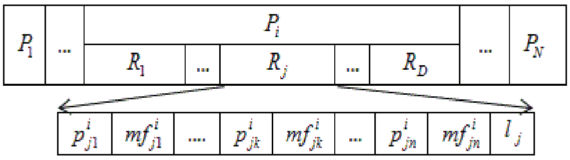

Figure 3: the coding structure of particle

C. *Initial population:*

Population initialization is a crucial task in evolutionary algorithms because it can affect the convergence speed and the quality of the final solution. If no information about the solution is available, then random initialization is the most commonly used method to generate candidate solutions (initial population). In proposed method, we replace the random initialization by the opposition based initialization method [20] in order to guarantee an initial population with certain quality and diversity.

D. *Fitness function:*

The fitness function is the Number of the Patterns Correctly Classified (NPCC) by the fuzzy rule base coded in corresponding particle *Pi:*

$$fitnessfunction(P_i) = NPCC(P_i) \quad \textbf{(9)}$$

As stopping condition we used a maximum number of generations. The new rule base is represented by the best particle with the best fitness value in the last generation.

E. *Realized Algorithm:*

A detail description of proposed algorithm is described by the following steps:

- Step 1: Initialization:

  -Number of particles *L,* number of rules in each particles *K,* number of iterations *G*, and the constants for the PSO (*γ, C1 and C2*), constant for BLX-α Mutation (α).

  -generate initial population of the fuzzy rules using opposition based initialization method

  -generate randomly initial velocity for all particles of the population

- Step 2: calculate the consequent class *C* for each rule by the procedure in section 3.

  - Calculate the fitness value of each particle:

  $fit_i = fit(P_i)$

  - Update P_{besti}, F_{besti}, P_{Gbest} and F_{Gbest}

  If $fit_i > F_{besti}$ then $F_{besti} = fit_i$ and $P_{besti} = P_i$

  If $fit_i > F_{Gbest}$ then $F_{Gbest} = fit_i$ and $P_{Gbest} = P_i$
  Else

  //BLX-α Mutation

  Find a new particle using equation (5)
  Let this particle as *Newp*
  If $fit(NewP) > F_{Gbest}$ then $F_{Gbest} = fit(NewP)$ and $P_{Gbest} = NewP$

  - Set *G=1*

- Step 3:
  - Update particles velocity by:
  $V_i = \gamma V_i + C_1 r_1 (P_{besti} - P_i) + C_2 r_2 (P_{Gbest} - P_i)$
  - Update particles position by: $P_i = P_i + V_i$

- Step 4: *G=G+1.*

  -If G> number of iterations then go to Step 5 else go to Step 2.

- Step 5: -The optimal set of fuzzy rules is desired by the best particle P_{Gbest} with the best fitness F_{Gbest}.

IV. EXPRIMENTAL RESULTS

A. *Used medical dataset:*

In this work, two classification problems are used to evaluate the performance of proposed method. The selected problems are Cancer and Diabetes.

The breast cancer data set that we have used is provided from the UCI (University of California Irvine) repository of machine learning [21]. This database can be used to predict the severity of breast cancer. The data base originally contained 699 cases and 10 attributes, but 16 of these contained missing class values, they so were discarded leaving 683. The dataset used consists of 2 classes where 444 cases were benign and 239 cases were malignant. The 10 attributes are:

1. Clump Thickness
2. Uniformity of Cell Size
3. Uniformity of Cell Shape
4. Marginal Adhesion
5. Single Epithelial Cell Size
6. Bare Nuclei
7. Bland Chromatin
8. Normal Nucleoli
9. Mitoses
10. Class: benign, malignant

The second database is Pima Indians Diabetes database [22].This database contains 768 patterns with 8 features that belong to two classes (Not Diabetic, Diabetic). The 8 features are the:

1. NPreg : Number of times pregnant
2. Glu: Plasma glucose concentration a 2 hours in an oral glucose tolerance test (mg/dl)
3. BP: Diastolic blood pressure (mm Hg)
4. Skin: Triceps skin fold thickness (mm)
5. Insulin: 2-Hour serum insulin (mu U/ml)
6. BMI: Body mass index (kg/m2)
7. PED: Diabetes pedigree function
8. Age

There are 500 patterns from patients who are not diabetic and 268 patterns from patients who are known to have diabetes, but here are some zero values of features that were not reasonable for humans' physical situation. After eliminating these patterns with illogical physical data the total number of patterns is 392 where 262 are normal cases and 130 are diabetes cases

B. Results and discussion:

The aim of this section is to demonstrate the effectiveness of the proposed method 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 diagnosis of breast cancer and diabetes.The specific parameters setting for the MPSO of proposed algorithm is listed in table 1

TABLE I. PARAMETER SPECIFICATION IN PROPOSED ALGORITHM

Parameter Specification	Value
Number of rules in each particle	20
Number of particles	50
Maximum number of iterations	80
Acceleration constants : C_1And C_2	2
The inertia weight : γ	0.7

In our study the *K*-fold cross validation (10-fold CV) is employed to examine the generalization ability of the proposed algorithm to classify the breast cancer and diabetes dataset. The training data is first partitioned into k equally (or nearly equally) folds and the algorithm is run *k* times, using a different fold as test set each time, with the other *k-1* folds as t

raining set. The results of the evaluation of the proposed method in terms of correct classification, sensitivity, specificity are summarized in table 2:

TABLE II. PERFORMANCE OF THE PROPOSED METHOD

	Number of rules	Classification rate	Se	Sp
Breast cancer	9	98.26	97.56	98.64
Diabetes	8	82.17	83.52	76.92

Basing on these results, it can be summarized that the proposed method generates automatically a knowledge base with just 8 rules for diabetes and 9 for breast cancer to justify the classification. The main advantage of our approach is to create a readable fuzzy classifier with a high accuracy. The results obtained for other classifiers from literature are shown in Table3 for breast cancer and diabetes databases.

TABLE III. COMPARISON OF RESULTS WITH OTHERS STUDIES

Methods	Accuracy (%)	Study
Brest cancer database		
Fuzzy-GA method [23]	97.36	Pena-Reyes et al. (1999)
LDW-PSO [8]	93.00	Sousa et al. (2004)
Constricted-PSO [8]	93.40	Sousa et al. (2004)
DPSO [8]	94.00	Sousa et al. (2004)
AS-NN [24]	95,60	Karabatak et al. (2009)
FRBCs Framework [25]	96.08	Gadaras and Mikhailov. (2009)
Proposed method	98.26%	OUR STUDY
Pima Indians Diabetes database		
GA-Fuzzy classifier [26]	71.49	Guzaitis et al (2009)
Fuzzy Modeling [27]	77.65	Sean et al (2008)
neural networks [28]	79.16	Temurtas et al (2009)
Ant-fuzzy [29]	79.48	Ganji et al (2011)
Proposed method	82.17	OUR STUDY

From table 3, we can find that the proposed method provided the highest classification accuracy. The results obtained in this paper are very interesting and can be used confidently to help clinician for decision making in their diagnosis problems. Therefore, we can conclude that the combination of Particle Swarm Optimization and Fuzzy Logic could be a very effective in the detection of breast cancer disease.

V. Conclusion

This paper presents a simple, efficient and reliable MPSO algorithm by incorporating mutation operators for the optimal design of the fuzzy classifier system. In the proposed approach, both rule base and the membership functions are evolved simultaneously with the objective of maximizing the correctly classified class and minimizing the number of rules. As it shown, the obtained results indicate a fine performance of the developed algorithm. The proposed method was also compared to other methods in literature. According to obtained results, MPSO algorithm could be powerful tool for biomedical engineers to apply it in automatic diagnosis problems.

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