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Hybrid Harmony Search and Genetic for Fuzzy Classification Systems

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Abstract

In this paper, a method based on Harmony Search Algorithm (HSA) is proposed for pattern classification. One of the important issues in the design of fuzzy classifier if the product of fuzzy if then rules. So that the number of incorrectly classified patterns is minimized. In the HSA-based method, every musician makes a musical note and it can be regarded as a solution vector. The algorithm uses Genetic algorithm based local search to improve the quality of fuzzy classification system. The proposed algorithm is evaluated on a breast cancer data. The results show that the algorithm based on improved genetic is able to produce a fuzzy classifier to detect breast cancer.

Keywords: Harmony Search Algorithm, Genetic Algorithm, Fuzzy Classification System.

1. Introduction

Breast cancer is the most common cancer among women and global statistics show that the incidence of the disease is rising [1, 2]. So that about %10 of them affects at different stages in their lives. This cancer is the most common malignancy among Iranian women and it is the main focus of attention in Iran.

In recent years, the rate of onset of the disease is a growing trend; In fact, the entire tumors are not cancerous and may be benign or malignant. Benign tumors grow abnormal, but they are rarely fatal. However, a number of benign breast lumps can also increase the risk of breast cancer. Also, it has increased in some women with a history of biopsy. On the other hand, malignant tumors were more serious and they are cancer but early detection of these cancers has increased the chances of successful treatment. Risk factors for breast cancer are family history, age at first pregnancy, early onset of menstruation, obesity, alcohol consumption and physical inactivity [3]. There are signs that the cancer can be detected. However, some of these symptoms may also be present in other diseases

Thus, in addition to the evaluation of test results, physicians must pay attention to previous decisions which made for patients in the same conditions. In other words, the physician needs both knowledge and experience for proper decision making. Therefore, the patients data should be stored to future decisions making by physicians [2].

To reduce the possible errors and help the expert, the classification system can be used. The use of Classifier systems in medical diagnosis is increasing gradually [4]. Also expert systems and different artificial intelligence techniques help experts in the classification. Many algorithms are proposed to diagnosis of benign or malignant breast cancer [5-7].

In the classification task, the goal is to assign each case record, sample 0 to one class, out of a set of predefined classes, based on the values of some attributes (called predictor attributes).Fuzzy systems based on fuzzy rules have been successfully applied to various control problems. In many application tasks, fuzzy rules were usually derived from human experts as linguistic knowledge. Because it is not easy to derive fuzzy rules by human experts, several methods have been proposed to automatically generate fuzzy rules from numerical data [8].

For pattern classification problems, several classification methods based on fuzzy set theory have been proposed [9]. There have been many well-known algorithms for classification, including decision trees, neural network (NN),support vector machine (SVM), fuzzy inference systems and so on. Among these techniques, decision tree is simple method and Neural network is efficient method and however it has the complex mathematic but it has high performance to classify the input samples[10]. Ishibuchi [11] has suggested a heuristic method for generating fuzzy rules, and a rule selection method based on genetic algorithms to select fuzzy rules [12]. Saniee et al [13, 14] combined the ACO and fuzzy logic for network intrusion detection. Fathi [15] has used ACO and fuzzy logic for diagnosis of diabetes disease.

This paper is organized as follows: Section 2 describes Harmony Search Algorithm. Section 3 describes structure of fuzzy classification systems, then in Section 4 we have proposed a algorithm. Section 5 describe HSA – based fuzzy classification systems and section 6 Fuzzy Inference. In section 7 improve proposed algorithm. Experimental results are reported in section 8, and section 9 is conclusion.

2. Harmony Search Algorithm

HS is a meta-heuristic stochastic global optimization (SGO) method similar in concept to other SGO methods in terms of combining the rules of randomness to imitate the process that inspired it [16].

Harmony search mimics the improvisation process of musicians, during which, each musician plays a note for finding a best harmony all together. When applied to optimization problems, the musicians represent the decision variables of the cost function, and HS acts as a meta heuristic algorithm which attempts to find a solution vector that optimizes this function. In the process, each decision variable musician in a band. Improvisation occurs when each musician tests and plays a note on his instrument such that optimizes this function. In the process, each decision variable (musician) generates a value (note) for finding a global optimum (best harmony). The harmony search algorithm has a novel stochastic derivative (for discrete variable) based on musician's experience, rather than gradient (for continuous variable) in differential calculus [17].

3. Structure of Fuzzy Classification Systems

When an M-class classification problem is considered, a rule base of a fuzzy classification system can be expressed as follows [11]:

RuleR_j : IF X_1 is A_{j1} and….and x_n is A_{jn} then class c_j, j=1, 2,….., N.

Where $x=(x_1,\ldots,x_n)$ is an n-dimensional pattern vector , A_{ji} is an antecedent linguistic value such as small and large(i=1,2,…..,n) , C_j is a consequent class (i.e., one of the given c classes) , and N is the number of fuzzy if- Then rules.

Each fuzzy if-then Rule is coded as a string the following symbols are used for denoting the five linguistic values (Fig. 1): small (A_1), medium small (A2), medium (A3), medium large (A4) and large (A5).

However, we can use any tailored membership functions in our fuzzy classifier system for a particular pattern classification problem. A collection of such rules are used as a knowledge base by the classifier upon which qualitative reasoning is performed to derive conclusion. When the harmony search algorithm produces a set of rules, that must be evaluated by the fitness function and the accuracy of the algorithm is calculated through fuzzy inference system.

4. Proposed Algorithm

In computer simulations, we used a typical set of linguistic values in Figure 1.as antecedent fuzzy sets. Then membership function applied to a fuzzy rule set is assumed to be isosceles- triangle functions and half-open trapezes as shown in Figure 1, where a_{ij} denotes the jth linguistic value of Feature A_i. A total of 6 membership points (z_{i1}, z_{i2}, z_{i3}, z_{i4}, z_{i5}, z_{i6}) are required for representing each input variable as a fuzzy set. In that 6 points, first and last points (z_1, z_6) are fixed which the minimum and maximum of the input variable. To compute other remaining four membership points we divided distance between endpoints by 5.

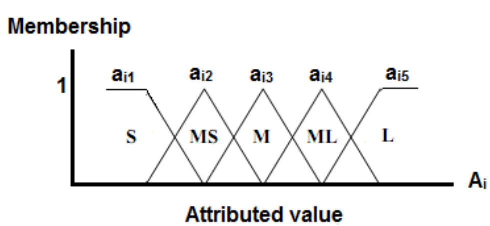

Figure 1. Attribute value A_i

Then we represent each membership function as a quintuplet (P_1, P_2, P_3, P_4, P_5). If a_i is lower or equal z_{i2} then P_1 is 1 and P_2, P_3, P_4, P_5 are 0. If a_i is lower or equal z_{i3} then P_2 is 1 and P_1, P_3, P_4, P_5 are 0 and….An example in Figure 2.represents the process of encoding membership function sets.

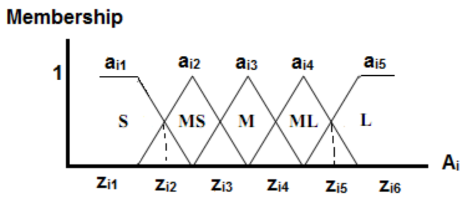

Figure2.The used antecedent fuzzy sets in the paper

S: Small	10000
MS: Medium Small	01000
M: Medium	00100
ML: Medium Large	00010
L: Large	00001.

5. HSA – based fuzzy classification systems

An HSA is applied to learn the fuzzy rules. So that, the learning process for each class is done independently. Proposed approach is as follows:

i. **Initial population:**

Let us denote the number of fuzzy if-then rules in each population in our fuzzy classifier system by N_{pop} (i.e., N_{pop} is the population size). To construct an initial population, N_{pop} fuzzy if-then rules are generated by randomly selecting their antecedent fuzzy sets from the five linguistic values. Each linguistic value is randomly selected with the probability of 1/5.

ii. **Evaluating each fuzzy if-then rule:**

The fitness value of each fuzzy if-then rule is evaluated by classifying all the given training patterns using the set of Npop fuzzy if-then rules in the current population. The fitness value of the fuzzy if-then rule R_j is evaluated by the following fitness function:

$$\text{Fitness}(R_j) = \{ ß_{j1}, ß_{j2}, \ldots, ß_{jh}\} \qquad 1 \le h \le C \tag{1}$$

Where $ß_{jh}(R_j)$ is the sum of the difference of the training patterns (binary strings) in Class h with the fuzzy if-then rule R_j.

iii. **Rule generation:**

This algorithm learns rules for each class separately; therefore a fuzzy if-then rule is generated by generated rules and Harmony operations, for each class. A HMCR operation is applied to the selected fuzzy if-then rule with a pre specified HMCR probability. With a pre specified PAR probability, each antecedent fuzzy set of fuzzy if-then rule is randomly replaced with a different fuzzy set after the

HMCR operation [16]. After generating of fuzzy if-then rules, the fitness value of each of the newly generated fuzzy if-then rules are determined.

iv. **Updating the current population:**

In our fuzzy classifier system, the worst rule with the smallest fitness value in each class is removed from the current population, and the newly generated fuzzy if-then rule is added if better. The above procedure is iterated until a pre-specified number of fuzzy if-then rules are generated.

v. **Stopping condition:**

We can use any stopping condition for terminating the algorithm. In computer simulations of this paper, we used the total number of generations as a stopping condition.

6. Fuzzy Inference

Let us assume that our pattern classification problem is a c-class problem in the n-dimensional pattern space with continuous attributes. We also assume that M real vectors $x_p=(x_{p1}, x_{p2}, \ldots, x_{pn})$, p=1, 2, …, M are given as training patterns from the c classes. When the algorithm generates fuzzy if-then rule for each class using M patterns, a fuzzy inference engine is needed to classify test patterns. Figure 3 illustrates fuzzy inference engine [18].

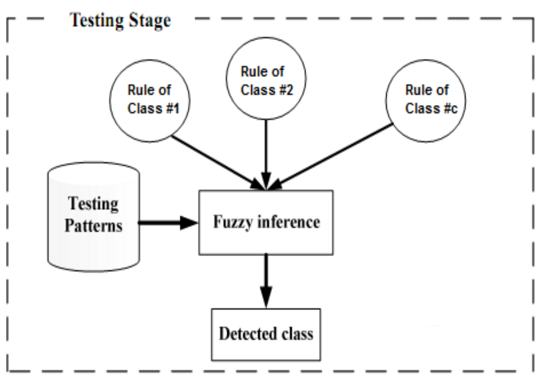

Figure 3.The Testing Stage

When a rule set S is given, an input pattern $x_p= (x_{p1}, x_{p2}, \ldots, x_{pn})$ is classified by a single winner rule R_j, in S, which is determined as follows[18]:

$$\mu_j\left(x_p\right) = \max\{\mu_j\left(x_p\right)\middle|R_j\} \tag{2}$$

7. Improvement of the proposed algorithm

In order to improve classification rates, genetic algorithms can be used in the production rules generated by the algorithm. Since in the harmony, musician seek optimum solutions at each stage using the generated rules in the previous steps, and Because harmony search algorithm does not work well in the local optimum[19] and this action increases the execution time and reduce convergence of the algorithm[20], we use a genetic algorithm. Genetic algorithm increases the search space to achieve universal or near-universal response [21].For this purpose, we use two operators of genetic algorithm, crossover and mutation; In addition search Harmony operators in the stage production rules. So we implement the two operators on generated rules.

8. Experimental Results

For evaluation of our proposed classification system we used from UCI data repository [22, 23] such as Wisconsin Breast Cancer (Wisconsin), diabetes (Pima) and Heart (Table 1.)[24].

Table 1. Data Sets

Data set	Instances	Attributes	Classes
Wisconsin	699	10	2
Pima	768	8	2
Heart	270	13	2

The classification rate being calculated according to (3).

$$\text{Classification rate} = \frac{(TP + TN)}{(TP + TN + FN + FP)} \tag{3}$$

Where

TP: true positives, the number of cases in our training set covered by the rule that have the class predicted by the rule.

FP: false positives, the number of cases covered by the rule that have a class different from the class predicted by the rule.

FN: false negatives, the number of cases that are not covered by the rule but that have the class predicted by the rule.

TN: true negatives, the number of cases that are not covered by the rule and that do not have the class predicted by the rule.

Also, Precision measures, Recall measure and F- Measure are computed by following equations. F-Measure is a trade-off between Precision and Recall.

$$\text{Precision} = \frac{TP}{TP + FP} \tag{4}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{5}$$

$$\text{F-Measure} = \frac{2 * \text{Precision} * \text{Recall}}{\text{Precision} + \text{Recall}} \tag{6}$$

Table 2-4. show the mean classification rate, precision, recall and F-measure for the generated rules by the proposed algorithm, improved algorithm and several well-known methods, that have been tested by Weka software.

Table 2. Wisconsin Breast Cancer Data Set

Method	Classification Rate	Precision	Recall	F-Measure
C4.5	0.946	0.946	0.946	0.946
NN	0.958	0.959	0.959	0.959
KNN	0.951	0.951	0.951	0.951
BayesNet	0.96	0.962	0.96	0.96
Proposed algorithm	**0.9778**	**0.978**	**0.978**	**0.978**
improved algorithm	**0.9834**	**0.984**	**0.984**	**0.984**

Table 3. Pima Data Set

Method	Classification Rate	Precision	Recall	F-Measure
C4.5	0.762	0.754	0.754	0.751
NN	0.753	0.75	0.754	0.751
KNN	0.702	0.696	0.702	0.698
BayesNet	0.743	0.741	0.743	0.742
Proposed algorithm	**0.793**	**0.798**	**0.795**	**0.795**
improved algorithm	**0.803**	**0.804**	**0.804**	**0.804**

Table 4. Heart Data Set

Method	Classification Rate	Precision	Recall	F-Measure
C4.5	0.762	0.766	0.767	0.767
NN	0.751	0.75	0.752	0.751
KNN	0.735	0.713	0.732	0.728
BayesNet	**0.811**	**0.811**	**0.811**	**0.811**
Proposed algorithm	0.767	0.762	0.76	0.76
improved algorithm	0.782	0.784	0.783	0.784

9. Conclusion

We have introduced a novel approach to fuzzy classification for medical diagnosis. This paper presents a mixture of Harmony Search Algorithm and Fuzzy Logic for classification. The proposed algorithm is used in the structure of a Michigan based evolutionary fuzzy system. In order to improve classification rate and Because harmony search algorithm does not work well in the local optimum and this action increases the execution time and reduce convergence of the algorithm, we used a genetic algorithm. Finally, for evaluating the proposed method, several well-known datasets from UCI-repository has been used. Our experiments have confirmed that the algorithm can classify the data with considerable classification accuracy.

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