A Method of Designing Interpretable Genetic Fuzzy Classification System Based On Mutating Parameters

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Abstract. This paper discusses the application of generating fuzzy rules with word computing in genetic fuzzy classification system, and proposes a new method to design genetic fuzzy classification system. The new algorithm generates initial fuzzy rules population with expertise of the randomly selecting samples, and adds mutating parameters to adjust the shape of membership function of fuzzy partition in order to expand the algorithm's search space. Experiments show that the new algorithm has better classification accuracy with shorter length of rules.

Introduction

The fuzzy sets which was proposed by professor Zadeh in 1965, has already been used widely in various application areas of the society[1][2]. Genetic fuzzy classification system is a hybridization of fuzzy logic and genetic algorithm, which was proposed in 1991, has become a hot spot in genetic algorithms[3][4][5][6]. There are two standards to judge whether a fuzzy classification system is good or not, accuracy and interpretability. Recently researches show that the two standards can not do best at the same time, it's better to find a compromise of them. Researchers proposed two approaches to solve it. One is generated fuzzy rules and the fuzzy rule sets by genetic algorithm to keep its accuracy first, and then promote its interpretability by some special methods, such as the similar simplify etc[7][8]. The other is generated both of them by humans' experiences to keep the interpretability first, and then promote its accuracy by genetic algorithm. Professor Zadeh[9] proposed to combine word computing to the second ways to adjust the shape of the membership function of fuzzy partition to promoting the accuracy while keep the interpretability. Li[10] chose four parameters represent "very", "little", "more or less", and "extreme" respectively. On the basis this paper proposes a new approach to design a fuzzy classification system, which generates initial fuzzy rules population with expertise of the randomly selecting samples, and adds mutating parameters to adjust the shape of the membership function of fuzzy partition during mutation process to expand search space of the algorithm to promote its efficiency. Experiments of wine data set show that the new approach has better classification accuracy and shorter rules length than the old ones.

The rest of this paper is organized as follows: Generate fuzzy partition with word computing is introduced in Section 2. The proposed algorithm is described in Section 3. The simulation and experimental results are presented in Section 4. Finally, concluding remarks are given in Section 5.

Research of generate fuzzy partition with word computing

Traditional fuzzy partition is split the whole search space into three or five parts with the same size. Although this fuzzy partition generation method is comprehensible, it has lower accuracy. Professor Zadeh considered that data information can connect with word computing by add language qualifiers to make the adjustment of fuzzy function equals to qualified language words, which made the fuzzy rules more interpretability. Li chose four parameters to adjust the shape of the function of every fuzzy partition, they are "very", "little", "more or less", and "extreme". Let us take wine data set for example to discuss the performance of the two methods. As we know wine data set has 13 attributes, if the algorithm uses five fuzzy partitions and "don't care" condition for

each of them, the search space will be $(5+1)^{13}$, and if the word computing is added, it will grow to $(25+1)^{13}$. Adding word computing made the algorithm has better accuracy but lower convergence speed.

A new design of genetic fuzzy classification system

According to above analysis, this paper proposes a new approach which generates initial fuzzy rules population with expertise of the randomly selecting samples, and adds four mutating parameters to adjust the shape of membership function of fuzzy partition. The system design as follows:

1) Population initialization

This paper uses Triangular membership function to represents fuzzy sets, using real – coded, in which (a,b,c) represents for the three vertex of the triangle.

$$f(x;a,b,c)=\max(0,\min(\frac{x-a}{b-a},\frac{c-x}{c-b})) \tag{1}$$

First, split the whole search space of each dimension into five parts with the same size, then randomly select M training samples from the training set, to each x_{pi} $(i\in[1,n])$, its compatibility U_i with candidate membership function defined as

$$U_i=\left|x_{pi}-b_{k,i}\right| \tag{2}$$

Where $b_{k,i}$ is the second vertex of the five triangles. Then we got the expertise of this sample corresponding to the minimized U_i of each dimension.

2) Consequent classes

To each rule R_j, its compatibility $u_j(x_p)$ with all training samples x_p defined as

$$u_j(x_p)=\prod_{\mathrm{i=1}}^{\mathrm{n}}u_{ji}(x_p) \tag{3}$$

To every consequent class, its $\beta_{classh}(R_j)$, sum of all training samples' $u_j(x_p)$ belongs to it defined as

$$\beta_{classh}(R_j)=\sum_{x_p\in classh}(u_j(x_p)) \tag{4}$$

We choose the class of max $\beta_{classh}(R_j)$ as the consequent class of R_j. If more than two classes have same max $\beta_{classh}(R_j)$, we choose one with small quantity.

3) Fitness value

The fitness value $fitness(R_{seti})$ is defined as

$$\underset{i\in[1,L]}{fitness(R_{seti})}=\begin{cases}CP(R_{seti})-\omega MP(R_{seti}), & MP(R_{seti})\le m\\ 0, & MP(R_{seti})>m\end{cases} \tag{5}$$

Where CP is the right classification and MP is the wrong classification, ω is parameter of wrong classification punishment, which is belongs to [0.2, 0.5], m is the max number of the wrong classification permitted.

4) Fuzzy genetic operations

Selection of this paper is combined roulette wheel selection strategy and elite selection strategy, and the mutation operation with mutating parameters as follows:

We select one rule from the rule set randomly, and choose two dimensions of it. To each dimension, change the first and the third vertex according to Eq.6 while keeping the second one unchanged.

$$a_{jn_1}{}'=\max\{b_{jn_1}-\delta(b_{jn_1}-a_{jn_1}),x\min_{n_1}\}\quad c_{jn_1}{}'=\min\{b_{jn_1}+\delta(b_{jn_1}-a_{jn_1}),x\max_{n_1}\} \tag{6}$$

Simulation experiments

Simulation results on wine data set under the same parameters are summarized in Table 1(with expertise) and Table 2(with out expertise).We choose 2/3 of it as training set, 1/3 of it as testing set.

Npop=50, M=6, Pc=0.9, Pm=0.1. We choose four mutating parameters 0.4, 0.7, 1.3, 1.6.

Table 1 20 Experiments on wine data set with expertise

Fuzzy partition	Training Set	Testing Set	Length of Rules
Five average fuzzy partitions	93.25%	86.38%	2.41
Fuzzy partition of word computing	95.08%	90.51%	2.54
Our approach	98.92%	91.03%	1.94

Table 2 20 Experiments on wine data set with out expertise

Fuzzy partition	Training Set	Testing Set	Length of Rules
Five average fuzzy partitions	86.67%	80.00%	2.8
Fuzzy partition of word computing	94.33%	88.79%	2.45
Our approach	93.75%	87.93%	1.75

Through the simulation results in Table 1 and Table 2, our approach has higher classification accuracy and shorter rules length than the five average fuzzy partitions and the fuzzy partition of word computing.

Conclusions

The new method expands the search space while remaining system's interpretability, which is demonstrated to be more efficiency according to the simulation results. It also shows that adding expertise has good efficiency of the simulation results.

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