Parallel Distributed Multi-objective Fuzzy Genetics-based Machine Learning Mid Term Report

Bowen Zheng, Shijie Chen, Shuxin Wang
Department of Computer Science and Engineering
Southern University of Science and Technology
Shenzhen, Guangdong, China

***Abstract*—In the second period of the project, we finished the design of fuzzy classifiers, GBML framework and the asynchronous parallel distributed system. We have implemented each part respectively and are working to integrate them together.**

I. Introduction

In this project, we aim to build a parallel distributed implementation of a multi-objective genetics based machine learning(GBML) algorithm. We choose a specific problem of a three-objective fuzzy rule-based classifier and fit it into a hybrid GBML framework. Then we develop a parallel mechanism to accelerate computation.

Code of the three parts have been completed. We will integrate them together, fix bugs and run some test problems in the next stage.

II. Fuzzy Rule-based Classifiers

The design and implementation of fuzzy classifier is based on [1].

A. Fuzzy Rules

We use the following "if-then" rules:

$$Rule\ R_q:\ if\ x_{pi}\ is\ A_{qi},\ i \in [1,n]\ then\ Class\ C_q\ with\ CF_q$$

TABLE I
NOTATION

Variable	Name
n	dimension of patterns
M	number of classes of patterns
S	a fuzzy classifier
I	number of membership functions
x_p	a pattern vector
x_{pi}	attribute of x_p value on i-th dimension
A_{qi}	antecedent fuzzy set
$\mu_{A_{qi}}(x)$	membership function of A_{qi}
$\mu_{A_q}(x_p)$	compatibility grade of x_p with A_q
A_q	antecedent part of q-th rule
R_q	q-th rule
C_q	consequent class for q-th rule
CF_q	rule weight for q-th rule

Input vectors are normalized to a hypercube $[0,1]^n$ using the following equation:

$$x_{pi} = \frac{x_{pi} - min(x_i)}{max(x_i) - min(x_i)}$$

The antecedent fuzzy set contains a membership function of the form:

$$\mu_{A_{qi}}(x_{pi}) = max\{1 - \frac{|a - x_{pi}|}{b}, 0\}$$

$$a = \frac{k-1}{K-1}$$

$$b = \frac{1}{K-1}$$

Where K is the number of intervals of fuzzy set A_{qi} and k is the order of the interval. As shown in fig.1. The $don't\ care$ condition is a constant function with value 1. As we will discuss in classification process, the feature x_{pi} with A_{qi} being $don't\ care$ is ignored.

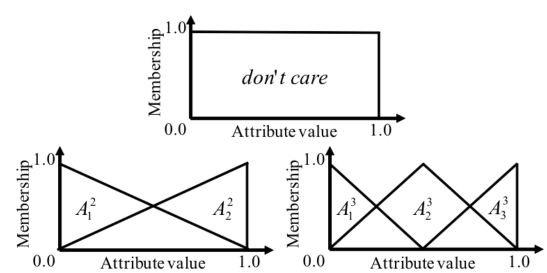

Fig. 1. Membership functions with at most 3 intervals

The antecedent part of R_q is a set of antecedent fuzzy sets.

$$A_q = \{A_{qi} | i \in [1,n]\}$$

We define the compatibility grade of an pattern x_p with rule R_q as

$$\mu_{A_q}(x_p) = \prod_{i=1}^{n} \mu_{A_{qi}}(x_{pi})$$

Then we determine the consequent class C_q and rule weight CF_q using training patterns as follows:

First, we compute the confidence of fuzzy rule R_q to each class $c(A_q \Rightarrow Class\ h), h \in [1, M]$

$$c(A_q \Rightarrow Class\ h) = \frac{\sum\limits_{x_p \in Class\ h} \mu_{A_q}(x_p)}{\sum\limits_{p=1}^{m} \mu_{A_q}(x_p)}$$

Then the consequent class C_q as the class with which R_q has the largest confidence.

$$c(A_q \Rightarrow Class\ C_q) = max\{c(A_q \Rightarrow Class\ h) | h \in [1, M]\}$$

At last, rule weight of R_q is given by the difference between its consequent class and other classes.

$$CF_q = c(A_q \Rightarrow Class\ C_q) - \sum_{h=1, h \neq C_q}^{M} c(A_q \Rightarrow Class\ h)$$

Rule weight shows the quality of a classification result given by a fuzzy rule. If a rule has negative rule weight, its abandoned.

B. Fuzzy Classifier

A fuzzy classifier S is a set of fuzzy rules. Given an input pattern x_p, the classification result C_w is produced by a winning rule R_w, chosen as follows:

$$\mu_{A_w}(x_p) \cdot CF_w = max\{\mu_{A_q}(x_p) \cdot CF_q | R_q \in S\}$$

C. Generate Fuzzy Rule From Training Patterns

At the initiation stage of our GBML algorithm, the population, set of fuzzy classifiers, is created from training data. We can use certain training patterns to create a fuzzy classifier and repeat the process to create a set of classifiers.

Each rule R_t in each classifier is generated from a training pattern x_t as follows:

We choose an antecedent fuzzy set according to each x_{ti} and form the antecedent part A_t of rule R_t so that x_t has the largest compatibility:

$$\mathsf{A}_{ti} = \arg\max_{\mu_j} \{\mu_j(x_{ti})\}, j \in [1, I]$$

Then, randomly change the antecedent fuzzy set to $dont't\ care$ according to a pre-specified probability p_{dc}. This step prevents overfitting and improves generalizing ability of fuzzy rules.

III. Hybrid Genetics-based Machine Learning Framework

IV. Asynchronous Parallel Distributed System Design

V. Contribution

- Bowen Zheng - Design & Implementation of parallel system
- Shijie Chen - Design & Implementation of fuzzy classifier, Design of parallel system
- Shuxin Wang - Design & Implementation of Hybrid GBML framework

Acknowledgment

References

[1] H. Ishibuchi and Y. Nojima, "Analysis of interpretability-accuracy tradeoff of fuzzy systems by multiobjective fuzzy genetics-based machine learning," *International Journal of Approximate Reasoning*, vol. 44, no. 1, pp. 4–31, 2007.