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MANUFACTURING RESOURCES CLASSIFICATION BASED ON FUZZY CLUSTERING ALGORITHM

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ABSTRACT

Today, for many companies, there are large numbers of manufacturing equipments. To better utilize manufacturing resources, it is necessary to classify the equipments into a few groups. In this paper, the hybrid algorithm of fuzzy clustering algorithm (FCM) and genetic algorithm (GA) is implemented to group manufacturing resources. An application sample is developed and its results are analyzed. The grouping result shows that the hybrid algorithm is reliable and effective.

Keywords: *Fuzzy C-Means Clustering; Genetic Algorithm; Manufacturing Resources Classification*

1. INTRODUCTION

With the development of technology and the competition in market, the processing capacity of manufacturing company is constantly improved. A product can be produced by different equipments with different costs, qualities and speeds. The quick selection of machining equipments according to different demands is very important for improve the competitiveness of manufacturer. The difference of processing ability between different equipments is more and more fuzzy. Clustering methods organize a set of items into clusters, by this mean the items in a cluster have a high degree of similarity, whereas items belonging to different clusters have a high degree of dissimilarity [1-5].In order to find the suitable equipments in the plentiful existed resources quickly, it is very necessary to group the equipments according to their property. In this paper, the hybrid algorithm of genetic algorithm and the fuzzy c-means clustering (FCM) is used to group the equipments. The GA [5-8] is mainly used to improve the global searching ability of fuzzy clustering algorithm. In this way, the optimum number of groups and classification can be obtained simultaneously.

2. THE CLUSTERING METHOD BASED ON FCM AND GA

2.1 Fuzzy C-Means Algorithm

Fuzzy c-means clustering algorithm can realize the fuzzy grouping of data, which has been widely used in many fields such as image processing, medical diagnosis, object identification and so on. According to principle of least square, FCM can obtain the data grouping by optimizing the object function with iteration [2]. The object function is shown as following:

$$J_m = \sum_{j=1}^{c} \sum_{i=1}^{n} u_{ij}{}^m \left\| x_i - v_j \right\|^2$$

(1)

$$\sum_{j=1}^{c} u_{ij} = 1 \qquad i = 1, 2, \cdots, 3$$

(2)

Where C is the number of clusters; $X = \{x_1, x_2, ..., x_n\}, x_i \in R^s$ is data sets, μ_{ij} is the value of the membership degree of the ith object belonging to the j^{th} cluster, *m* is fuzzy weight, m=2.

Applying the standard Lagrange multipliers minimization method, the fuzzy cluster centers and fuzzy matrix can be expressed as following:

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$$u_{ij} = \frac{1}{\sum_{k=1}^{c}\left(\frac{\|x_i - v_j\|}{\|x_i - v_k\|}\right)^{2/m-1}} \quad \|x_i - v_j\| > 0 \ \forall i \text{ and } k \tag{3}$$

$$v_j = \frac{\sum_{i=1}^{n}(u_{ij})^m x_i}{\sum_{i=1}^{n}(u_{ij})^m} \quad \forall j,\ j = 1, 2, \cdots, c \tag{4}$$

FCM is a local searching algorithm so it is easy to get in the local optimum and is very sensitive to the initialization. GA is a widely used global optimization algorithm in practice which has a lot of advantages such as universality, fitness for concurrent processing and simplicity. By this mean, a Fuzzy c-means algorithm based on GA not only has the ability of local searching of FCM but also the ability of global searching of GA. In this way, the problem that the FCM is sensitive to initialization can be solved and the velocity of convergence be increased.

2.2 Application Of The Hybrid Algorithm

The hybrid algorithm based on FCM and GA is composed of inner iteration and outer iteration. The outer iteration is used to determine the optimal number of cluster by GA and the inner iteration is used to determine the optimal partition by using FCM clustering based on GA.

In this paper, the equipments are grouped according to the features which can be processed by these equipments such as plane, hole, blind hole, step, slot, blind slot, pocket, cylindrical protrusion, curved surface, and so on. But because of the tolerance requirements, size of feature or parts and other requirements the same feature can not always be processed by the same equipment. So the size of part and processing accuracy are also considered as the attributes of the processing equipments. If there are N processing equipments and s features altogether, processing equipment vector is shown as Eq. 5 and Eq. 6.

$$x_i = (x_{i1}, x_{i2}, \cdots\cdots, x_{is}, p_i, a_i)$$
$$i = 1, 2, \cdots\cdots, N$$
(5)

$$x_{ik} = \begin{cases} 1 & \text{equipment i can process feature k} \\ 0 & \text{equipment i can not process feature k} \end{cases} \quad k = 1, 2, \cdots, s \tag{6}$$

$$p_i = \begin{cases} 1 & \text{equipment i can process large-sized parts} \\ 0 & \text{equipment i only can process small and medium parts} \end{cases}$$

$$a_i = \begin{cases} 1 & \text{equipment i can be used in finish machining} \\ 0 & \text{equipment i can not be used in finish machining} \end{cases}$$

2.3 Inner Iteration

In the inner iteration, by using the hybrid algorithm the optimal classification matrix corresponding to the number of cluster is obtained and the optimal classification is obtained according to maximum membership degree principle. The main questions of the hybrid algorithm include encoding, constructing fitness function, selecting genetic operators, determining parameters and so on.

The objective of fuzzy clustering is to get the minimum objective function (loss function). The objective function of fuzzy clustering J_m is smaller, the classification is more reasonable and the corresponding fitness function of GA should be bigger. The fitness function is defined as following with the objective function J_m :

$$F(U,V) = \frac{1}{J_m + \varepsilon} = \frac{1}{\sum_{k=1}^{c}\sum_{i=1}^{n}\mu_{ik}{}^m d_{ik}{}^2 + \varepsilon} \tag{7}$$

The coding method is real coding on cluster center v. A chromosome is composed of c clusters which is shown as $chr = v_1 v_2 \cdots v_c$, $v_i\,(i = 1, 2, \cdots, c)$. Because every cluster has s characters so the length of chromosome is $c \times s$. A chromosome is shown as follows:

$\{v_{11}, v_{12}, \ldots, v_{1s}, v_{21}, v_{22}, v_{2s}, \ldots\ldots, v_{c1}, v_{c2}, \ldots, v_{cs}\}$ .The double-point crossover operator is employed. The combination of the remainder stochastic sampling with replacement and the optimum individual maintaining strategy is used as selection operator.

After on generation, FCM is used to optimize the population, the fuzzy martix U and clustercenters V is revised according to the code of every chromosome, then the new fuzzy matrix is coded as the new chromosome and the value of objective function is recalculated.

2.4 Outer Iteration

For FCM algorithm, the number of clustering has to be determined in advance and it can not be optimized. The typical genetic algorithm is implemented in outer iteration to determine the optimal number of clustering. A good clustering method should consider not only the degree of compaction of one partition but also the degree of separation of different partitions. The average distance between cluster centers is used to

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characterize the dispersion among the different partitions. The bigger the value of average distance between cluster centers is, the greater the degree of deviation of different partition is. Here, D is used to indicate the average distance between cluster centers, shown as follows:

$$D = \frac{\sum_{i=1}^{C} \left\| v_i - v_j \right\|}{C} \tag{8}$$

The objective of out iteration is the maximum objective function Jm and the minimum average distance between partitions D. The fitness function of outer iteration is defined as:

$$F'(U,V) = \frac{1}{J_m(U,V) + D} \tag{9}$$

In outer iteration, the coding method is binary coding on the number of clustering. The genetic operator is the same as the inner iteration. The number of cluster corresponding to each chromosome is calculated and the corresponding optimum partition in obtained by using the inner iteration.

3. IMPLEMENTATION OF THE HYBRID ALGORITHM

The equipment is expressed by pattern vector. The length of the pattern vector is 8. The pattern vector is composed of 0 and 1, if the equipment can process the feature the corresponding value is 1 or 0, if the equipment can process large-size component the corresponding value is 1 or 0, if the equipment can be used in finish processing the corresponding value is 1 or 0. For example, vertical milling machine can process plane and groove, it can not process large-size part and can be used in finish processing, so the vector is 01100001, lathe 2 can process cylinder and taper, plane, groove and hole, and it can not process the large-size part and be used in finish processing, so the vector is 11110000, shown in Figure 2. To check the validity of the proposed algorithm, the pattern vector of the 22 processing equipments is shown in Table 1, and these equipments will be grouped in few groups by using the proposed algorithm.

	Cylinder and taper	Plane	Groove	Hole	Curved surface	Step	Large-size part	Finish processing
Vertical milling machine	0	1	1	0	0	0	0	1
Lathe 2	1	1	1	1	0	0	0	0

Figure 1 The Vector Representation of Manufacturing Resources

Table 2 Classification Result of Manufacturing Resources

Number Of Cluster	Machining Equipment	Feature
5, 13, 22	Lathe 2, Lathe 3, Milling and drilling machine, Milling machine 5, Broaching machine	Cylinder and taper, plane, groove, hole, curved surface, step
2, 3, 4, 7, 8, 19	Drilling machine 1-5, Lathe 1, Lathe 5, Horizontal fine-boring machine, Internal grinding machine,	Cylinder and taper, hole
1, 11, 12, 17, 20	Vertical milling machine, Milling machine 1, Milling machine 3, Milling machine 4, Planning machine 1, Surface grinding machine	Plane, groove, step, finish processing
14, 15, 21	Milling machine 2, Milling machine 6-8, Planning machine 2	Plane, curved surface, large-size part, finish processing
6, 18	Lathe 4, Cylindrical grinder	Cylinder and taper, hole, finish processing
9, 10, 16	Lathe 6, Boring-milling machine 1-3, Coordinate setting boring machine	Cylinder and taper, plane, groove, hole, large-size part, finish processing

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The proposed algorithm was implemented in C++. The population size of the inner iteration and outer iteration are 40 and 20 respectively. The evolutional generation of the hybrid algorithm is 100, crossover rate and mutation rate are 0.8 and 0.1 respectively.

Table 1 A Set Of Equipments

Number	Device Name	Features	Pattern Vector
1	Vertical milling machine	Plane, groove, finish processing	011000 01
2	Drilling machine 1	Hole	000100 00
3	Drilling machine 3	Hole, large-size part	000100 10
4	Lathe 1	Cylinder and taper, hole	100100 00
5	Lathe 2	Cylinder and taper, plane, groove, hole	111100 00
6	Lathe 4	Cylinder and taper, hole, finish processing	100100 01
7	Drilling machine 4	Hole	000100 00
8	Drilling machine 5	Hole	000100 00
9	Coordinate setting boring machine	Plane, groove, hole, large-size part, finish processing	011100 11
10	Boring-milling machine 2	Plane, groove, hole, large-size part, finish processing	011100 11
11	Milling machine 1	Plane, groove, finish processing	011000 01
12	Milling machine 3	Plane, groove, step, finish processing	011001 01
13	Milling machine 5	Plane, groove, hole, step, finish processing	011101 01
14	Milling machine 6	Plane, large-size part, finish processing	010000 11
15	Milling machine 7	Plane, large-size part, finish processing	010000 11
16	Boring-milling machine 3	Plane, hole, large-size part, finish processing	010100 11
17	Planning machine 1	Plane, groove	011000 00
18	Cylindrical grinder	Cylinder and taper, finish processing	100000 01
19	Internal grinding machine	Hole, finish processing	000100 01
20	Surface grinding machine	Plane, finish processing	010000 01
21	Planning machine 2	Plane, large-size part, finish processing	010000 11
22	Broaching machine	Plane, curved surface, finish processing	010010 01

The variation of objective function of fuzzy clustering Jm and the average distance between cluster centers D with respect to the number of cluster is shown in Figure 2. Jm is monotone decreasing and D is monotone increasing as the number of cluster increasing. According to the proposed algorithm the optimal number is 6 and the optimal classification is obtained according to maximum membership degree principle, the optimal classification of the manufacturing resources is shown in Table 2.

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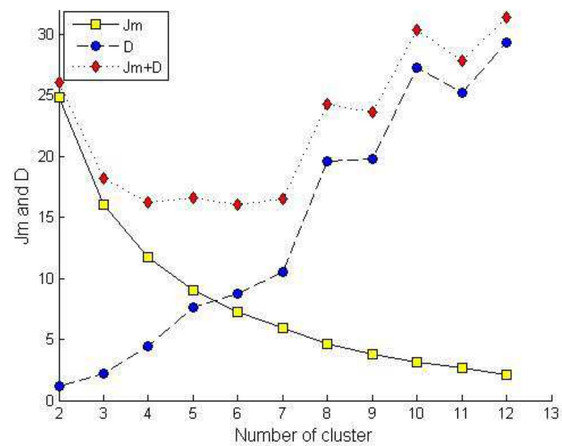

Figure 2 Relationship Between Jm, D And The Number Of Cluster

Every manufacturing resource only belongs to one class but every single feature could belong to more than one class. The second group and the fifth group can process cylinder and taper and hole features of small and medium parts, but the equipments in the fifth group can be used in finish processing, so these processing equipments are partitioned in the two different group. The first group and the sixth group can process cylinder and taper, hole, plane and groove features, but the equipments in the sixth group can process these features of large-size part and be used in finish processing, these equipments are partitioned in different groups although they can process the same features. The main content of manufacturability evaluation is to evaluate whether every feature of part has the corresponding processing equipments.

4. RESULTS

In this paper, a hybrid algorithm of genetic algorithm and fuzzy c-means is proposed to group the processing equipments according to the manufacturing and geometric features which can be processed by the equipments. The fuzzy rules employed can cope with the problem of the difference between processing capability of modern processing equipments. An application has been developed to test the algorithm. In the mentioned sample, the mathematical model of algorithm is built, and 22 processing equipments are partitioned to test the algorithm. The result shows that the algorithm is reasonable and effective and it is insensitive to the initial value. In this way, the searching time and searching space of processing equipments are decreased so the manufacturer can select the proper machining equipments according the requirements. And the manufacturing resources classification is the base of manufacture resources model and manufacturability evaluation. The further work should be focus on how to builde the resources model based on resources classification and integrate the resources model into the manufacturability evaluation system.

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