Model Design Reuse Method Based on Fuzzy Theory

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***Abstract*—At present, research on the reuse of design information resources mainly focuses on the representation and modeling of its information. Neglecting the design information itself can be used as a starting point for design reuse. Based on the existing instance model of the enterprise, this paper firstly divides the function of the instance model; it uses the fuzzy clustering analysis method to classify the existing instance model in a fuzzy manner; then decomposes the customer requirements and compares the similarities to determine the reuse example. The model alternative set; finally, the fuzzy decision method based on the basic feedback extension is used to find the optimal scheme, and the scheme of the selected design reuse model is improved and used as the final scheme of the new model design. This paper takes the design reuse process of consumer drones as an example to verify that this method has certain feasibility and effectiveness.**

Keywords-Design Reuse; Fuzzy Clustering; Model Alternative Set; Fuzzy Decision

I. INTRODUCTION

Design is the initial stage of building a new product. According to research, about half of the products in new product development are identical to existing products. 30%-40% of the products can be obtained by improving existing products. Only 10% of the products belong to innovative designs[1-2].

In view of the above problems, the existing model examples are used to make reference to the new model design. Shahin and Blessing pointed out that design methodology should be used to guide the design during the conceptual design phase. Design methodology has a certain guiding significance for the idea of design reuse, and some design methodology itself can be used as a reuse method.[3-4] Wu Shoufei introduced the concepts of family, standardization and serialization into the design reuse process through the research on the reuse strategy under the mass customization environment to meet the purpose of design diversification.[5-6]

Based on the above problems, this paper proposes a function-driven design reuse method to reuse existing design information from existing model instances in the current market.

II. MODEL FUNCTION DIVISION

The model function is defined as a description of the model function, There are many factors involved in the model function. Therefore, using these functions as the starting point of the design model can not only ensure that the final shape of the model meets the functional requirements, but also clarify the model design ideas to improve the design efficiency of the model.[7]

The model function F is decomposed into several sub-function influence factors. As shown in Figure 1, F_1, F_2, F_3, ..., Fn represent the main influencing factors of the functional model, and in turn are affected by these factors smaller than its own unit, m, l, k, representing the number of functional influencing factors. Units, these influencing factors interact, and the function of the model is ultimately determined by all functional components.

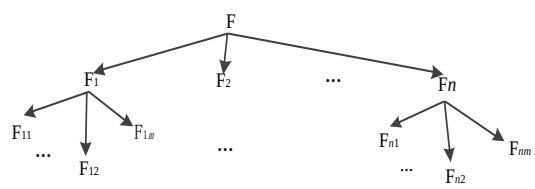

Figure 1. Model function decomposition

III. EXISTING EXAMPLE MODEL FUZZY PARTITIONING

In order to use the collected model examples as a guide for design reuse, the model function is used as a starting point to standardize and normalize them into mathematical data. The model classification steps of function-based fuzzy clustering are as follows:

A. Select the model and extract functional information

The function of the model is used as the basis for the division and construction. All the functions of the model are represented by the letter *M*, which is denoted as $M=(M_1,$

M_2, ...M). Each model M_i has its corresponding function, and one can use one. Group data (n data units) is represented. The model function is shown in the formula:

$$M_i=F_i=(F_{i1}, F_{i2}, F_{i3}, \ldots, F_{in}), i=1,2,3,4,\ldots, t \quad (1)$$

B. Model similarity

After the model is selected, the degree of similarity is calculated by abstraction, and the category screening is divided. Here, L_{ij} is used to indicate the similarity between the model M_i and the model M_j. L_{ij} is the key to establish the fuzzy similarity relationship. The difference in value determines whether it belongs to one type. The value of L_{ij} belongs to a value between 0 and 1, and can take 0 or 1. If the value of L_{ij} is 0, it means that there is no correlation between the two models. If the value of L_{ij} is calculated, When it is 1, it means that the two models are completely similar in function. If the L_{ij} value is one of the values, then the value of the value is used to determine the similarity of the two models. Thus the original matrix is converted to a standardized matrix, as follows:

$$\mathrm{M}_{ij}^{'} = F_{ij}^{'} = \frac{F_{ij} - \bar{F}_j}{\sigma_j}, i = 1,2,3\cdots \mathrm{t}; \mathrm{j} = 1,2,3\cdots, n \quad (2)$$

$$\bar{F}_j = \frac{1}{t}\sum_{t=1}^{t} F_{ij}, \sigma_j^2 = \frac{1}{t}\sum_{t=1}^{t}\left(F_{ij} - \bar{F}_j\right)^2, j = 1,2,3\cdots, n \quad (3)$$

In the normalization process, 1~5 ladder level is adopted, the “1” ladder level indicates the worst level of function influence, and “5” indicates the optimal level of function influence. After normalizing the model function, the fuzzy similarity matrix is constructed by using absolute value subtraction, as follows:

$$L_{ij} = 1 - c \bullet \sum_{k=1}^{m} \left| x_{ik} - x_{jk} \right| \quad (4)$$

Since c is an appropriate number, c=0.1 is taken here.

C. Constructing fuzzy equivalence relation matrix

The similarity relation L established by the above is not a fuzzy equivalence relationship. In the application, the fuzzy similarity matrix L has no transitivity. Therefore, on this basis, the fuzzy equivalence relation of L needs to be modified, thereby obtaining the model functional category. Usually, the transitive closure R of L is transformed into R by the flat method. At this time, R is the fuzzy equivalence relation matrix of the model, which satisfies the transitivity in practical applications.

D. Determining the model function class

On the basis of obtaining the model fuzzy equivalence matrix R, clustering R is as follows:

$R \to R^2 \to \left(R^2\right)^2 \to \cdots \to R^{2^k}$ There is a certain number k $R^{2^k} = R^{2^{k-1}}$ According to the accuracy requirement, choose a number λ in the middle, which satisfies the following formula:

$$R_{ij}(\lambda) \begin{cases} 1, r_{ij} \geq \lambda \\ 0, r_{ij} \leq \lambda \end{cases} \quad (5)$$

Given a confidence level λ, if 1, then the instance models are grouped into one class, thereby forming a model class. Through the fuzzy clustering analysis based on fuzzy equivalence relation, the existing model can obtain different similarity values according to different functions, and divide it into different model functional classes. The algorithm flow is shown in Figure 2.

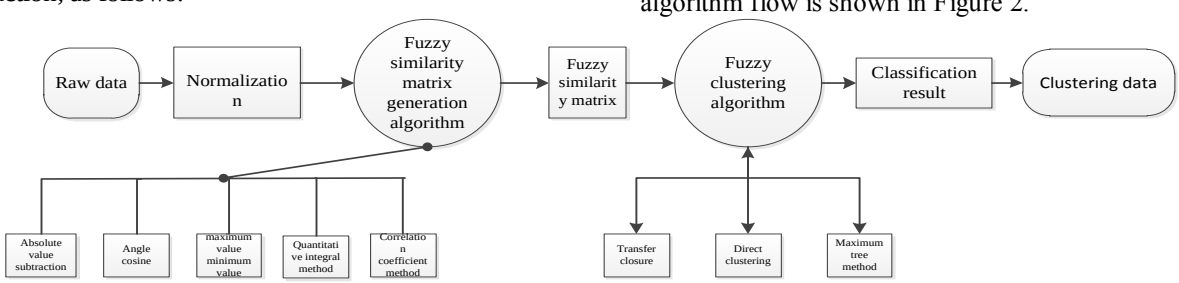

Figure 2. Fuzzy clustering based on fuzzy equivalence relation

IV. SIMILAR INSTANCE MODEL RETRIEVAL BASED ON CUSTOMER NEEDS

The designer analyzes the customer's demand. Currently, there is a collaborative filtering recommendation algorithm based on user attribute clustering and project division to perform similar instance retrieval.[10-11] Collaborative filtering algorithm is the most widely used and most successful recommendation algorithm. Although the algorithm considers the similarity calculation that has an important influence on the retrieval accuracy, it does not consider the weight ratio of each influencing factor.[12] Therefore, based on the obtained model functional classes, this paper finds the most similar classes by calculating the similarity between the influencing factors of the demand model function and the assigned model classes, and matches them to give corresponding thresholds. , an alternative set of reuses above this threshold. For the existing model instance C fuzzy clustering, there are N classes, namely $C=(C_1, C_2, ..., C_N)$. The model function C_R required by the customer is divided into N sub-function

comprehensive influencing factors, namely CR=(C_{R1}, C_{R2}, ... C_{RN}).

Definition 1: From one of the N categories, one instance is randomly selected, and the similarity of the model performance of the customer's demand to the extracted instance is calculated by the following formula. Define the functional class in which the largest instance model of similarity is located as a reused alternative set.

$$s(C_R, C_i) = \frac{k}{N}\sum_{j=1}^{k}(\omega_j \times Sim(C_R^j, C_i^j)), i = 1, 2, \cdots n; j = 1, 2, \cdots, N \quad (6)$$

V. DECISION SET OPTIMIZATION

The main idea of the decision-making method based on the basic feedback extension is that when we discuss the extension of a certain scheme, such as: excellent, good, medium, and poor, it is easy to make decisions according to the principle of maximum membership. When the extension is unknown, it can be converted into a full-factor extension that determines the scheme, but the whole factor is more complicated, and can be indirectly converted into a full-factor extension of the performance extension joint construction of several simple factors.[13-14]

VI. INSTANCE VERIFICATION

A. Consumer drone functional module division

The flight control function system is mainly embodied in the obstacle avoidance capability of the drone during flight. It has the front obstacle avoidance, avoiding obstacles before and after, avoiding obstacles before and after, and avoiding obstacles before and after.

This paper mainly considers the above functions of consumer-class drones, and normalizes the factors affecting these functions. Standardized processing, using 1~5 grades as shown in the following table

TABLE I. NORMALIZED REPRESENTATION

Functional influence factor	Specifications				
	1	2	3	4	5
Flight duration(min)/Flight altitude（m）	15/100	25/150	35/200	45/250	55/300
Maximum remote control distance（m）	1000	2000	4000	7000	8000
Obstacle avoidance function	Before	Before and after	Front and rear	Front, back, left, and right	
Maximum load（g）	500	1000	1500	2000	3000

B. Customer private demand function

Since a customer belongs to amateur aerial photography enthusiasts, the drone can be used to satisfy the city and the classic travel self-timer. After the designer analyzes the customer's needs, the flight duration and flight altitude can choose 45/250 to meet the long-term travel aerial photography. In some high-rise buildings, the maximum remote control distance can meet the general distance. Due to the large number of urban buildings, the most comprehensive obstacle avoidance function is selected. The maximum load, according to the SLR weight of the market, chooses a load of 2000g.

C. Consumer-class UAV model instance library clustering and establishment of optimal candidate set

Through the collection and organization of existing model instances, as shown in Table 2.

TABLE II. EXISTING MODEL INSTANCE

model	duration /height	Remote control distance	Avoidance	Load	model	duration /height	Remote control distance	Avoidance	Load
M_1	3	3	4	4	M_{10}	2	2	3	5
M_2	3	5	4	3	M_{11}	2	3	4	4
M_3	4	3	3	5	M_{12}	3	3	4	5
M_4	3	3	2	2	M_{13}	3	4	3	5
M_5	3	5	2	3	M_{14}	2	3	3	4
M_6	3	2	2	5	M_{15}	1	2	2	2
M_7	4	3	4	4	M_{16}	2	1	2	2
M_8	5	4	3	4	M_{17}	1	1	1	2
M_9	4	3	3	4					

The original data is processed by Matlab programming to obtain the similarity matrix. Secondly, the fuzzy equivalent matrix is obtained by the iterative calculation program, and then the threshold is used to perform the cut-off cluster analysis. Matlab analysis data programming code flow chart shown in Figure 3.

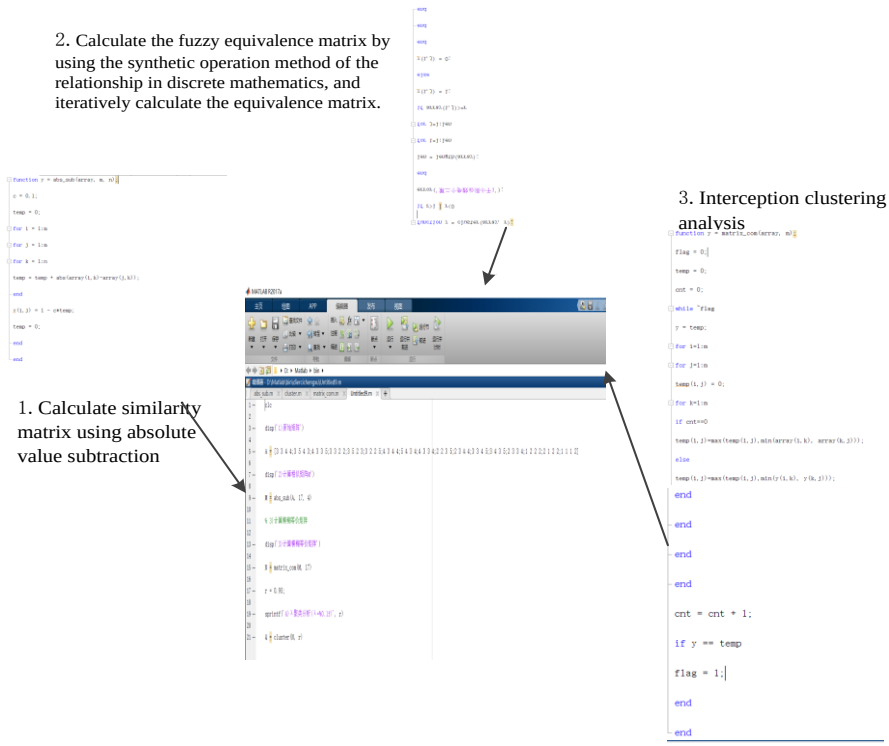

Figure 3. Matlab flow chart

And given a threshold of 0.85, the matrix shown in Figure 4 is obtained.

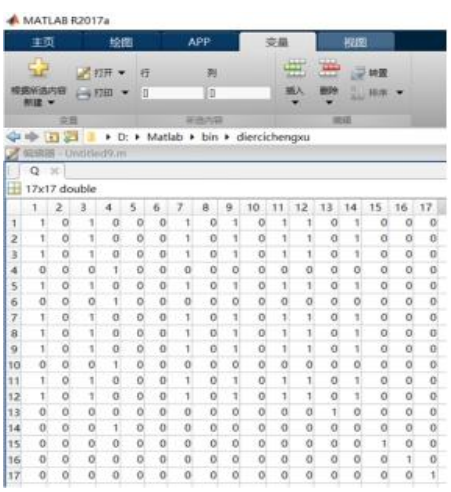

Figure 4. Fuzzy equivalent matrix shown in matlab program

Assign weights to the four functional indicators, $\varpi_1 = 0.3, \varpi_2 = 0.2, \varpi_3 = 0.2, \varpi_4 = 0.3$ The M_{13}, M_{14}, M_{15}, M_{16}, and M_{17} are randomly selected as the representative, and the similarity between the customer demand and the model instance is calculated by Equation 6 as shown in Table 3 below:

TABLE III. SIMILARITY

Model instance	Similarity value
(C_R, M_{14})	0.52
(C_R, M_{15})	0.62
(C_R, M_{16})	0.58
(C_R, M_{17})	0.74
(C_R, M_{13})	0.86

It can be seen that the first category is closer to the customer's demand, but the number of the first type of instances is large. To improve the efficiency, the maximum value of the cutoff value in the first category is 0.9, and the optimal model set above this threshold is: (M_3, M_7, M_{13}).

D. Basic feedback extension decision optimization

According to the optimization decision of the above alternative set, $U = [M_{13}, M_7, M_3] = [u_1, u_2, u_3]$, Let Z be the "best model instance reuse case" $\varphi = \{Z\}$ F_1 = sustainable time and its flight altitude, f_2 = maximum remote control distance, f_3 = obstacle avoidance function, f_4 = maximum load.

Take the 4-dimensional t-module as the algorithm multiplier and thus have:

$$\varphi(1)(x_1,x_2,x_3,x_4)=\prod[\varphi(f_1)(x_1),\varphi(f_2)(x_2),\varphi(f_3)(x_3),\varphi(f_2)(x_2)]$$
$$=\varphi(f_1)(x_1)\bullet\varphi(f_2)(x_2)\bullet\varphi(f_3)(x_3)\bullet\varphi(f_4)(x_4)$$

So get:

$$Z(u1)\approx\varphi(1)(1u_1)=\varphi(1)\left(f_1(u_1),f_2(u_1),f_3(u_1),f_4(u_1)\right)$$
$$=\prod\left[\varphi(f_1)\left(f_1(u_1)\right),\varphi(f_2)\left(f_2(u_1)\right),\varphi(f_3)\left(f_3(u_1)\right),\varphi(f_4)\left(f_4(u_1)\right)\right]$$
$$=\varphi(f_1)\left(f_1(u_1)\right)\bullet\varphi(f_2)\left(f_2(u_1)\right)\bullet\varphi(f_3)\left(f_3(u_1)\right)\bullet\varphi(f_4)\left(f_4(u_1)\right)$$
$$=3\times4\times3\times5=180$$

Similarly, $Z(u_2)$=192 and $Z(u_3)$=180, which can be used as the model case of M_7 as the last reuse.

VII. SUMMARY

It is a general method. How to design the reuse system used by the designers in the enterprise according to the functional characteristics of the model resources, combine the existing resources, and realize the automation design in the enterprise application is the focus of the later work.

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