3D CAD Model Representation and Retrieval Based on Hierarchical Graph

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Abstract**—Due to 3D CAD models are often characterized with complicated geometry and topology, how to help the designers quickly and accurately find the object models from the database containing massive amount of models using the relatively rough query instance is still a big challenge. In this paper, a novel representation of 3D CAD models using hierarchical graph (HG) is proposed. The model descriptors are divided into shape feature descriptors and topology relationship descriptors. These two descriptors can be extracted from HG. In this way, coarse-grained and fine-grained 3D CAD model retrieval are implemented. On this basis, a 3D model retrieval method is proposed based on genetic algorithm (GA) and ant colony optimization (ACO), which are employed to detect the common sub-graph in the corresponding the hierarchical graphs of different models. This method can improve the accuracy and efficiency of 3D CAD model retrieval. Based on the above researches, a 3D model retrieval system HUST-CMRS is developed. Our experimental results show that, the algorithm proposed in this paper can implement multi-mode indexing and satisfy personalized need of users.**

Index Terms**—3D CAD models representation, 3D CAD models retrieval, hierarchical graph, genetic algorithm, ant colony optimization**

I. INTRODUCTION

With the rapid increase in the number of available 3D models, the ability to accurately and effectively search for 3D model is crucial for many applications such as industrial design, engineering, and manufacturing area[1]. According to one estimate, nearly 80% design work of new product is based on reuse of existing examples and design knowledge [2]. Therefore, it becomes a problem that how to search an existing model as reference value for a new design. 3D CAD model retrieval has received extensive attention in the academic community.

3D CAD model retrieval studies focus on model shape matching. Since direct comparison of 3D shape is not convenient, some intermediate shape description data generated from original models are usually adopted for the comparison purpose. Most shape description methods developed in computer graphics community can be classified into histogram-based, transform-based, view-based, graph-based and the combinations of the above [3]. This paper mainly researches graph-based 3D CAD model retrieval. A novel representation of 3D CAD models using hierarchical graph (HG) is proposed. HG contains topology relationship and the shape feature information in high-level. In this way, coarse-grained and fine-grained 3D CAD model retrieval is implemented. On this basis, a 3D model retrieval method is proposed based on genetic algorithm (GA) and ant colony optimization (ACO). GA is adopted to obtain suboptimal solutions. The pheromone of ACO is initialized according to the suboptimal solutions, and then a further search among the suboptimal solutions is operated for better solution. And finally, the optimal solutions of the product design can be searched. This method can improve the accuracy and efficiency of 3D CAD model retrieval.

II. RELATED WORK

Graph-based descriptors are more suitable for the representations of shapes in various scopes and support more precise shape matching. Zhang et al. [4] proposed an approach for 3D prismatic model retrieval by geodesic connected graph. The geodesic-connected graph is a shape descriptor of local features on model surfaces, and can be used in several CAD model analysis tasks, manufacturing feature recognition and model retrieval. Cicirello and Regli [5] examined issues pertaining to graph-based data structures and proposed a model dependency graph (MDG) approach to determine the machining features. Li et al. [6] described CAD models and their decomposed components with feature dependency directed acyclic graph (FDAG) for reusable model retrieval, which can capture some related engineering knowledge besides their shapes. Benkuider et al. [7] present the global information extracted from the image Bidimensinal Empirical Mode Decomposition (BEMD) together with the Generalized Gamma (GG) Density. In this paper, the feature dependency graph (FDG) is utilized to represent 3D CAD models, which not only can represent information in different levels but also their relationship.

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For graph-based model descriptions, graph matching and sub-graph matching are the major means for realizing the model retrieval. The similar subparts are obtained according to the principle that the corresponding graphs of two models have common sub-graphs if the models have similar sub-parts. The Ant Colony Optimization ACO algorithm to solve the problem of the common sub-graphs was proposed by Fenet in 2003 [8]. Recently, the meta-heuristic methods such as genetic algorithm (GA) [9] and particle swarm optimization (PSO) [10] also have been extensively applied in 3D CAD model retrieval field in order to deal with dynamic search optimization problems. Indeed, these methods allow a more accurate formulation of the problem and the attainment of results in reasonable computation times. On the other hand, special attention must be paid to the choice of the appropriate method, depending on the particular features of the problem at hand [11].

III. 3D CAD MODEL REPRESENTATION METHOD BASED ON REPRESENTATION

A. Hierarchical Graph

A novel representation of 3D CAD models by hierarchical graph (HG) is proposed. HG contains the model information described by feature dependency graph (FDG) [12] and property adjacency graph (PAG) [13]. The model descriptors which can be extracted from HG, are divided into shape feature descriptors and topology relationship descriptors. The shape feature descriptors, which are corresponding to coarse-grained retrieval, describe the overall shape of models. And the topology relationship descriptors, which are corresponding to fine-grained retrieval, describe the local details of models. These two-level model descriptors are able to increase the efficiency of 3D CAD model retrieval. HG-based 3D CAD model retrieval, always determines the overall trend of the matching by coarse-level information, assisted by fine-level information to adjust local details of the matching. This matching program is in line with human cognitive processes, but also to ensure that the model matching consistency among multiple levels.

This paper presents a method that achieving multi-level descriptions of 3D CAD model by constructing HG. HG contains the model information described by FDG and PAG. Fig. 1 is a CAD modeling. Solid arrow refers to one feature, hollow arrow refers to one face of one feature. Fig. 2 is the hierarchical graph based on the FDG and AAG.

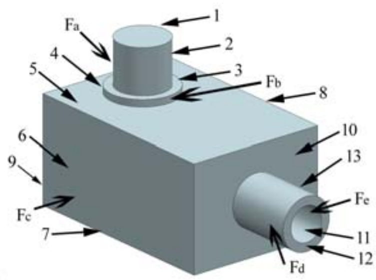


Figure 1. A CAD modeling

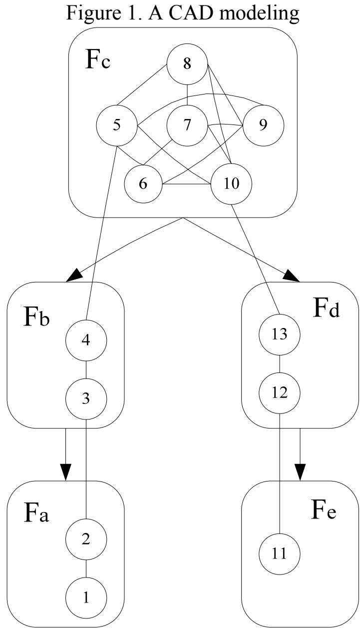


Figure 2. Hierarchical graph

Definition 1 HG is a tree represented by the five-tuple: $HG=(V,E,\eta,\alpha,\beta)$, where V is the node set of HG, each node corresponds to one feature of CAD modeling and contains its own set of entities (e.g. shape, parameters and constraints), and all model constraint instances; $E\subset V\times V$ is edge set of HG, each edge represents a dependency relation, and is oriented towards the dependent feature or model constraint; $\eta:V\rightarrow PAG$ is a mapping from node set to PAG set, for each node $v\in V$, and $\eta(v)\in PAG$, it means v corresponds to one PAG; $\alpha:V\rightarrow W_V$ is a mapping from node set to attribute set, W_v is attribute set of nodes; $\beta:E\rightarrow W_E$ is a mapping from edge set to attribute set, W_v is attribute set of edges.

HG is different from the general diagram. There are two types of nodes in HG: nodes in the PAG and nodes corresponding to features for hierarchical graph itself. Accordingly, there are edges belonging to internal PAG and edges corresponding to HG. In the retrieval process, not only to consider their matching nodes and edges of the hierarchical graph itself, but also to consider matching nodes and edges of the internal PAG. They are mutual connected and influenced. In this paper, the model descriptors are divided into shape feature descriptors and topology relationship descriptors. The shape feature descriptors can extract the feature information for hierarchical graph itself, as shown in TABLE I. The topology relationship descriptors can extract the connection relations and the adjacency relations among the point, line, surface and ring of CAD model, as shown in TABLE II. The matching of HG takes coarse-level information as dominant information as dominant information to determine the overall matching trend throughout the process, and takes fine-level information as assistant to adjust local details of the matching process.

TABLE 1.
SHAPE FEATURE INFORMATION

Number	Property	Explanation
a	Type	Types of features in HG. The types of features are divides into general feature and application feature.
b	Dependency relation	Dependency relations between features. Dependency relations include: direct dependency, indirect dependency and independent relation.
c	Level	Features belong to levels in HG.

TABLE II.
TOPOLOGY RELATIONSHIP INFORMATION

Number	Property	Explanation
a	Geometry type of face	plane
		cylindrical surface
		conical surface
		spherical surface
		others
b	Convexity and concavity of face	plane
		convex face
		concave face
		others
c	Geometry type of outer edge	straight edge
		arc edge
		others
d	Convexity and concavity of outer edge	straight edge
		convex edge
		concave edge
		others
e	Start angle and end angle coding of outer edge	$0^{\circ} < \alpha < 90^{\circ}$
		$\alpha = 90^{\circ}$
		$90^{\circ} < \alpha < 180^{\circ}$
		$\alpha = 180^{\circ}$
		$180^{\circ} < \alpha < 270^{\circ}$
		$\alpha = 270^{\circ}$
		$270^{\circ} < \alpha < 360^{\circ}$
		$\alpha = 0^{\circ}$

B. Matching Principles of HG

The matching principles of HG are as follows:

1. Matching principle for those are same level: the matching of HG only considers whether the nodes are comparable from the same level and those nodes from different level, which represent the shape information of different sizes of CAD models, even through the corresponding local area may be similar, still not comparable. For example, the shapes of man's leg and toe are columnar, but they are in different sizes, so they are not comparable.

2. Interaction principle between nodes: in HG, coarse grain represents the overall shape of the model, to describe the main model information; fine grain represents more detail of the local information of the model. So maximizing the coarse-grained information is primary prerequisite of matching process. When several matching schemes exist in coarse-grained nodes and users need the more accurate modeling, then the matching schemes of fine-grained nodes would be taken into consideration. Therefore, the model matching should follow the following these principles: (1) Matching between fine-grained nodes is affected by matching of coarse-grained nodes. (2) Matching between coarse-grained nodes ignore the effect from matching conditions of their child nodes; (3) Matching between fine-grained nodes is affected by matching conditions of its child nodes; (4) In HG, the edges recorded dependencies between nodes of adjacent layers. Only if the edge is comparable, the matching between nodes of adjacent levels may be mutually consistent and not conflict.

3. Topology matching principle: during fine-grained retrieval, CAD model matching focuses on the topology information of models. Topology information is to describe the connection relations and the adjacency relations among points, lines, surfaces and rings of CAD model. When the two compared nodes have similar overall shape and size, then the retrieval would determine by topology matching, avoiding geometry interference to matching of the model.

In this paper, the CAD model is represented by HG, therefore the problem of 3D CAD model retrieval is converted into the problem of detecting the maximum group of HG. The definition of the sub-maximum group and the maximum group is given as follows:

Definition 2 sub-maximum groups: The sub-maximum of FDG refers to a node set, in which every two nodes share an edge. If a group is not contained by any other group, namely it is not other any group's real subset, then this group is called the sub-maximum group.

Definition 3 maximum groups: The sub-maximum group containing the most nodes is called maximum of FDG.

IV. 3D CAD MODEL RETRIEVAL BASED ON GA-ACO

The ACO algorithm to solve the problem of the maximum group was proposed by Fenet in 2003. At first, the pheromone model based on the node is constructed. Then, the ACO algorithm is employed to search the maximum group by using global pheromone updating and local searching strategy. But the method is vulnerable to fall into premature convergence, and it is difficult to get detail characteristics of CAD modeling. In this paper, a combinatorial GA and ACO method to solve the problem of the maximum group is proposed. The hybrid approach is accomplished in convergence efficiency and solution precision. The CAD modeling searched contains detail characteristics and satisfies user's personalized need.

Because HG-based 3D CAD model retrieval is divided into coarse-grained retrieval and fine-grained retrieval, we choose retrieval method according to the user's needs. If users need the overall shape of CAD model, the local details of the model can be ignored, the coarse-grained retrieval is used. If users need the local details of CAD model, the fine-grained retrieval is used. In this paper, both of coarse-grained retrieval and fine-grained retrieval adopt GA-ACO method to detect common sub-graph. The fine-grained retrieval result is found by the further cycling based on coarse grain retrieval. Here is an example using coarse-grained retrieval to introduce 3D CAD model retrieval based on GA-ACO method.

C. GA for Suboptimal Solutions

GA is an optimization method based on the process of natural selection in biological systems. GA works with a population of possible solutions that can be used for searching and optimization [14]. In this paper, GA is applied with meta-heuristics to obtain the suboptimal solutions. The pheromone of ACO is initialized according to the suboptimal solutions, and then a further search among the suboptimal solutions is operated for better solution.

(1) Initial population: The designers provide the features of CAD modeling $F=\{F_1,F_2,...F_n\}$.

(2) Coding: To apply GA to search for the suboptimal solutions, firstly, we need a coding scheme to encode all the parameters used to generate suboptimal solutions. Usually a binary representation proposed by Holland is used to encode the parameters to be optimized. A CAD modeling is composed of several features F_i. Each feature contains several feature properties F_{ij}. For example, a rectangle feature can add a variety of additional characteristics, such as the rectangular with fillet, the rectangular with chamfer. In this paper, the features F_i are encoded by binary representation. If A CAD model is composed of k characters, one of which is F_k. An additional characteristic is added into F_i, which is expressed as F_{i2}. Then its corresponding code is 0010. On a CAD model can generate multiple chromosome coding chromosomes. Fig. 3 shows one of chromosome.

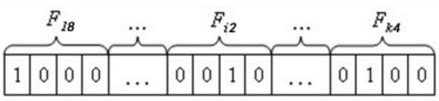


Figure 3. Illustration of one chromosome

(3) Fitness function: A CAD modeling is made up of several features. The dependency relations exist between these features. If feature F_1 depends on feature F_2, then F_2 is father feature, F_1 is child feature. The father feature drives the child feature. In order to improve the algorithm convergence speed, the individuality including the father feature is given the larger fitness value, which is the more easily selected. According to the father-child relationship between features, the fitness values of features are given as *$\{T_i\}(i=1,2,...n)$*, the ancestor feature is given the largest fitness value as $T_{\max}=\{T_q;T_q\geq T_i, i=1,2,...,n\}$, the leaf features are the smallest fitness value as $T_{\min}=\{T_p;T_p\leq T_i, i=1,2,...,n\}$. The fitness values of the leaf features are set to1. The fitness values of the father features of the leaf features are set to 2. And so on, it should plus 1 when the fitness value of features on the higher level. To standardize the fitness values of features by [0,1] as shown in Eq. (2) :

$$S_{(T_i)}=\frac{(T_i-T_{\min})}{(T_{\max}-T_{\min})} \tag{1}$$

Fitness function as shown in Eq. (3):

$$\overline{S}_{(T_i)}=\sum_{i=1}^{n} S_{(T_i)}/n \tag{2}$$

Where i and n are positive integers, $1\leq i\leq n$ 。

(4) Select: roulette.

(5)Crossover: The crossover operator is a one-point crossover operator. A crossover point is randomly chosen. A pair of chromosomes with high fitness values is chosen. The first part of parent P1 is copied into the offspring. The rest of the chromosome is filled by reading the information of the second parent P2. The jobs that are not already in the offspring are copied, preserving the permutation property. See Fig. 4.

P_1 F_1 F_2 F_3 F_4 F_5 F_6 F_7

P_2 F_1 F_4 F_3 F_7 F_5 F_6 F_2

O_1 F_1 F_2 F_3 F_4 F_7 F_5 F_6

Figure 4. Crossover operator

(6)Mutation: the mutation operator permutes two property features randomly chosen in the chromosome. This mutation is done under a probability P_m. In this paper, we chose $P_m = 0.25$. See Fig. 5.

F_1 F_2 F_3 F_4 F_5 F_6 F_7

F_1 F_5 F_3 F_4 F_2 F_6 F_7

Figure.5. Mutation operator

D. ACO for the Optimal Solutions

ACO is an algorithm, which simulates the behaviors of natural ant colonies. The algorithm uses a set of agents which cooperate for the research of new solutions acting simultaneously[15]. Suboptimal solutions $F'=\{F_1',F_2',...,F_n'\}$ are obtained by GA. The pheromone of ACO is initialized according to the suboptimal solutions, and then a further search among the suboptimal solutions is operated for the optimal solutions. In this paper, a pheromone model is constructed based on the node, the pheromone model is represented as $\Phi(\tau_1,\tau_2,...,\tau_n)$, where $n=|V|$, τ_i is the pheromone concentration value in nodes. The larger its value means that the higher probability that the node is selected. τ_0 represents the pheromone initialization value of the nodes selected by GA, τ_0' represents the pheromone initialization value of the nodes unselected by GA, and $\tau_0>\tau_0'$.

For a certain ant k placed in a node with a larger pheromone initialization value. The ant k moves towards a new node, which has dependency relations with the current node. The current node set S_c expands unceasingly, until becomes a sub-maximum group. The probability of this ant choosing the next trail leading to another node is given by

$$p(v_i) = \frac{(\tau_i)^\alpha}{\sum_{v_j \in V} (\tau_j)^\alpha} \tag{3}$$

Where α is the pheromone updating parameter, ruling its decay and its reinforcement.

Local updating is executed when any ant has completed to structure a sub-maximum group S_c. It is performed using the function:

$$\tau(v_i) = \begin{cases} \tau(v_i) - \tau'_0 \bullet \frac{|s_b|}{|s_c|}, v_i \in S_c \\ \tau(v_i), otherwise \end{cases} \tag{4}$$

Where S_b represents the initialized maximum group, which is given by the obtained suboptimal solutions through GA. The local updating of the pheromone is applied to eliminate unpromising search directions and dynamically creates new candidate solutions. This mechanism is used to prevent premature convergence and simulate the natural phenomenon of evaporation, thus also indirectly guides subsequent ants to choose the unselected path.

The optimal solution S_{op} in the current iteration is obtained by S_c when all ants have completes an entire tour for exploration. S_{op} is used to judge S_b whether need to be updated. If S_b needs to be updated, it is performed using the function:

$$\tau(v_i) = (1-\rho)\tau(v_i) + \omega\Delta\tau(v_i) \tag{5}$$

$$\Delta\tau(v_i) = \begin{cases} \frac{1}{|S_b| - |S_{op}|}, v_i \in S_{op} \\ 0, otherwise \end{cases} \tag{6}$$

Where, the parameter ρ is the coefficient represents the evaporation rate of the trail. ω is a constant, which means that it will add up ω times of pheromone in nodes with the current optimal solutions. The global updating encourages the exploitation of the most promising solutions, namely the overall less costly solutions. The iterations continue after the global updating is completed, until the algorithm finds the optimal solutions or reaches total iteration number.

V. System Implementation

In this section, we developed a 3D CAD model retrieval prototype system-HUST-CMRS. HUST-CMRS supports the global retrieval based on HG, and contains two retrieval methods of coarse-grained and fine-grained. It also can help users find the right model quickly and easily. The system can shorten product design cycles, accelerate new product development and improve product quality.

A. Overall Framework of HUST-CMRS

HUST-CMRS is built on the following software development environment: operating system platform: Windows 7; programming language: Microsoft Visual C++7.l; database server: SQLServer2008, geometry engine: ACIS13.0; application frameworks: MFC and HOOPS11.0 .

The overall framework of HUST-CMRS is shown in Fig. 6. The system is designed to help designers find the model in the product design process quickly and easily, inspire the design ideas and accelerate the design process.

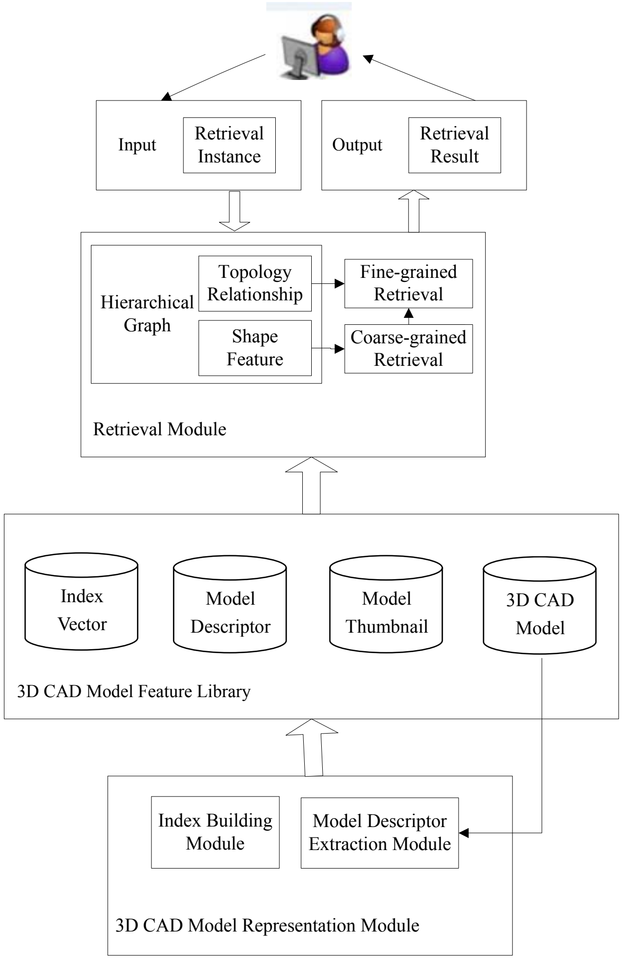


Figure 6. Overall framework of HUST-CMRS

The menu of HUST-CMRS system has nine specified menu, which are: File, Edit, Input, Search, Operate, Library, Tool and Help. More specifically, File menu contains operations such as new model, new project, open, save, save as, close, import, export, etc; and operations such as cut, copy, paste are included in to Edit menu; View is mainly for setting view options of model, like perspective view and front view and so on. Input provides users with inputting retrieval instance as well. And for Search, it contains two retrieval mode： grain-based global retrieval and coarse-grain-based global retrieval, hence, users can select which retrieval is more suitable to their needs; Operate contains CAD operations such as translation, rotation and zoom, etc; Library includes some basic operations on database, such as browse, manage and update the database; Tool contains operations such as browse model topology, generate XML model information and set system parameters. Finally, the Help menu is the instruction about HUST-CMRS and help document.

3D CAD model retrieval method based on GA-ACO has been verified by National Design Repository (NDR), which is developed by Bespalov. NDR categorizes the most of typical CAD models, more than 700 representative CAD model is included. Users only need to input simple retrieval instant, 3D CAD models which similar to the overall shape and contains more details information can be found. Users only need to input simple retrieval instant, and then a 3D CAD model which similar to the overall shape and contains more details information can be found. The retrieval instance is inputted by user shows in Fig. 7.

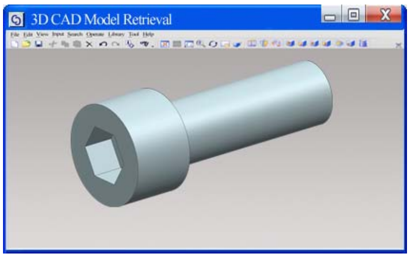


Figure 7. Retrieval instance

When users submit the retrieval instance and select the retrieval method in the retrieval interface, HUST-CMRS will automatically build up the model descriptors of retrieval instance and implement filtering and matching. The retrieval interface finally displays retrieval results that satisfy user's personalized need in descending order. As shown in Fig. 8, the figure shows five retrieved CAD models, which are in descending order.

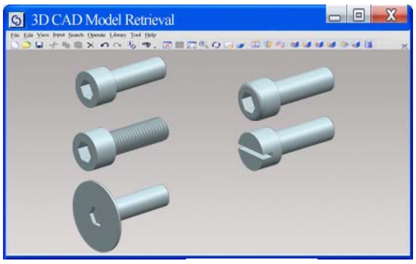


Figure 8. Retrieval result

B. Experimental Example and Analysis

Parameter initialization of GA- ACO: α =1， ρ =0.90， ω =2， τ_0 =0.02， τ_0' =0.01， total iteration number *N*= 2000, total ant number *M*=10.

Test results of HUST-CMRS are shown in TABLE III and TABLE IV. TABLE III shows the coarse-grain-based global retrieval method. TABLE IV shows the fine-grain-based global retrieval pattern. In the figure, what sitting on left column is the retrieval mode; the middle one is a retrieval instance inputted by user; the right one is CAD models retrieved from NDR library. The retrieval only gives the four highest similarity retrieval results and displays them in descending order according to similarity.

TABLE III.
GLOBAL RETRIEVAL MODE EXAMPLE BASED ON COARSE GRAIN

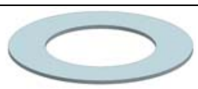
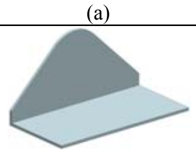
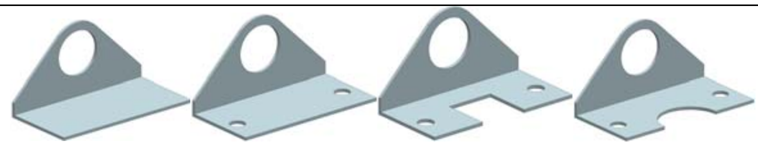
Retrieval mode	Retrieval instance	Retrieval result
Coarse-grain retrieval	 (a)	
	 (b)	

TABLE III shows that, in coarse-grain-based global retrieval mode, users only need to input simple retrieval instance, and then 3D CAD models which are similar to the overall shape of the instance and more details information can be found. The overall shape of first retrieval result is nearly consistent with the input retrieval instance, so it is arranged at the forefront. On the contrary, the overall shape of the fourth retrieval result is totally different from the retrieval instance, so it is placed at the bottom.

TABLE IV.
GLOBAL RETRIEVAL MODE EXAMPLE BASED ON FINE GRAIN

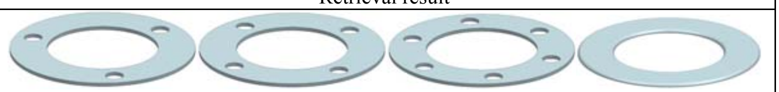
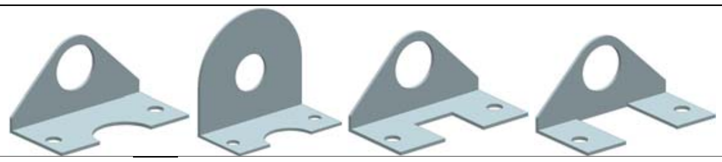
Retrieval mode	Retrieval instance	Retrieval result
Fine-grain retrieval	 (a)	
	 (b)	

TABLE IV shows that, in the fine-grain-based global retrieval mode, only the results of CAD model with overall shape and detail information which are similar to the retrieval instance would be selected. In TABLE IV, the similarity of the CAD models in the first column and retrieval instance is 100%. They are totally the same to retrieval instance in overall shape and detail information. And the model afterward is slightly similar to the retrieval instance in overall shape but not consistent in detail information.

On purpose a GA-ACO, suitably adapted in order to improve convergence efficiency and solution precision, has been implemented. In order to compare the performance of GA-ACO and common GA, a test was on them to get a recall ratio-precision ratio curve. Figure 9 clearly indicates that the performance of GA-ACO is significantly higher than common GA.

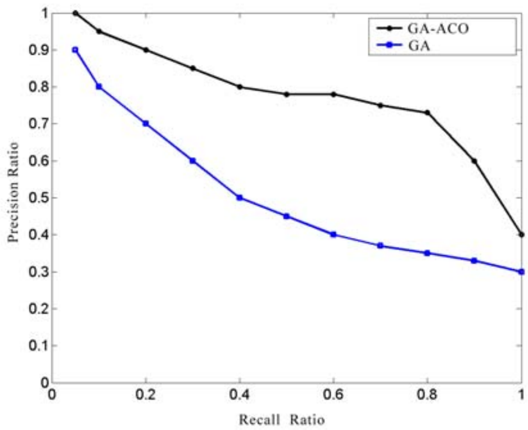


Figure 9. Recall ratio-precision ratio curve

IV. CONCLUSION

In this paper, 3D CAD model representation and retrieval method based on HG is proposed. At first, a CAD model is represented by HG. Then, the combinatorial GA and ACO are employed to detect the maximum group of HG. At last, based on the maximum group, the desired CAD modeling is obtained quickly. Based on the above researches, a 3D model retrieval system HUST-CMRS is developed. Our experimental results show that, the method proposed in this paper is accomplished in convergence efficiency and solution precision, and the obtained CAD modeling satisfies user's personalized need.

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