Assembly Model Retrieval Combining Parts-level and Global-level Parameter Descriptions

Shungang Hua[1], Xinbao Wang[2], Shouguang Xie[3], Dan Feng[4] and Hengzhen Dai[5]

[1]Dalian University of Technology, hsgang02@dlut.edu.cn
[2]Dalian University of Technology, wangxinbao@mail.dlut.edu.cn
[3]Dalian University of Technology, xsg_1001@mail.dlut.edu.cn
[4]Dalian University of Technology, fengd@mail.dlut.edu.cn
[5]Dalian University of Technology, hengzhendai@163.com

Corresponding author: Hengzhen Dai, hengzhendai@163.com

Abstract. There exist multiple storage formats of CAD assembly models. Some of them contain geometric and shape information only but lack assembly relationship and constraint information, such as standard exchange format IGES and STEP files. To apply to assembly models in various formats, a retrieval method using CAD model parameters is proposed. Firstly, the geometric parameters and attribute data of part models in an assembly are directly obtained from the CAD system, and parameter vectors are created to represent parts by normalization. The parameter vectors of all parts in the assembly are synthesized into a set as a descriptor of the assembly at the parts-level. The Modified Hausdorff Distance is used to measure the dissimilarity between two assemblies through many-to-many parts matching. Secondly, the global parameters of the assembly model are gotten and normalized, and a vector is generated as a descriptor at the global-level. The Manhattan Distance is used to calculate the dissimilarity. Finally, the weighted dissimilarities of the parts-level and the global-level are added together for the retrieval of assembly models. Our method supports both the global retrieval and the local retrieval. The experimental results show that the proposed method is fast and efficient, suitable for CAD models of multiple format files, and can obtain satisfactory results.

Keywords: assembly model retrieval, CAD model parameters, parts-level and global-level descriptions, dissimilarity, Modified Hausdorff Distance.
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1 INTRODUCTION

The digital design and manufacturing technology has been widely used in various fields of engineering design, and enterprises have accumulated a large number of CAD models. In the fierce market competition, enterprises need to make continuous innovation to produce better products. Model reuse is one of the significant and effective means during new product development. Engineers can design new products by referring to or modifying existing models that contain a lot of design knowledge and ideas. In order to realize model reuse, the effective CAD model retrieval technology is essential. Through model retrieval, designers can find out their desired models and combine their design ideas and experience to achieve a better innovative design. The CAD model retrieval has become an important research content in the field of intelligent design and manufacturing.

The CAD model retrieval is classified into the part retrieval and the assembly retrieval. There are already a large number of retrieval methods for part models. Using these methods can obtain satisfactory results and promote the reuse of part models. However, the product generally exists as the assembly. Therefore, the retrieval of assembly models has more practical significance for the product design. The existing assembly retrieval methods could be roughly divided into two categories: topology-based method and shape-based method [13].

The topology-based method employs the topological information, namely the relationship among part models, within the assembly for retrieval. Deshmukh et al. [3] constructed a graph structure based on the matching requirements between parts, used a pruning and depth-first algorithm to carry out the graph matching, and then retrieved assembly models. Chen et al. [2] used topological structure, assembling semantics, geometric information and other useful information in the assembly to form a multi-level assembly descriptor, and implemented rapid retrieval by utilizing the indexing mechanism. Lupinetti et al. have done a lot of meaningful works. They detected and analyzed the interferences between parts to compute their degrees of freedom and kinematic pairs [12], exploited the information on components' shape to extract contact relationships from the STEP descriptions [16] and detected regular patterns of repeated elements [9] for the retrieval of CAD assembly models. They also characterized CAD models to retrieve globally and partially similar assemblies according to multiple user-specified search criteria [10, 11]. Han et al. [5] extracted attribute information, connection relation and assembly constraint information to construct attribute adjacency graph, calculated the similarity between assembly models in the database by utilizing the weighted bipartite graph and Kuhn-Munkres algorithm [8, 14]. And then a spectral clustering algorithm is used to divide the similarity into several clusters, where the indexing mechanism is adopted to speed up the retrieval. For the topology-based method, in some cases, the desired topology information is unavailable from assembly models. Even if there exist assembly constraints within CAD assembly models, a complex reasoning process is required to obtain high-level information and this reasoning process could go wrong.

The shape-based method takes every constituent part model within an assembly into consideration, and utilizes shape descriptors, such as shape distributions [15] and Light Field Descriptors [1], to gain the shape information of parts. Hu et al. [6] proposed a lightweight assembly retrieval method, extended the original vector space model, and worked out the similarity between assemblies by using a typical part-based matching and greedy algorithm. Wang et al. [17] represented the assembly model as a point set by using shape distribution, and employed Earth Mover's Distance algorithm to evaluate the dissimilarity between assemblies. Based on the literature [17], a different assembly matching method was proposed by Zhang et al. [18], using the Modified Hausdorff Distance to calculate the difference among assemblies. The method of Kim et al. [7] calculated the part-shape dissimilarities and assembly relation dissimilarities independently to generate the overall dissimilarities of assembly model. However, the shape-based method requires point sampling on the surface of the parts and statistical analysis. It is time-consuming.

In this study, we directly employ CAD model parameters to retrieve the assembly model and the Modified Hausdorff Distance (MHD) metric is utilized to match parts and compute the dissimilarity. The parameter descriptions of both the parts-level and the global-level are combined to improve the precision of retrieval.

Our main contributions are as follows:

- A retrieval method combining parts- and global-level parameters is proposed for CAD assembly models in multiple file formats.

- The parameter vector with invariance to scale and orientation is generated by normalizing and sorting parameters that have the same attribute.
- The global retrieval and local retrieval could be realized by our method to meet diverse demands.

This paper is organized as follows. Section 2 explains the generation of parts-level parameter vector in detail. Section 3 gives the example of assembly descriptor at the parts-level. Section 4 introduces the calculation method of the dissimilarity at the parts-level. Section 5 expounds on the generation of the descriptor and calculation method of the dissimilarity at the global-level. Following this section, the experiments and discussions are presented in Section 6. Finally, we make a summary of our method.

2 CONSTRUCTING PARAMETER VECTOR OF PARTS

An assembly model is composed of several parts. The part model contains much useful information, such as geometric parameters, attribute data. These parameters can express the shape and characteristics of parts. In this study, we first built a vector with these parameters for a part model, and integrate the vectors of all parts to construct a set to describe an assembly model at the parts-level.

As we know, the bounding box of parts can indicate its dimensions in three orthogonal axes. If the shape of parts is different, the moment of inertia is also different. The product of inertia represents the symmetry information of parts. Vertices, edges, faces, and loops are basic components of parts; their number could represent the feature of parts. Volume and surface area can express the overall size of parts. For similar parts, the maximum surface area may be close. Therefore, we choose the above parameters to describe the part model in this work. However, the scale, direction, size and reference coordinate of the model may be different due to the different modeling environment, which makes it difficult to match between models. In order to realize the scale-invariant and orientation-invariant model retrieval, these parameters should be normalized. The detailed explanations are described as follows.

We define the dimensions of bounding box of parts along the x , y and z axes as x_{box} , y_{box} , and z_{box} , respectively, then get $\gamma_1 = x_{box} + y_{box} + z_{box}$ to normalize the dimensions as x_{box}/γ_1 , y_{box}/γ_1 , z_{box}/γ_1 and assign to a_1 , a_2 , a_3 in ascending order.

Let I_{xx} , I_{yy} , I_{zz} denote the moment of inertia of parts about x , y , z axes, and I_{xy} , I_{xz} , I_{yz} represent the product of inertia of parts relative to xy , xz , yz rectangular axes, respectively. These six parameters are gotten at the center of mass of the part model and related to x , y , and z axes of the reference plane. If the coordinate system is different, their sequence would be disparate. In order to realize the orientation-invariant retrieval, we rank and reassign values of I_{xx} , I_{yy} , and I_{zz} in ascending order, and adjust the sequence of I_{xy} , I_{xz} , and I_{yz} accordingly.

Then, we add the moment of inertia like this $\gamma_2 = I_{xx} + I_{yy} + I_{zz}$, and normalize as $a_4 = I_{xx}/\gamma_2$, $a_5 = I_{yy}/\gamma_2$, and $a_6 = I_{zz}/\gamma_2$. Also, for the product of inertia, $\gamma_3 = |I_{xy}| + |I_{xz}| + |I_{yz}|$, and $a_7 = |I_{xy}|/\gamma_3$, $a_8 = |I_{xz}|/\gamma_3$, $a_9 = |I_{yz}|/\gamma_3$. Specifically, if $\gamma_3 = 0$, we set $a_7 = a_8 = a_9 = 0$.

Let N_{face} , N_{edge} , N_{vertex} , and N_{loop} be the number of faces, edges, vertices, and loops of parts, respectively. We sum them with the formula $\gamma_4 = N_{face} + N_{edge} + N_{vertex} + N_{loop}$, and normalize them as $a_{10} = N_{face}/\gamma_4$, $a_{11} = N_{edge}/\gamma_4$, $a_{12} = N_{vertex}/\gamma_4$, and $a_{13} = N_{loop}/\gamma_4$.

v and s_{all} are the volume and surface area of parts. The volume and surface area of the bounding box are $\gamma_5 = x_{box} \cdot y_{box} \cdot z_{box}$ and $\gamma_6 = 2\ x_{box} \cdot y_{box} + x_{box} \cdot z_{box} + y_{box} \cdot z_{box}$, respectively. We can gain $a_{14} = v/\gamma_5$ and $a_{15} = s_{all}/\gamma_6$, where a_{14} represents the proportion of the volume of parts to that of its bounding box, and a_{15} indicates the proportion of the surface area.

$D_{\min}$ is the shortest distance from the center of mass of parts to its surface. If the center of mass is inside the parts, $D_{\min}$ is positive, otherwise, it is negative. Then we define $a_{16} = D_{\min}/x_{box}$.

Suppose $s_{\max}$ be the area of the largest surface of parts, we can get $a_{17} = s_{\max}/s_{all}$.

Through normalizing and sorting processing above, we can gain CAD model parameters with scale-invariant and orientation-invariant. A vector describing a part model is written as:

$$\boldsymbol{p} = \ a_1, a_2, a_3, a_4, a_5, a_6, a_7, a_8, a_9, a_{10}, a_{11}, a_{12}, a_{13}, a_{14}, a_{15}, a_{16}, a_{17} \tag{2.1}$$

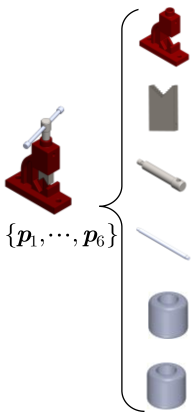
3 ASSEMBLY DESCRIPTION USING PART PARAMETERS

According to the above operation, these parameters are extracted and normalized to form parameter vectors for each part model within an assembly. Then the vectors are combined to generate a vector set of the parts-level to describe the assembly:

$$\boldsymbol{P} = \ \boldsymbol{p}_1, \boldsymbol{p}_2, \boldsymbol{p}_3, \cdots, \boldsymbol{p}_n \tag{3.1}$$

where n denotes the number of parts in an assembly.

An assembly model of pipe vice is shown in Figure 1, which is composed of 6 parts, namely base, vice jaw, tornillo, handle and handle cap. In our study, part model parameters are acquired by SolidWorks API functions. For example, GetPartBox() for the dimensions of the part bounding box, GetEdgeCount() for the number of edges and GetFaceCount() for the number of faces. Then these parameters are normalized to generate 6 vectors associated with these parts. These vectors are integrated into a set to serve as a descriptor $\boldsymbol{P} = \ \boldsymbol{p}_1, \boldsymbol{p}_2, \boldsymbol{p}_3, \boldsymbol{p}_4, \boldsymbol{p}_5, \boldsymbol{p}_6$ for the pipe vice.



$$\boldsymbol{P} = \{\boldsymbol{p}_1, \cdots, \boldsymbol{p}_6\}$$

$$\boldsymbol{p}_1 = (0.15, 0.42, 0.43, 0.20, 0.33, 0.47, 0.58, 0.39, 0.03, 0.18, 0.39, 0.21, 0.22, 0.25, 0.77, -0.09, 0.11)$$

$$\boldsymbol{p}_2 = (0.16, 0.31, 0.53, 0.19, 0.35, 0.46, 0.00, 0.00, 0.00, 0.15, 0.40, 0.26, 0.19, 0.81, 1.16, 0.24, 0.21)$$

$$\boldsymbol{p}_3 = (0.13, 0.13, 0.74, 0.02, 0.49, 0.49, 0.00, 0.00, 0.00, 0.24, 0.24, 0.02, 0.50, 0.46, 0.66, 0.40, 0.58)$$

$$\boldsymbol{p}_4 = (0.05, 0.05, 0.90, 0.01, 0.49, 0.50, 0.00, 0.00, 0.00, 0.28, 0.24, 0.00, 0.48, 0.76, 0.77, 0.50, 0.90)$$

$$\boldsymbol{p}_5 = (0.32, 0.34, 0.34, 0.33, 0.33, 0.34, 0.00, 0.00, 0.00, 0.28, 0.24, 0.00, 0.48, 0.63, 0.88, -0.03, 0.42)$$

$$\boldsymbol{p}_6 = (0.32, 0.34, 0.34, 0.33, 0.33, 0.34, 0.00, 0.00, 0.00, 0.28, 0.24, 0.00, 0.48, 0.63, 0.88, -0.03, 0.42)$$

Figure 1: A pipe vice model and its descriptor.

We take the last part model in Figure 1 as an example to demonstrate the meaning of parameters. Its parameter vector is $\boldsymbol{p}_6$. The first three parameters 0.32, 0.34, 0.34 indicate the dimensions of its bounding box. For the cylinder, two dimensions of the bounding box are identical. And three parameters 0.33, 0.33, 0.34 denote its moment of inertia. The above parameters are scale-invariant and orientation-invariant by normalizing and sorting, and their sum is equal to 1 for the same attribute data. The next three parameters, namely the product of inertia of the handle cap, are equal to 0 due to symmetry. The following parameters 0.28, 0.24, 0 and 0.48 are the number of faces, edges, vertices and loops after normalizing, respectively. The parameters 0.63, 0.88 are the ratios of the parts' volume and surface area to its bounding box's. Because the center of mass is not inside the solid, a_{16} is negative. The last parameter 0.42 declares the largest surface of the parts occupies nearly half of the overall surface.

4 DISSIMILARITY CALCULATION USING THE MODIFIED HAUSDORFF DISTANCE

After describing the assembly model with part parameters, the difference between assembly models can be assessed by comparing their descriptors. However, the number of parts may be disparate for different assemblies, that is, the dimension of the vector sets may be different from each other. Besides, the order of parameter vectors in the descriptor is also random. So, the difference assessment among the assemblies is a typical many-to-many matching problem. Here, we adopt the Modified Hausdorff Distance (MHD) metric for parts matching and the dissimilarity calculation between assemblies.

The Hausdorff Distance is used to measure how far two subsets of a metric space are from each other. It can process information from multiple points to gain similarity between any two sets of points. The MHD metric takes the average distance between two sets of points as the measurement of comparison. It combines the effects of both dissimilar and similar points between two sets [18].

For two assembly models $\boldsymbol{A}$ and $\boldsymbol{B}$, the dissimilarity between them is calculated as follows:

$$\begin{cases} Dissimi_1 = \max(mhd(\boldsymbol{P}_A, \boldsymbol{P}_B), mhd(\boldsymbol{P}_B, \boldsymbol{P}_A)) \\ mhd(\boldsymbol{P}_A, \boldsymbol{P}_B) = \dfrac{1}{m} \sum\limits_{p \in \boldsymbol{P}_A} \min\limits_{q \in \boldsymbol{P}_B} \left\| \boldsymbol{p} - \boldsymbol{q} \right\| \\ mhd(\boldsymbol{P}_B, \boldsymbol{P}_A) = \dfrac{1}{n} \sum\limits_{q \in \boldsymbol{P}_B} \min\limits_{p \in \boldsymbol{P}_A} \left\| \boldsymbol{q} - \boldsymbol{p} \right\| \end{cases} \tag{4.1}$$

where $\boldsymbol{P}_A$, $\boldsymbol{P}_B$ are vector sets associated with assemblies $\boldsymbol{A}$, $\boldsymbol{B}$; m, n are dimensions of $\boldsymbol{P}_A$, $\boldsymbol{P}_B$, and $\boldsymbol{p}$, $\boldsymbol{q}$ are parameter vectors in $\boldsymbol{P}_A$, $\boldsymbol{P}_B$, respectively; $\left\| \boldsymbol{p} - \boldsymbol{q} \right\|$ indicates the distance between $\boldsymbol{p}$ and $\boldsymbol{q}$ by the Manhattan Distance.

For the local retrieval, the query model could be regarded as a subset of the target model to some extent. From this point, only matching the query model to parts of the target model and calculating the distance are enough. For this scenario, the dissimilarity between the query $\boldsymbol{A}$ and the target model $\boldsymbol{B}$ is

$$Dissimi = mhd(\boldsymbol{P}_A, \boldsymbol{P}_B) \tag{4.2}$$

5 ASSEMBLY DESCRIPTOR AND DISSIMILARITY CALCULATION USING GLOBAL-LEVEL PARAMETERS

In addition to describing the assembly at the parts-level, we should also describe it at the global-level to obtain satisfactory search results. In this study, global-level parameters of the assembly model, such as the moment of inertia, the product of inertia, volume and surface area, are selected for this purpose.

Similar to the parts-level, X_{box}, Y_{box}, and Z_{box} are the dimensions of assembly bounding box along X, Y, and Z axes, respectively. After setting $\gamma_7 = X_{box} + Y_{box} + Z_{box}$, we get X_{box}/γ_7, Y_{box}/γ_7, and Z_{box}/γ_7 to assign to b_1, b_2, and b_3 in ascending order.

Let I_{XX}, I_{YY}, I_{ZZ} be the moment of inertia of the assembly with respect to X, Y, Z axes, and I_{XY}, I_{XZ}, I_{YZ} be the product of inertia of the assembly relative to XY, XZ, YZ rectangular axes, respectively. We sort and reassign I_{XX}, I_{YY}, and I_{ZZ} in ascending order, and adjust I_{XY}, I_{XZ}, I_{YZ} accordingly.

Then, we set $\gamma_8 = I_{XX} + I_{YY} + I_{ZZ}$ to calculate $b_4 = I_{XX}/\gamma_8$, $b_5 = I_{YY}/\gamma_8$, and $b_6 = I_{ZZ}/\gamma_8$. Also, $\gamma_9 = |I_{XY}| + |I_{XZ}| + |I_{YZ}|$ to get $b_7 = |I_{XY}|/\gamma_9$, $b_8 = |I_{XZ}|/\gamma_9$, and $b_9 = |I_{YZ}|/\gamma_9$. Likewise, if $\gamma_9 = 0$, then $b_7 = b_8 = b_9 = 0$.

V_{all} is the sum of the volume of all parts within an assembly. The volume of bounding box of an assembly is $\gamma_{10} = X_{box} \cdot Y_{box} \cdot Z_{box}$. Thus, $b_{10} = V_{all}/\gamma_{10}$ indicates the proportion of the volume of the assembly to that of its bounding box.

Usually, the larger part model is dominant for the assembly, and it could make a greater contribution to the dissimilarity. Here, $V_{\max}$ and $S_{\max}$ denote the largest part volume and surface area within an assembly respectively, and S_{all} is the sum of the surface area of all parts. We can get $b_{11} = V_{\max}/V_{all}$ and $b_{12} = S_{\max}/S_{all}$. They represent the proportion of the largest part volume and surface area to the sum of that of all parts, respectively.

Through acquiring and normalizing parameters at the global-level, we could describe an assembly with a vector which can be written as:

$$\boldsymbol{Q} = b_1, b_2, b_3, \cdots, b_{12} \tag{5.1}$$

Some examples of assembly models and their descriptors with global-level parameters are shown in Table 1.

Assembly models	Descriptors	Assembly models	Descriptors
	$\boldsymbol{Q} = (0.21, 0.39, 0.40, 0.21, 0.33, 0.46, 1.00, 0.00, 0.00, 0.23, 0.62, 0.49)$		$\boldsymbol{Q} = (0.21, 0.22, 0.57, 0.11, 0.44, 0.45, 0.01, 0.99, 0.00, 0.07, 0.44, 0.49)$
	$\boldsymbol{Q} = (0.22, 0.39, 0.39, 0.20, 0.33, 0.47, 0.99, 0.01, 0.00, 0.22, 0.71, 0.46)$		$\boldsymbol{Q} = (0.13, 0.23, 0.64, 0.09, 0.44, 0.47, 0.02, 0.98, 0.00, 0.10, 0.44, 0.49)$

Table 1: Assembly models and their descriptors.

It can be seen that similar assemblies have near parameter vectors because of their similar shapes, while the parameter vectors are different obviously among the assemblies belonging to different categories.

After describing the assembly model with global-level parameters, we could compute the dissimilarity between two assemblies at the global-level. The Manhattan Distance is utilized in this study. For two assemblies $\boldsymbol{A}$ and $\boldsymbol{B}$, their distance is denoted as $d_{AB} = \|\boldsymbol{Q}_A - \boldsymbol{Q}_B\|$. Then, their dissimilarity at the global-level is:

$$Dissimi_2 = d_{AB} \tag{5.2}$$

By considering both the parts-level and the global-level, we can get the final dissimilarity between two assemblies as follows:

$$Dissimi = Dissimi_1 + \beta \cdot Dissimi_2 \tag{5.3}$$

where β is the weighted coefficient of dissimilarity for the global-level.

6 EXPERIMENTS AND DISCUSSION

Under Visual Studio 2015 and SolidWorks 2018 environment, an assembly retrieval system combining parts- and global-level CAD parameters was developed. The SolidWorks API is adopted to get CAD parameters by C++ programming. The system runs on a desktop computer with Intel Core i5-6402P 2.80GHz CPU and 8G RAM. It is suitable to the CAD models in multiple file formats, such as "x_t", "IGS", "STEP", "asm" and "sldasm". The display interface of the query and search results is shown in Figure 2. The query model lies in the top-left corner, and on the right side, the top 20 models obtained are arranged in ascending order of dissimilarity values. The smaller the dissimilarity is, the more similar the assembly is to the query model.

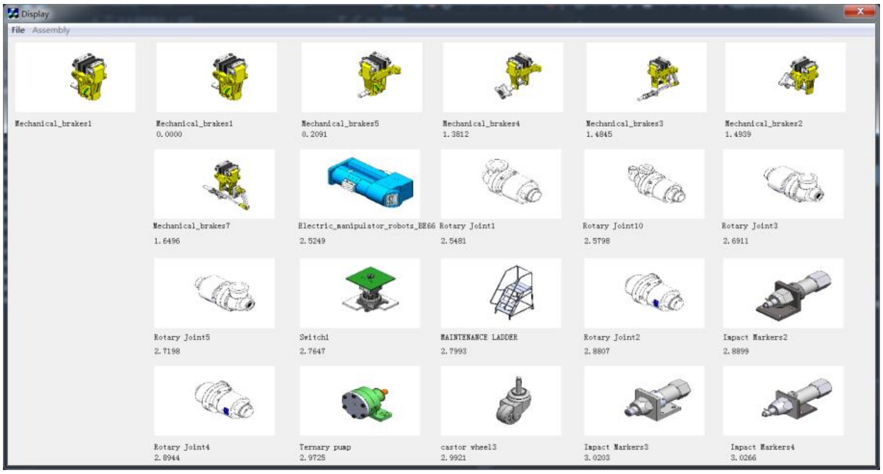


Figure 2: The display interface of the query and search results.

To test the retrieval performance of the proposed method, we collected 421 CAD assembly models (including 5531 parts) and stored them in a model database. Most of them are downloaded from the open Internet model library [4, 19], and a few are drawn by ourselves.

6.1 Assembly Retrieval

The assembly retrieval experiment is conducted with the proposed method. Figure 3 shows some examples of the retrieval. For the query model, eight models with minimum dissimilarity are listed on the right, and the dissimilarity values relative to the query models are shown under their snapshots.

As shown in Figure 3, all of seven models belonging to the same category are listed ahead, which represents our method is able to gain satisfactory results.

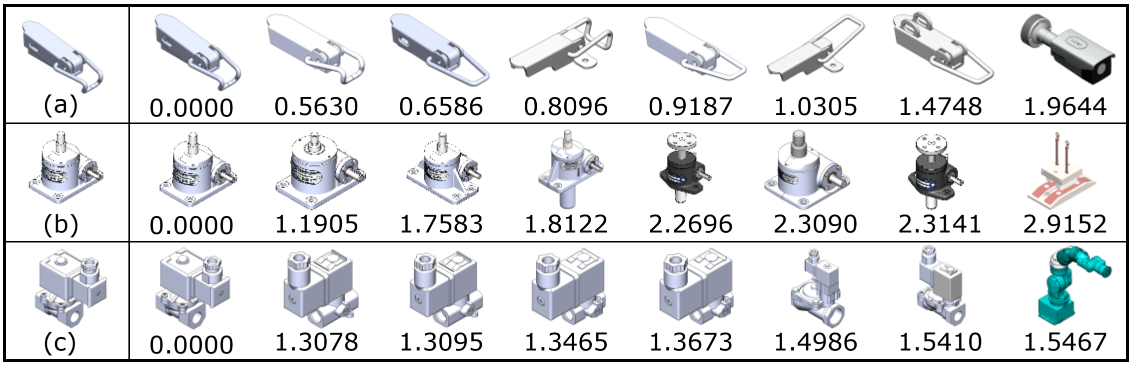


Figure 3: Three queries (left) and corresponding search results (β =0.5).

Through experiments, we found that sometimes a part model is a combination merging several parts in the CAD system. Marching such combination with individual parts of the target assembly could not gain correct results. Additionally, in rare cases, two dissimilar parts may have similar parameter vectors, which would influence results negatively. Therefore, in this study, we combine parts- and global-level parameter descriptions so as to get reasonable search results.

6.2 Local Retrieval

We conduct the local retrieval experiments by MHD metric with Equation (4.2). As shown in Figure 4, for the queries (left), eight models with minimum dissimilarity are listed on the right side. The dissimilarity values relative to the queries are shown under their snapshots.

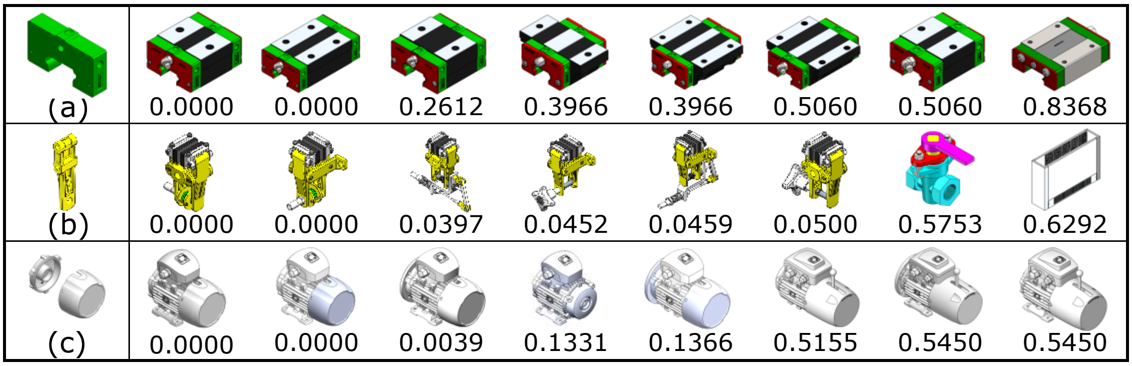


Figure 4: Examples of local retrieval for three queries.

In Figure 4, the query model (a) is a tail cover, which is a single part model involved in the sliding table model. In the search result, the first two sliding table models contain this model, so their dissimilarities are zero, and the rest assemblies contain similar parts. Query (b) consists of several parts from assembly of the mechanical brake. It can be seen that the first six models obtained are all related models, and the 7th model, is not relevant to the query, so the dissimilarity value suddenly increases. Query (c) is two parts (end shield and fan cover) involved in the motor, and models ranking ahead are all of motors in the search result.

With our retrieval system, we could carry out local retrieval by querying a single part model, package parts, or sub-assembly for various requirements and purposes.

6.3 Discussion About Coefficient β

For the retrieval of assembly models, parameters of both the parts-level and the global-level are important. In general, the positions of some parts may be flexible and variable in a certain assembly, so relative positions among parts are likely to be different for the same/similar assembly, which would affect the similarity of the global-level negatively. Taking into consideration that detailed information of the assembly could be obtained from the parts-level, we assign a large weight to the parts-level to ensure a better search result. In this work, we set 1 to weighted coefficient of the parts-level, and take a smaller value to that of the global-level to achieve such purpose.

In order to investigate the impact of the coefficient β, a total of 37 models (see Figure 5), including mechanical brake, clamps vertical, rigid latch and rotary joint, are selected as query inputs to retrieve assemblies from the model database.

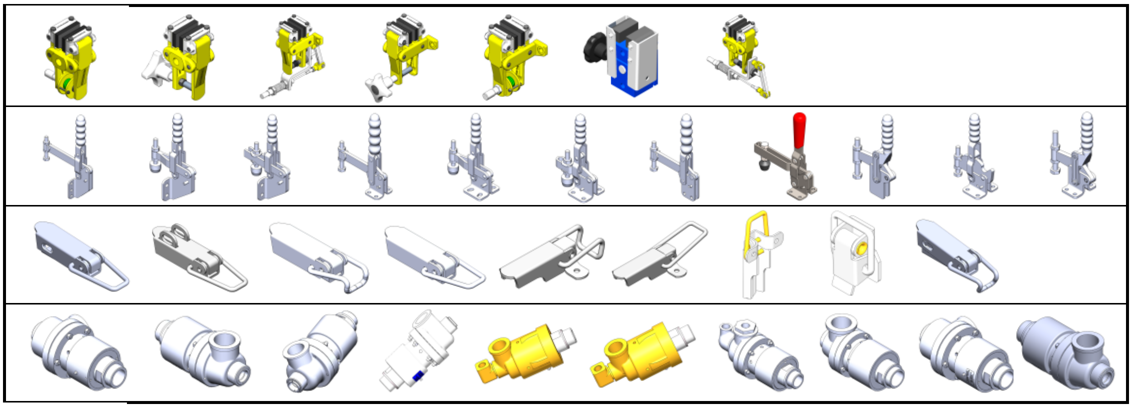


Figure 5: Query models for retrieval experiment.

The obtained precision-recall curves associated with different weighted coefficients are shown in Figure 6.

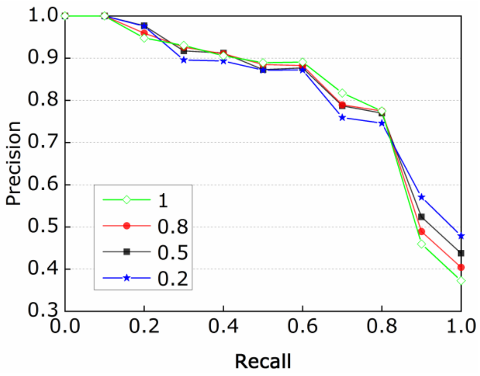


Figure 6: Precision-recall curves with different coefficients.

In experiments, we set β = 0.2, 0.5, 0.8 and 1, respectively. We found that, for larger β, the precision is higher relatively when the recall is smaller than 0.8, and lower when larger than 0.8. That is because the few models ranked very low tend to have totally different global shapes relative to the others of the same category; their dissimilarities of the global-level are large. It means that they have different shapes but the same function to the others.

To select an optimal coefficient β, we integrate each curve for all β to get the bounding area of the curve, namely, the average precision. The values of average precision are 83.23%, 83.54%, 83.18% and 83.02% corresponding to β = 0.2, 0.5, 0.8 and 1, respectively. The average precision reaches the highest at 83.54% when β = 0.5. Therefore, we set β = 0.5 in our method, so as to gain better results.

6.4 Retrieval Performance

We conduct the retrieval experiments to evaluate the retrieval efficiency and effectiveness by our method, and the experiment condition is the same as the above section.

Firstly, we compare the consuming-time of the method combining shape distribution and EMD [17] with ours, which includes the time of marching parts, calculating the distance and recording results. We count up consuming-time once after adding four query assemblies, and the relationships between the retrieval time and the number of query assemblies are shown in Figure 7.

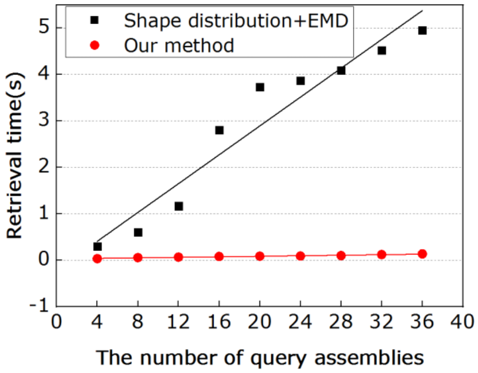


Figure 7: Relationships between the retrieval time and the number of query assemblies.

In Figure 7, the consuming-time by our method is less and it is constant basically with the increase of the number of query assemblies, because a vector with 17 CAD parameters is used to describe a model instead of a 1024-dimension vector. Hence, our method is time-saving vastly.

Secondly, we compute the precision rate with respect to the recall rate, and draw the curves as shown in Figure 8. It could be seen that our method is significantly better than combining the shape distribution and EMD. It demonstrates that CAD parameters of the parts- and global-level are effective for describing the detailed and global information of the 3D assembly model.

7 CONCLUSIONS

In this work, a retrieval method for CAD assembly models is proposed by combining parts- and global-level parameter descriptions. Our strategy is to describe the solid model intuitively using fewer CAD parameters instead of surface point-sampling or view projection. These parameters are acquired through API functions of the CAD software. By grouping and normalizing parameters with the same attribute, we could compute the vector differences among parts of different scales. Our method is scale-invariant and orientation-invariant, so users do not have to care about the impact of model size, scale and environmental factors on parts matching and dissimilarity calculation. For the parts-level, we adopt the MHD metric to carry out many-to-many parts matching between assembly models.

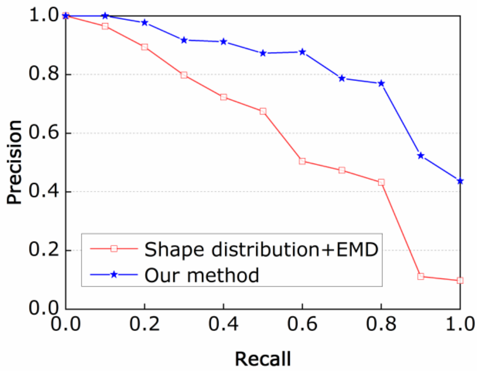


Figure 8: Precision-recall curves with two different methods.

Our method is practical, fast and efficient for the global retrieval and the local retrieval. Owing to employing geometric and shape information of CAD solid models only, it can be applied to the retrieval of CAD assembly models in standard exchange formats and multiple commercial CAD software formats.

Shungang Hua, http://orcid.org/0000-0003-2423-5173
Xinbao Wang, http://orcid.org/0000-0001-7711-9702
Shouguang Xie, http://orcid.org/0000-0003-0524-3290
Dan Feng, http://orcid.org/0000-0001-9338-5955
Hengzhen Dai, http://orcid.org/0000-0001-9684-2330

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