A New Kind of Dual-level Retrieval Approach for CAD Models

Wanbin Pan[1], Yuncan Yang[2,3] and Shuming Gao[3]

[1]Hangzhou Dianzi University, panwanbin@hdu.edu.cn
[2]Hangzhou Dianzi University, YuncanYang@outlook.com
[3]Zhejiang University, smgao@cad.zju.edu.cn

Corresponding author: Shuming Gao, smgao@cad.zju.edu.cn

Abstract. As the first step of a common case-based design, retrieving a candidate CAD model meeting the new requirements quickly and effectively has a profound effect on the subsequent product design. Accordingly, a new kind of dual-level retrieval approach for CAD models is proposed in this study. It combines geometric information with topological information to carry out model retrieval in a coarse-to-fine manner. In detail, to accurately describe the global and local (geometric) shapes of the query model, a new geometric descriptor is designed based on D2 and Point Feature Histogram. Using the geometric descriptor to make a coarse retrieval, the CAD models that have similar global and local shapes will be found as preliminary candidate models. Then, to finely find the one(s) that has the most similar topology with the query model from them, as well as see their primarily global and local shapes through their geometric details, a new topological descriptor is designed after determining the key faces of each CAD model. The experiments show that the accuracy of our proposed approach is better than that of MVCNN++ based on deep learning on average. Compared with the approaches developed based on D2 and attributed graph, the precision of our proposed approach is improved by about 10% on average; and the recall is improved by 5% on average as well. Moreover, our proposed approach improves the efficiency of graph-based retrieval.

Keywords: CAD model retrieval; D2 shape distribution; Point Feature Histogram; face attribute adjacency graph
DOI: https://doi.org/10.14733/cadaps.2023.465-478

1 INTRODUCTION

With the continuous development of product digital design, CAD models have gradually become the key content of a product design, and their numbers and varieties are also increasing. CAD models, indicating plenty of design intent, design experience knowledge, and functional semantics, are one of the most outstanding reusable resources for new product development [1]. It is reported that there are about 80% of new designs are created by reusing the existed designs directly or adopting

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

them after minor modifications [2]. Thus, to promote the process of a product design, it would be reasonable and useful to retrieve reusable CAD models according to the requirements on hand.

Presently, content-based CAD model retrieval is the most popular manner to do model retrieval at the product design stage. The first kind of retrieval approach in this manner is based on geometry, whose prominent characteristic is retrieving CAD models based on the statistics information of geometric attributes (i.e., spatial distance [3-7]) of each CAD model. Generally speaking, this kind of retrieval approach usually has high efficiency, but relatively low accuracy [2]. One of the main reasons for this problem is that their descriptors are usually difficult to represent a CAD model's global and/or structures. The second kind of retrieval approach related to the above-mentioned manner is based on topology, which aims to retrieve CAD models by seeing their essences (structures) through the phenomena (geometric shapes), such as the studies based on the attributed graph [8-12]. Although this kind of retrieval approach usually has a good discrimination capability in structure and/or local shape [11], its efficiency is often vulnerable and sensitive to the geometric details of a CAD model which deeply affect the scale and complexity of a topological descriptor [12]. The third and most recent kind of retrieval approach related to the above-mentioned manner is based on deep learning, which usually studies model retrieval based on multiple views [13, 14]. Yet, their effectiveness usually relies on large-scale training datasets which embody the models of definite/accurate labels/classifications (knowledge) respectively. It makes them hard to be implemented in CAD model retrieval since most CAD models are customized and difficult to assign a label/classification accurately.

In this study, we propose a new kind of dual-level retrieval approach for CAD models. The input of the proposed approach is a query model whose underlying data structure is Boundary Representation (B-rep). In particular, to make a CAD model retrieval more general and knowledge-independent, the proposed approach is mainly developed based on the information on the geometry and topology of each CAD model. To be efficient and effective, the proposed retrieval approach is carried out in a coarse-to-fine manner. In detail, first, a fast coarse retrieval at the geometric level is applied based on the input query model with our new geometric descriptor, which offers the preliminary candidate models; then, an accurate fine retrieval at the topological level is applied based on the input query model with our new topological descriptor, which offers the final candidate models from the preliminary ones.

2 RELATED WORKS

2.1 Geometry-based CAD Model Retrieval Approach

Geometry-based CAD model retrieval approach usually makes a statistical analysis of the geometry information related to each CAD model and represents the analysis result by using a histogram or vector. Based on these geometric descriptors, the (geometric) similarities between different CAD models can be evaluated by distance measurement. For example, Osada et al. [3] constructed a shape descriptor, i.e. D2 shape distribution, which can be applied to any three-dimensional model. Ip et al. [4] divided distances into IN, OUT, and MIXED to construct D2 histograms. Wang et al. [5] proposed an assembly retrieval approach that is based on D2 and Earth Mover's Distance and enables a fuzzy retrieval. Based on D2 and a modified Hausdorff distance, Zhang et al. [6] proposed an efficient assembly retrieval method by using an overall and flexible retrieval of the assembly model. Renu et al. [7] also used a histogram-based similarity score to retrieve assembly solid models. Katayama et al. [15] used a 3D Radon transform and a spherical harmonic transform for the assembly model, which makes similarity evaluation robust to translation and rotation. Generally, although the retrieval approach based on geometry has a high retrieval efficiency, it usually cannot exactly describe the global and/or local structures of a CAD model, which makes it usually has low accuracy.

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

2.2 Topology-based CAD Model Retrieval Approach

Topology-based CAD model retrieval approach usually represents each CAD model by using a graph. Based on these topological descriptors, the (topological) similarities between different CAD models can be evaluated by a graph matching algorithm. For example, El-Mehalawi et al. [8, 9] used an attributed graph to represent each CAD model and presented an approach for retrieving and matching similar designs between the CAD models. Giannini et al. [10] exploited the B-rep data of the CAD model to build an attributed graph containing geometric, topological, and spatial information. Huangfu et al. [11] designed a hierarchical model descriptor that transforms CAD models into labeled attribute adjacency graphs by extracting B-rep information. Tao et al. [12] created face adjacency graph descriptions for the query models from their B-rep data and proposed a retrieval method for 3D CAD solid models based on region segmentation. In general, the retrieval approach based on topology has a high retrieval accuracy, but it usually has low efficiency because of the time-consuming graph matching algorithm.

2.3 Deep Learning-based CAD Model Retrieval Approach

Deep learning-based CAD model retrieval approach usually gets potential knowledge related to the shape of each CAD model and represents the shape of each CAD model by using a feature vector. Based on these feature vectors, the similarities between different CAD models can be evaluated by vector angles. For example, Su et al. [13] first presented multi-view convolutional neural networks (MVCNN), which generates shape descriptor to offer even better recognition performance by combining information from multiple views of a 3D shape. Angrish et al. [14] extended MVCNN architecture by adding engineering metadata and proposed MVCNN++ for the classification and retrieval of CAD models. Sinha et al. [16] converted the 3D model into geometry images and used convolutional neural networks to learn 3D shapes for classification and retrieval tasks. Kim et al. [17] proposed a Part Geometry Network, which utilizes complementary properties of the face and volumetric representations to learn robust feature descriptors for object classification. Ordinarily, the retrieval approach based on deep learning is aimed at mesh or point cloud, which is difficult to be directly used in a B-rep model. Furthermore, the retrieval accuracy usually depends on the scale of the training dataset and the consistency of model labels/classifications. It is not easy to construct a CAD model training dataset meeting the above requirements, because the CAD models include a large number of personal customized models, which are diverse and widely used.

3 OVERVIEW

To make the CAD model retrieval effective, efficient, and knowledge-independent, a new kind of dual-level retrieval approach is proposed in this study. The input of the approach is a CAD model called query model whose underlying data structure is a manifold B-rep, and its global and local shapes reflect the new design requirements. The flowchart of the proposed approach is illustrated in Figure 1.

Step 1. The Coarse retrieval is carried out, and the preliminary candidate models are returned. First, a new geometric descriptor is generated for the query model. Then, based on the geometric descriptor, the geometric similarity is evaluated between the query model and each CAD model in a dataset. According to the geometric similarity value, the retrieved CAD models are ranked. If the number of the preliminary candidate models is represented as R_c, the CAD models ranked in the top R_c are selected as the preliminary candidate models.

Step 2. The fine retrieval is carried out, and the final candidate models are returned. First, a new topological descriptor is generated for the query model. Then, based on the topological descriptor, the topological similarity is evaluated between the query model and each preliminary candidate model. According to the topological similarity value, the CAD models are ranked. If the number of the final candidate models is represented as R_f, the CAD models ranked in the top R_f are selected as the final candidate models.

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

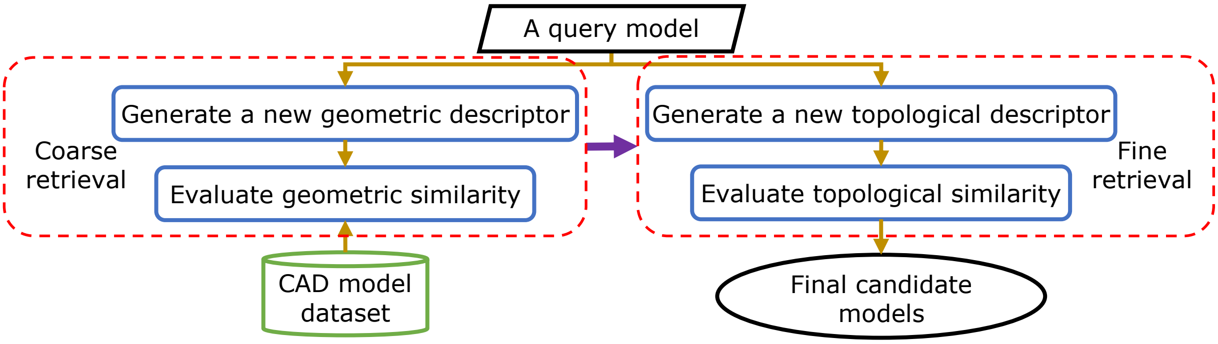


Figure 1: The dual-level CAD model retrieval flowchart.

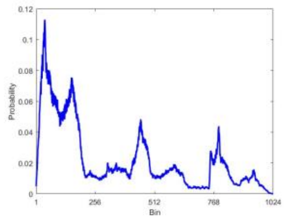
4 DESIGNING A NEW GEOMETRIC DESCRIPTOR FOR COARSE RETRIEVAL

To make the geometric descriptor enable fast coarse retrieval, D2 can be adopted to represent each CAD model for its well-known discrimination in describing a model's global shape; and can efficiently realize similarity evaluation in model retrieval. Furthermore, to make the geometric descriptor effectively describe the local shape of the CAD model as well, we combine D2 with Point Feature Histograms (PFH) [18] (for its excellent capability in local shape representation) to form the new geometric descriptor D2P in this study. After defining the geometric similarity evaluation method, coarse retrieval can be carried out.

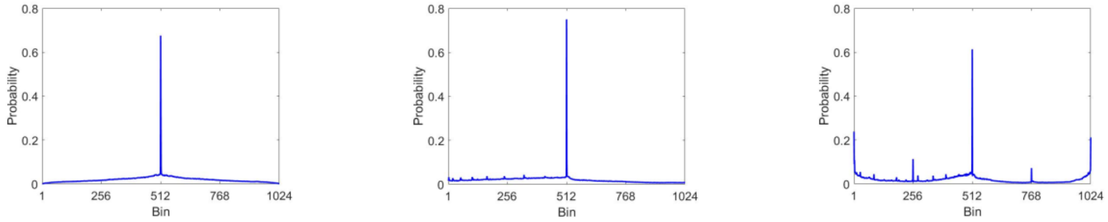
4.1 The Design of D2P

As a geometric descriptor, D2P consists of two aspects, i.e., D2 and PFH. Figure 2 shows an example of D2P for CAD model 1 in Figure 2a. Here, the model's corresponding D2 histogram and the angle histograms [19] of PFH are respectively shown in Figure 2b and Figure 2c. In particular, the horizontal axis and vertical axis of these histograms indicate the indexes of the bin and probability, respectively. Here, each histogram has 1024 bins. Besides, to effectively construct the D2P, a set of points is generated for each CAD model by sampling points uniformly on the face of the model.

(a) CAD Model 1



(b) D2 histogram



(c) Angle histograms of PFH

Figure 2: CAD model 1 and its D2P.

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

Herein, the D2 histogram represents the distribution of Euclidean distances between all pairs of sampled points on the face of each model [3], and is computed as follows: (1) Two different points are randomly sampled on the face of a CAD model and the Euclidean distance is calculated between the above two points. This should be repeated N^2 times (2) The values of distances are normalized to reduce the difference between different model sizes. (3) D2 histogram with B bins is formed to show the distribution of the normalized values of the distances. According to [3], the experiments had shown that it can ensure enough resolution and high robustness of the shape description when N and B equal 1024.

D2 histogram is a global description and can't describe the local shape of a model. PFH is adopted to represent the local geometry of each model, which complements the D2 histogram. The calculating steps of PFH are given in the following: (1) All points in the k-neighborhood of a point are selected. According to [18], the distance D and angles (α, φ, θ) are calculated between any two points in the k-neighborhood. This should be repeated until all points are visited. (2) The PFH with the same bins of D2 histogram is formed to show the distribution of the local geometry of a model. In particular, PFH in this study ignores the histogram corresponding to distance D to reduce the difference between different model sizes. Table 1 shows the angle histograms of PFH in different neighborhoods of CAD model 1. If k is increased, the angle histograms have diverse distribution. In this study, k is set at 1024.

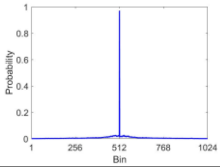
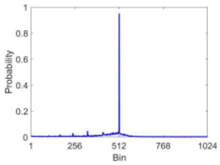
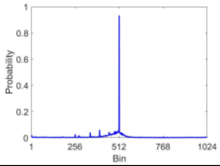
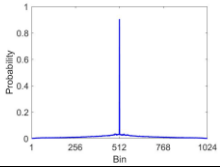
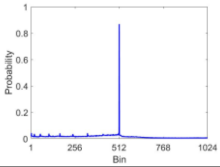
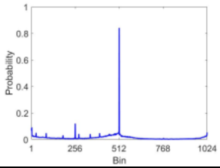
k-neighborhood	angle α histogram	angle φ histogram	angle θ histogram
k = 128			
k = 512			

Table 1: The angle histograms of PFH in different neighborhoods of CAD model 1.

According to the above sense, each D2P describes not only the global shape of a CAD model but also the local shape of the model at different levels when changing the value of k. This provides an important basis for accurate model retrieval.

4.2 Geometric Similarity Evaluation Based on D2P

To carry out a fast coarse retrieval, the geometric similarity between two CAD models can be evaluated by Euclidean distance based on their D2P. The geometric similarity is represented as Sim_G, and two CAD models are represented as Q and T. The geometric similarity $Sim_G(Q,T)$ between Q and T is defined as Equation (4.1) to (4.4).

$$Sim_G(Q,T) = (1-\beta) * Sim_{D2}(Q,T) + \beta * Sim_{PFH}(Q,T) \tag{4.1}$$

$$Sim_{D2}(Q,T) = 1 - \left\| F_{D2}(Q) - F_{D2}(T) \right\|_2 \tag{4.2}$$

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

$$Sim_{PFH}(Q,T) = \frac{1}{3}(Sim_{\alpha}(Q,T) + Sim_{\varphi}(Q,T) + Sim_{\theta}(Q,T)) \tag{4.3}$$

$$\begin{cases} Sim_{\alpha}(Q,T) = 1 - \left\| F_{\alpha}(Q) - F_{\alpha}(T) \right\|_2 \\ Sim_{\varphi}(Q,T) = 1 - \left\| F_{\varphi}(Q) - F_{\varphi}(T) \right\|_2 \\ Sim_{\theta}(Q,T) = 1 - \left\| F_{\theta}(Q) - F_{\theta}(T) \right\|_2 \end{cases} \tag{4.4}$$

Here, Sim_{D2} and Sim_{PFH} represent D2 similarity and PFH similarity respectively. Sim_{α}, Sim_{φ}, and Sim_{θ} represent the similarities of angle α, φ, and θ. F_{D2}, F_{α}, F_{φ}, and F_{θ} represent the vectors of the corresponding histograms. β represents a parameter, and its value is usually set at 0.5. Table 2 shows the top 4 candidate models of a retrieval instance based on D2P. The values under the candidate models are the geometric similarities between the query model and the candidate models.

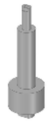
Query model	The top 4 candidate models			
	 0.9781	 0.9766	 0.9688	 0.9669

Table 2: Retrieval instance by D2P.

5 DESIGNING A NEW TOPOLOGICAL DESCRIPTOR FOR FINE RETRIEVAL

It is considered that describing and using the topologies of the essential characteristics of CAD models can realize an accurate CAD model retrieve in global and/or local structures. However, if the topological descriptor contains too many geometric details (such as the typically attributed graphs [8, 10-12]), retrieval accuracy will be sensitive to the difference in geometric detail among CAD models; moreover, the retrieval efficiency is usually low. Otherwise, when the topological descriptor contains too few geometric details (such as the skeleton graph [20-22]), it is difficult to ensure high retrieval accuracy. To balance the retrieve efficiency and accuracy, the key faces (i.e., a set of faces), which reflect the primarily global and local (geometric) shapes through geometric details, are found first on each CAD model in this study. After that, a key-face-attributed adjacency graph (KFAAG) is developed based on the above-mentioned key faces to represent the high-level and concise topology (i.e., primary topology) of the CAD model. Finally, after defining the topological similarity evaluation method, fine retrieval can be carried out.

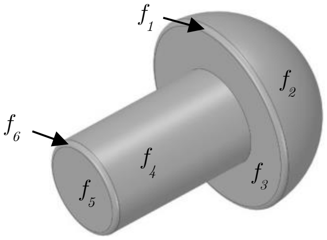
5.1 Key Faces Determination Based on PSO

The kay faces are defined as those faces that can represent the primarily global and local (geometric) shapes of the model. Because D2P can describe the global and local shapes, the shape of each face set is described by D2P. The computation of the D2P of each face set is similar to the D2P of the model, but the difference is that points are randomly sampled on the faces in the face set. The D2P of each face set is compared with the D2P of the corresponding CAD model to find the most suitable face set. Here, to make the above process efficient and effective, the particle swarm optimization method (PSO) [23] is employed for its potential capability in finding the global optimal solution.

In PSO, the position of each particle corresponds to a solution (i.e., a set of faces), which is represented as an n-dimensional vector. Figure 3b shows an example, where each dimension in the position of a particle corresponds to a face of CAD model 2. In particular, if one dimension in the position of a given particle equals 1, its corresponding face is deemed as a key face in the current

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

solution. Therefore, all the key faces of a CAD model indicated by a randomly generated particle can be collected by analyzing each dimension value in its position.



(a) CAD model 2

f_1	f_2	f_3	f_4	f_5	f_6
0	1	1	1	1	0

(b) Particle' position

Figure 3: CAD model 2 and particle's position.

Herein, the i-th particle's position and velocity are denoted by $x_i = (x_{i1}, x_{i2}, ..., x_{in})$ and $v_i = (v_{i1}, v_{i2}, ..., v_{in})$, respectively. The historical best position of the i-th particle is represented as $p_i = (p_{i1}, p_{i2}, ..., p_{in})$. The global best position of all particles is represented as $g = (g_1, g_2, ..., g_n)$. The i-th particle update at iteration t is defined as Equation (5.1) to (5.3).

$$x_{ij} = \begin{cases} 1, Sigmoid(v_{ij}) \geq 0.5 \\ 0, else \end{cases} \tag{5.1}$$

$$Sigmoid(v_{ij}) = \frac{1}{1+e^{-v_{ij}}} \tag{5.2}$$

$$v_i(t+1) = wv_i(t) + c_1 r_1 \left[p_i(t) - x_i(t)\right] + c_2 r_2 \left[g(t) - x_i(t)\right] \tag{5.3}$$

Here, j represents each dimension of the particle's position or velocity. w, c_1, and c_2 represent three weights that equal 0.5, 2, and 2 by trying several experiments. r_1 and r_2 are two random real numbers in the range [0,1].

To determine the set of faces of a CAD model that has the highest geometric similarity to the model (i.e., to determine the key faces of the model), the corresponding fitness function is defined as Equation (5.4).

$$F^* = \arg\min_F \left|Sim_G(M,F) - \eta\right| \tag{5.4}$$

Here, M represents a given CAD model; F represents a face set on the CAD model; F^* represents a set of key faces. Sim_G is the geometric similarity between the face set and the corresponding CAD model. If $|Sim_G(M,F)-\eta|$ reaches the minimum, all faces in F are key faces. η is a similarity threshold that is used to control the degree of geometric similarity between the CAD model and the key faces. It equals 0.9 in this study.

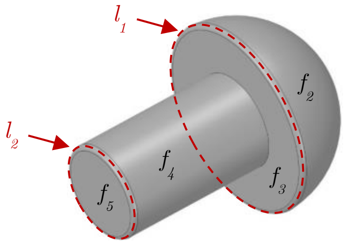
According to the above method, Figure 3b shows the key faces of CAD model 2. The number of key faces is 4 which is less than the face quantity of CAD model 2. Furthermore, the key faces of CAD model 2 not only represent the primary topology of the model but also reflect the very similar global and local shapes to those of CAD model 2.

5.2 The Design of KFAAG

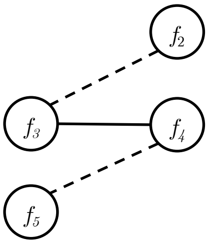
After obtaining the key faces of each CAD model, here, we describe the primary topology of the model by constructing a KFAAG. Here, Figure 4b demonstrates an example. Each KFAAG = (N, E) is

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

composed of the graph node set N and the graph edge set E. Each graph node represents a key face of the CAD model. For example, the graph nodes f_2 represents key face f_2. The attributes of each graph node include face type (such as plane, cylinder, sphere, etc.), area ratio, and D2P. There are two kinds of graph edges: real graph edge (connecting two graph nodes with a solid curve) and virtual graph edge (connecting two graph nodes with a dash-dot curve). If two key faces have an intersection by no extension, two graph nodes corresponding to two key faces connect with a real graph edge. For example, the key faces f_3 and f_4 in Figure 4a intersect at one line, so the corresponding graph nodes f_3 and f_4 in Figure 4b connect with a real graph edge. If two key faces have an intersection by key face extension, two graph nodes corresponding to two key faces connect with a virtual graph edge. For example, the extensions of key faces f_4 and f_5 in Figure 4a intersect at l_2, so the corresponding graph nodes f_4 and f_5 in Figure 4b connect with a virtual graph edge. To determine whether any two key faces or the extensions of any two key faces intersect, each key face and the other key faces need to be visited. If there are n key faces, the time complexity of constructing KFAAG is $O(n^2)$.



(a) CAD model 2 after face extension



(b) KFAAG

Figure 4: Construction of KFAAG.

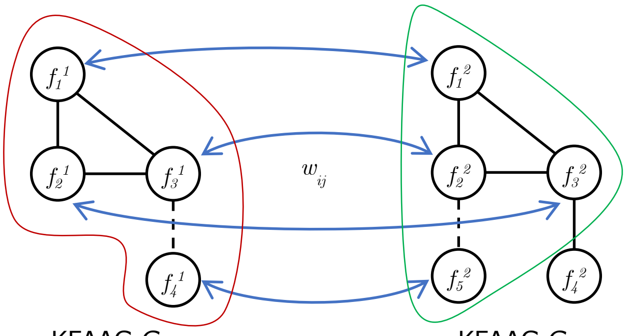


Figure 5: KFAAG matching.

5.3 Topological Similarity Evaluation Based on KFAAG

After describing the primary topology of each CAD model by using a KFAAG, the topological similarities among CAD models can be evaluated based on graph matching. In particular, it is believed that the requirements indicated by the query model should be indicated/reflected by each retrieved candidate model as much as possible. Therefore, the pair of the found isomorphic subgraphs having the

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

maximum graph nodes and maximum geometric similarity in the face is deemed as the best-topological-matched subgraphs between two KFAAGs (respectively belonging to the query model and a CAD model). Furthermore, in this study, we assume that the best-topological-matched subgraph of the KFAAG of the query model is itself, as it is a common phenomenon that the query model usually has a simpler shape (both in topology and geometry) compared to each candidate model. That is, each graph node in the KFAAG of the query model has a corresponding graph node in the KFAAG of the candidate model, as shown in Figure 5. Accordingly, the Kuhn–Munkres algorithm [1] is employed to promote the above-mentioned matching process. Herein, to evaluate the topological similarity between two matched subgraphs, Equations (5.5), (5.6), and (5.7) are defined.

$$Sim_T(Q,T) = \frac{\max \sum_{i \in Q, j \in T} w_{ij}}{n} \tag{5.5}$$

$$w_{ij} = \frac{1}{3}(Sim_{FaceType}(i,j) + Sim_{AreaRadio}(i,j) + Sim_G(i,j)) \tag{5.6}$$

$$Sim_{AreaRadio}(i,j) = 1 - \left| AreaRadio(i) - AreaRadio(j) \right| \tag{5.7}$$

Here, Sim_T represents the topological similarity. Q and T represent two CAD models, and n is the minimum number of key faces between Q and T. i represents a key face of the query model, and j represents a key face of the candidate model. w_{ij} represents the similarity between i and j. $Sim_{FaceType}$ is used to evaluate whether two faces have the same type or not, that is, if two faces have the same type, $Sim_{FaceType}$ = 1, otherwise, $Sim_{FaceType}$ = 0. The types of face include plane, cylinder, sphere, cone, torus, and NURBS surface. $Sim_{AreaRadio}$ represents the similarity of area radio, and $AreaRadio$ represents the area ratio of a key face area in the surface area of the corresponding CAD model. Sim_G represents the geometric similarity between two key faces.

The KFAAG can not only describe the essential/primary topology structure information but also represent the primary local shapes of the CAD model. Table 3 shows the top 4 candidate models of a retrieval instance based on KFAAG. The values under the candidate models are the topological similarities between the query model and the candidate models.

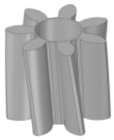
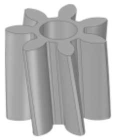
Query model	The top 4 candidate models			
	 0.9984	 0.9951	 0.9517	 0.9124

Table 3: Retrieval instance by KFAAG.

6 EXPERIMENTS AND DISCUSSIONS

The proposed approach has been implemented by using C# based on SolidWorks 2020 whose API is adopted to get the B-rep data from CAD models. Generally speaking, the large-scale CAD model datasets that can be directly adopted here are still rare (such as the ABC dataset [24]), especially the ones where each model has been classified (the model classification is one of the common basis to evaluate the precision and recall of a retrieval approach). As a result, we build a dataset to verify the effectiveness and characteristics of the proposed approach. In particular, each model in the built dataset is downloaded from the publicly accessible Web sites and classified by ourselves. Here, the dataset has been shared in https://github.com/YangYunCan/CAD-Models, which has 25 classes and 1004 parts as shown in Figure 6.

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

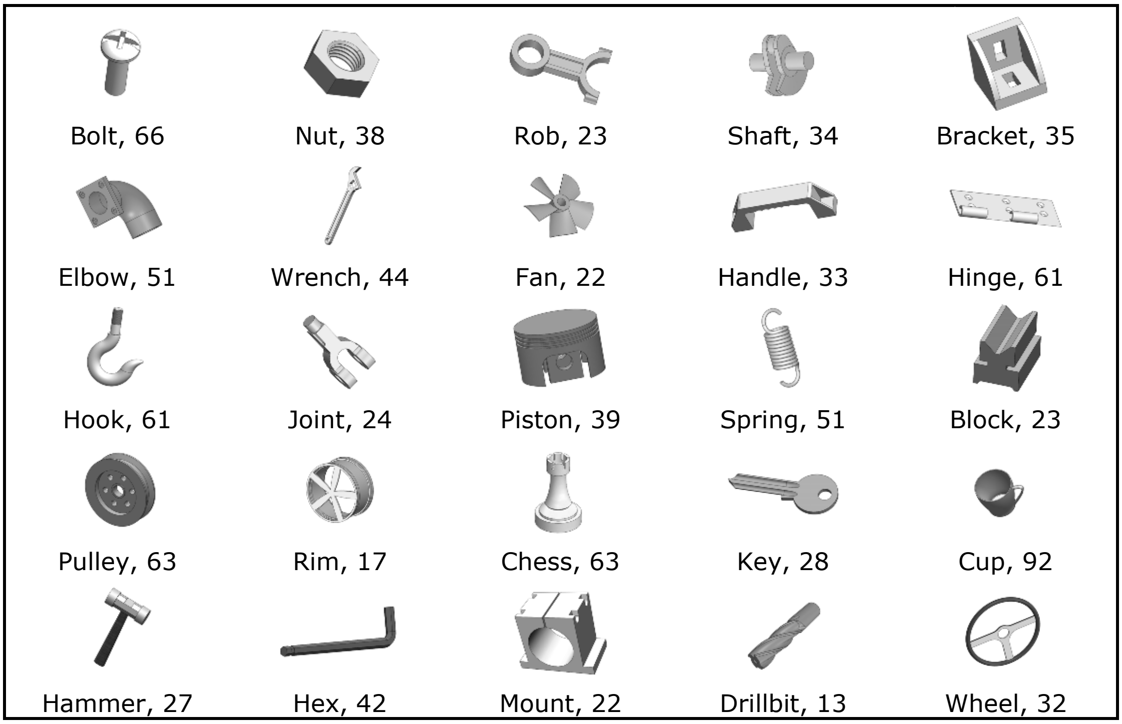


Figure 6: CAD model dataset.

6.1 Retrieval Cases and Analysis

Three typical CAD models are selected as query models to retrieve the candidate models. The number of preliminary candidate models (retrieved based on D2P) R_c is set at 50. The number of final candidate models (retrieved based on KFAAG) R_f is set at 4.

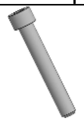
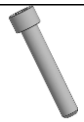
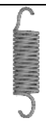
Query model	The top 4 candidate models			
 Bolt	 0.7497	 0.7465	 0.7377	 0.7194
 Spring	 0.9890	 0.9288	 0.8286	 0.7892

Table 4: Two typical cases using dual-level retrieval.

Table 4 shows two cases based on our dual-level retrieval approach. On the one hand, the bolt model as one query model has 5 faces without any geometric detail. The candidate models corresponding to the bolt model belong to the bolt label and have a bolt head as well as a bolt body. On the other hand, the spring model as the other query model has 9 faces. Furthermore, most of them are free-

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

form faces. The candidate models corresponding to the spring model belong to the spring label and have two hooks at the ends of the spring.

Table 5 shows a case using different retrieval way. Using only D2P, the spatial distribution of the primary local shape (such as the position of blades) is indistinguishable on the candidate models. Because the dual-level retrieval adds the topological refinement based on D2P, the blades of candidate models have more similar distribution to the fan model as the topological similarity increased.

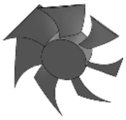
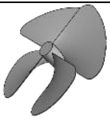
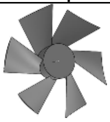
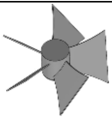
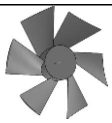
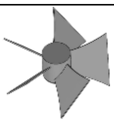
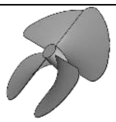
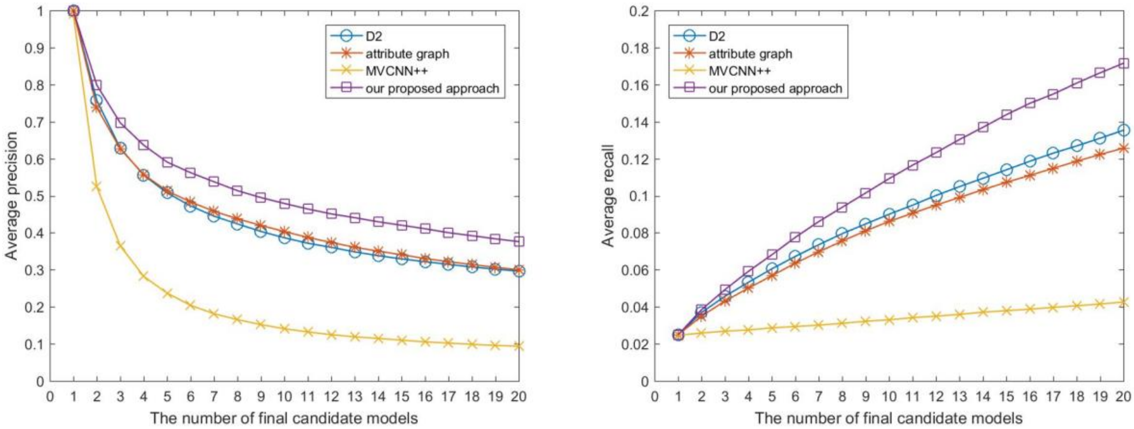
Query model	Retrieval way	The top 4 candidate models			
 Fan	Using only D2P	 0.7671	 0.7512	 0.7273	 0.6893
	Using dual-level retrieval	 0.7161	 0.6955	 0.6891	 0.6780

Table 5: A case using different retrieval way.

6.2 Retrieval Accuracy Demonstration

To evaluate retrieval accuracy of our proposed approach, each model in the dataset as the query model to study the average precision and recall of our proposed approach compared with D2 [3], attribute graph [8], MVCNN++ [14]. The average precision and recall are as shown in Figure 7. R_f (the number of final candidate models) varies from 1 to 20. The higher the precision and recall are, the more accurate the retrieval approach is. Figure 7 shows that our proposed approach has the highest accuracy in the above four approaches.



(a) Average precision curves (b) Average recall curves

Figure 7: The comparison of accuracy.

6.3 Time Complexity Analysis and Retrieval Efficiency Demonstration

The proposed approach is carried out in a coarse-to-fine manner. In coarse retrieval stage, the time complexity depends on geometric similarity evaluation and geometric similarities ranking. If there

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

are n CAD models in dataset, the time complexity is $O(n)$ in geometric similarity evaluation between a query model and n CAD models. The time complexity for ranking is $O(nlogn)$ by using Quicksort algorithm for n values of geometric similarity. The coarse retrieval including geometric similarity evaluation and geometric similarities ranking has a time complexity $O(nlogn)$.

In fine retrieval stage, the time complexity depends on topological similarity evaluation and topological similarities ranking. The time complexity for topological similarity evaluation between a query model and another model is $O(m^3)$ by using Kuhn–Munkres algorithm, where m represents the graph node number of KFAAG of the query model. If there are k preliminary candidate models, the time complexity is $O(km^3)$ in topological similarity evaluation between a query model and k preliminary candidate models. The time complexity for ranking is $O(klogk)$ by using Quicksort algorithm for k values of topological similarity. The fine retrieval including topological similarity evaluation and topological similarities ranking has a time complexity $O(km^3+klogk)$.

The proposed retrieval approach consists of coarse retrieval and fine retrieval, so the proposed retrieval approach has a time complexity $O(nlogn+km^3+klogk)$.

Query model	D2	attribute graph	MVCNN++	our proposed approach
Bolt	25	53322	26	4376
Spring	26	49990	26	4204
Fan	25	60437	27	5115

Table 6: The comparison of retrieval time (: millisecond).

To illustrate the retrieval efficiency, the bolt model, spring model, and fan model are selected as query models, respectively. For each query model, each retrieval experiment is independently performed 20 times and runs on a PC with i7-9700 CPU 3.00 GHz as well as 16 GB RAM. Table 6 shows the average time consumption of D2, attributed graph, MVCNN++ and our proposed approach, respectively. In particular, the time consumption here only contains the one spent on retrieval.

As seen from Table 6, the average time consumption of D2 is close to the one of MVCNN++, and both of them have higher efficiency. This is because D2 and MVCNN++ describe models with 1024-dimension vectors, respectively; and the evaluating similarity between vectors is fast. Attributed graph takes the most retrieval time as it uses time-consuming graph matching to evaluate topological similarity. The retrieval time of our proposed approach is composed of two aspects: coarse retrieval and fine retrieval. The coarse retrieval time is close to D2 and MVCNN++. The fine retrieval time is less than attribute graph, because the number of models used to evaluate topological similarity is less. Therefore, the retrieval time of our proposed approach is less than attribute graph, but more than D2 and MVCNN++.

7 CONCLUSION AND FUTURE WORKS

To make the CAD model retrieval be effective, efficient, and knowledge-independent, this work proposes a new kind of dual-level retrieval approach. The experiments show that the proposed approach has a higher retrieval accuracy compared with D2, attributed graph, or MVCNN++. Because of the coarse-to-fine manner, the retrieval efficiency of the proposed approach is higher than attribute graph, but lower than D2 and MVCNN++. Besides, the proposed approach also has the following characteristics: (1) By integrating D2 with PFH, the geometric descriptor, i.e., D2P, can effectively describe the global and local (geometric) shapes of a CAD model. (2) By improving the traditional PSO, the key faces related to the primarily global and local shapes of a CAD model can be determined. (3) Aided with the key faces, a high-level and concise topological descriptor (named KFAAG)

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

is proposed for each CAD model, which can be effectively used to accurately retrieve CAD models based on their primary/essential topologies.

Future works can be conducted to make the proposed approach more general. For example, (1) The complexity of model shape could be considered when sorting candidate models after retrieving. (2) In the construction of KFAAG, all key faces are extensible. The influence of the extension of the maximal faces with respect to the global shape could be investigated. (3) The candidate models are returned according to the geometric similarity or topological similarity. Future research could explore this issue further by combining the topological similarity with geometric similarity. (4) To provide a more comprehensive assessment of the retrieval approach, the Engineering Shape Benchmark could be considered while expanding the CAD model dataset. (5) The experimental dataset is classified by experts, but the classification labels have certain subjectivity. A more objective standard could be developed to eliminate the ambiguities of classification.

ACKNOWLEDGMENTS

This study is supported by the National Key R&D Program of China(2020YFB1709200), the National Natural Science Foundation of China (61702147), and the Zhejiang Provincial Science and Technology Program in China (2021C03137).

Wanbin Pan, https://orcid.org/0000-0002-7557-3060
Yuncan Yang, https://orcid.org/0000-0001-9206-6389
Shuming Gao, https://orcid.org/0000-0002-7061-9912

REFERENCES

[1] Han, Z.; Mo, R.; Yang, H.; Hao, L.: CAD assembly model retrieval based on multi-source semantics information and weighted bipartite graph, Computers in Industry, 96, 2018, 54-65. https://doi.org/10.1016/j.compind.2018.01.003

[2] Kim, H.; Cha, M.; Mun, D.: Shape distribution-based retrieval of 3D CAD models at different levels of detail, Multimedia Tools and Applications, 76(14), 2017, 15867-15884. https://doi.org/10.1007/s11042-016-3881-5

[3] Osada, R.; Funkhouser, T.; Chazelle, B.; Dobkin, D.: Matching 3D models with shape distributions, International Conference on Shape Modeling and Applications, 2001. Genova, Italy. https://doi.org/10.1109/SMA.2001.923386

[4] Ip, Y. C.; Regli, W. C.: Content-Based Classification of CAD Models with Supervised Learning, Computer-Aided Design and Applications, 2(5), 2005, 609-617. https://doi.org/10.1080/16864360.2005.10738325

[5] Wang, P.; Li, Y.; Zhang, J.; Yu, J.: An assembly retrieval approach based on shape distributions and Earth Mover's Distance, The International Journal of Advanced Manufacturing Technology, 86(9), 2016, 2635-2651. https://doi.org/10.1007/s00170-016-8368

[6] Zhang, J.; Pang, J.; Yu, J.; Wang, P.: An efficient assembly retrieval method based on Hausdorff distance, Robotics and Computer-Integrated Manufacturing, 51, 2018, 103-111. https://doi.org/10.1016/j.rcim.2017.11.012

[7] Renu, R.; Mocko, G.: Retrieval of Solid Models based on Assembly Similarity, Computer-Aided Design and Applications, 13(5), 2016, 1-9. https://doi.org/10.1080/16864360.2016.1150708

[8] El-Mehalawi, M.; Allen Miller, R.: A database system of mechanical components based on geometric and topological similarity. Part I: representation, Computer-Aided Design, 35(1), 2003, 83-94. https://doi.org/10.1016/S0010-4485(01)00177-4

[9] El-Mehalawi, M.; Allen Miller, R.: A database system of mechanical components based on geometric and topological similarity. Part II: indexing, retrieval, matching, and similarity assessm

© 2023 CAD Solutions, LLC, http://www.cad-journal.net

ent, Computer-Aided Design, 35(1), 2003, 95-105. https://doi.org/10.1016/S0010-4485(01)00178-6
[10] Giannini, F.; Lupinetti, K.; Monti, M.: Identification of Similar and Complementary Subparts in B-Rep Mechanical Models, Journal of Computing and Information Science in Engineering, 17(4), 2017. https://doi.org/10.1115/1.4036120
[11] Huangfu, Z.; Zhang, S.; Yan, L.: A method of 3D CAD model retrieval based on spatial bag of words, Multimedia Tools and Applications, 76(6), 2017, 8145-8173. https://doi.org/10.1007/s11042-016-3456-5
[12] Tao, S.; Wang, S.; Chen, A.: 3D CAD solid model retrieval based on region segmentation, Multimedia Tools and Applications, 76(1), 2017, 103-121. https://doi.org/10.1007/s11042-015-3033-3
[13] Su, H.; Maji, S.; Kalogerakis, E.; Learned-Miller, E.: Multi-view Convolutional Neural Networks for 3D Shape Recognition, 2015 IEEE International Conference on Computer Vision (ICCV), 2015. Santiago, Chile. https://doi.org/10.1109/ICCV.2015.114
[14] Angrish, A.; Bharadwaj, A.; Starly, B.: MVCNN++: Computer-Aided Design Model Shape Classification and Retrieval Using Multi-View Convolutional Neural Networks, Journal of Computing and Information Science in Engineering, 21(1), 2020. https://doi.org/10.1115/1.4047486
[15] Katayama, K.; Hirashima, T.: A Retrieval Method for 3D CAD Assembly Models Using 3D Radon Transform and Spherical Harmonic Transform, IEICE Transactions on Information and Systems, E103.D(5), 2020, 992-1001. https://doi.org/10.1587/transinf.2019DAP0010
[16] Sinha, A.; Bai, J.; Ramani, K.: Deep Learning 3D Shape Surfaces Using Geometry Images, European Conference on Computer Vision, 2016. Amsterdam, The Netherlands. https://doi.org/10.1007/978-3-319-46466-4_14
[17] Kim, S.; Chi, H.-g.; Ramani, K.: Object Synthesis by Learning Part Geometry with Surface and Volumetric Representations, Computer-Aided Design, 130, 2021, 102932. https://doi.org/10.1016/j.cad.2020.102932
[18] Rusu, R. B.; Blodow, N.; Marton, Z. C.; Beetz, M.: Aligning point cloud views using persistent feature histograms, 2008 IEEE/RSJ International Conference on Intelligent Robots and Systems, 2008. Nice, France. https://doi.org/10.1109/IROS.2008.4650967
[19] Rusu, R. B.; Blodow, N.; Beetz, M.: Fast Point Feature Histograms (FPFH) for 3D registration, 2009 IEEE International Conference on Robotics and Automation, 2009. Kobe, Japan. https://doi.org/10.1109/ROBOT.2009.5152473
[20] Rossi, L.; Torsello, A.: Coarse-to-fine skeleton extraction for high resolution 3D meshes, Computer Vision and Image Understanding, 118, 2014, 140-152. https://doi.org/10.1016/j.cviu.2013.10.006
[21] Ju, T.; Baker, M. L.; Chiu, W.: Computing a Family of Skeletons of Volumetric Models for Shape Description, Geometric Modeling and Processing - GMP 2006, 2006. Berlin, Heidelberg. https://doi.org/10.1007/11802914_17
[22] Sundar, H.; Silver, D.; Gagvani, N.; Dickinson, S.: Skeleton based shape matching and retrieval, 2003 Shape Modeling International, 2003. Seoul, South Korea. https://doi.org/10.1109/SMI.2003.1199609
[23] Kennedy, J.; Eberhart, R.: Particle swarm optimization, ICNN'95 - International Conference on Neural Networks, 1995. Perth, WA, Australia. https://doi.org/10.1109/ICNN.1995.488968
[24] Koch, S.; Matveev, A.; Jiang, Z.; Williams, F.; Artemov, A.; Burnaev, E.; Alexa, M.; Zorin, D; Panozzo, D.: ABC: A Big CAD Model Dataset for Geometric Deep Learning, 2019 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR), 2019. Long Beach, CA, USA. https://doi.org/10.1109/CVPR.2019.00983

© 2023 CAD Solutions, LLC, http://www.cad-journal.net