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

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Keywords:
CAD model retrieval, D2 shape distribution, Point Feature Histogram, face attribute adjacency graph

DOI: 10.14733/cadconfP.2022.128-133

Introduction:
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 for the subsequent product design. Accordingly, lots of works have been developed to improve the CAD model retrieval, such as the ones retrieving models based on geometry, topology, and deep learning. Generally speaking, the retrieval approaches based on geometry usually have a high efficiency but relatively low accuracy [1], because their descriptors are usually difficult to represent model's structure and/or local shape. On the other hand, the retrieval approaches based on topology usually have good discrimination in structure and local shape [2]. However, their efficiencies are often vulnerable and sensitive to a model's geometric details which usually determine their topological descriptors' scales and complexities [3]. Recently, some deep learning-based approaches are proposed for model retrieval [4, 5]. Yet, their effectiveness usually relies on large-scale training datasets which embody the models with 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.

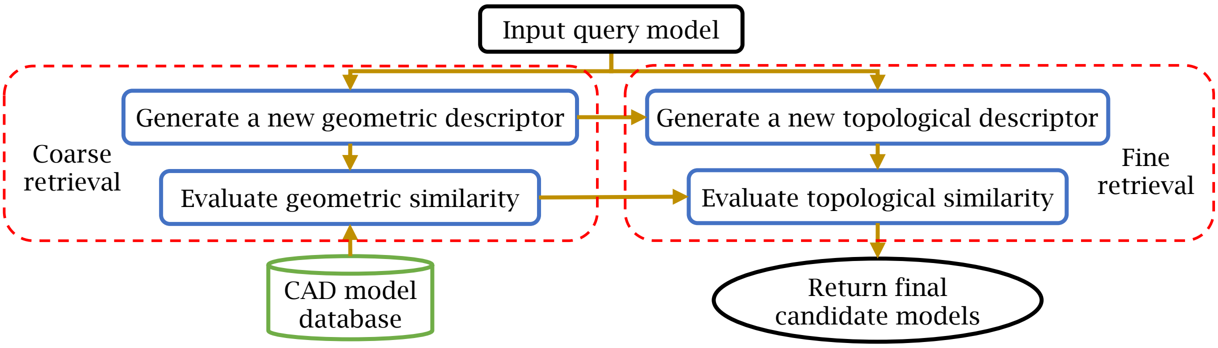


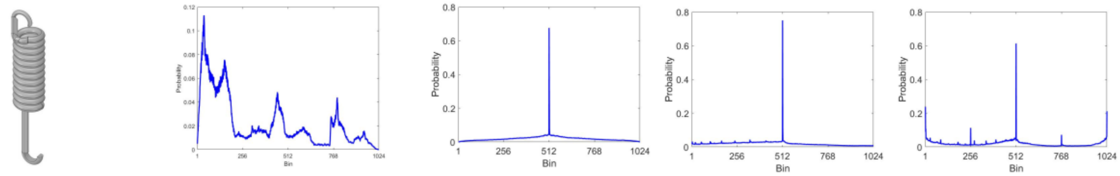
Fig. 1: The flowchart of the proposed approach.

To be effective, efficient, and knowledge-independent, a new kind of dual-level retrieval approach for CAD models is proposed in this work. It combines geometric information with topological information to carry out model retrieval in a coarse-to-fine manner. The input of the approach is a CAD model (with a boundary representation) called query model. In detail, to effectively describe the global and local shape of the query model, a new geometric descriptor is designed based on D2 shape distribution [6] and Point Feature Histogram (PFH) [7]. Using the geometric descriptor to retrieve, the CAD models that have a similar global shape and local shape (i.e., k-order local neighborhood) will be found as candidate models. Then, to efficiently and effectively determine the one(s) that has the most similar topology as the query model from them, i.e., seeing their major structures and local shapes through their geometric details, a new topological descriptor is developed by determining the key faces of each CAD model. The flowchart of the proposed approach is shown as Fig. 1.

Geometric descriptor design:

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 be evaluated efficiently. Furthermore, to make the geometric descriptor effectively describe the local shape of the CAD model as well, we combine D2 with PFH (for its excellent capability in local shape representation) to form the new geometric descriptor D2P in this work. After defining the geometric similarity evaluation method, coarse retrieval for CAD models can be carried out.

CAD model 1 is shown in Fig. 2(a), and its corresponding D2 histogram and the angle histograms of PFH are respectively shown in Fig. 2(b) and Fig. 2(c). The horizontal axis and vertical axis of the histograms are the index of bin and probability respectively. D2 histogram represents the distribution of Euclidean distances between pairs of randomly sampling points on the surface of a 3D model. The angle histograms of PFH represent curvature change distribution in the k-neighborhood of any sampling point, which can effectively capture the shape change of the model surface.



(a) CAD Model 1 (b) D2 histogram (c) Angle histograms of PFH

Fig. 2: CAD model 1 and its D2P.

Geometric similarity evaluation based on D2P:

The D2P of each CAD model is essentially a vector with the same dimension. To carry out fast coarse retrieval, the geometric similarity Sim_G between two models Q and T can be calculated by Euclidean distance based on D2P. It is defined as Eq. (3.1) to (3.4):

$$Sim_G(Q,T) = (1-\beta) * Sim_{D2}(Q,T) + \beta * Sim_{PFH}(Q,T) \tag{3.1}$$

$$Sim_{D2}(Q,T) = 1 - \left\| Norm(F_{D2}(Q) - F_{D2}(T)) \right\|_2 \tag{3.2}$$

$$Sim_{PFH}(Q,T) = \frac{1}{3}(Sim_\alpha(Q,T) + Sim_\varphi(Q,T) + Sim_\theta(Q,T)) \tag{3.3}$$

$$\begin{cases} Sim_\alpha(Q,T) = 1 - \left\| Norm(F_\alpha(Q) - F_\alpha(T)) \right\|_2 \\ Sim_\varphi(Q,T) = 1 - \left\| Norm(F_\varphi(Q) - F_\varphi(T)) \right\|_2 \\ Sim_\theta(Q,T) = 1 - \left\| Norm(F_\theta(Q) - F_\theta(T)) \right\|_2 \end{cases} \tag{3.4}$$

Here, Sim_{D2} and Sim_{PFH} are D2 similarity and PFH similarity respectively. Sim_α, Sim_φ, and Sim_θ are the angle similarities of PFH. F_{D2}, F_α, F_φ, and F_θ are the vectors of the corresponding histograms. β is a parameter used to balance D2 similarity and PFH similarity, and it is usually set as 0.5 empirically. Tab. 1 shows the top 5 candidate models of a retrieval instance, generated by D2P. The geometric similarities are shown under the candidate models.

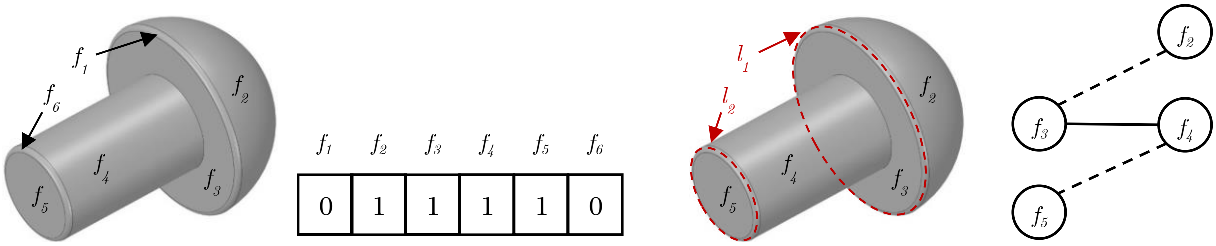
Query model	Candidate models				
					
	1	0.9781	0.9766	0.9688	0.9669

Tab. 1: Retrieval instance by D2P.

<u>Topological descriptor design:</u>
By describing the topology of the essential characteristics of CAD model, it is expected to accurately retrieve CAD model. However, if the topological descriptor contains rich geometric details, the retrieval accuracy is sensitive to the difference of geometric details between CAD models, and the retrieval efficiency is usually low; if the topological descriptor contains few geometric details, it is difficult to ensure the retrieval accuracy. To balance retrieval efficiency and accuracy, the key faces, which reflect the primarily global and local shapes through geometric details, are found first on each CAD model.

If only the global shape of the CAD model is considered, a simple way is to remove the faces with a smaller area. But the smaller faces may exist in local shape, it is not appropriate to determine key faces by removing the smaller faces. To determine the face set that can represent the primarily global and local shapes of the model but have fewer faces, we describe the shape of each face set by using D2P and compare it with the CAD models to find the key faces. Here, to make the above process efficient and effective, the particle swarm optimization (PSO) [8] is employed for its potential capability in finding the global optimal solution.

In the PSO of determining the key faces, the particle's position is constantly updated, as shown in Fig. 3(b). Each dimension of particle's position, which corresponds to a face of the CAD model, is 0 or 1. If its value equals 1, the corresponding face is a key face; if its value equals 0, the corresponding face is not a key face.



(a) CAD model 2 (b) Particle' position (c) key face extension (d) KFAAG

Fig. 3: Construction of KFAAG.

After the key faces are obtained by the PSO, the topology of a CAD model can be represented by constructing a key face attribute adjacency graph (KFAAG), as shown in Fig. 3(d). Each KFAAG = (N, E) is composed of the node set N and the edge set E. Each node represents a key face of the CAD model. For example, the node f_2 represents key face f_2. The attributes of each node include face type (such as plane, cylinder, etc.), area ratio and D2P. There are two kinds of edges: real edge and virtual edge. The real edges represent the original adjacency relationship between key faces. For example, the real edge $<f_3, f_4>$ represents the original adjacency relationship between key faces f_3 and f_4. The virtual edges represent the adjacency relationship between the extended key faces. For example, as shown in Fig 3(c), the extensions of key faces f_2 and f_3 intersect at l_1. Therefore, as shown in Fig 3(d), the virtual edge $<f_2, f_3>$ represents the adjacency relationship between the extended key face f_2 and the extended key face f_3.

<u>Topological similarity evaluation based on KFAAG:</u>
After the topology of the CAD model is represented by KFAAG, topological similarity evaluation between CAD models is transformed into a graph matching problem. To carry out accurate fine retrieval, topological similarity is evaluated by constructing a weighted bipartite graph. As shown in Fig. 4, the nodes of the weighted bipartite graph are key faces of CAD models, and the edge weights w_{ij} are determined by the similarities between two key faces.

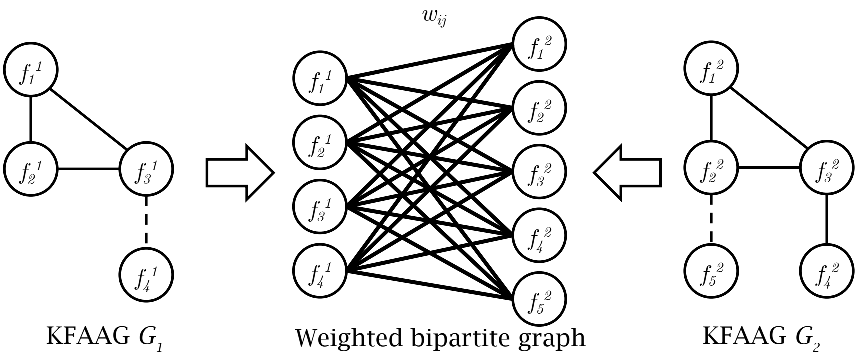
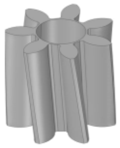
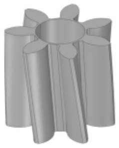
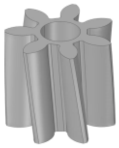
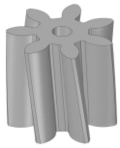


Fig. 4: Construction of weighted bipartite graph.

To solve the problem of weighted bipartite graph matching, the KM algorithm [9] is used for maximum weight matching, and the topological similarity Sim_T between two models Q and T is defined as Eq. (5.1).

$$Sim_T(Q,T) = \frac{\max \sum_{i\in Q, j\in T} w_{ij}}{n} \tag{5.1}$$

Here, w_{ij} is the similarity between two key faces, and n is the minimum number of key faces between two CAD models. The KFAAG can not only describe the essential topology structure information, but also represent the local shape of the CAD model. Tab. 2 shows the top 5 candidate models of a retrieval instance, generated by KFAAG , and the topological similarities are shown under the candidate models.

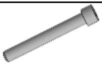
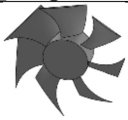
Query model	Candidate models				
	 1	 0.9984	 0.9951	 0.9517	 0.9124

Tab. 2: Retrieval instance by KFAAG

Proceedings of CAD'22, Beijing, China, July 11-13, 2022, 128-133

Retrieval Efficiency Demonstration:

To evaluate the retrieval efficiency, the bolt model, spring model and fan model are selected as query models. For each query model, retrieval is performed 20 times and run on a PC with i7-9700 CPU 3.00 GHz as well as 16 GB RAM. Tab. 3 shows the average time consumption of D2, attribute graph [10], and the proposed approach respectively. The CAD model database has 1004 parts.

Query model	D2	Attribute graph	Proposed approach
 Bolt model	25	53322	4376
 Spring model	26	49990	4204
 Fan model	25	60437	5115

Tab. 3: The comparison of retrieval time (ms).

Conclusions:

CAD model retrieval is a key to effectively carrying out product innovation design based on model reuse, but there are few fast and accurate approaches at present. The proposed dual-level CAD model retrieval approach combining geometry shape and topology structure can take care of both retrieval efficiency and accuracy.

Acknowledgments:

This work is supported by the National Key R&D Program of China(2020YFB1709200) and the National Natural Science Foundation of China (61702147).

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