An Integrated Approach for 3D Part Search with Multiple Shape Signatures

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ABSTRACT

Automatic 3D part search is advantageous to reducing duplicate designs and facilitating component outsourcing in new product development. Previous studies converted a CAD model into a shape signature and compared the signatures of different models according to a pre-defined similarity function. Various definitions of the shape signature have been proposed and each has its own limitations in discriminating 3D shapes. Any comparison scheme only based on a single signature may not offer satisfying discernability. Therefore, this research develops a novel search scheme that adopts multiple shape signatures for part comparison. It transforms a solid model into a form-feature adjacency graph with node as a single feature or the shape of feature intersections, and edge indicating the connectivity between nodes. Each node corresponds to a topological graph of the B-Rep volume it represents. Such a hybrid approach can effectively solve the feature intersection problem, and capture the user's intent more accurately during the search. In addition, we propose a set of heuristic algorithms for accelerating the graphs comparison in the similarity assessment. A shape distribution algorithm is applied at the last stage for discriminating the geometric information that the feature or topology-based methods fail to handle. The implementation results validate the practicality of this work in 3D part search.

Keywords: Part Search, Similarity, Feature, Shape Distribution.

1. INTRODUCTION

The design stage plays a critical role in a product life cycle. 80% of the cost of a new product is committed at this stage, while the opportunities for cost reduction are less than 25% after that [1]. However, it is estimated that 75% of design activity consists of design modification, or case-based design [2]. Indeed, when the project of a new product development initiates, engineers seldom start with nothing and perform a top-down approach from first principles. Most engineering design adapts existing products or standard components to meet new requirements, to improve functionalities or reliability, and to reduce cost. An effective part search mechanism is vital to retrieve the right design models among vast amounts of corporate legacy data. Many companies have implemented PDM software for storing and managing their product design information, mostly CAD files and related documents. A naming (or coding) rule must exist as a prior for data access in most PDM systems. Every company has its own unique naming convention. It may not carry out the design function of a part, and is more often set to be the item number when the part is released to mass production. As a result, any search mechanism based on the part name is of little practical use. The search purpose is to identify existing parts that are similar to the current design rather than a perfect match. 3D part search is also beneficial to collaborative product development. Normally, a manufacturer (e.g. a notebook assembly company) outsources a large amount of components and/or customized designs to its suppliers. To broaden their supplier base and to leverage external design resources become an imperative for most companies, particularly SME's, to remain competitive in the global competition. Some of them have gone online for seeking potential sourcing partners through Internet trading networks [3] or e-Catalogue [4]. Part similarity assessment can be an effective tool for supplier selection in this situation. Other applications in product design and manufacturing include digital library management [5] and knowledge management [6]. A good mechanism of automatic 3D part search and shape similarity assessment creates the following values for companies: (1) Avoid duplicate design: engineers can search existing designs in company database, find similar parts, and modify them for new product design. Duplicate designs can be thus eliminated, reducing the cost and time of the new product development. (2) Lower product cost: reuse of existing parts increases the economic scale, and thus lowers the cost of mass production or their purchasing price. (3) Design knowledge management: intelligent part search promotes design reuse and transferring of knowledge fragments. (4)

Accelerate supplier selection: a designer can evaluate and analyze the components that have been produced. A supplier of “similar” parts would be a potential candidate of outsourcing and engineering collaboration.

There have been several techniques developed for accessing similarity among 3D parts [7]. Most previous studies conduct the similarity assessment by generating a “shape signature” from CAD and then compare the signatures of different models according to a pre-defined distance function (or similarity function). The shape signature is abstraction of the CAD model, and thus possesses a limited discrimination capability. Signatures based on single shape characteristic are generally not able to provide good discrimination or computational efficiency for practical uses. To overcome this deficiency, we propose a computation scheme for automatic 3D part search that utilizes multiple shape characteristics in defining the similarity function. This scheme transforms a B-Rep model into a form-feature adjacency graph with node corresponding to single features or the volume element with feature intersections in the model, and edge representing the connectivity between nodes. Each node in the graph includes a topological graph that specifies the connectivity information between the faces of the volume it represents. Moreover, we develop a set of heuristic algorithms that accomplish the graph comparison in a polynomial time. A shape distribution approach is applied at the last stage for ranking the parts with the same similarity, which complements the limitations of the feature or topology-based methods. The proposed scheme and related algorithms are implemented in a commercial CAD system. The test results verify the advantages of the scheme over previous methods as well as the feasibility of this work.

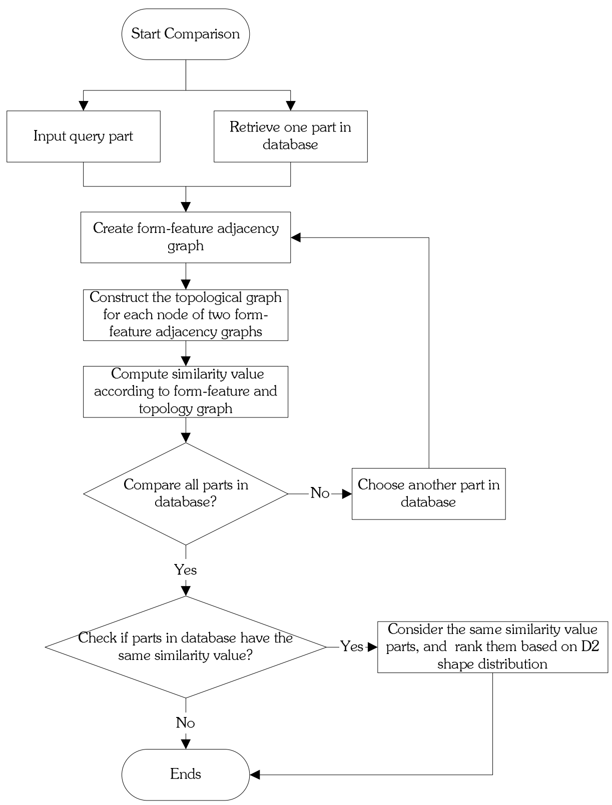

Fig. 1. Part search procedure with multiple shape signatures.

2. LIMITATIONS OF VARIOUS METHODS FOR SHAPE SIMILARITY

Methods for accessing 3D shape similarity can be classified based on the discrimination criteria adopted in the shape signature. There are six major approaches: feature-based, spatial function, shape histogram, section image, topological graph, and shape statistics [7]. This research combines the topological graphs with the form-feature based method in order to solve the feature interaction problem. In addition, it utilizes the D2 shape histogram to rectify the drawbacks with which the topology and feature-based methods inherit, i.e. they fail to effectively consider the geometric information in the comparison. The feature-based approach essentially produces a dependency graph for the 3D models under assessment and computes the largest common sub-graph among them [8]. The graph node represents the features comprising the model, which are extracted according to a pre-defined list of machining features. An edge exists between two nodes when the corresponding feature volumes have intersection. This graph characterizes how the features construct a 3D model, or the topological relationship of the features. A common drawback of feature-based methods is the problem of feature interaction. A volume with feature interaction has multiple ways of feature decomposition and corresponds to different feature sets. Each one specifies a dependency graph, and thus a unique shape signature does not exist. On the other hand, a graph-based data structure [9,10] is introduced to characterize the topological relationship of the faces in a B-Rep model. Each node represents a face of the model and an edge connects two nodes if the corresponding faces are adjoining. Other face attributes such as the surface type, surface area, and surface normal can also be stored at the nodes. Similarly, the edges may carry additional information like the curve length, concavity/convexity, and the angle extended by the sharing faces. In theory, a B-Rep model has a topological graph free of ambiguity. However, the similarity of two B-Rep models is determined by comparing their corresponding graphs, which is very time-consuming. Storing additional attributes in the nodes and edges improves the discrimination capability of the graph, but it further increases the computational load in the part comparison. Finally, the shape signature based the topological graph fails to preserve high-level design intent.

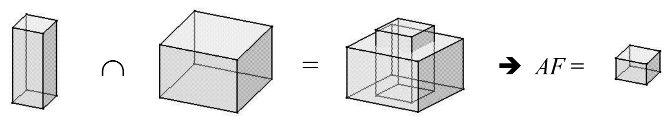

Fig. 2. Generation of additive feature.

(a)

(b)

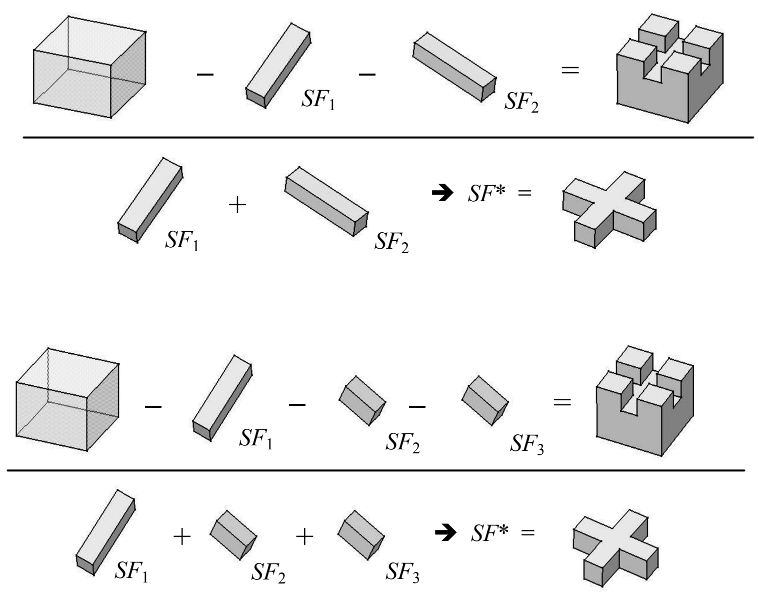

Fig. 3. (a) Generation of SF with feature interaction and (b) with face adjacency.

3. INTEGRATION OF TOPOLOGICAL AND FORM-FEATURE GRAPHS

3.1 Form-Feature Adjacency Graph

We propose a hybrid approach to complementing various methods for shape similarity assessment. Figure 1 illustrates the comparison procedure of two 3D parts. An attributed graph G = (V, E) characterizing the connectivity of form features in a B-Rep model serves as a major shape signature. This approach adopts a feature-based signature because design functions are more associated with high-level features than the faces of a B-Rep model or their topological information. A graph node in this work denotes either the volume of a single feature f or the volume element with multiple feature interaction. We only allow a form-feature volume to be constructed by sweeping a closed planar contour along a direction. The features created like this are distinguished between additive feature (AF) and subtractive feature (SF). Notably, the feature volume represents the effective volume added or removed by the geometric operation creating it (see Figure 2). The node is generated in two ways:

(1) Single feature (AF or SF) without feature interaction.
(2) Union (vol f) and f = {SF | Intersection (vol SFi, vol SFj) ≠ Φ or SFi and SFj share a common face or faces}, as shown in Figure 3.

An edge connects two graph nodes when one of the following conditions is satisfied:

(1) Two AF's share a common face or faces, as shown in Figure 4(a).
(2) Intersection (vol AF, vol SF) ≠ Φ, as shown in Figure 4(b).

The intersection is a regularized operation, i.e. two volumes sharing a face (or any other degenerate entity) do not count in the second condition. Notably, the separation of single features and features with interaction is a crucial step that overcomes the feature interaction problem in conjunction with the following topological graph. The title should be in 12-point Souvenir Lt BT bold. It should be no longer than one line, two if it is absolutely necessary. No abbreviations are allowed unless they are well known, e.g. NURBS, STL or IGES. Author names may be listed in any order, each given a superscript representing the author's affiliation. Each author requires only an affiliation, e.g. University or company, and an e-mail address. No mailing address, phone and fax numbers are allowed.

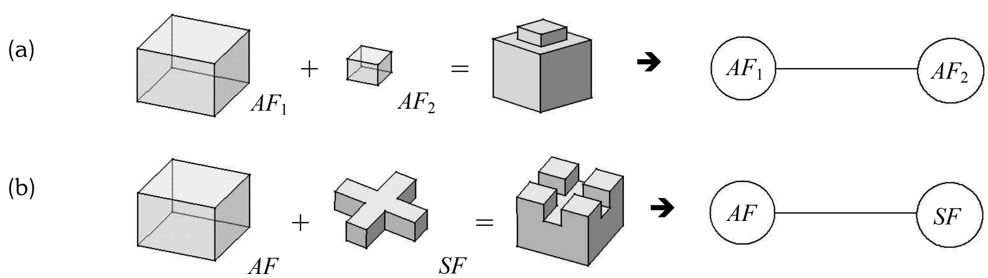

Fig. 4. Generation of an edge in the form-feature graph.

3.2 Topological Graph

Each node in the form-feature graph represents a topological graph of the corresponding feature volume. The topological graph describes the connectivity information among the faces that construct a B-Rep model. A graph edge links two nodes sharing an edge in the model. Our approach adopts an attributed graph that records the face and edge types in the graph node and edge, respectively. Previous studies [9-11] employed additional attributes such as surface area, orientation, and edge length in the graph to increase its discrimination capability.

3.3 Shape Distribution

The above graphs essentially characterize the topological relationships for feature volumes (form-feature adjacency graph) and faces of a B-Rep model (topological graph), respectively. These topology-based shape signatures may successfully distinguish the geometric construction procedure of 3D objects, but they do not consider geometric information such as size, position, and orientation. To overcome this deficiency, this work adopts a similarity function based on shape distribution [12] for sorting the parts that have been accessed with the topology-based methods, as shown in the last step of Figure 1. The result serves as an auxiliary tool for the user to select the part or parts that fit the design intent better.

4. SIMILARITY COMPARISON ALGORITHMS

4.1 Graph Comparison

To determine if two graphs or their sub-graphs are isomorphic is a NP-Complete problem [13]. Fortunately, it is not necessary to do an exact graph comparison in shape assessment. This research utilizes heuristics to accelerate the computation process by estimating two graphs "almost" similar rather than an exact match. The assumption made in these heuristics still guarantees the node constraint proposed by El-Mehalawi and Miller [10], i.e. a graph node to be matched to at most one node in another graph, but at the same time it relaxes the connectivity matching in a global sense. The resultant algorithms perform the similarity assessment among graph cliques [13] in which the links connected to each node are simply satisfied locally.

4.1.1 Form-Feature Graph Comparison

This section describes a computation scheme that compares the similarity between two form-feature adjacency graphs $G_1 = (V^1, E^1)$ and $G_2 = (V^2, E^2)$, where $V^1 = \{f_1^1, ... f_n^1\}$ and $V^2 = \{f_1^2, ... f_m^2\}$ with n and m as the node number in each graph. The superscript indicates the graph index. The scheme consists of the following steps:

1. Compare each node pairs between G_1 and G_2 based on their corresponding topological graph (see the next section) and generate a similarity matrix S_T with dimensions n×m as:

$$\mathbf{S}_T = \begin{bmatrix} S_T(f_1^1, f_1^2) & \cdots & S_T(f_1^1, f_m^2) \\ \vdots & \ddots & \vdots \\ S_T(f_n^1, f_1^2) & \cdots & S_T(f_n^1, f_m^2) \end{bmatrix}_{n\times m} \tag{1}$$

2. The above matrix only considers the similarity between nodes (or the corresponding feature volumes). We have to also estimate the adjacency condition of a given node among other nodes by comparing the graph edges connected to it. $A(f_i)$ characterizes the similarity for the neighboring nodes of f_i as:

   $A(f_i) = \{f_{i,1}, \cdots, f_{i,a}\}$ where a is the number of nodes connected to f_i in the graph. (2)

3. Given nodes f_i^1, f_j^2 belonging to two different graphs, we describe their adjacency similarity as $\Gamma[A(f_i^1) \times A(f_j^2)^T]$, where Γ is the maximal one-to-one mapping value for a matrix produced by $A(f_i^1)$ and $A(f_j^2)^T$. The next section will explain how to calculate the mapping value. An adjacency matrix is thus defined as:

$$\mathbf{AS}(f_i^1, f_j^2) = \begin{bmatrix} \Gamma[A(f_1^1) \times A(f_1^2)^T] & \cdots & \Gamma[A(f_1^1) \times A(f_b^2)^T] \\ \vdots & \ddots & \vdots \\ \Gamma[A(f_a^1) \times A(f_1^2)^T] & \cdots & \Gamma[A(f_a^1) \times A(f_b^2)^T] \end{bmatrix}_{a\times b} \tag{3}$$

   We then combine Eq.(1) (the node similarity) and Eq.(2) (the adjacency similarity) for a the similarity of a feature pair (f_i^1, f_j^2) according to:

$$S(f_i^1, f_j^2) = w_f \times S_T(f_i^1, f_j^2) + (1 - w_f) \times \frac{\Gamma[\mathbf{AS}(f_i^1, f_j^2)]}{\max(a, b)} \tag{4}$$

   where w_f indicates a weighting factor for the node similarity value. The denominator of the last term acts as a penalty when the number of edges connected to a feature is not equal to that of the other, namely a ≠ b. S_T is the similarity value determined by the topological graphs of the corresponding feature volumes (see later).

4. Applying Steps 2 and 3 to each possible feature pairs between the two graphs being compared results in a matrix **S** expressed as:

$$\mathbf{S} = \begin{bmatrix} S(f_1^1, f_1^2) & \cdots & S(f_1^1, f_m^2) \\ \vdots & \ddots & \vdots \\ S(f_n^1, f_1^2) & \cdots & S(f_n^1, f_m^2) \end{bmatrix}_{n\times m} \tag{5}$$

   Finally, the similarity value between G_1 and G_2 is computed as:

$$\text{Similarity}(G_1, G_2) = \frac{\Gamma[\mathbf{S}]}{\max(n, m)} \tag{6}$$

4.1.2 Topological Graph Comparison

The similarity assessment for the topological graph is similar to that of the form-feature graph. Assume a topological graph is expressed as $TG = (\mathrm{V}, \mathrm{E})$ with $\mathrm{V} = \{F_i\}$, $\mathrm{E} = \{E_j\}$, and $1 \le i \le m$, $1 \le j \le n$ where F_i and E_j represent the *i*-th face and the *j*-th edge respectively in the graph. Next, $Adj(F_i) = \{adj(F_1), ...adj(F_k)\}$ indicates the adjacency condition of F_i in a B-Rep model and this face has *k* neighboring faces. The graph similarity should take into account the differences in the node type, the edge type, and the adjacency condition of each node.

1. The similarity of the node adjacency depends on two factors: the similarity of each edge connected to the node being considered as well as the similarity between each of its neighboring nodes. The similarity function $\Psi(F_i^1, F_j^2)$ is thus written as:

$$\mathbf{\Psi}(F_i^1,F_j^2)=\begin{bmatrix} \Psi(E(F_1^1),E(F_1^2),adj(F_1^1),adj(F_1^2)) & \cdots & \Psi(E(F_1^1),E(F_b^2),adj(F_1^1),adj(F_b^2)) \\ \vdots & \ddots & \vdots \\ \Psi(E(F_a^1),E(F_1^2),adj(F_a^1),adj(F_1^2)) & \cdots & \Psi(E(F_a^1),E(F_b^2),adj(F_a^1),adj(F_b^2)) \end{bmatrix}_{a\times b} \quad (7)$$

which suggests F_i^1 has *a* neighboring faces (edges) and F_j^2 has *b* neighboring faces. $\Psi(E(F_a^1), E(F_b^2), adj(F_a^1), adj(F_b^2))$ is computed as: $\Psi(E(F_a^1),E(F_b^2),adj(F_a^1),adj(F_b^2)) = w_a v_e + (1 - w_a) v_{adj}$

$$v_e = \begin{cases} 1 & \text{if type of } E(F_a^1) = \text{type of } E(F_b^2) \\ 0 & \text{otherwise} \end{cases} \qquad v_{adj} = \begin{cases} 1 & \text{if type of } adj(F_a^1) = \text{type of } adj(F_b^2) \\ 0 & \text{otherwise} \end{cases} \quad (8)$$

w_a is a weighting factor for the similarity of the edge type.

2. Now the similarity of two nodes $S_{TG}(F_i^1, F_j^2)$ can be written as:

$$S_{TG}(F_i^1,F_j^2) = w_{TG} v_F + (1 - w_{TG}) \times \frac{\Gamma[\mathbf{\Psi}(F_i^1,F_j^2)]}{\max(a,b)} \qquad v_F = \begin{cases} 1 & \text{if type of } F_i^1 = \text{type of } F_j^2 \\ 0 & \text{otherwise} \end{cases} \quad (9)$$

Similar to Eq.(4), w_{TG} is a weighting factor for the comparison result of the face type. The following matrix represents the similarity between two B-Rep models in a form of the topological graph as:

$$\mathbf{S}_{TG}(TG^1,TG^2) = \begin{bmatrix} S_{TG}(F_1^1,F_1^2) & \cdots & S_{TG}(F_1^1,F_m^2) \\ \vdots & \ddots & \vdots \\ S_{TG}(F_n^1,F_1^2) & \cdots & S_{TG}(F_n^1,F_m^2) \end{bmatrix}_{n\times m} \quad (10)$$

The value is estimated as the maximal one-to-one mapping value of S_{TG} penalized by the node number difference as:

$$S_T(TG^1,TG^2) = \frac{\Gamma[\mathbf{S}_{TG}(TG^1,TG^2)]}{\max(m,n)} \quad (11)$$

4.2 Matrix Mapping

Matrix mapping plays a crucial role in the graph comparisons of this work. The main goal is to find the best match between two sets of nodes, i.e. their most similar mapping. Such a mapping implicitly assumes that a general graph has been transformed into a set of graph cliques for the comparison. With this heuristic, the mapping becomes a one-to-one dispatching problem [14], which can be expressed as a linear programming (LP) model as:

$$Max \sum_{i=1}^{n}\sum_{j=1}^{m} c_{ij}x_{ij} \quad \text{with } c_{ij}\text{: similarity value of assigning } i \text{ to } j. \quad (12)$$

$$\text{subject to} \quad x_{ij} = \begin{cases} 1 & \text{if assign } i \text{ to } j \\ 0 & \text{if not} \end{cases} \quad \sum_{j=1}^{m} x_{ij} \le 1 \quad \sum_{i=1}^{n} x_{ij} = 1, 1 \le i \le n, 1 \le j \le m.$$

The famous Hungarian Method [14] has been proposed to solve this optimization scheme in a polynomial time.

4.3 Shape Distribution

The shape distribution of a 3D model is generated based on a chosen shape function. There are several shape functions available such as A3, D1, D2, and D3 [12]. Most previous studies consider the D2 function a better discrimination criterion among them. Therefore, this research employs D2 for calculating the shape distribution. It is defined as the distance between two random points on the surface of the 3D model. The algorithm for the distribution generation consists of three steps:

1. The first step is to produce random points on the model surface in the STL format. Suppose $T = \{t_1, t_2, ..., t_k\}$ represents the set of triangular facets in the STL file:

(1) Calculate the surface area of each triangular facet and compute the total area *TA* in an accumulating manner.

(2) Generate a value between [0, *TA*] with a random number generator and estimate which facet the value corresponds to.

(3) Produce two random values r_1, r_2 between [0, 1] in the same manner; then calculate a random point $\mathbf{p}$ with the three vertices $\mathbf{p}_1$, $\mathbf{p}_2$, and $\mathbf{p}_3$ of the facet and r_1, r_2 according to: $\mathbf{p} = (1-\sqrt{r_1})\mathbf{p}_1 + \sqrt{r_1}(1-r_2)\mathbf{p}_2 + \sqrt{r_1}r_2\,\mathbf{p}_3$

2. The shape distribution is estimated as:

(1) Compute the distance between two random points obtained in the first step for a given number of times.

(2) Calculate the average value of the distances and choose the “bin width” as 1.5% of the value.

(3) Place each distance value into the corresponding bin in the histogram.

(4) Generate a shape distribution $H(h_i, \delta_i)$ based on the distance value (the accumulated bin h) and the occurrence probability δ.

3. Given two shape distributions H^1 and H^2, the dissimilarity function is written as:

$$L(H^1, H^2) = \sum_{i=0}^{n} \left| h_i^1 - h_i^2 \right| \quad \text{where n is the bin number.} \tag{13}$$

4.4 Complex Analysis

Graph comparison is the most time-consuming step in the proposed algorithms. This section conducts a complexity analysis and thus shows that the required comparisons can be finished in a polynomial time. The analysis is focused on the calculation of similarity based on the topological and the form-feature graphs. The worst case of the similarity assessment for two topological graphs occurs when the node being compared connects to all the other nodes. The time complexity is $O(\mathrm{V}_{TG}^1 \mathrm{V}_{TG}^2)$ where V_{TG}^1 and V_{TG}^2 indicate the node numbers, i.e. the face numbers of the corresponding feature volumes. Such a comparison must be applied for each possible node pair generated by the two graphs, $\mathrm{V}_{TG}^1 \mathrm{V}_{TG}^2$ possible combinations in total. Thus to complete this comparison process is $O((\mathrm{V}_{TG}^1)^2 (\mathrm{V}_{TG}^2)^2)$. Likewise, the worst-case time complexity for the comparison of two form-feature graphs is $O((\mathrm{V}_F^1)^2 (\mathrm{V}_F^2)^2)$. Each node of the form-feature graph contains a topological graph of the corresponding volume; therefore, the complete similarity assessment has a time complexity

$$O((\mathrm{V}_F^1)^2 (\mathrm{V}_F^2)^2 (\mathrm{MaxV}_{TG}^1)^2 (\mathrm{MaxV}_{TG}^2)^2) \tag{14}$$

where MaxV_{TG} denotes the maximum face number of any feature volume in the form-feature graph.

5. IMPLEMENTATION

The proposed scheme and related algorithms have been implemented in CATIA V5™ with CAA (Component Applications Architecture) C++ API’s [16]. A software module is constructed that enables the user to upload a CATIA V5 model and search similar parts among the existing ones in a part library. Currently the part library contains 400 CATIA models with various shapes created for testing (http://prl.ie.nthu.edu.tw/PartComparison/). Figure 5 illustrates the search results with a query part shown at the top. The first 20 models retrieved from the library are placed in the order of decreasing similarity. This figure also lists the similarity values calculated according to the form-feature graph and the D2 shape distribution. We choose the weightings $w_f = 0.75$ and $w_{TG} = 0.67$ in the former computation and the bin number as 1500 in the latter. Note that the shape distribution is applied only when multiple parts have the same similarity value (see Figure 1), i.e. their form-feature graphs and related topological graphs are isomorphic. Figure 6 shows the query results using different query models. Only the best three models are included in each case. These tests demonstrate that the scheme has a good discrimination capability in 3D shapes. Several interesting issues are observed from the results and discussed as the follows:

1. Any part search mechanism must recognize the part identical to the query model. Result #1 of Query 1 shown in Figure 6 validates this property. More importantly, the test results indicate that our approach is able to look for parts almost similar to the one being queried.

2. Our approach is advantageous over other methods based on single shape signature. In Figure 7, a model with feature interaction can have multiple shape signatures and different similarity values, depending on the manner of feature decomposition. Embedding the topological graph of B-Rep into the feature adjacency graph as this work has suggested eliminates this ambiguity, i.e. the shape signature becomes unique.

3. However, any shape signatures that merely employ the topological information (form-feature or faces in B-Rep) as the discrimination criteria cannot effectively discern the geometric information. Figure 8 shows such a drawback. The two parts retrieved from the search have the same similarity based on their form-feature and related topological graphs, but they do not look alike in shape or size.

4. On the other hand, the shape distribution approach has its inheriting flaw, too. It fails to utilize higher-level design functions in the search process. Since the similarity assessment is a random process, parts that are almost the same in shape but distinct in design function cannot be effectively differentiated. Figure 9 shows how this condition occurs: the first part has a thin protrusion, the second one has two such features, and the last one contains a shallow pocket in addition to a thin protrusion. These parts have nearly identical D2 shape distributions, so the similarity assessment based on them cannot precisely distinguish the difference. In contract, the form-feature graphs clearly disclose their discrepancy.

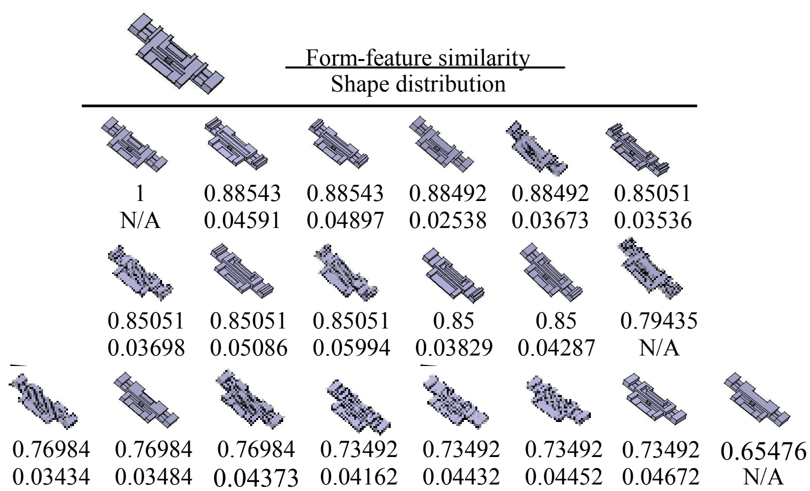

Fig. 5. Search results of a query part in the part library

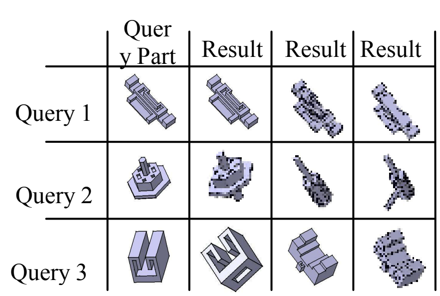

Fig. 6. The test results of different query models

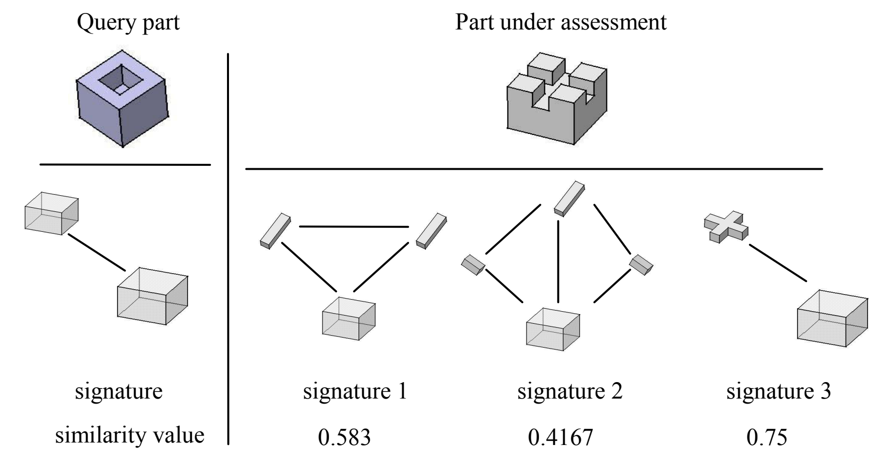

Fig. 7. The proposed approach can eliminate the ambiguity caused by feature interaction

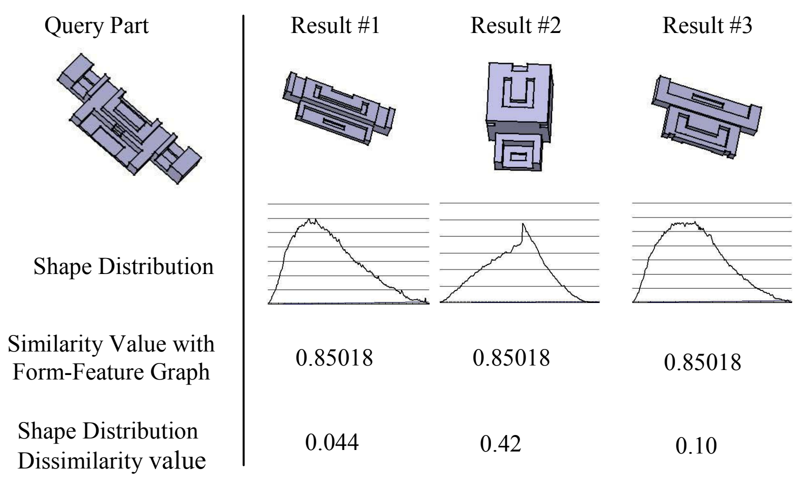

Fig. 8. Limitation of the shape comparison only based the topological information

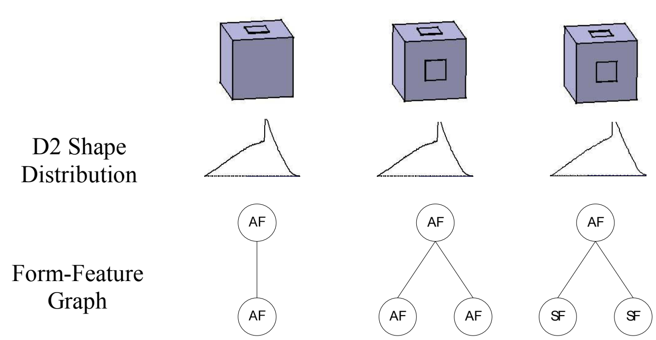

Fig. 9. Shape distributions cannot discern minor geometry variations

6. CONCLUSIONS

This paper has developed a novel computation scheme for 3D part search. A B-Rep model is transformed into a form-feature adjacency graph with the node as single features or the union volumes with feature interaction, and the edge indicating the connectivity condition between the nodes. Each node contains a topological graph corresponding to the volume it represents. We introduce a set of algorithms that computes the similarity value between two parts by comparing the corresponding graph information. A similarity function defined for two topological graphs measures the dissimilarity of a node pair in the form-feature graph comparison. Integrating the topology and form-feature shape signatures in this manner solves the feature interaction problem on one hand, and accelerates the search process on the other hand, i.e. the proposed algorithm completes the graph comparison in a polynomial time. Moreover, the scheme adopts a shape distribution method at the last stage in order to distinguish the variation in part geometry. Finally, this work has been implemented in a commercial CAD system and tested against a group of simple parts for demonstrating the practicality of the scheme. The implementation results also illustrate the advantages of our approach over other shape assessment methods using single shape signature. Specifically, it overcomes the feature interaction problem, captures the design intention more accurately than pure topology-based methods, and performs better in discriminating small geometry variations than using only shape distribution.

This work can be further improved in several areas. First, only allowing additive and subtractive form-features in part shape is limited in that the corresponding algorithms cannot deal with parts with modification features like chamfer and fillet. Shape signature should include engineering attributes such as tolerance, fit, and design descriptions so that it can capture the user intentions more accurately in part search. Second, the scheme adopts several weighting factors currently determined by heuristics. AI techniques can be applied to estimate these values in a more systematic manner. Consequently, we are developing a nonlinear neural network method that generates the weightings from the results determined by humans. After all, a part search algorithm must to a large extent reflect the user's intent. Finally, the function of a single part depends on the role it plays in a system or product. Hence, any part search of practical significance has to consider the position of the part in an assembly hierarchy and the arrangement with respect to other components in the assembly. Our future research is focused on this.

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