# Retrieving Similar Mechanical 3D Models by Freehand Sketches

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**Abstract.** This paper proposes a method for retrieving CAD models of mechanical parts by free hand sketches. Two shape signatures is proposed to describe the geometry and the topology of a CAD model respectively. A relevance feedback mechanism is introduced to combine the two dissimilarity distances measured by the two signatures. Experiments are conducted to evaluate the performance of the proposed method.

## Introduction

Content-based shape search of CAD models enables users to retrieve similar models that are alike in appearance or structure. Compared with traditional textual searching, the content-based shape search has three major advantages: 1. The 3D shape of an object overpasses the barrier of language and naming differences. 2. The shape similarity assessment is content-based. The shape feature is extracted and compared by algorithms automatically, no manual intervention being needed. 3. Measure the similarity between products or parts by shape is the natural way engineers think. Instead thinking in textural descriptions, what's initially in an engineer's mind is just "something like this".

Recent years many 3D shape retrieval systems have been proposed. Most previous studies focus on extracting a "shape signature" from 3D objects. A shape signature describes the shape information of a 3D object in a compacted numerical format. The similarity between 3D objects can be measured by computing the distance between signatures under a predefined metric. According to the genre of shape information that a signature describes, shape signature can be generally classified as follows: geometry based, topology based and feature based [1, 2]. Signature is an abstraction of 3D shape, so the capability of shape discrimination of single signature is limited [3].

This paper proposed a method for searching 3D CAD models of mechanical parts with freehand sketches. Users can draw three 2D outline sketches and a skeleton sketch to represent the shape of query. The 2D outline sketches describe the geometrical information of a 3D shape, and the skeleton sketch conveys the topological information of the 3D shape. A relevance feedback mechanism was introduced to combine the two similarity degrees measured by 2D outlines and skeleton. Figure 1 illustrates the outline sketches and a skeleton sketch of a 3D model.

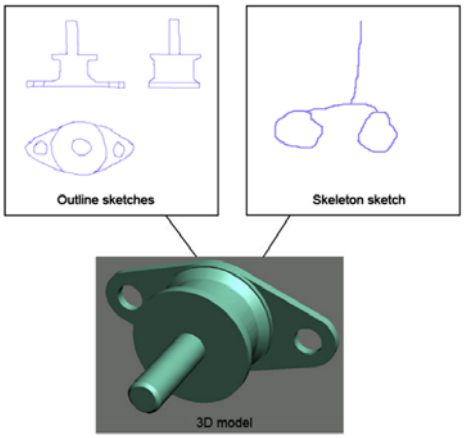


Fig. 1 Outline sketches and skeleton sketch of a 3D model

 

## Geometrical signature

Geometrical signature describes the shape of a 3D model by a set of 2D silhouette views. The geometrical similarity between two 3D models is assessed by comparing their 2D views. The following two sub-sections explain the modules to implementation geometrical signature in detail.

2D view generation is to obtain a series of projection views from a 3D model. These views represent the shape of the 3D model in form of 2D image.

The projection of a 3D model can be defined by a projection box. Each face of the box is a projection plan. For a 3D model may have arbitrary orientation in space, along which direction should the 3D model be projected? In many cases, a method called PCA (Principal Component Analysis) [4] is used to normalize the orientation of 3D objects, but PCA based methods are not robust [5]. This paper proposes a method for 2D view generation by using multiple projection boxes. Our method is similar with the LFD (Light Field Descriptor) [6]. But LFD is complicate and computational consuming. Our algorithm turns out to be simpler and efficient than LFD.

Our method applies a number of projection boxes with different rotating angles to a 3D model. To cover every possible viewing angle, the bounding boxes needed to be evenly distributed around the 3D model. This algorithm rotates each bounding box around x-, y- and z- axis by an offset angle respectively. By applying these projection boxes to a 3D model, views from different viewing angles can be obtained.

When the projection boxes are positioned, the next step is to generate the views from the 3D model. We use silhouette as the view shape of a 3D model [7]. For a 3D polygonal object, silhouette is defined as the edges that share a front- and a back-facing polygon. Intuitively, silhouette represents the outline of a 3D object. Figure 5 illustrates a 3D model and its silhouette.

Once the silhouette views of a 3D model have been generated, we can measure the similarity between 3D models by comparing their silhouette views.

Due to the reflective symmetry of silhouette, projections along opposite directions are identical. Thus, for a projection box, there are only three different silhouette views being generated. However, the corresponding relationship between the views of two models is unknown. Each permutation of three views of a model's projection box is a possible match to that of the other model.

We compare user's three sketches with each permutation of three outline views, and define the minimal dissimilarity distance between three sketches and three outline views over all permutations as the distance between user's 2D outline sketches and a projection box.

$$D_1 = \min_{l}(dis_{box}) \quad l = 1,2,...,L^3 \tag{1}$$

To measure the similarity between a user's sketch and an outline view, we use the Angular Radial Partitioning (ARP) proposed by Chalechale et al [8] to address our problem.

## Topological signature

Topological signature uses a skeleton graph to describe the shape of 3D models. Skeleton is a "central-spine" like 1D line representation of a 3D object. Skeleton retains the topology of the original object [9]. The following sub-sections will explain the modules to implement topological signature.

To extract the skeleton, a 3D model needs to be represented as a voxel model [10]. The process of extracting the skeleton from a voxel model is called skeletonization. Researchers in the computer graphics community have proposed lots of skeletonization algorithms.

The skeletonization method we use here is a kind of the so-called thinning algorithm [11]. Thinning is an iterative object reduction technique. It produces one voxel width skeleton by deleting points in the voxel model if they satisfy deletion conditions that preserve topology. Compared with other skeleonization methods, the advantages of adapting thinning algorithms in our work are: 1) Producing one voxel width skeleton, which is convenient for the later skeleton graph generation. 2) Efficient to compute and relatively easy to implement

After the skeleton of a model has been extracted, we convert it to a graph data structure. A

skeleton graph is generated by this way:

1) Node: a node represents the voxel at the end of a line, or the voxel at a cross.

2) Edge: an edge represents the connection between nodes.

Once a graph is generated, we perform a loop detection algorithm on it. The algorithm will find all the loops in a graph and replace it with a node. An attribute value is attached to each node to distinguish them, L for nodes of loop, N for other nodes. Loop detection and elimination will bring out two benefits:

1) A graph is reduced to a tree-like structure by removing internal loops. This will make the graph comparing more rapid.

2) A loop in a graph denotes a hole in the original model. Hole is an important feature for engineering models. Identifying loop is to recognize this feature. Users can search for models with holes by searching for graphs with L nodes.

We define a similarity metric between graph $G_1$ and $G_2$, representing a weighted sum of three similarity metrics based on different features of the graphs.

$$D_2(G_1,G_2) = 1 - \frac{num\_node(G')}{max(num\_node(G_1), num\_node(G_2))} \tag{2}$$

This metric defined by $dis_{nnode}(G_1,G_2)$ is based on the nodes number of the maximum matching subgraph. The function $num\_node$ returns the number of total nodes in a graph. $G'$ is the maximal common subgraph of $G_1$ and $G_2$. More similar are two graphs, closer will be the ratio to 1. To find the $G'$, it involves the process of graph isomorphism [12].

**Similarity degree combination**

Now, we get two dissimilarity distances measured by two metrics: the distance measured by the geometrical signature ($D_1$) and the distance measured by the topological signature ($D_2$). A simple approach for combining the dissimilarity distances measured by different metrics is to compute the weighted sum of them. However, it is not a good approach, for the difficulty to choose the weights that provide a good retrieval performance in general. Our method for resolving this problem is to treat the weights as probability and use the information from Relevance Feedback (RF) to estimate them. RF makes the search process as an interaction between the computer and users. For a RF based search process, the system first retrieves similar models and returns them to the user. Then, the user provides feedback regarding the relevance of some of the retrieval results (users mark the relevant objects in the results and submit them back to the search system). Finally, the system uses the feedback information to improve the performance in the next iteration.

Suppose $w_i$ is the weight of the similarity degree of 1- $D_i$, which should reflect the effectiveness of $D_i$ in retrieval. More tightly does a metric make the known relevant model distribute in its feature space, more effective is it.

Suppose that $q$ represents the query of a user and $R$ is the set of relevant models marked by user in the initial retrieval result. $w_i$ is estimated by the following formulas:

$$\begin{aligned} w_t &= \frac{1}{1+\sum_{i=1}^{n+1} maxdis(r_i')} \\ maxdis(r_i') &= \max_{r_j' \in R'}(D_t(r_i', r_j')) \\ t &= 1,2 \qquad R = \{r_1, r_2, \ldots r_n\} \qquad R' = \{q\} \cup R = \{r'_1, r'_2, \ldots, r'_{n+1}\} \end{aligned} \tag{3}$$

Where $maxdis$ is the maximum distance between a given element and other elements in $R'$ under the metric $D_i$. The sum of $maxdis$ over all elements in $R'$ reflects the tightness of known relevant objects. A smaller sum indicates a more tight set, vice versa.

## Implementation and experiment

In order to evaluate the validity and performance of our method, we implemented a prototype system and conduct some experiments on it.

To evaluate the retrieval performance of a search system, a ground-truth database is required to assess the relevance of models. We designed a ground-truth database including 421 3D CAD models and 39 classes for the test. The models in the database are classified manually by three of our research assistant students.

The performance of our prototype system with two RF iterations is compared with that of three other widely discussed 3D shape retrieval methods:

1) Sphere harmonic descriptor: a rotation invariant representation of shape feature obtained by computing the norm of each harmonic frequency of a function on concentric spheres [13].

2) D2 Shape Distribution: a histogram of distances between pairs of points on the surface of 3D objects [14].

3) Shape histogram: a histogram of distances from the center of mass to points on the surface of 3D objects [15]

The precision-recall curves are illustrated in Figure 2. It can be seen that our proposed method has the best retrieval performance.

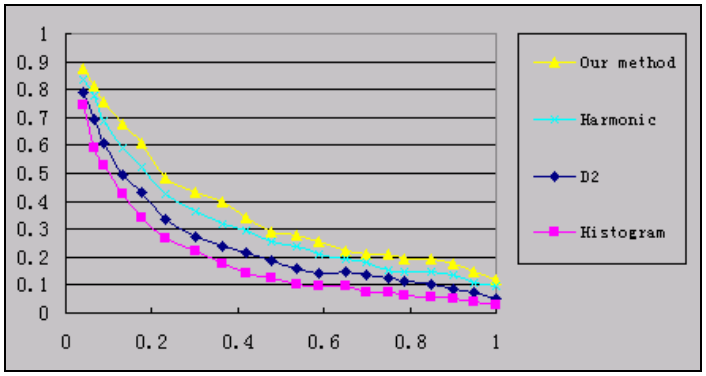


Fig. 2 Precision and recall plot of 3D model retrieval algorithms

## Conclusion and future work

This paper proposed a method for searching 3D CAD models of mechanical parts with freehand sketches. For mechanical CAD models, both geometrical information and topological information are important for similarity assessment. We proposed two shape signatures to describe the geometry and the topology of a mechanical CAD model respectively. A relevance feedback mechanism is introduced to combine the two dissimilarity distances measured by the two signatures. Experiments demonstrate that the performance of our method is satisfactory.

In the feature, we will conduct extensive experiments to test advanced relevance feedbacks algorithm and interaction. We also will incorporate our system with commercial PDM software, in which users can search for similar CAD models in real product database.

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