

## Similarity Comparison of Mechanical Parts

Taesik Hong<sup>1</sup>, Kunwoo Lee<sup>2</sup>, Sungchan Kim<sup>3</sup>, Chongnam Chu<sup>4</sup> and Hyunchan Lee<sup>5</sup>

<sup>1</sup>Seoul National University, [pockshik@cad.snu.ac.kr](mailto:pockshik@cad.snu.ac.kr)

<sup>2</sup>Seoul National University, [kunwoo@cad.snu.ac.kr](mailto:kunwoo@cad.snu.ac.kr)

<sup>3</sup>Seoul National University, [sungchan@cad.snu.ac.kr](mailto:sungchan@cad.snu.ac.kr)

<sup>4</sup>Seoul National University, [cnchu@snu.ac.kr](mailto:cnchu@snu.ac.kr)

<sup>5</sup>Hongik University, [hlee@wow.hongik.ac.kr](mailto:hlee@wow.hongik.ac.kr)

### ABSTRACT

It is very often necessary to search for similar parts during designing a new product because modifying existing similar parts is a commonly used way of creating new parts with ease. In this way, the design time and cost can be reduced. Thus it would be nice to have an efficient similarity comparison algorithm that can be used anytime in the design process.

In this research, the solid parts are represented by B-rep and similarity comparison is performed in two steps from overall appearances to detail features. First, geometric information is used in low level of detail for easy and fast pre-classification by overall appearances. Then feature information is used to compare the detail shape in high level of detail to find more similar design.

To realize the idea above, a multi resolution algorithm is proposed so that a given solid is described by a low resolution appearance and detail features in high resolution. Using this multi-resolution representation, parts can be compared based on the overall appearance first to reduce the number of parts to be compared in high resolution, and then detail features are evaluated to retrieve the most similar part. In this way, computational time can be saved by fast classification in the first step and reliability can be preserved by detail comparison in the second step.

**Keywords:** Similarity Comparison, Level of Detail, Multi Resolution

### 1. INTRODUCTION

In the industry, most new product designs are obtained by partially modifying some existing products. It is very rare that entirely new products have to be designed from scratch. Thus much time and money would be wasted if all new products were designed from scratch without looking for the similar products. So in many cases, the designers want to use existing product data during a new product design process. These days, most mechanical designers use a feature-based 3D modeling system. In this system, new models can be created easily by modifying some constraints of existing models instead of totally recreating them. So if designers have efficient methods to search for similar models, both time and money can be saved.

There have been many approaches to compare similarity between mechanical parts. Many of them focused on the issues related to the process planning, and most of them depended on machining features. But, the geometrical appearance and feature shape are more important in the design process. Therefore, it is difficult to use these methods directly for the product design process and the shape similarity should be considered.

Previous researches for the shape similarity comparison techniques can be grouped into two categories. One method compares only geometrical similarity and the other compares some pre-defined typical features. The former allows any input data structure because it compares parts only with geometrical data. But if the parts are so complex, it takes long time and the results are not so good. The latter can not deal with all formats and needs more information because it should extract typical features like holes, fillets and concave regions from the parts and compare them. Although it needs more information, it needs less computational load and produces more reasonable results than the geometrical technique in cases of complex parts.

In this approach, models to be compared are represented by B-rep because it is used in most 3D modeling systems for the product design. Therefore, the input generality of the geometrical data method is not an important issue. And feature information can be extracted easily from B-rep. Thus it would be more reasonable for us to use the typical feature based similarity comparison method. But if the part is originally very simple or simplified for some purposes,

there may be no typical feature to be compared. So, in that case, we have no choice but to use the geometrical data technique for comparison.

In the general searching method, if the database is clustered well and there are some robust methods to compare them, computational time can be reduced dramatically by discarding useless groups in retrieval. This concept can be applied to retrieving the similar part to a given mechanical part. But the clustering standards and algorithms should be sound and efficient for the robust and fast result.

In this paper, all the models to be compared are clustered into some groups with respect to their overall appearances because overall appearance similarity is relatively more important than detail features in design process. In this stage, low detail level models are used for efficient comparison because the comparison is focused just on the overall appearances. The models are simplified by adding or removing typical features to ignore details. In this simplified state, feature based similarity comparison can not be used because there are not enough features to be compared. So, geometrical data comparison method is used for the classification. If the parts are complex it takes long time to compare, but by using simplified models, computational time can be reduced drastically because the number of sampling data can be far reduced.

Once the group that has the most similar appearance with the query part is found, typical features of the query part should be compared to each part in the selected group. The number of the same type and similar size features existing between the parts can be the measure of the similarity. The feature information can be obtained in the simplification procedure because the feature must be recognized if it has to be removed. With this detail comparison, the parts that are similar only in the overall appearance but too much different in details will be excluded and the most similar part can be obtained.

This paper is organized as follows. Section 2 reviews the previous feature recognition methods. Section 3 is devoted to explaining some background information needed to understand this paper. Section 4 presents an algorithm for comparison and recognition. Section 5 shows some implementations and following results. Section 6 includes advantages and drawbacks of the proposed algorithm, and future works.

## **2. RELATED WORKS**

Each in this section, a brief survey of the works related to similarity comparison, model simplification, and database techniques are given.

### **2.1. Similarity Comparison**

#### *2.1.1. Geometry Based Comparison*

Many 3D models are used in many fields, for example, mechanical engineering, computer graphics, bio mechanics, etc. Each field has its own data structure to store 3D objects. In mechanical CAD systems, B-rep is the dominant data structure, but even B-rep structures are still different from one CAD system to another.

For this reason, many shape similarity comparison algorithms use just the polygonal mesh as their input to prevent the loss of generality. They can even compare some degenerate models because they use only the geometry itself.

Osada et al. [9] used the shape distribution graph for comparison. Ip et al. [3] improved Osada's method. Ip divided Osada's shape distribution graph into three to make the results more accurate. Ohbuchi et al. [10] used the moment of inertia to judge the similarity.

Although these methods can keep the generality, it still has computational complexity when the part is simple. The method doesn't reflect the complexity because it just uses fixed sample points regardless of the complexity of the parts. The computational load can be reduced only by changing the number of sample points manually.

#### *2.1.2. Feature Based Comparison*

The feature based similarity comparison mainly focuses on how the models are formed by features especially machining features. So, models are clustered by some typical machining features like holes, pockets, fillets, etc. Elinson et al. [1] and McWherter et al. [4] explain this method very well. The typical features can be also used for comparison at high level of detail because it can reduce the computational load compared with the geometrical similarity comparison in that level. However, the features used in this paper are a bit different from machining features.

This method can also reflect the complexity of a part because the number of typical features can be regarded as proportional to the part's complexity. So the different criteria can be used up to the complexity of the parts and additional useless computation can be prevented. But if the parts are so simple that there is no typical feature to be compared, this method may not be performed so well.

#### *2.1.3. Topological Similarity Comparison*

There is another way to compare similarity using topological structure. Topological structure means the connectivity and adjacency of the vertices, edges and faces of the part. In this method, two parts are regarded similar if their

topological structures are similar. Hilaga et al. [6] and Shokoufandeh et al. [2] explain this method. However, topological similarity can not guarantee the shape similarity. For example, a sphere has the same connectivity of vertices, edges and faces with a torus but their appearances are quite different.

#### 2.1.4. Using Convex Decomposition

Mukai et al. [11] researched this method. In this method, the given object is decomposed into convex components and a hierarchical tree structure containing those convex components is constructed. Then, for the first, they compare the tree structure. After that, the shape and pose of the parts are compared. This method looks simple but it has some drawbacks. Like topological comparison, it compares the tree structures first. Therefore even geometrically similar parts can be discarded because of the difference between tree structures regardless of their real appearances.

## 2.2. Model Simplification for Multi Resolution

To reduce the computational cost dramatically, model simplification is very important. If we choose a wrong simplification method, we may lose accuracy. There is an overview of some works related to this topic below.

### 2.2.1. Surface Simplification

This method focuses on the simplification of the polygonal meshes. To reduce the computational cost, the minimum numbers of meshes that can represent the required detail level are used. Therefore, the surfaces of the original model are approximated at each level. Kim et al. [13] and Garland et al. [7] use this method to embody the multi resolution. In the field of computer graphics or bio mechanics, it is a reasonable method. But in mechanical CAD systems, surface approximation is not so good because it can distort the original surface too much at the low detail level and it is so hard to reconstruct the original model from the low level.

### 2.2.2. Feature Based Simplification

For greater efficiency, we employ the feature based simplification concept. Zhu and Menq [5] explain that the method embodies the multi resolution representation by suppressing or regenerating some complex features of the model. In doing this, the models can be simplified in a manner that is suitable for our goal. Zhu suppresses only fillets and rounds from the models to make the model simpler. Kim et al. [12] suppresses more features like chamfers, passages, concave regions, and smooth out features. Kim's method will be used in this approach

## 2.3. Solid Model Indexing and Clustering

After the similarity comparison method and model simplification method are chosen, indexing and clustering of parts in the database should be considered for retrieval. McWherter et al. [4] and Peabody et al. [8] explain the techniques of clustering and indexing databases for CAD Models. They give indexes to the parts using a model signature graph which is drawn by the topological information. Then they cluster it into 'k' clusters with minimum total square error. The number 'k' is set manually. Though the topological information is not used in our approach, this method of clustering and indexing databases is used as a reference.

## 3. BASIC NOTIONS

### 3.1. Level of Detail

These days, computing hardware has been improved so much that the performance of graphic devices are much better and faster. But when the complex objects are to be displayed, there are so many elements to be shown and very complicated matrix calculations are needed. For instance, when we want to embody virtual reality, it should show the object and its movement as real time streaming. It will still take a long time and use large memory storage even with modern computer systems. Thus it is necessary to display the complex implementation results efficiently. To archive this, the LOD concept is used. LOD stands for level of detail and it means that different levels of detail can be used for each purpose. For example, when we need to show a gear part, we must show all details of the gear, including the teeth. But if we just want to know the approximate size of that gear, we can represent it as a disk or a cylinder. If the level of detail of a part is lower, the computational load needed to display it is smaller. Using this technique, the memory usage and the computation can be optimized for each goal.

There are some methods to implement LOD. In computer graphics, the most commonly used method is to reduce the number of facets of the surfaces. In mechanical engineering, and especially in mechanical CAD systems, there is a similar method. It reduces the complexity of data by simplifying its geometry. For example, if a part is stored in a B-rep data structure, it has some topological information and geometrical information. If it uses more detailed geometry to display the part preserving its original topology, it can make the part more detailed. By the reverse process it can make the part simpler. But if we use these methods to simplify the model, the original shape can be distorted and may not be

able to be restored exactly what it was. Furthermore, it is harder to cluster and index parts because they may have no meaningful appearance at the lowest level.

There is another way to implement level of detail. This method reduces or restores the complexity by removing or adding some portion of the original part. The portion to be added or removed is not chosen randomly, because it can change the characteristic appearance of the whole body. Usually the passage, chamfer, blend are added or removed, because these features provide additional information of the part but the overall appearance of the part is not drastically changed when they are added or removed. Also, they can be used as clues to indexing when we cluster our database. Our goal is to cluster and index the parts in our database, and retrieve a part that we want. So the second LOD concept is more efficient for our purpose.

There are some examples of LOD in Fig. 1.



Fig. 1. Two types of Level of Details

### 3.2. Multi Resolution Algorithms

In this approach, in order to embody the level of detail, some portion of the part is added or removed. We call it “Multi Resolution operation”. There are two operations called “Wrap-around” and “Smooth out” to realize multi resolution. These operations are explained well in Kim et al. [12]’s research.

Wrap-around operation removes the features like blends, chamfers, passages and general concave regions in a B-rep model which are considered as the elements to make the model complex. If the face-set composing these features is removed and the adjacent faces to the face-set are extended, only the selected feature can be removed while preserving the remaining topological and geometric data of the overall shape as shown in Fig. 2(a).

Smooth out operation removes the additive feature like boss and rib as shown in Fig. 2(b). They have a small volume compared to the total model. If they are removed, more smooth shape is generated and then wrap-around and other simplification operations can be applied again.

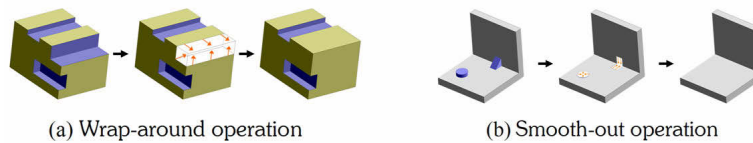


Fig. 2. Multi Resolution Operation

Both of the operations save the removed features as sheet bodies, so the simplified parts can be restored to the original body by sectioning or union operation. And the features are removed in the order according to the magnitude of the area of the face-set composing the feature because we can think intuitively that the feature which has the smaller area has a smaller effect on the original part when it is removed.

The examples of typical features are shown in Fig. 3.

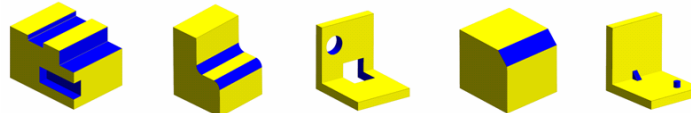


Fig. 3. Concave, blend, passage, chamfer, smooth out feature

## 4. SIMILARITY COMPARISON ALGORITHM

### 4.1. Process Overview

The goal of this approach is to find the most similar part to the part being designed. So we must define what similarity means in that process. These days, most of the mechanical parts are designed by feature based modeling systems. In this modeling system, designers can modify many kinds of pre-defined features by adjusting their constraints to create new features of the desired part. For example, look at Fig. 4. Fig. 4(a) is the original part. Fig. 4(b) and 4(c) are the

modified ones. The original part consists of one base feature and some sub features. The base feature is the extruded feature that is colored green. And a grey colored extruded feature is added on it. Finally two passages are added. This part can be modified in two different ways. First, like (b) in Fig. 4, base feature can be modified by changing its constraints. Second, like (c) in Fig. 4, some sub features can be modified and even can be added or removed.

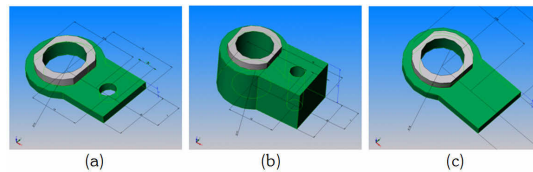


Fig. 4. Feature based modeling (using SolidWorks™ 2003)

When the designer wants to find the similar part, two conditions must be regarded. First of all, base feature should be similar to the concept that he or she has. Because no matter how similar the sub features are, if the base feature is quite different, we must re-design it and may lose most of the sub features if there are interdependent relations between features. This is true for many feature-based modelers. Once the base feature of a part is similar to the concept, then it would be good to evaluate the number of similar sub features to reduce the time for creating new sub features.

To achieve this, two steps are used. In the first step, geometry data are used to cluster the parts according to the appearance of the base feature. Then B-rep information of the parts is used to check the similarity of sub features.

#### 4.2. Pre-classification

If base features of the parts are similar, their overall appearances are also similar. The overall appearances can be compared using the shape distribution graph suggested by Osada et al. [9]. In that research, Osada sampled the fixed number of point on the part's surface and calculates Euclidian distances of every pairs of points. Then draw a distribution graph with those distances as shown in Fig. 5(a). The graph has some typical trends according to the overall appearance of the part as shown in Fig. 5(b). So the similarity in the overall appearance can be evaluated with those graphs and parts can be clustered to several groups.

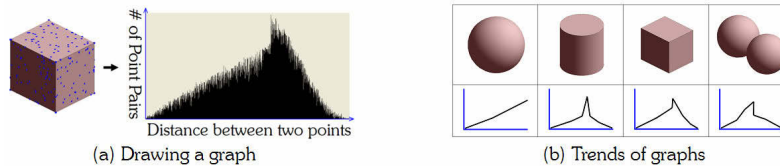


Fig. 5. Shape distribution graphs

Osada's method has many advantages. It uses simple calculation and doesn't require to concern about location and posture of the parts. But it has some drawbacks also. First, the result may not be reliable if small numbers of sample points are used. However increasing the number of the sample points will require more time to draw the graph. Second, if all the parts are very complex, the distribution graphs of all the parts will have the similar form of normal distribution. So the graphs cannot be used to distinguish the parts.

In Osada's research,  $1024^2$  samples were used for each part. It may be reasonable for his research but it is too large for ours because the database to be clustered is very huge. In the proposed approach, only  $300^2$  samples are used. Because the reasonable trend in the shape of graph can be obtained with this amount of samples if the parts are simple. But  $300^2$  samples may be insufficient for complicated parts. Therefore, the comparison based on the shape distribution graph is used only for the simplified parts that characterize the overall appearance in the proposed approach. The effect of simplification on the shape distribution graph is shown in Fig. 6.

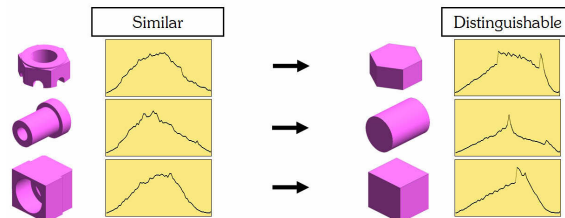


Fig. 6. Effect of simplification on shape distribution graph

Once all parts are simplified properly, shape distribution graphs of all parts are obtained and used for clustering. The simple version of k-means clustering introduced by MacQueen is used for clustering [8].

Terms are defined as follows,

- Distance between two Shape Distribution Graphs; Integration of the square difference between two graphs.
- Averaged Shape Distribution Graph (ASDG); Average of all the graphs in the group.
- Square Error; Sum of the distances of Shape Distribution Graphs from ASDG of that group.
- Total Square Error; Sum of the square errors of every group.

then the clustering process is as follows.

1. Shape Distribution Graphs (SDG) are generated for parts.
2. 'k' clusters are created and seeded with 'k' SDGs.
3. Select an unclustered SDG,  $g_i$ .
4. Find cluster,  $c_n$ , whose ASDG is closest to  $g_i$ , and insert  $g_i$  into  $c_n$ .
5. Recalculate the ASDG for  $c_n$ .
6. Repeat steps 3-5 until no more uncluster SDGs remain.
7. Select two clusters,  $c_1$  and  $c_2$  with the largest Square Error.
8. Select two SDG,  $g_1$  from  $c_1$  and  $g_2$  from  $c_2$ , furthest from the ASDG.
9. Swap  $g_1$  and  $g_2$  if the swap reduces the Total Square Error of the clustering.
10. Repeat steps 7-9 for 1000 iterations.

### 4.3. Detailed Comparison

After the parts in database are clustered into some groups, a query part can be compared with the references in the most similar group to find the most similar one. For this, the similarity index between the parts is calculated. It indicates how much one part is similar to others. It can be calculated with the delta volumes of passage, chamfer, blend, concave, and smooth out features. Delta volume is the absolute value of the difference of the part volume between before and after removal of the corresponding feature. The larger the index is, the more similar the parts are. The detailed formula of the similarity index is given below.

$$\text{Similarity Index} = \frac{1}{\sum_{n=1}^5 \left[ \sum_{k=1}^{I_n} \left\{ \left( \frac{DV_{k,n,q}}{V_{Q,simplified}} - \frac{DV_{k,n,r}}{V_{R,simplified}} \right)^2 \times VR \times FND \right\} \right]} \quad (1)$$

The definition of the variables in the equation (1) is as follows.

$DV_{k,n,q}$ : Delta volume of the 'k'th 'n' type feature in the query part. (n=1, 2, 3, 4, 5 and k varies from 0 to the total number of type 'n' feature in the part) There are 5 types of features being considered. Specifically, n is equal to '1' for a passage, '2' for a chamfer, '3' for a blend, '4' for a concave feature, and '5' for a small protruded feature to be smooth-out.

$V_{Q,simplified}$ : The volume when the query part is fully simplified.

$DV_{k,n,r}$ : Delta volume of the 'k'th 'n' type feature in the reference part. (n=1, 2, 3, 4, 5 and k varies from 0 to the total number of type 'n' feature in the part)

$V_{R,simplified}$ : The volume when the reference part is fully simplified.

'VR' is  $DV_{k,n,q}/V_{Q,simplified}$  as its default value. If the number of features of a certain type in the query part is smaller than that of the reference part, then VR is changed to  $DV_{k,n,r}/V_{R,simplified}$ . For example, the number of passage features in the query part is 3 and that in the reference part is 4,  $VR = DV_{k,n,q}/V_{Q,simplified}$  from k=1 to k=3 and  $VR = DV_{k,n,r}/V_{R,simplified}$  when k=4. The reason why we set VR in this way is that we want to give the feature in the query part a priority because the query part is the main body of the comparison. If there is no more feature in the query part, we can conclude that large delta volume of the features in the reference part means large difference from the query part because there is no match for them in the query part.

'FND', the last term in denominator, stands for the difference of the number of faces between features. This term is used to consider the formation of the feature. Though features can not be identified perfectly from the number of faces composing them, their shapes can be guessed roughly. Consider an example in Fig. 7. Therefore, the difference of the number of faces between the features can be considered as one of the metric for comparison. FND can be calculated

with the absolute value of the difference of the number of faces between the features and 1 should be added to prevent *FND* from being zero.

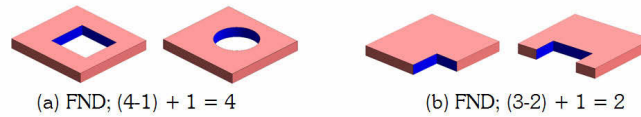


Fig. 7. Calculations of FND

$I_n$  is the larger one between the number of the existence of a certain feature in query and reference part. For example, if the number of blend features in the query part is 7 and that in the reference part is 5, then  $I_n$  will be 7. In this situation  $DV_{6,3,r}$  and  $DV_{7,3,r}$  are set to be zero. In this way, not only the deviation of the delta volume but also the difference in the number the features can be reflected in shape similarity calculation.

Note that there is an order to be followed in calculating the equation (1) such that delta volumes of the features of the similar size are calculated in a pair. If the sizes of the features are ignored, the result may be unreliable. Consider an example in Fig. 8. If calculated with wrong order, the denominator of equation (1) will increase and the similarity index will decrease although the parts are so similar.

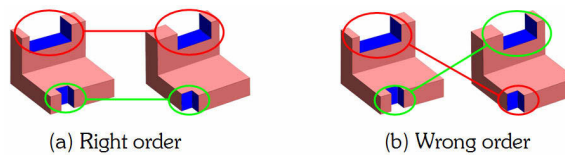


Fig. 8. Calculation order

The reason why delta volume is used in comparison is that it is the most reasonable value to show the influence of the feature in the part. We may consider using the area of the faces composing the feature. This will be a good substitute for the delta volume in most cases. However, in some situations, the area may not reflect the effect of the feature as its importance. Consider an example in Fig. 9. If the area of the faces composing the passage feature in the center is used, the feature is regarded to be insignificant because the area is very small. However its effect on the overall shape is significant if the hole occupies the major portion of the surface. This problem can be avoided by using the delta volume.

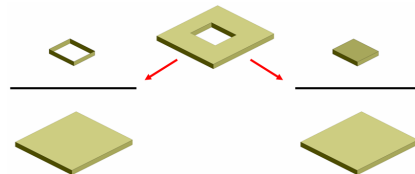


Fig. 9. Face set and delta volume

Also note that delta volume is divided by the volume of the fully simplified model instead of the full detail model for the normalization. If the original part volume is used, there can be a situation where the divided value becomes greater than 1 when delta volume is very large. In this case, the weight of that feature in the total model can be confused because it can not be regarded as the portion of the part anymore.

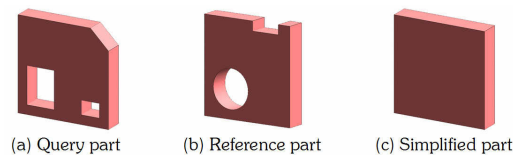


Fig. 10. Example parts

There is a simple example of calculating similarity index. Fig. 10(a) is query part and Fig. 10 (b) is reference part. Both of the parts are simplified as Fig. 10(c) but dimension orders are different. Simplified volume of query part is 200 and



that of reference part is 200000. There are two passages and a chamfer in query part. The bigger passage's delta volume is 24, the smaller passage's delta volume is 6. The delta volume of chamfer is 4. There are one passage and one concave feature in reference part. The delta volume of the passage is 26101 and that of concave is 6000. So,  $V_{Q,simplified}$  is 200,  $V_{R,simplified}$  is 200000,  $DV_{1,1,q}$  is 24,  $DV_{2,1,q}$  is 6,  $DV_{1,2,q}$  is 4,  $DV_{1,1,r}$  is 26101 and  $DV_{1,4,r}$  is 6000. With these values, similarity index of two parts can be calculated as follows.

$$\text{Similarity Index} = \frac{1}{\left[ \left( \frac{24}{200} - \frac{26101}{200000} \right)^2 \times \frac{24}{200} \times 4 \right] + \left[ \left( \frac{6}{200} \right)^2 \times \frac{6}{200} \right] + \left[ \left( \frac{4}{200} \right)^2 \times \frac{4}{200} \right] + \left[ \left( \frac{6000}{200000} \right)^2 \times \frac{6000}{200000} \right]} = 8694.1$$

In this way, we can calculate similarity index of each reference part.

**5. IMPLEMENTATION RESULT**

The proposed method has been implemented and tested with 174 mechanical parts. The parts were collected from "www.procentral.com".

**5.1. Pre-classification**

If the parts are clustered into many small groups, the number of detail comparison will be decreased. It can save computation time. But if the groups are too many, the difference between the groups may not be so clear. Therefore setting the proper number of the group is important. Considering the tradeoff between the computation time and the accuracy of the comparison, the database is clustered into 8 sub-groups with 8 seeds shown in Fig. 11. The seeds are selected according to the drifts and the position of maximum values of the graphs. Every part is simplified for the pre-classification. The result is shown in Fig. 12.

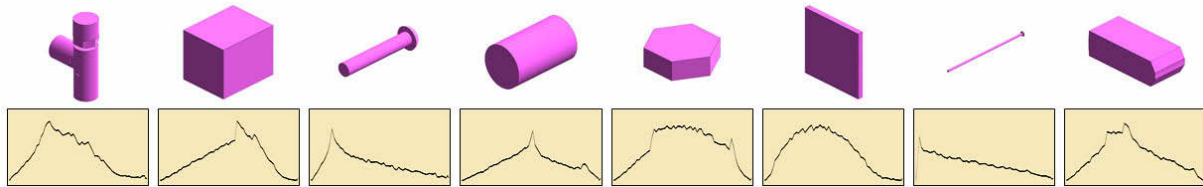


Fig. 11. Seeds for pre-classification

No	Parts
1	[A collection of 3D parts belonging to group 1, including various bolts and nuts]
2	[A collection of 3D parts belonging to group 2, including various nuts and washers]
3	[A collection of 3D parts belonging to group 3, including various pins and shafts]
4	[A collection of 3D parts belonging to group 4, including various cylinders and rollers]
5	[A collection of 3D parts belonging to group 5, including various hexagonal nuts and washers]
6	[A collection of 3D parts belonging to group 6, including various plates and blocks]
7	[A collection of 3D parts belonging to group 7, including various pins and shafts]
8	[A collection of 3D parts belonging to group 8, including various bolts and nuts]

Fig. 12. Pre-classification result



## 5.2. Part Retrieval

Three kinds of retrievals are tested for a given query part. the query part is chosen from the group 5 of Fig. 12. It is the part surrounded by red square in Fig. 13 to 15. The closest 10 parts are shown as a result of each test.

First, only shape distribution graph is used for comparison for the whole data base without considering the pre-clustered groups. The result is shown in Fig. 13. In this test, the shape distribution graph of the fully simplified model is used for the comparison. Though the retrieval is performed over the whole database, the closest 10 parts are all the member of group 5. It shows that pre-classification performed well. But the order of similarity is not so good. Even the query part itself takes just the fourth position. And it can be changed every time the retrieval performed again because shape distribution graph is based on the random sample points.

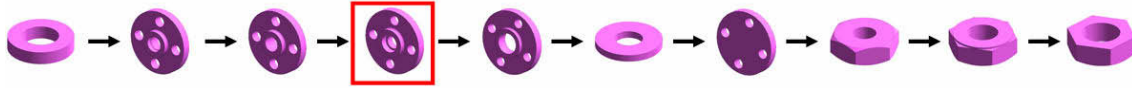


Fig. 13. Retrieval result 1

Now, look at Fig. 14. which shows the result of the second test. Only the feature information is used at this time. The numbers below each part are the similarity indices. In this case, the first part in Fig. 14. has the infinite similarity index because the denominator of equation (1) is zero when the feature information is perfectly matched. It means that it is the query part itself. And the result of retrieval will be the same whenever it is performed. But there are some parts that are quite different from the query part in appearance because this method compares only the feature type and delta volume difference.

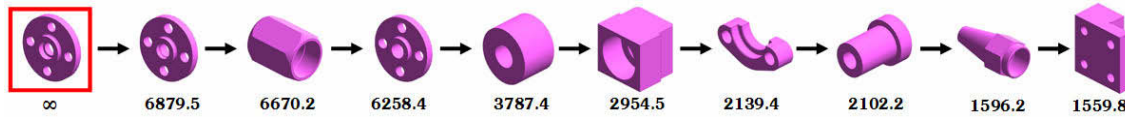


Fig. 14. Retrieval result 2

Finally, the proposed mixed method is used. It performs the retrieval just from the group which is the closest to the query part. It is the group 5 in Fig. 12., in this case. The result is shown in Fig. 15. Note that the overall appearances of all the retrieved parts are similar and the detailed comparison seems to be reasonable. Therefore, it can be concluded that the proposed method yield a more fast and robust result. There are some more results using the proposed method in Fig. 16.

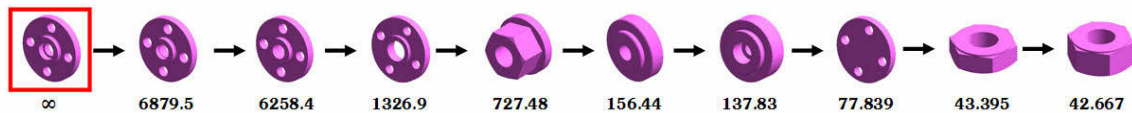


Fig. 15. Retrieval result 3

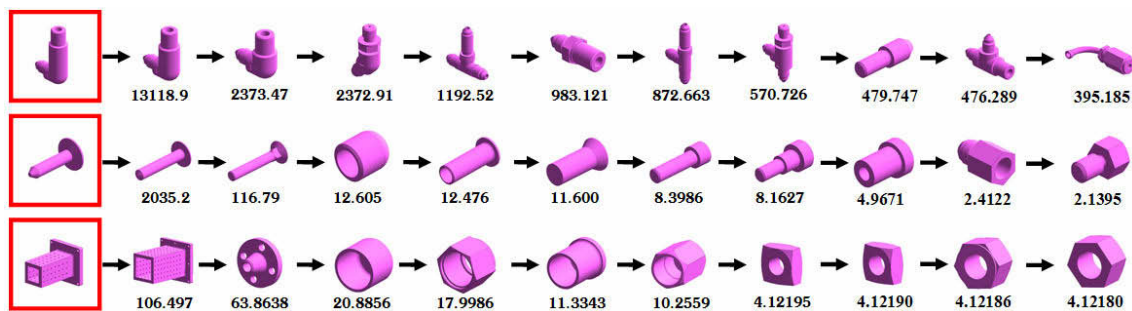


Fig. 16. Results of retrieval

## 6. CONCLUSION

The main purpose of this paper is to compare the similarity of the mechanical parts to reuse the existing similar parts in the design process. The existing methods for the similarity comparison can be generally categorized into two groups. One uses only the geometrical data, the other uses typical feature information that can be derived from B-rep. Both of

them have their own strengths and drawbacks. In this approach, a mixed method is used to take advantages of the strengths and to overcome the drawbacks. Specifically, the overall appearances of the parts are compared using geometrical information and the detail features derived from B-Rep are used for detail comparison. For this purpose, a multi-resolution algorithm is used so that the low resolution models of the part are used for the overall appearance comparison and the high resolution models are used for the detail shape comparison. Overall appearance can be compared faster and the detail features can be recognized more efficiently by using this algorithm.

The robustness of the multi-resolution algorithm is very important in the proposed approach. If a part can not be simplified appropriately, the overall appearance comparison may not be performed well. And if a detail features can not be recognized in the multi-resolution algorithm, it can not be used for the detail comparison. In fact, our multi-resolution algorithm can not find all the features, and can not simplify all the recognized features. Therefore improving this algorithm to be more general and robust is the very important issue for the future.

Shape distribution graph is used in this approach to compare the overall appearance of the parts because of its simple computation. Though it is very simple and fast, sometimes the classification result may be too rough. Therefore to find the easy and robust appearance comparison method would be another important work for reliable clustering and retrieval.

## 7. ACKNOWLEDGMENTS

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