LETTER

Matching 3D CAD Assembly Models with Different Layouts of Components Using Projections

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SUMMARY We present a matching method for 3D CAD assembly models consisting of multiple components. Here we need to distinguish the layouts and the materials of the components in addition to their shapes. A set of the feature quantities of an assembly model is extracted using projections from various angles. We show the effectiveness of our method experimentally for 3D CAD assembly models.

key words: 3D CAD assembly model, projection, matching

1. Introduction

3D CAD softwares have become widely used to manufacture various products. In designing new or improved products, the reuse of existing models is helpful. Therefore it is important to develop methods to find necessary models efficiently for reuse. In this paper, we present a matching method for 3D CAD assembly models which consist of multiple components. Here we have to distinguish 3D CAD assembly models by not only their global shapes, numbers and types of components but also geometric layouts of the components. Figure 1 shows an example of two assembly models with different layouts of their components. They have the same global shape and consist of the same components. The green components and the red ones have the same shape but different layouts. Although several methods for searching 3D CAD assembly models are proposed \([1]–[3]\), few works focus on this problem.

For matching 3D CAD assembly models, we take a similar approach to the view-based method which is one of the most effective ways for searching 3D shape models \([4]\). We voxelize the models and convert them into 3D arrays. According to components constituting an assembly model, a specific value is assigned to each element of the array. We compute projections of the 3D array from various angles as shown in Fig. 2. The projections of an assembly model are transformed into a set of its feature quantities. We call the set of the feature quantities for an assembly model the feature set. In order to obtain the feature set which is tolerant to 3D translation and rotation of the model, we use the 2D Radon transform and the Fourier transform. Of course, we cannot make it completely tolerant to the 3D rotation by this transform. The similarity between two assembly models is computed by comparing their feature sets based on the phase-only correlation. We evaluate experimentally our matching method using several 3D CAD assembly models which we obtain by modifying the models downloaded from the web \([5]\). The results show that we can distinguish the difference in layouts of components constituting otherwise identical assembly models.

2. Related Work

A large number of methods for retrieving rigid or non-rigid 3D models have been proposed \([4], [6]\). However there are not many studies on retrieving 3D CAD assembly models. Deshmukh et al. \([1]\) represent an assembly model as a graph called a mating graph and develop a retrieval method based on a graph search algorithm. A node of the graph corresponds to a component constituting the assembly model. Two nodes are connected by a directed edge when they have a specific relation. The nodes and the edges have several attributes. Chen et al. \([2]\) represent a multilevel semantical and geometrical structure of an assembly model as a hierarchical graph. Similar models are also searched based on graph matching algorithms. Hu et al. \([3]\) proposed a retrieval
method for assembly models based on vector space model. They decompose an assembly model into the components and use Light Field Descriptor [7] as their features. The features are mapped into a vector space. The similarity between assembly models is defined based on a combination of features of their components. However, in these works, detailed differences of layout of components constituting an assembly model, on which we focus in this paper, are not considered.

3. Our Matching Method

We voxelize a 3D assembly model represented as mesh data and convert it into a 3D array. In order to distinguish each of the components constituting the assembly model, we assign a specific value to the corresponding elements of the array. For example, the assigned values can represent materials or identifiers of components.

3.1 Features of Assembly Models

We compute the feature of an assembly model represented as a 3D array using a set of projections from multiple angles. An angle is specified by a pair of the azimuthal angle $\theta$ and the polar angle $\phi$ in spherical coordinates as shown in Fig. 2. Assembly models are rotated and located anywhere in the coordinate system. The result of a projection is stored in a 2D array of a specific size. A value of an element of the 2D array is the sum of values assigned to the elements of the 3D array on a line perpendicular to the projection plane. This projection is not affected by the distance between the projection plane and the model. If we use the projections from more angles in computing the feature set, it will become more tolerant to 3D rotation of the models. However it costs more to compute the projections and the feature set. To reduce the number of projections without sacrificing the tolerance to 3D rotation largely, we apply the 2D radon transform to the projections. Of course, we cannot make the feature set completely tolerant to the 3D rotation by this transform in 2D. Then we compute the discrete Fourier transform of the result along the radial coordinate in polar coordinates. The result is equal to the discrete 2D Fourier transform of the original projection by the Fourier Projection-Slice Theorem. It makes the feature set tolerant to translation of assembly models in 3D space. This is the preparation for computing the phase-only correlation between the feature sets of two assembly models as the similarity measure. Algorithm 1 shows the procedure to compute the feature set of an assembly model.

3.2 Similarity between Assembly Models

An assembly model is characterized as a set of the 2D arrays computed by Algorithm 1. We define the similarity of two 2D arrays in the feature sets as the maximum value of the phase-only correlation of the arrays. The similarity of two assembly models is defined as the average of the similarities among all combinations of of two 2D arrays contained in each of the feature sets. Algorithm 2 shows the detail.

4. Experimental Evaluation

We evaluate the ability of the proposed method to discriminate 3D CAD assembly models with different layouts of the components. We prepare three kinds of 3D CAD assembly models, a clutch, a gear, and a die, each of which consists of multiple components as shown in Fig. 3. For each model, we also prepare three types, A, B, and C, of assembly structures as shown in Fig. 4. We call these nine models prepared models. We denote a clutch of type A as Clutch A, for example. A model of type A and a model of type B consist of the same components and have the same layouts of all components except two with the same shape. For example, in Clutch A and Clutch B, the layouts of two kinds of springs with the same shape are different. A model of type A and a model of type C also have the same layouts of all components except two with the same shape, where both the numbers and the kinds differ. In Clutch A and Clutch C, the location of the two kinds of springs with the same shape are inverted and the number of each kind of spring differs. The prepared models are translated and rotated arbitrarily. For each kind of models, we also make a query model as a tar-

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**Algorithm 1 ComputeFeature**
\[\text{Input: } m, \text{ a set of projection angles in Spherical Coordinates, a set of projection angles in Polar Coordinates} \]
\[\text{Output: } F(\theta, \phi) \]

1: \[\text{convert } m \text{ to a } 3D \text{ array } d\]
2: \[\text{for all } a^{3D} \in A^{3D} \text{ do}\]
3: \[\text{compute a projection of } d \text{ to a } 2D \text{ plane from } a^{3D}\]
4: \[\text{store the result in a } 2D \text{ array } p(d, a^{3D})\]
5: \[\text{compute the discrete Radon transform of } p(d, a^{3D}) \text{ from each angle in } A^{3D}\]
6: \[\text{store the result in a } 2D \text{ array } r(p(d, a^{3D}))\]
7: \[\text{compute the discrete Fourier transform of } r(p(d, a^{3D})) \text{ along the radial coordinate}\]
8: \[\text{store the power spectrum in a } 2D \text{ array } f(r(p(d, a^{3D})))\]
9: \[\text{add } f(r(p(d, a^{3D}))) \text{ to } S\]
10: \[\text{end for}\]
11: \[\text{return } F\]

**Algorithm 2 ComputeSimilarity**
\[\text{Input: } m_1, m_2, \text{ sets of projection angles in Spherical Coordinates, a set of projection angles in Polar Coordinates} \]
\[\text{Output: } \text{similarity of } m_1 \text{ and } m_2 \]

1: \[F_1 \leftarrow \text{ComputeFeature}(m_1^{3D}, A^{3D})\]
2: \[F_2 \leftarrow \text{ComputeFeature}(m_2^{3D}, A^{3D})\]
3: \[\text{for all } f_1 \in F_1 \text{ do}\]
4: \[\text{for all } f_2 \in F_2 \text{ do}\]
5: \[\text{compute the phase-only correlation between } f_1 	ext{ and } f_2\]
6: \[\text{add the maximal value to } S\]
7: \[\text{end for}\]
8: \[\text{end for}\]
9: \[\text{return the average of the values in } S\]
get for comparison by rotating and translating the assembly model of type A.

These models are represented as 3D arrays and specific positive integers are assigned to elements of the arrays for each component of the models. We assign different values to different components. Table 1 shows the assignment of values to the components in the experiments. In this table, “type A,B” means that the values are assigned to components constituting models of type A and type B. “30(3),70(3)” means that we assign two integers, 30 and 70, to three components, respectively. “10-80” means that we assign integers between 10 and 80 to other components. Table 2 shows the sizes of arrays in Algorithm 1 in this experiment. \( A_{1}^{3D} \) and \( A_{2}^{3D} \) in Algorithm 2 are the same sets of projection angles, respectively. All of the assembly models are obtained from the website [5] and simplified by removing several components from them. We develop all the programs with MATLAB 2012b on Windows 7 Professional 64 bit and use a PC with a 2.8GHz Intel Core i3 processor and 16GB RAM.

### 4.1 Discrimination of Different Layouts of Components

Here we evaluate the discriminative power of the matching method for assembly models with different layouts of components. In this experiment, the cardinalities of \( A_{1}^{3D} = A_{2}^{3D} \) and \( A_{1}^{2D} = A_{2}^{2D} \) in Algorithm 2 are 120 and 180, respectively. Figure 5 shows the similarities between the three query models and the nine prepared models. The assembly models of the same type as the queries, that is, Clutch A,
Die A and Gear A, have always the highest similarities. The similarities between the same models of different types are lower than the similarities between the same models of the same types. The different models from the queries, which have essentially different shapes, have much lower similarities than any type of the same prepared models. These mean that we can discriminate the CAD models with different assembly structures by our method.

4.2 Effects of Number of Projections

The discrimination power for assembly models and the computational cost are affected by the number of projections used to compute the feature set. So we examine the effects on the similarity value and the processing time of the number of projections for an assembly model. In this experiment, the cardinalities of $A_{1^{3D}} = A_{2^{3D}}$ vary but the cardinalities of $A_{1^{2D}} = A_{2^{2D}}$ is fixed at 180. Figure 6 shows the similarities between three types of clutches of the prepared models and Clutch A of the query models with varying the number of projections. We observe that we can discriminate the different assembly models when the number of projections are more than 70. Figure 7 shows the average processing time for two assembly models in the above experiment. The processing time includes the time to compute projections of two assembly models and the time to compute their feature sets by Algorithm 1, and the time to compute their similarity by Algorithm 2. The time to convert the mesh data of assembly models to 3D arrays by Algorithm 1 is not included in it. Since we use a simple way for computing the projections and the similarity, they make up a large fraction of the whole processing time.

5. Conclusion

We present a matching method for 3D CAD assembly models, which can discriminate not only their global shapes, the numbers and the kinds of components but also the geometric layouts of components. We show the effectiveness of our method experimentally. It remains to improve the discrimination power for assembly models and particularly reduce the processing time as a future work.

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