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Research on Evaluation of Model Similarity Based on Face Match

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Abstract

Model similarity measurement is an important problem in retrieval of CAD models. In order to compute the similarity degree between two models correctly, a method of model similarity evaluation based on face match is proposed in this paper. Here, face adjacent graph is adopted to describe topological structures in model and construct the face matching matrix between two models. At the same time, greedy algorithm is applied to compute the similarity between these two models. In experiments, the proposed method is used to measure the similarity degree between target model and source model. Experimental results show that the method can evaluate the difference of models efficiently.

Keywords: *model similarity, face adjacent graph, face matching matrix, greedy algorithm*

1. Introduction

The similarity calculation between CAD models is an important problem in 3D model retrieval, which has a great effect on efficiency and reliability of model retrieval systems. Many retrieval algorithms of models can not describe local features in CAD models adequately. Bai presents a retrieval algorithm of 3D CAD model based on maximum common sub-graphs for this inadequate status. B-rep information in CAD model is extracted, and it is described by attribute adjacent graph. Maximum common sub-graphs are applied to detect similar features in CAD models. The similarity of CAD models is evaluated based on these similar features [1]. Zhang puts forward an algorithm to compare shape similarities of CAD models with attribute adjacent graphs. A sequence of graph vertexes is constructed based on adjacent matrix of graphs and attributes of vertexes. Dynamic programming algorithm is used to get maximum common sub-graph and shape similarity between CAD models is computed. According to shape similarity between known model and unknown model, unknown model are tagged automatically with semantic labels [2]. Wang extracts histograms and Zernike moment features in boundary directions of its depth image for 3D CAD model. The similarity between two models is evaluated based on feature distance [3]. Wang uses models' B-rep to obtain faces which are similar to the retrieved faces. Those similar local structures are separated from the retrieved model. The similarity coefficient between the separated structure and the retrieved structure is computed based on an optimal matching algorithm of bipartite graph. The similarity degree between these models is measured [4]. Tao uses an attributed relational graph to describe CAD models. At the same time, surface boundaries in a solid model are decomposed into convex, concave and plane. In the process of decomposition, the number of geometric features is minimized. Region codes are applied to represent surface regions and their relationships in CAD models. The similarity between two models is evaluated by comparing region codes [5]. Wang selects randomly several points on faces of 3D models and records normal vectors of all points. Two points are connected to form a line

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segment. Euclidean distance of the line segment is calculated. The angle between the normal vector and the line segment are computed. The line segment is divided into three sets according to these two angles. For each set, the shape distribution curve is constructed based on Euclidean distance. The similarity of two models is calculated by comparing three shape distribution curves [6]. Supasasi uses Reeb graphs to represent structural properties of 3D models. Then, the model is decomposed into several subparts. Pose oblivious shape signature is applied to describe surfaces of each subpart. Maximum common sub-graphs are used to represent its topological structures and the similarity degree between 3D models is measured [7]. Wei selects a large number of sample points from surfaces in a 3D CAD model and obtains the reachable cone of every sample point. Then, a plane grid is constructed to show the distribution of a reachable cone, and statistical distributions of sample points are obtained. The similarity degree between two reachable cones' matrices is calculated based on L_1 distance, with which the similarity between models is measured [8]. Li projects a 3D CAD model from different points of view. Disambiguation features are extracted from those projected images and represented by PHOG descriptors. Similarities between those projected images from different points of view are accumulated, with which the similarity between two models is measured [9]. Gao presents a similarity computation and retrieval approach of CAD models based on skeleton expansion. The skeleton expansion graph is used to represent CAD models. This graph contains all skeletons, topological information and geometric information. To compute the shape similarity of models is converted to the match of skeleton expansion graphs [10]. Liu decomposes a model into several regions and calculates each region's entropy. All regions' entropies are accumulated as disambiguation features. Based on disambiguation features, Euclidean distance is used to compute the similarity between different models [11]. Sun uses a topological neighbor approximation algorithm to find the optimal boundary match, with which the similarity between two models is measured [12].

In this paper, face adjacent graph is applied to represent topological structures in CAD models. The match degree between two faces is measured based on the difference of edges' numbers. The similarity degree of two models is calculated by accumulating the match degrees between source faces and target faces.

2. Match Source Face and Target Face based on Greedy Strategy

Face adjacent graph is an undirected graph, which describes relationships between faces in CAD model. It can be formally defined as FAG=(F, R). Here, $F=\{face|face\in model\}$, $R\subseteq F\times F\backslash\{(face, face)|face\in E\}$. F contains all boundary faces in model. R is a set of adjacent relationships between boundary faces. If $face_i$ is adjacent with $face_j$ in model, there is an adjacent relationship between them. If faces in F are regarded as nodes and adjacent relationships in R are viewed as edges, face adjacent graph can be built. A CAD model is composed of faces, and a face is made up of edges. In order to calculate the similarity between two models easily, edge numbers are recorded in nodes of face adjacent graph. For the model described in Figure 1, its corresponding face adjacent graph is shown in Figure 2. Face adjacent graph is denoted as G=(V, E). V is a set of vertexes in graph. E is a set of nodes in graph. Face f_i in CAD model corresponds to a unique node v_i in G. If face f_i is adjacent with face f_j in CAD model, there is a corresponding edge between v_i and v_j in G.

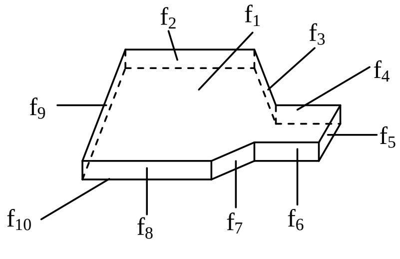


Figure 1. CAD Model

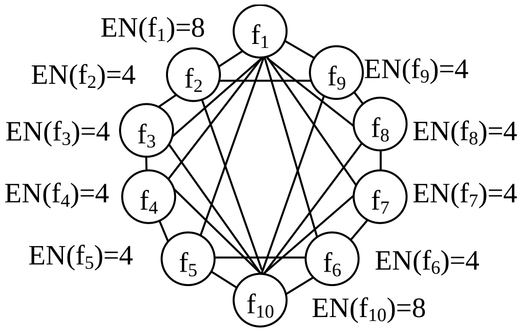


Figure 2. Face Adjacent Graph

If there is a large difference in edge numbers between face f_i and face f_j, the possibility that they are matched with each other is little. In this paper, differences in edge numbers between two faces are adopted to measure their similarity. The similarity SEN(f_i, f_j) between f_i and f_j is shown in formula (1).

$$S_{EN}(f_i, f_j) = 1 - \frac{|EN(f_i) - EN(f_j)|}{\max(EN(f_i), EN(f_j))} \quad (1)$$

From formula (1), it can be seen that if the difference in edge numbers between f_i and f_j is less, the value of SEN(f_i, f_j) is larger. When EN(f_i) is equal to EN(f_j), face f_i is matched with face f_j perfectly.

Here, source model M_s is surrounded by faces f_{s1}, f_{s2}, …, f_{sm}. Target model M_t is surrounded by faces f_{t1}, f_{t2}, …, f_{tn}. The similarity calculation between M_s and M_t is essentially to find an optimal matching sequence in source face set {f_{s1}, f_{s2}, …, f_{sm}} and target face set {f_{t1}, f_{t2}, …, f_{tn}}. The optimal matching sequence should ensure that the similarity between M_s and M_t in all matching sequences is the largest. Here, greedy strategy is applied to the process of matching faces. Face adjacent graph of M_s is FAG_s, and face adjacent graph of M_t is FAG_t. At the same time, m is equal to or less than n. The matching algorithm between source face and target face based on greedy strategy is shown as follows:

(1)Edge numbers EN(f_{s1}), EN(f_{s2}), …, EN(f_{sm}) of faces f_{s1}, f_{s2}, …, f_{sm} are extracted from FAG_s. Edge numbers EN(f_{t1}), EN(f_{t2}), …, EN(f_{tn}) of faces f_{t1}, f_{t2}, …, f_{tn} are extracted from FAG_t.

(2)The similarity SEN(f_{si}, f_{tj}) between face f_{si} and face f_{tj} is calculated according to formula (1), where, i=1, 2, ..., m, j=1, 2, ..., n.

(3)Use values of SEN(f_{si}, f_{tj}) to construct face matching matrix A_{mn}, where, A[i, j]=SEN(f_{si}, f_{tj}), i=1, 2, …, m, j=1, 2, …, n.

(4)Set face matching set P=Ø, total=0.

(5)Scan all columns in matrix A and count the number of columns whose values are -1. Its value is set to total.

①Scan matrix A, find A[i, j] whose value is largest.

②Put order pair (i, j) into set P.

③In matrix A, all elements of row i are set to -1.

④In matrix A, all elements of column i are set to -1.

⑤Scan columns in matrix A and count the number of columns whose values is -1. Its value is set to total and go to (6).

(7)Output all order pairs in set P.

Rows of face matching matrix A correspond to faces in source model, where, m<=n. Its columns correspond to faces in target model. The ith source face's shape is the same with the jth target face's shape and they are located in different positions. One is located in the ith position and the other is located in the jth position. In the ith row of face matching matrix A, A[i, j] is only 1 and other elements are less than 1. In the jth column of face matching matrix A, A[i, j] is only 1 and other elements are less than 1. Here, greedy algorithm is used to find the largest element A[i, j] whose value is 1 from A. So, the ith face in source model is matched with the jth face in target model.

Rows of face matching matrix A correspond to source faces f_{s1}, f_{s2}, …, f_{sm}. Columns of face matching matrix A correspond to target faces f_{t1}, f_{t2}, …, f_{tn}. Order pairs in set P describe a local optimal matching solution between faces f_{s1}, f_{s2}, …, f_{sm} and faces f_{t1}, f_{t2}, …, f_{tn}. If m is equal to or less than n, n-m faces in target faces are not matched. In matrix A, there are n-m columns whose values are not -1.

If n is less than m, SEN(f_{tj}, f_{si}) is computed when face matching matrix A is constructed, where, j=1, 2, …, n, i=1, 2, …, m. Rows of matrix A correspond to target faces f_{t1}, f_{t2}, …, f_{tn}. Columns of matrix A correspond to source faces f_{s1}, f_{s2}, …, f_{sm}. After greedy algorithm is used, m-n faces in source faces are not matched. In matrix A, there are m-n columns whose values are not -1.

3. Calculate the Similarity of Models

Travel source model M_s and target model M_t. If the matching possibility of all corresponding faces is higher, the overall similarity between M_s and M_t is higher. The steps of calculating the similarity between M_s and M_t are shown as follows:

(1)If m is equal to n, calculate the similarity between face in source model M_s and face in target model M_t according to formula (1). The similarities between source faces and target faces are accumulated. The result is divided by n, which is used to measure the similarity between M_s and M_t.

(2)If m is less than n, the number of faces in source model M_s is less than the number of faces in target model M_t. Sub-model SM_t which is most similar with M_s is searched from M_t, and the number of faces in SM_t is m. The similarity between M_s and SM_t is calculated according to step (1), and then the result is divided by n, which is used to measure the similarity between M_s and M_t.

(3)If m is larger than n, the number of faces in source model M_s is larger than the number of faces in target model M_t. Sub-model SM_s which is most similar with M_t is searched from M_s, and the number of faces in SM_s is n. The similarity between SM_s and M_t is calculated according to step (1), and then the result is divided by n, which is used to measure the similarity between M_s and M_t.

If m is less than n, the similarity calculation between M_s and M_t is transformed into the similarity computation between source model and sub-model of target model. If m is larger than n, the similarity calculation between M_s and M_t is transformed into the similarity computation between sub-model of source model and target model. But in either case, two models which contain the same number of faces will be compared.

If m is less than or equal to n, order pairs (s_{i1}, t_{i1}), (s_{i2}, t_{i2}), …, (s_{im}, t_{im}) are obtained. Similarities between faces in source model M_s and faces in target model M_t are accumulated. Then, the similarity $S_{Model}(M_s, M_t)$ between M_s and M_t is calculated according to formula (2). From formula (2), it can be seen that when source model M_s and target model M_t are traveled, the optimal matching sequence between them is gotten. If there is less difference in edge numbers between faces in M_s and faces in M_t, the overall similarity between M_s and M_t is higher.

$$S_{Model}(M_s, M_t) = \frac{1}{n}\sum_{k=1}^{m} S_{EN}(f_{si_k}, f_{ti_k}) \tag{2}$$

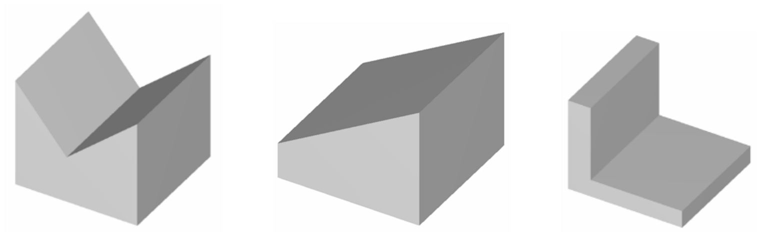
If m is larger than n, order pairs (t_{j1}, s_{j1}), (t_{j2}, s_{j2}), …, (t_{jn}, s_{jn}) are obtained. The similarity between faces in target model M_t and faces in source model M_s is accumulated. Then, the similarity $S_{Model}(M_s, M_t)$ between M_s and M_t is calculated according to formula (3).

$$S_{Model}(M_s, M_t) = \frac{1}{m}\sum_{k=1}^{n} S_{EN}(f_{tj_k}, f_{sj_k}) \tag{3}$$

4. Experiment

HUST-CAID system is developed by Institute of Computer Application Technology in Harbin University of Science and Technology. The system has been used to carry on design for a long time. A large number of CAD design models have been accumulated. Four design models are selected for experiments. The target model is shown in Figure 3. It contains 7 faces. It has 2 faces whose edge number is 5. It has 5 faces whose edge number is 4. Three source models are shown in Figure 4.

Figure 3. Target Model



Source model A   Source model B   Source model C

Figure 4. Source Models

The similarity between target model and source model A is calculated according to the proposed method. Its similarity is 1. The proposed method is applied to compute the similarity between target model and source model B and its similarity is 0.629. The similarity between target model and source model C is calculated according to the proposed method. Its similarity is 0.592. In the sight of design shape, source model A is consistent with target model. So, the similarity is maximal. Source model B is slightly different from target model and the similarity is higher. There is a large difference between source model C and target model. So the similarity value is minimal. Based on results of the similarity calculation, this method can measure shape differences between two models effectively.

5. Conclusions

To compute similarities of CAD models is important for research on 3D model retrieval. In this paper, boundary faces in model are viewed as nodes and adjacent relationships between boundary faces are regarded as edges. At the same time, face adjacent graph is constructed. The similarity between source face and target face is computed based on the difference in edge numbers and the face matching matrix between two models is constructed. The optimal face matching sequence between source model and target model is searched by greedy strategies. According to the optimal face matching sequence and similarities between source faces and target faces, the overall similarity between two models is comprehensively measured. Experimental results show that the method can measure differences between two models effectively.

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