

A Powerful Partial Relevance Feedback for 3D Model Retrieval

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Abstract—Relevance feedback(RF) has been proved to be an effective way to improve the precision and recall of 3D model retrieval. However, the existing RF approaches do not consider which local part of the feedback example is similar or dissimilar with the query model although they recorded whether the whole model is similar or not. In this study, a partial relevance feedback(PRF) method which overcomes this deficiency is discussed. First, an improved silhouette based descriptor is proposed to satisfy the PRF method. Second, a new mathematical model for partial relevance feedback is set up and optimal solution is also given: a SVM based classifier is trained to classify the models; the variables which have influence on similarity measurement are optimized to minimize the average distance between the query model and the feedback examples, and then the similarities between the query model and all the models in database are recalculated. At last, Some experiments are given to illustrate the outperformance of the proposed method over the other methods.

Index Terms—3D model retrieval, Partial retrieval, Partial relevance feedback, relevance feedback, Image retrieval

I. INTRODUCTION

In these years, many papers have discussed the topic of 3D model retrieval[1]. Relevance feedback(RF) has been proved one of the most important ways to narrow the semantic gap in 3D model retrieval[2-7]. By interacting with the computer to tell which models are wanted and which models are not wanted, RF helps a lot for the refinement of 3D retrieval. Different kinds of methods have been proposed which can be classified into the following categories:

A. Query Optimization Based Methods

In the work of Bang H. et. al feature space wrapping approach was brought forward[2]. All the models in database will move to the relevant models or the irrelevant models in the feature space through interaction. The movement of each model is the compound effect of the feedback examples, and the closer relevant/irrelevant

models give more contribution to the movement than the further ones. In the method in [3], Atmosukarto I. adjusted the weights to improve the distance measurement, and multiple integer queues were used to record the rank of the models. With these queues, the similarity between the query model and the relevant models is generally set to 1, which ensures the number of relevant objects in the retrieval result will increase monotonically with the number of feedback iterations. All the relevant models span a hyper sphere in the feature space, and the weight of each feature was determined by proportion of the relevant models to models included in that hyper-sphere. In the approach by Papadakis[4], the author introduced pseudo RF into 3D model retrieval. In this method, the m -most similar models are used as training data, and all similar move to the centroid of the cluster. In the method by Biao et.al[5], both the relevant set and the weight of the descriptors will be updated to refine the retrieval result. A new method based on parallel optimization has been introduced in to CAD model retrieval by Hu B.k et.al and brought good feedback result in[6]

B. Classifier Based Methods

The initial work related to application of RF technology into 3D model retrieval appeared in[7] where Eland M. introduced kernel based method into the retrieval of VRML models. In this method, A support vector machine (SVM) based classifier is trained and used to divide the models in library into two subgroups-the relevant and the irrelevant. Leifman G. et al. combined linear discriminant analysis (LDA) with biased discriminant analysis(BDA) in their method in[8], where a compound classifier was constructed with the goals of maximizing the distance between the different classes and minimizing the distance within the same class at the same time.

Some articles focused on the survey of 3D RF have appeared recently. Novotni M.[9] compared the existing algorithms with Princeton Shape Benchmark (PSB)[10]. Some useful and interesting conclusion can be founded in his experiments such as the kernel based RF approach in [7] outperformed the others.

Notwithstanding the excellent work on RF in the field

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of 3D model retrieval, a common flaw for these methods in existence is that although it is very simple for the user to indicate whether a model is similar or not, it is rather difficult to indicate which local part of the model is similar or not. This baffles the user intention expressed more clearly since for 3D models, it is often true while compared with the query model that some parts of these models are similar and the other parts are dissimilar.

In ref. [11], we put forward a new method for the first time to satisfy the requirement of 3D retrieval. Here we call this method as partial relevance feedback (PRF), and the other existing methods are called as global relevance (GRF) methods. In this PRF method, not only the information of the whole model but also that of the local parts of a model are used to improve the result of 3D model retrieval.

This paper, firstly a short review of the method in [11] is given, secondly further detail on how to classify the local parts submitted by the user, thirdly an optimal solution of the mathematic model is given to optimize the feedback result as far as possible, lastly the power of the proposed method is illustrated by experiments.

II. PREVIOUS WORK

First of all, let's recall motivation of PRF discussed in [11]. In the existing retrieval system, models are represented by their images in the result list, and users determine whether a model is the positive example (PE) or the negative example (NE) by tick or cross according to his comprehension of the corresponding image, as shown in Fig. 1. But this is not reasonable since it is often hard to imagine the integral shape of the model from a single view of a complex model.

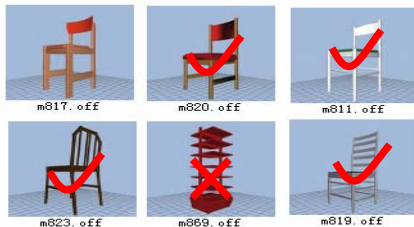


Figure 1 Demonstration of user interface of existing feedback methods

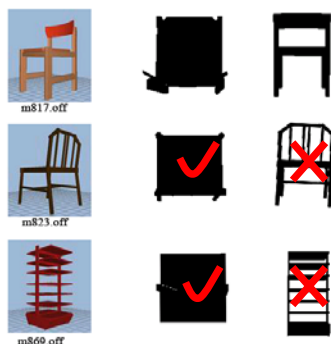


Figure 2. Different viewpoints producing different silhouette. First column: original models; middle column: top view; last column: left view

It is observed that there are many models which are

similar to the query model in some local parts or seen from some points, but are quite different in the other local parts or seen from the other points. Let's study the silhouettes in binary image as illustrated in Fig. 2. While looked down, the chair model "m823.off" and the shell model "m869.off" are almost the same as model "m817.off", which is the query model in Fig. 1 and Fig. 2; but while looked from the right side, both are quite different. In other words, though the model "m869.off" is dissimilar, it has a similar silhouette, and though the model "m823.off" is similar, it also has a dissimilar silhouette. Such examples are called as binary examples (BE) which are very valuable for the refinement of the 3D model retrieval result since they contain both information about which kind of feature is desired and which kind undesired. This type of information is called as partial information in this paper.

Unfortunately, BEs are regarded as ambiguous and often neglected in existing RF methods. Because it is hardly to get the partial information while using 2D images to stand for the corresponding models in the result list. One direct way to overcome this shortage is to replace the images in the result list with corresponding 3D models, then the user may point out the difference of two models and use this information to refine the result furthermore. but this method is not feasible for two reasons: first, rendering all models in the result list in real-time is time consuming, especially when the number of models show in the result list is bigger; second, when the model picked out can be rotated freely as the query model, it is hard to point out the difference directly without alignment.

To overcome this shortage PRF was first brought out in [Hu 2008] where each 3D model is decomposed into a serial of local parts according to a certain rule, and each part is represented by the improved light field descriptor which will be discussed in the following section. In this method, the information about whether a certain local part of one model is similar or not while compared with that of the query model is sufficiently used to realize the user's intent. With this critical information, the retrieval results can be improved remarkably.

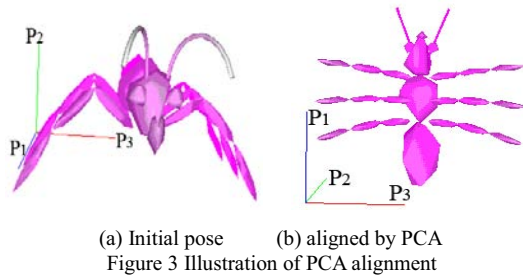
III. IMPROVED LIGHT FIELD DESCRIPTORS

As said in last section, the first task is to decompose the mode into local parts and represent the local parts with a descriptor containing partial information. Although there are a lot of descriptors for 3D model retrieval, but few support partial information. Such type of descriptor is one of the most important goal of research on partial retrieval. Here, an improved light field descriptors based on alignment is brought to satisfy the requirement of PRL. Light Field Descriptors (LFD) is one of the best descriptors by far [12]. However, there are 5460 rotations used to represent the 3D model with LFD [13]. For each rotation, there is a distance between silhouettes of the two models; the minimum of these values is regarded as the similarity between the two models.

A major problem of this method is that the model must be rotated many times to generate a large number of

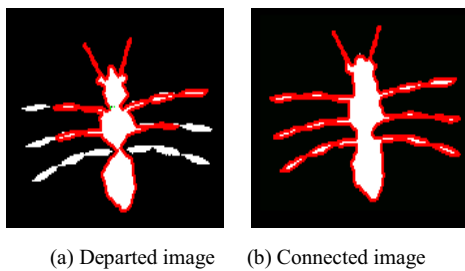
sample views to ensure the descriptors invariant with rotation. This will decrease the performance of the retrieval dramatically. Here, Principle Component Analysis (PCA) is used to normalize the pose of the models. After the models are aligned, only ten views from the vertex of the surrounding dodecahedron of the model are generated, which is enough to represent the original model. Thus the complexity reduces dramatically. As shown above, Fig. 3a is the original pose and Fig.3b is the model after PCA alignment.

Another important advantage arising from PCA alignment is that comparing the silhouettes of two models snapped from the same view point in the world coordinate system becomes possible. This makes it feasible to indicate the difference of two models directly. In other words, if the models are different while seen from the same view point, we can put a mark on the corresponding views and deliver the message to the RF algorithm.



(a) Initial pose (b) aligned by PCA
Figure 3 Illustration of PCA alignment

However, there is still a problem while computing Fourier descriptors: the binary silhouettes of models may be composed by a lot of separated components. For such cases, the silhouettes must be repaired by connecting the boundaries together with morphological operation *open*. As shown in Fig.4, the silhouette in Fig.4a is divided into several separated areas, the one bounded in red is the max area; whereas Fig.4b is the repaired image of Fig.4a, connected by morphological operation *open*.



(a) Departed image (b) Connected image

Figure 4 Connecting detached components together by mathematical morphology

For the repaired silhouettes, coefficients of 2D Zernike moment order m with repetition n is :

$$A_{n,m} = \frac{n+1}{\pi} \iint_{\rho \leq 1} f(\rho, \theta) V_{n,m}^*(\rho, \theta) d\rho d\theta \quad (1)$$

Where $V_{n,m} = R_{n,m}(\rho)e^{jm\theta}$, $V_{n,m}^* = V_{n,-m}$, $\theta = \tan^{-1}(y/x)$, $x^2+y^2 \leq 1$, $j = \sqrt{-1}$, $m=0$, $m-|n|=2k$ ($k = 1, 2, \dots$; $n = 1, 2, \dots, N$), $|n| \leq m$, ρ is the square root of $x^2 + y^2$, and

$$R_{n,m} = \sum_{s=0}^{(n-|m|)/2} \frac{(-1)^s (n-s)! \rho^{n-2s}}{s! (\frac{n+|m|}{2} - s)! (\frac{n+|m|}{2} + s)!}$$

And the Fourier descriptors for the binary images are calculated by the following equation:

$$\left\{ \frac{|F(1)|}{|F(0)|}, \frac{|F(2)|}{|F(0)|}, \dots, \frac{|F(n)|}{|F(0)|} \right\} \quad (2)$$

Where. $F(n) = \frac{1}{N} \sum_{t=0}^{N-1} r(t) \exp(\frac{-j2\pi nt}{N})$

IV. PARTIAL RELEVANCE FEEDBACK

A. Mathematical Model of Similarity in PRF

As in [11], the global similarity of two models is calculated following the mathematical model, in which q stands for the inputted query model, M_i is a feedback example, and each model is composed totally by J local parts, that is, $M_i = [P_1, \dots, P_J]$. Further, each local part is represented totally by K features, such as Fourier descriptor, Zernike moment descriptor, etc. Then the j^{th} local part of model M_i can be represented as $P_j = [f_1, \dots, f_K]$, where each feature is represented by a vector (descriptor), i.e. $f_k = [f_{k1}, \dots, f_{kD_k}]$, q_k is the k^{th} feature vector of P_j of the query model. S_i is the global similarity between the i^{th} model and the query model, S_j^p is the corresponding similarity of j^{th} local part of the two models, and S_k^f is corresponding similarity of the k^{th} feature of the j^{th} local part of the two models, then the similarity of two models can be formulated as following:

$$\begin{cases} S_i = \mathbf{u} \bullet S^p \\ S_j^p = \mathbf{v} \bullet S^f \\ S_k^f = (q_k - f_k) \bullet \mathbf{W}_k \bullet (q_k - f_k)^T \end{cases} \quad (3)$$

Where: $S^p = [S_1^p, \dots, S_J^p]^T$, $S^f = [S_1^f, \dots, S_K^f]^T$, $\mathbf{u} = [u_1, \dots, u_J]$, $\mathbf{v} = [v_1, \dots, v_K]$, \mathbf{W}_k is a matrix used to compute the generalized Euclid distance of two feature vector. \mathbf{u} is composed by the weights of all local parts, in this paper, the local parts are the silhouettes. Let S stand for the total distance to the query model of all the feedback examples as in equation(4), we try to minimize S to make the feedback examples cluster around the query model as close as possible, then

$$S = \sum S_i \quad (4)$$

Similarity of two models will be computed out following equation (3) with this improved LFD, and partial information is included in the information.

B. Algorithm of PRF

One important concept must be mentioned before we go into detail of the PRF algorithm is that the evaluation

matrix $E = \{e_{ij}\}$. This evaluation matrix for all the feedback examples automatically during interaction. The element of matrix E , (i.e, e_{ij}) is the class label (-1 or +1) of the j^{th} part of model M_i marked by the user. Supposing there are N feedback examples (N_+ PEs, N_- NEs and N_b BE, $N_+ + N_- + N_b = N$). In each round of RF, the evaluation matrix E obtained from the interaction is used to train SVM classifier.

With the improved LFD and the similarity model, our PRF is carried out by two stage. First, classify the local parts of all models with SVM; second, optimize the weight and recomputed the similarity of each model, then sort the result with the new similarity. The algorithm is composed of ten steps, and the detail is as following:

- 1) Initialize u, v, W_k ;
- 2) Calculate S_k^f, S_j^p and S_i^g ;
- 3) Get evaluation matrix E which has partial information by interaction.
- 4) For the i^{th} local part, use the i^{th} column of matrix E as the class label, the corresponding descriptor of this local part of feedback examples as the training set, train the corresponding SVM classifier;
- 5) Use the trained SVM classifier to evaluate the corresponding local part of all the models in database. For each model, increase its score if the corresponding local part is relevant to that of the query model;
- 6) Optimize matrix W_k ;
- 7) Get the optimal weight vector u ;
- 8) If all the similarities are recalculated and the local parts are classified, go 9); else go 4)
- 9) Recomputed the distance of each model to the query model with the new weight vector u and matrix W_k ;
- 10) Return the result sorted by the new distances.

The steps 4-7 are critical in this algorithm. And some key points for them will be discussed in detail in the following sections.

C. Partial Classification

From above discussion, it can be seen that the classifier plays an important role in the PRF. In this paper, C-SVM is used as the classifier. C-SVM is an upgraded version of the basic SVM[14]. The object of C-SVM is to find the best decision hyper plane defined by the equation (5) through minimize the formula (6)

$$f = \text{sgn}[(w^* \bullet x) + b^*] \tag{5}$$

$$\min_{w,b,\xi} \left(\frac{1}{2} w^T w + c \sum_{i=1}^l \xi_i \right) \tag{6}$$

Where $y_i (w^T \varphi(x_i) + b) \geq 1 - \xi_i$, ξ is called as the slack variable and $\xi_i \geq 0, i = 1, \dots, N$; $C > 0$ is the upper boundary, w is the normal of the decision hyper plane, b is the threshold, w^* and b^* is the best value which maximize the margin of the two sub datasets, and $\varphi(x)$ map the dataset from a low-dimensional space to a high dimensional space, $K(x_i, x_j) = \varphi(x_i)^T \varphi(x_j)$ is called as kernel function. Based on the theory of quadratic

optimization, the the optimal decision hyper plane is found.

For a dataset coming from real world problem such as descriptors of all the models in database, it is often too hard to get an exactly separate line which can exactly divide the data within the space in to two classes. But if the dataset is mapped into a higher dimensional space by a kernel function, there might be a hyper plane which might exactly separate the data.

In this paper, the kernel function is $K(x_i, x_j) = x_i^* x_j$. The i^{th} column vector of matrix E (N rows and 10 columns) stands for the evaluation on the i^{th} local part of all the feedback examples. Each column vector is a training sample, The N examples provide N vectors composing the training set to train classifier. And the optimal decision hyper plane which can divide the set of k^{th} feature vector of all the feedback examples into two categories under the rule of minimum structure risk error is figured out through the training dataset to classify the models in database. As shown in Fig. 5, the red points are the similar models, and the blue models are dissimilar models, the hyper plane separate the similar models from the dissimilar models.

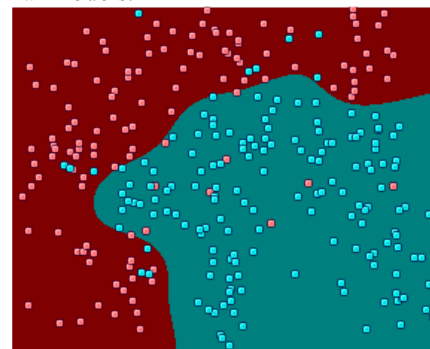


Figure 5. Separating the dataset of descriptors of all the models in the database. Each point is corresponding to a model, by mapping the point into a high dimensional space, an optimal hyper plane is figured out which divide the s into two groups: what are desired and what are undesired.

For each descriptor of i^{th} local part, a C-SVM classifier is trained with the feedback matrix E . Here, there are 20 C-SVM classifiers trained to classify the models in database from all descriptors and all local parts. These C-SVM classifiers will evaluate each model and give a score according to the result, the higher score, the more likeness.

D. Optimal Solution

In this section, we give a solution to compute the optimal weight vector u, v and W_k . The objects of equation(3-4) is to minimize the distance sum from all the feedback examples to the query models, that is minimize S . The mathematical model in equation(3-4) has three layers, it is very hard to get the optimal analytic solution for the high order optimal problem. But if we set u to a const value, we can get the analytic optimal solution.

It is know that u reflect the importance of different local parts which are silhouettes in this paper. Form observation in Fig. 6 we can see that information of different silhouette is largely decided by the area of the

silhouette. i.e, the larger silhouette contains more information about the model than the small silhouette. It is easier to guess what the model looks like from the larger silhouette than the smaller silhouette. Based on this observation, we set the weight vector \mathbf{u} as the normalized area of each silhouette of the query model. With this assumption, we can work out the optimal solution of equation (4). Two additional constraints as in equation must be added to equation(4) to assure that \mathbf{v} and \mathbf{W}_k do not equal to zero.

$$\begin{cases} \sum \frac{1}{v_j} = 1 \\ \det(w_k) = 1 \end{cases} \quad (7)$$

Then this problem is an unconstraint problem with Lagrange multipliers, and the final object function is :

$$F = \sum S_i - \alpha(\sum \frac{1}{v_j} - 1) - \beta(\det(w_k) - 1) \quad (8)$$

then let

$$\frac{\partial F}{\partial q_k} = 0 \quad (9)$$

$$\frac{\partial F}{\partial v} = 0 \quad (10)$$

$$\frac{\partial F}{\partial w_k} = 0 \quad (11)$$

the optimal \mathbf{q}_k , and \mathbf{v} is as follows:

$$\mathbf{q}_k^* = (\sum \mathbf{f}_k) / I \quad (12)$$

$$v_k^* = \sum_{l=1}^K \sqrt{\frac{S_l^f}{S_k^f}} \quad (k = 1, \dots, K) \quad (13)$$

The distance weight matrix \mathbf{W}_k has great influence on the distance of two feature vector, as shown in equation (3). In this study, the matrix \mathbf{W}_k switches between diagonal matrix and full matrix automatically[15]. If $N < D_k$, \mathbf{W}_k takes the form of diagonal matrix, the optimal \mathbf{W}_k is represented as the following equation:

$$\mathbf{W}_k(m, m) = 1/\sigma_r \quad (14)$$

Where, \mathbf{r} is the vector composed by the m^{th} components of k^{th} descriptor, σ_r is the standard deviation of \mathbf{r} .

If $N > D_k$, \mathbf{W}_k takes the form of full matrix and then the optimal \mathbf{W}_k is represented as the equation (15):

$$\mathbf{W}_k^* = (\det(\mathbf{C}_k))^{-\frac{1}{D_k}} \bullet (\mathbf{C}_k)^{-1} \quad (15)$$

Where \mathbf{C}_k is the $D_k * D_k$ weighted covariance matrix of \mathbf{f}_k , 'det' is the determinant of \mathbf{C}_k .

With these optimal weights and the score by SVM classifier of each local part, the distances of all models to the query model will be recomputed, and in the new result list, models will be sorted by the distances in

ascendant order.

V. IMPLEMENTATION AND EXPERIMENTS

A. Implementation

The proposed method and algorithm is implemented with Microsoft Visual C# 2005, SQL Server 2005, and DirectX 2007 SDK. Two libraries are used to test the proposed method. One is the PSB which has 1814 mesh models including animals, plants, vehicles, people and so on. Another is 3D CAD model library which has 180 typical CAD models including classes of parts and assemblies[6].

Totally 36 Zernike coefficients and 62 Fourier Descriptors are pre-computed according to equation (1) and equation(2) to represent the local parts of the models. After that, descriptors will be normalized firstly, for the t^{th} dimension of feature vector f_k , that is:

$$f_{kt} = \frac{f_{kt} - f_{\min}}{f_{\max} - f_{\min}} \quad (16)$$

Where f_{\min} , f_{\max} are the minimum and maximum values of the t^{th} dimension of f_k .

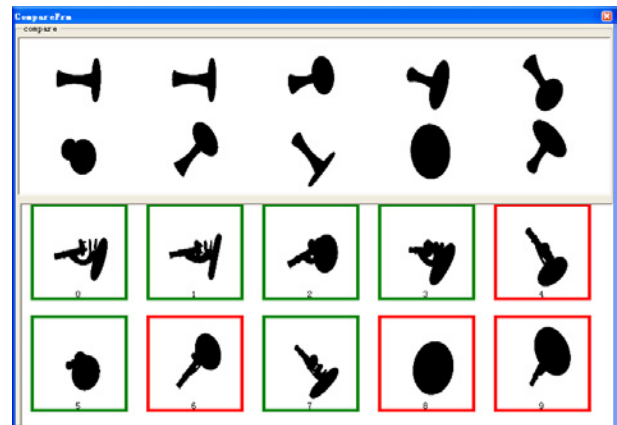


Figure 6 Partial relevance feedback interface. silhouettes in red rectangle are similar and in green rectangle are dissimilar

Fig. 6 demonstrates the interface for the proposed PRF method. Right clicking on any model regarded as BE in the result list will active this interface. On the top are the silhouettes of the query model and on the bottom are the silhouettes of the feedback example model. if some silhouettes of the feedback example are dissimilar(similar) in contrast with that of the query model, put a green(red) rectangular mark on it. Both similar and dissimilar silhouettes of the BEs are recorded to generate matrix \mathbf{E} .

B. Examples

Since there is no other PRF technology by far, the proposed method is compared with the GRF method [7] It is reported Eland's kernel based method is the best GRF method in 3D model retrieval[9] This experiment compares the result of Eland's method to that of the proposed PRF. In all cases of Fig. 7, the first models are the query models. We want to find some models of man similar to the query models. Fig. 7 demonstrates the results of PRF method and GRF method correspondingly.

Fig.7 are the results of first round of different feedback approaches. Figures in the first column are produced by the proposed partial method, and the second column are produced by Elands' method . The input models in the three case are a able, a man and a part respectively, Both the results of PRF method and GRF method are very well judging from the figures. But there is some difference.

In the first result list produce by GRF method, some round tables appear, but they disappear in the result list produced by PRF method. The round table and the square table belong to the same class and the difference between them is little. But if the user care for this little difference, the GRF method cannot provide any help for further refinement. Things are different for the proposed PRF, in the top-down view, the round silhouette is marked as irrelevant and the square silhouette is marked as relevant. So the little difference can be labeled out and used to refine the retrieval result furthermore.

The advantage of PRF method over GRF method is also demonstrated by the man case in Fig.7b No woman appears again in Fig.7 b(1), but some other women still appear in Fig. 7 b(2). The reason of why the result of PRF is more accurate than that of the global method is that the GRF method cannot make use of the partial difference between models of men and women but the PRF can. In the GRF method between the silhouettes of man and woman are ignored, but for the PRF this nuance is taking into consideration.

This is also demonstrated by Fig. 7c. the user can tell the machine that the parts like model 8 and model 10 are undesired. With this partial information, the models in the result list produced by PRF method are more like the query model than the models in the result list produced by Eland's method.

From these experiments, it can be seen that partial information is very helpful to capture the local character of models, which is one of the most important advantage over the global RF methods. Taking advantage of the partial information sufficiently with the PRF, we can make the retrieval result more accurate.

C. Performance Analysis

In this section, different typical models are selected as query models to test the performance of the proposed PRF and some other mainstream GRF methods[2,5, 7, 8]. Six models from Princeton library and six models from CAD library. They represent six categories in the two libraries respectively. Each query model has enough similar models in its lib, but the user is not satisfied with the retrieval result. By human-machine interaction, the wanted and unwanted models are submitted to the system, after a specific number of rounds of RF, the final result will be returned.

The measurement Discounted cumulative gain (DCG) takes the sequence of the relevant models appeared in the result list into consideration together with the evaluation by the user. i.e., the models in the front of the result will be assigned to larger weights than the other models. The measurement of precision is the average precision for the six query models after the RF procedure finished.

Fig. 8 demonstrates the relation between the DCG

--which is represented by the y-axis, and the round number of the RF-- which is represented by the x-axis. It is obvious from Fig. 9 that the first round is the most important, and the measurement DCG increases with the round number of the interaction increasing. The proposed method has the largest increment on DCG from the first round in all the five methods, especially tested by our CAD lib.

While evaluated by the second tier measurement as in Fig. 9, the y-axis is the percentage of the similar models appeared in the first K models, where $K = 2 * (|C| - 1)$ and C is the number of models in the same class of the query model. The higher value of y-axis, the higher precision. The x-axis are the six query models respectively, and the five bars in each cluster stand for the five methods, including the proposed method. It can be seen from the diagrams in Fig. 10 that while evaluated by the second tier measurement, the proposed method shows good ability on both the PSB and CAD.

In Fig. 10, the six clusters of bars on x-axis stand for the DCG of six different query models, each cluster has five bars representing the proposed method and the other four methods, the height of these bars are the corresponding DCG tested by PSB lib (left) and CAD lib(right). It can be seen that the proposed method outperforms the other methods in most case while testing by PSB and by our CAD Library.

In the left figure, in case of the sixth query model of PSB lib, the DCG of our method is about 11.1% and 18.4% higher than that of Eland's method and Biao's method respectively, especially in case of the fifth query model and the six query model. While in case of the first method, the proposed method gain a rather-thin win on Eland's method. The reason is that the first input model is a head model which has no characteristic binary silhouette, the difference between silhouettes is too small to exhibit the power of PRF sufficiently. If the silhouettes are independent, the advantage of PRF may be more manifest. In the right figure, the proposed method has an obvious advantage over the other methods in most cases as well. Because the CAD models are almost created by designers. Different silhouettes of CAD models are less dependent than that of nature things.

TABLE 1. COMPARISON OF TIME COST BETWEEN THE PROPOSED METHOD AND THE OTHER FOUR METHODS

Bang	0.047
Leifman	1. 205
Eland	0.106
Biao	0.075
Our	0.131

For the PRF algorithm, most time is spent on train SVM classifier as the GRF method in [7], So there is little difference on time cost between the two methods. The comparison of computational cost is demonstrated in the Table 1, where time is measured by second. Our method is as fast as Eland's method.



Figure 7. Comparing the feedback result of the proposed PRF with the result of Eland's method

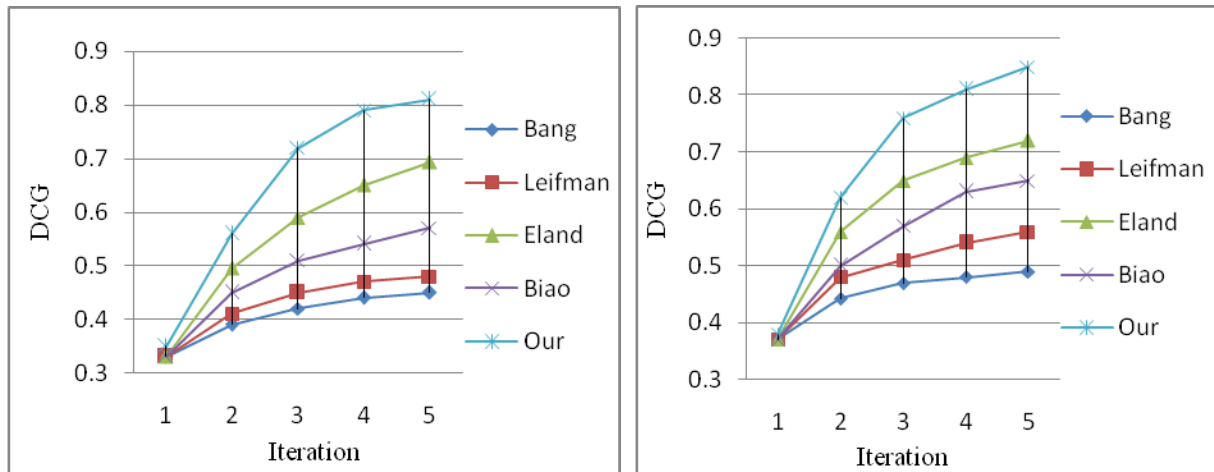


Figure 8. Relation between the average discounted cumulative gain (DCG) and the RF round. DCG increases with the number of RF round increasing. Left is the result tested by PSB lib and the right is the result tested by CAD lib

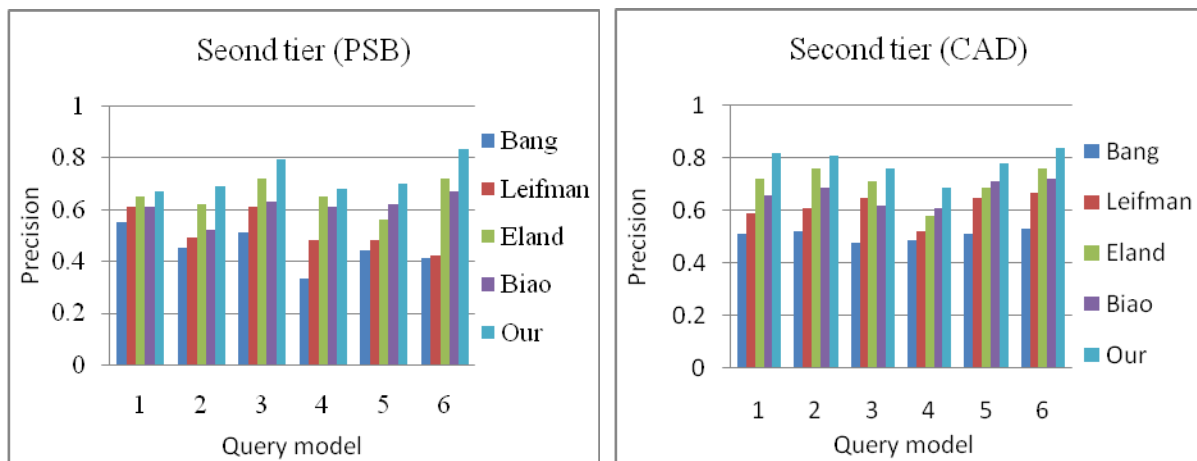


Figure 9 Evaluation with the second tier measurement, tested by the PSB lib(left) and the CAD lib(right).

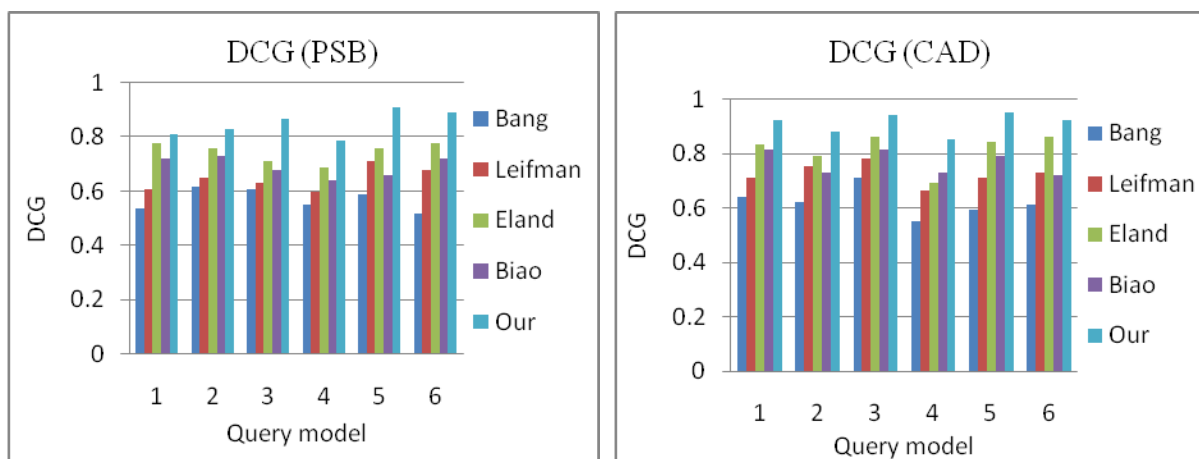


Figure 10 Accumulative DCG for the six query models from PSB lib (left) and CAD lib (right) respectively

VI. CONCLUSION

In this paper, we intensive studied the PRF in 3D model retrieval proposed in previous work. In the proposed PRF method, each model is decomposed into several local parts, and the global similarity of two models is regarded as the total similarity of all the local parts. With the hierarchical model of similarity, the

information about whether the corresponding local parts of two models are similar or not is used to find the real retrieval intention of the user and finally improve the result of 3D model retrieval. PRF may be a promising technique for improve 3D model retrieval since its advantages on GRF methods: first it's more powerful than GRF; second, it can be applied into partial retrieval; third, it is very helpful for the machine to understand the

real intent. The experimental results show that the proposed PRF approach outperforms the global feedback approaches a lot.

Our future work is to find a method to make the divided local parts independent with each other. And the interior information of each local part should be taken into consideration. Finally, PRF can be applied into feature based CAD model retrieval, where the feature type, the topology relation and the geometric relation between the features can also be used to improve the retrieval result with the PRF method.

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