Journal of Zhejiang University SCIENCE A
ISSN 1673-565X (Print); ISSN 1862-1775 (Online)
www.zju.edu.cn/jzus; www.springerlink.com
E-mail: jzus@zju.edu.cn

Support Vector Machine active learning for 3D model retrieval*

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Received June 12, 2007; revision accepted Aug. 14, 2007

Abstract: In this paper, we present a novel Support Vector Machine active learning algorithm for effective 3D model retrieval using the concept of relevance feedback. The proposed method learns from the most informative objects which are marked by the user, and then creates a boundary separating the relevant models from irrelevant ones. What it needs is only a small number of 3D models labelled by the user. It can grasp the user's semantic knowledge rapidly and accurately. Experimental results showed that the proposed algorithm significantly improves the retrieval effectiveness. Compared with four state-of-the-art query refinement schemes for 3D model retrieval, it provides superior retrieval performance after no more than two rounds of relevance feedback.

Key words: 3D model retrieval, Shape descriptor, Relevance feedback, Support Vector Machine (SVM), Active learning
doi:10.1631/jzus.2007.A1953 **Document code:** A **CLC number:** TP37; TP31

INTRODUCTION

With the rapid development of 3D scanner technology, graphic hardware, and World Wide Web, the proliferation of 3D objects over various digital archives is prevailing. In order to make use of these models, the techniques of effective 3D model retrieval become increasingly crucial. 3D models can be annotated by keywords at first, facilitating the text-based retrieval. However, this is not a promising approach, because annotations are manually created in most cases, and what is more, they are prohibitively expensive and subject to some conditions. To overcome the disadvantages of annotation-based strategy, a so-called content-based 3D model retrieval, using the object itself, has been proposed as an alternative mechanism (Paquet and Rioux, 1999). As applied in many fields, the 3D model retrieval has attracted a large amount of research in recent years. In computer-aided design (Regli and Cicirello, 2000), the similar search for standard parts is handy for achieving higher speed with lower cost. In bioinformatics (Yeh *et al*., 2005), the detection and retrieval of similar protein molecules are applied. Other cases can be found in entertainment industry, visual reality, and computer aided design, etc.

In spite of so many attempts in recent years, the retrieval performance of 3D shape descriptors is very limited, even admittedly unsatisfactory, according to the evaluations (Shilane *et al*., 2004; Vranic, 2005; Bustos *et al*., 2005). One of the essential reasons is that descriptors capture various properties of objects, and diverse model classes are best represented by different characteristics. Another principal cause is due to object similarity. In previous methods, the similarity is measured only with geometrical distance of shape descriptors, and the geometrically similar but semantically dissimilar model is a case in point. This is one of the manifestations of semantic gap, i.e., the gap between high-level semantic knowledge and low-level object representation. To deal with the problem, the relevance feedback, an iterative search tactics filling in the semantic gap is introduced. At first, the system retrieves the similar objects only with shape descriptors in descending order. Then, the user marks the models as "relevant", "no opinion" or "ir-

* Project supported by the National Basic Research Program (973) of China (No. 2004CB719401) and the National Research Foundation for the Doctoral Program of Higher Education of China (No. 20060003060)

relevant" based on his/her perception. At last, the system learns from the labelled objects and filters out semantically dissimilar models in the next iteration, as demonstrated in Fig.1.

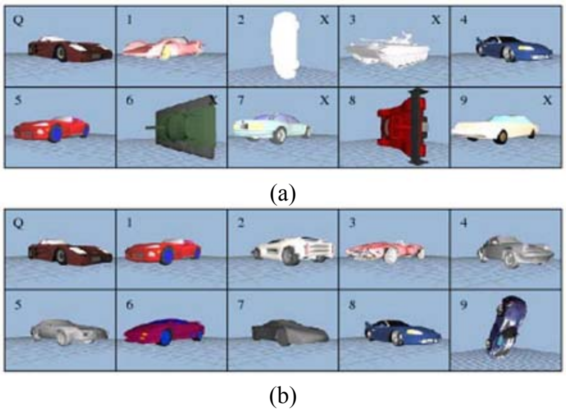


Fig.1 Removing geometrically similar but semantically dissimilar models (query model is the top-left one, and the semantically dissimilar models are marked with "x"). (a) Initial search; (b) After one iteration

In this paper, we propose an original Support Vector Machine (SVM) active learning algorithm for 3D model retrieval. As opposed to the current relevance feedback schemes learning from the most positive 3D models, our approach brings two kinds of most informative objects into the 3D model retrieval. After learning from the marks, the proposed algorithm captures the user's semantic knowledge quickly and precisely, and then constructs a boundary taking the relevant models away from the irrelevant ones. Based on the publicly available 3D model criterion Princeton Shape Benchmark (PSB), the experimental results demonstrated that the 3D model search engine using relevance feedback has achieved a significant improvement in retrieval effectiveness. Compared with the four state-of-the-art relevance feedback algorithms for 3D model retrieval, our method offers better retrieval effectiveness after no more than two iteration rounds.

This paper is organized as follows. Section 2 discusses the related work about 3D shape descriptors and relevance feedback. The original SVM active learning algorithm is proposed in Section 3. Section 4 introduces some evaluation measures and the 3D model retrieval system, and then describes the experiments and some detailed results. Finally, the conclusions and further work are shown in Section 5.

RELATED WORK

Content-based 3D model retrieval has become a hot research issue in the past few years, and a large number of 3D shape descriptors are explored to characterize various attributes of 3D models. Meanwhile, the relevance feedback strategy has become a new research area in 3D model retrieval to improve the retrieval performance.

3D shape descriptors

Recently, a variety of shape descriptors have been proposed for 3D model retrieval, and they are generally classified into two categories: geometry-based and shape-based descriptors. Geometry-based descriptors match 3D models using the information and distribution of vertices and mesh triangles (Osada *et al*., 2002; Funkhouser *et al*., 2003; Kazhdan *et al*., 2004; Vranic, 2004). Shape-based ones distinguish 3D models by taking the projected images into account (Chen *et al*., 2003; Kolonias *et al*., 2005; Pu and Ramani, 2006; Ansary *et al*., 2007). Having defined certain object aspects, numerical values are extracted from a 3D object. These values describe the 3D object and form a feature vector of usually high dimensionality (Bustos *et al*., 2005). Thus, the shape descriptor or the feature extraction method is replaced by the feature vector. For the latest developments in content-based 3D model retrieval, please refer to (Iyer *et al*., 2005; Funkhouser *et al*., 2005; Bustos *et al*., 2005).

Early research of content-based 3D model retrieval mainly focuses on exploring various shape descriptors, hoping to find the "best" one to represent 3D models. Shilane *et al*.(2004) compared 12 different descriptors on the criterion of 3D model database Princeton Shape Benchmark (PSB) given by the Shape Retrieval and Analysis Group at the University of Princeton, and Light Filed Descriptor (LFD) (Chen *et al*., 2003) was declared as the best. Vranic (2005) proposed a composite shape descriptor called DESIRE, and the experiments displayed that DESIRE outperforms LFD.

Relevance feedback

As a powerful technique, relevance feedback has been successfully used in the text classification (Sebastiani, 2002), image retrieval (Zhou and Thomas, 2003) and music retrieval (Mandel *et al*., 2006). But it is still a new research area in 3D model retrieval, as the number of relevant algorithms (Elad *et al*., 2001; Bang and Chen 2002; Leifman *et al*., 2005; Atmosukarto *et al*., 2005; Novotni *et al*., 2005) targeted in 3D model retrieval is very limited. Elad *et al*.(2001) first brought the technique concept of SVM algorithm into 3D model retrieval, in which the distance between objects was measured using the square of Euclidean distance. For comparison, this method is called "Elad2001" in this paper. Bang and Chen (2002) proposed a relevance feedback method called "SpaceWarping", which shifts the objects' data points in a controlled manner responding to user feedback. A method that ranks relevant (irrelevant) objects on top (bottom) was presented by Atmosukarto *et al*.(2005). Leifman *et al*.(2005) investigated a relevance feedback technique combining Biased Discriminant Analysis (BDA) and Linear Discriminant Analysis (LDA) on the learned feature subspace, and this algorithm is called "Leifman2005". The experiments illustrated that Leifman2005 was a little better than SVM and the SpaceWarping approach was the worst. On the contrary, Novotni *et al*.(2005) compared several relevance feedback methods for 3D model retrieval, and found that the SVM algorithm performed the best closely followed by Leifman2005.

SVM ACTIVE LEARNING

In this section, a novel SVM active learning algorithm is proposed by combining the dominant classification system SVM with the concept of active learning for effective 3D model retrieval.

Support Vector Machine

SVM is a supervised classification technique and its basic idea is to find the hyperplane. It not only separates two classes of training data, but also distinguishes future untrained data.

Given a set of training data $\{x_i, y_i\}_{1\le i\le N}$ ($x_i\in\mathbb{R}^d$) are feature vectors, $y_i\in\{-1, 1\}$ is the class label to which x_i belongs. Any hyperplane dividing two classes has the form:

$$y_i(w\cdot x_i+b)>0,\quad 1\le i\le N, \tag{1}$$

where "·" denotes inner product. Let w_k be the set of hyperplanes, in which the maximum margin hyperplane maximizes the distance to the closest points of each class. Once the constraints in the equation are associated with non-negative Lagrange multipliers $\{\alpha_1, \dots, \alpha_N\}$, the maximum margin hyperplane is defined by

$$w=\sum_{i=1}^{N}\alpha_i y_i x_i, \tag{2}$$

where Lagrange multipliers maximize

$$L_D=\sum_{i=1}^{N}\alpha_i-\frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\alpha_i\alpha_j y_i y_j x_i x_j \tag{3}$$

subject to

$$\sum_{i=1}^{N}\alpha_i y_i=0. \tag{4}$$

Support vectors lying on the margin belong to a subset of training data. The classification function is defined as

$$f(x)=\sum_{i=1}^{N}\alpha_i y_i x_i\cdot x+b. \tag{5}$$

Since the data point x is merely related to dot production, it can be transformed to another feature space via a function $\Phi(x)$. The dot production can be replaced by $K(u, v)=\Phi(u)\cdot\Phi(v)$ when the kernel K satisfies Mercer's condition (Burges, 1998). In our implementation, we select the radial basis function (RBF) kernel:

$$K(u,v)=\mathrm{e}^{-\gamma(u-v)\cdot(u-v)}. \tag{6}$$

Active learning

In the practical situation, the user may be impatient or uncooperative, and makes only a few subjective judgments. In contrast, SVM has access to all 3D models in the repositories. Therefore, it is critical for the learner to make good use of the limited training data. As opposed to the current relevance feedback schemes learning from the most positive models for 3D model retrieval, the active learning system should make inquires about the most informative samples in order to get as much information as possible. Consequently, the most important issue for active learning is to find out different ways to acquire the most informative samples.

Tong and Chang (2001) proposed a criterion for determining the most informative request using the notion of version space. The duality between points and hyperplanes in feature space and parameter space can be interpreted with x_i as points and w_k as hyperplane normals, or on the other hand, w_k as points and x_i as hyperplane normals. In parameter space, all the w_k together are recognized as version space, which is a connected region on the surface of a hypersphere. Finding the maximum margin hyperplane in the original space is equivalent to finding the point at the center of the largest hypersphere in version space (Mandel *et al*., 2006). According to the criterion in (Tong and Chang, 2001), the training data points reduce the size of version space in parameter space. Thus the effective active learner ought to be able to shrink the version space as fast as possible. To put it another way, the ideal strategy should halve the version space with each application of training data. Taking advantage of the duality between feature space and parameter space, the most informative sample is the one closest to the decision boundary, called the decision boundary point (DBP):

$$DBP = \arg\min_{1\le i\le N}(|f(x_i)|). \tag{7}$$

As has been noted, relevance feedback can filter out geometrically similar but semantically dissimilar (GSSD) models. However, the first iteration is a key milestone in SVM active learning, mainly because the similarity distance between models is measured from the pure geometrical feature space to the mixed geometrical and semantic feature space subsequent to the examination of the labelled models. With the increase of the number of iterations, the similarity distance inclines to semantic similarity. Moreover, in the mixed feature space, the semantically similar but geometrically dissimilar (SSGD) models move towards the relevant models, while on the other hand, the GSSD ones move away from the relevant models. As a result, the SSGD models belong to the most informative samples as well. The similarity distance between the SSGD models and the relevant models decreases gradually with the increment of relevance feedback rounds. Then, the tendency speed (TS), which describes the tendency degree of models moving towards the relevant models in the mixed feature space, is defined as

$$TS(x_i) = \begin{cases} f_j(x_i), & j=1, \\ f_j(x_i) - f_{j-1}(x_i), & j\ge 2, \end{cases} \tag{8}$$

where j denotes the iteration round, e.g. j=0 for the initial search, and j=1 for the first iteration. The greater the value of TS, the quicker the model moves toward the relevant models in adjacent iteration rounds. Hence, the most informative sample has the biggest value of TS, and is regarded as the biggest tendency speed point (BTSP).

$$BTSP = \arg\max_{1\le i\le N}(TS(x_i)). \tag{9}$$

It has been noted that there are more than 90 model classes in PSB (Shilane *et al*., 2004), and for each class the proportion of model number to total number is less than 6%. In other words, for the query model, there are only a small number of relevant models in the database. For randomly sampled unlabelled 3D models, without any additional evidence, the probability of a negative label is extremely high. Therefore, prior knowledge of the random sample can be used in the initial search to improve the retrieval performance.

To summarize, the SVM active learning algorithm performs the following in each round of relevance feedback:

(1) In the initial search, it asks the user to label twenty models in descending order depending on the geometrical distance. Meanwhile, the approach randomly selects twenty additional models, which are automatically marked as irrelevant.

(2) In the iteration rounds (e.g. first iteration, second iteration), it presents twenty of the most informative models for the user to label. Half of them are DBPs, the others BTSPs.

EXPERIMENTS

In this section, the 3D model repositories and several standard measures are introduced at first. Secondly, several 3D shape descriptors are compared, and the best one is selected as the feature vector in the SVM active learning algorithm. Then, we describe the 3D model retrieval system “ModelSeek” that we have implemented using the proposed relevance feedback method. Finally, experimental results are compared with a few state-of-the-art relevance feedback algorithms, and present some discussions.

Evaluation measures

The experiments are based on the publicly available benchmark of 3D model repositories PSB (Shilane *et al*., 2004), which contains 1814 objects of general categories like human, building, vehicle, etc. In the experiments, each model is used as a query object, and the models belonging to the same class are considered relevant.

To estimate the effectiveness of 3D model retrieval, we discuss several evaluation methods which have been widely applied in information retrieval.

(1) Precision vs. Recall (Shilane *et al*., 2004). Let α be the set of models that belong to the same class as the query model, and β the set of retrieved models. Then $\gamma=\alpha\cap\beta$. The precision P and recall R are defined as

$$P=\gamma/\beta, \tag{10}$$
$$R=\gamma/\alpha, \tag{11}$$

where P indicates the accuracy of retrieval performance, while R shows the robustness of retrieval performance.

(2) Nearest neighbor (Shilane *et al*., 2004). This describes the percentage of the closest match that belongs to the same class as the query model.

(3) First-tier/Second-tier (Shilane *et al*., 2004). First-tier and Second-tier measures are associated with relevant models among the first M retrieved models. Let C be the size of query model class (excluding the query model). In the first-tier $M=|C|$, while $M=2|C|$ for the second-tier.

(4) Discounted Cumulative Gain (DCG) (Shilane *et al*., 2004). Let G be the gain list converted from the ranked list, where the ith entry G_i is 1 if the ith retrieved model is in the same class as the query model and 0 otherwise. DCG is defined as

$$DCG_i=\begin{cases} G_1, & i=1, \\ DCG_{i-1}+G_i/\log_2 i, & \text{otherwise.} \end{cases} \tag{12}$$

Then this result is divided by the maximum possible DCG to give the final score:

$$DCG=\frac{DCG_k}{1-\sum_{|C|}^{j=2}[\log_2 i]^{-1}}, \tag{13}$$

where k is the number of models in the database, and $|C|$ is the size of the class to which the query model belongs.

Feature vectors

In the experiments, several 3D shape descriptors are implemented, such as Ray (Vranic and Saupe, 2002), Silhouette (Vranic, 2004), GEDT (Funkhouser *et al*., 2003), Dbuffer (Vranic, 2004), LFD (Chen *et al*., 2003) and DESIRE (Vranic, 2005). We chose L_1 (Manhattan) distance as a similarity measure, as the experiments in (Vranic, 2004) show that L_1 acquires the best retrieval results compared with other similarity measures.

Fig.2 shows the average retrieval effectiveness of six shape descriptors using several measures. It is obvious that the most precise shape descriptor is DESIRE, followed by LFD, Dbuffer, GEDT, Silhouette and Ray. It indicates that the composite descriptors, i.e. DESIRE and LFD, achieve better retrieval performance than others. Therefore, the best descriptor DESIRE is selected as the feature vector in the proposed SVM active learning algorithm.

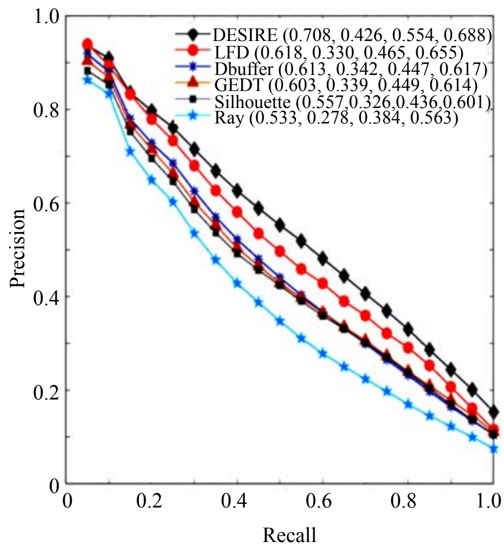


Fig.2 Average precision vs. recall for DESIRE, LFD, Dbuffer, GEDT, Silhouette and Ray (the legend includes nearest neighbor, first-tier, second-tier and DCG values)

3D model search engine

The 3D model retrieval system "ModelSeek" implements the proposed SVM active learning algorithm with the best shape descriptor DESIRE. The system supports three modes of interaction: keyword based search, search by query model, and retrieval using relevance feedback. The main user interface is shown in Fig.3.

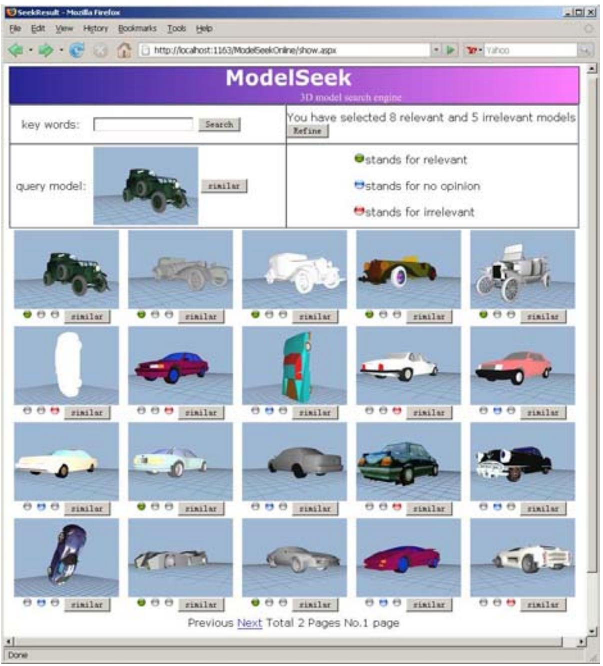


Fig.3 The user interface of the 3D model retrieval system "ModelSeek"

The user can input the keyword to browse the desired models to start, or use one of the randomly displayed 3D models as the query model by clicking the "similar" button. The retrieval results are ranked from top-left to bottom-right. After the initial search, the user can select several models from this page to comment on, to choose one of the three circle buttons under each result: the left with the green background indicates "relevant" feedback, the middle with the blue background indicates "no opinion", and the right with the red background indicates "irrelevant" feedback. Once the user clicks the "Refine" button, the system grasps the user's semantic input quickly and accurately, and then provides better retrieval results tuned to the specific query.

The dominant 3D models retrieval systems from the University of Princeton (Funkhouser *et al*., 2003), the National Taiwan University (Chen *et al*., 2003), the University of Konstanz (Vranic, 2004), and the National Technical University of Athens (Daras *et al*., 2006) cannot learn from the user's specific retrieval need, which makes the retrieval results unchangeable with the same query model by different people. To the contrary, the 3D model search engine "ModelSeek" asks the user to provide perceptual feedback and returns different retrieved models according to the user's marks.

Experimental results

Table 1 illustrates the average retrieval performance of the SVM active learning algorithm over four rounds. From the initial search to the first iteration, there is a dramatic rise of average precision from 52.86% to 68.88%, a sharp increase of 30.31%, which indicates that a search engine using relevance feedback has achieved a significant improvement in retrieval effectiveness. With the increase of the number of iterations, the increment decreases little by little, but the retrieval performance becomes superior after only a few rounds of relevance feedback. What is more, the nearest neighbor of the second iteration reaches as much as 97.02%, which means the closest matched model is almost in the same class as the query model. Compared with the initial search, the fourth iteration provides a significant increment of 66.57%, 48.75%, 108.06%, 67.37% and 40.43% in terms of average precision, nearest neighbor, first-tier, second-tier and DCG respectively.

Then the proposed SVM active learning algorithm is compared with four state-of-the-art relevance feedback methods for 3D model retrieval: Elad2001 (Elad *et al*., 2001), SpaceWarping (Bang and Chen 2002), Leifman2005 (Leifman *et al*., 2005) and SVM (Novotni *et al*., 2005). Table 2 displays the

Table 1 The retrieval performance of the SVM active learning algorithm from the initial search to the fourth iteration

Search round	Average precision	Nearest neighbor	First tier	Second tier	DCG
Initial search	0.5286	0.6582	0.4045	0.5133	0.6631
1st iteration	0.6888	0.8842	0.6143	0.6774	0.8165
2nd iteration	0.8290	0.9702	0.7670	0.8032	0.9030
3rd iteration	0.8607	0.9779	0.8139	0.8363	0.9213
4th iteration	0.8805	0.9791	0.8416	0.8591	0.9312

comparison of five relevance feedback algorithms in the second iteraiton using several evaluation measures. It is evident that the retrieval effectiveness of our method is the best among the several methods. Compared with the algorithm SVM, the proposed method provides an improvements of 6.08%, 1.38%, 5.90%, 6.16% and 4.02% in terms of average precision, nearest neighbor, first-tier, second-tier and DCG respectively.

Fig.4 demonstrates the results using various evaluation criteria, in which the 2×11 bars show the average performance for the 11 biggest model classes of SVM and our method. Table 3 enumerates the class name and class size for the corresponding class number. These results indicate that our method achieves better retrieval performance than the SVM.

Fig.5 compares the retrieval performance of different approaches in the fourth iteration. The proposed method clearly outperforms the other four relevance feedback algorithms. The average precision of our method at the fourth iteration is 88.05%, and the precision curve sustains the near-perfect precision for most recall levels with lots of degradations at very

Table 2 The comparison of five relevance feedback algorithms in the second iteration

Algorithm	Average precision	Nearest neighbor	First tier	Second tier	DCG
Elad2001	0.6858	0.9349	0.6209	0.6465	0.8072
SpaceWarping	0.5922	0.9107	0.4770	0.5317	0.7525
Leifman2005	0.6685	0.9449	0.5738	0.6177	0.8126
SVM	0.7815	0.9570	0.7243	0.7566	0.8681
Our method	0.8290	0.9702	0.7670	0.8032	0.9030

Table 3 The biggest model classes in PSB

Class No.	Class name	Class size
1	Fighter-jet airplane	50
2	Human biped	50
3	Rectangular table	26
4	Potted plant	25
5	Human-arms-out	21
6	Rifle gun	19
7	Sports car	19
8	Helicopter aircraft	17
9	Face body-part	17
10	Chess-piece	17
11	Military-tank vehicle	17

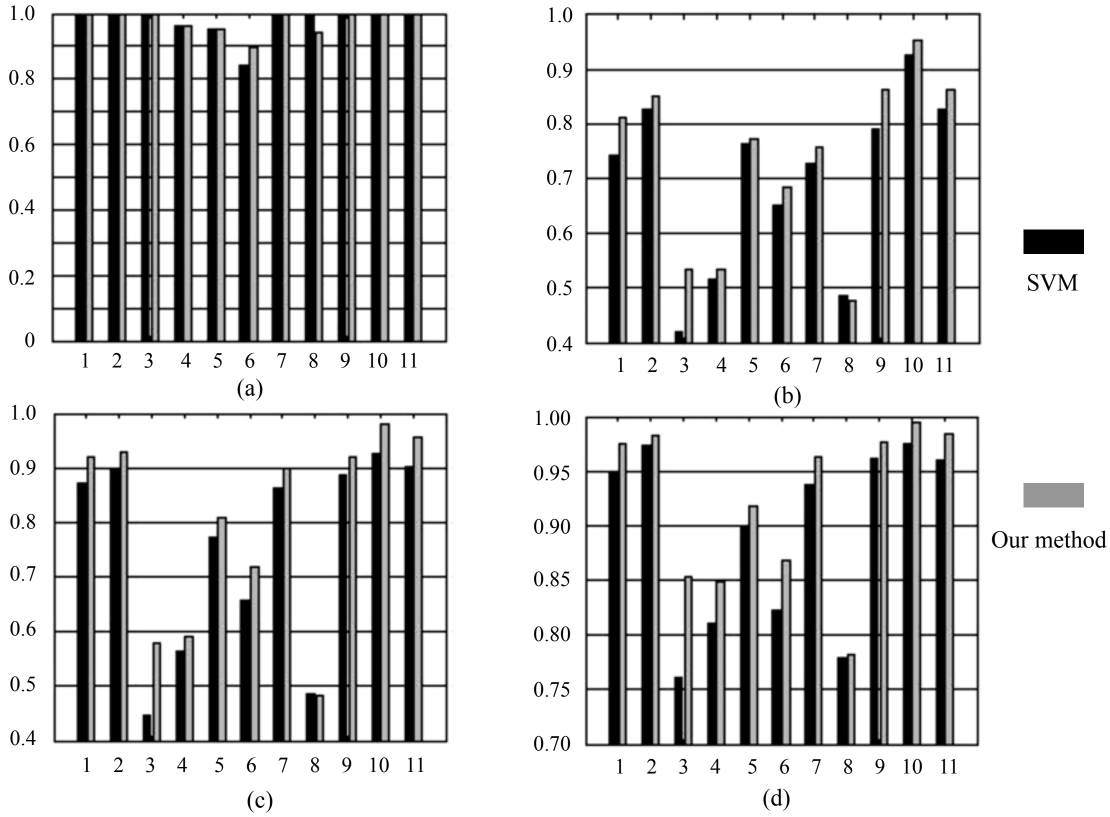


Fig.4 The comparison of retrieval effectiveness between SVM and our method with the biggest model classes in the second iteration using various criteria. (a) Nearest neighbor; (b) First-tier; (c) Second-tier; (d) DCG

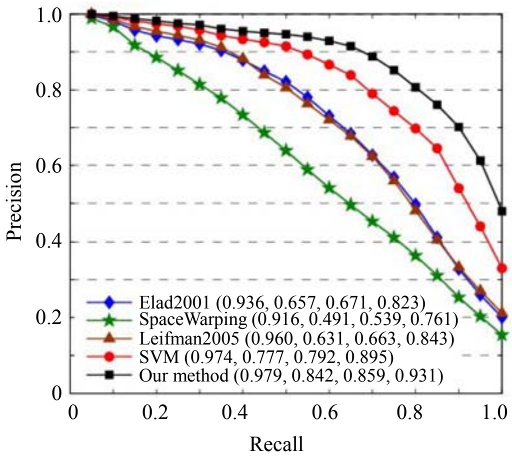


Fig.5 Comparison of retrieval effectiveness (average precision vs. recall in PSB) among different relevance feedback algorithms in the fourth iteration

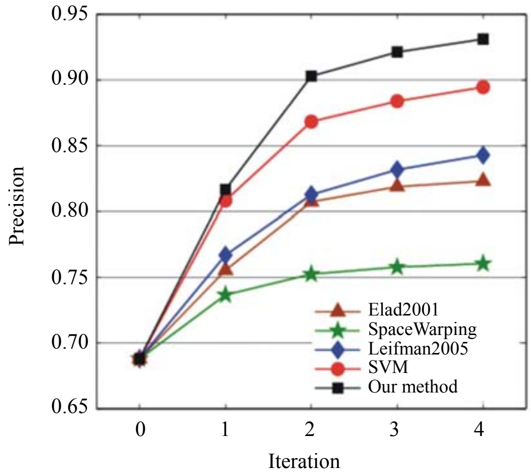
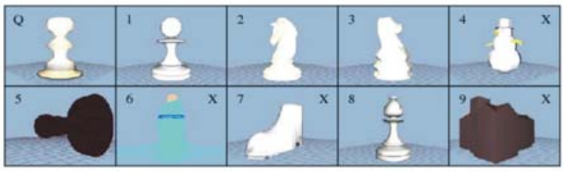


Fig.6 Retrieval performance (DCG) in different iterations

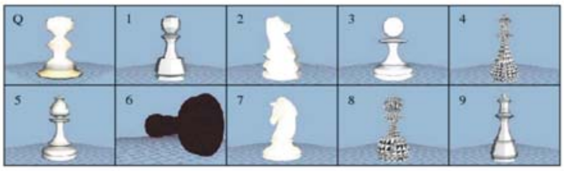
high recall levels. The second-tier of the proposed algorithm is 8.46% higher than that of SVM. Compared with SpaceWarping, the first-tier is improved from 0.491 to 0.842, for an increase of 71.49%, which is significant in terms of retrieval answer quality.

DCG takes account of the position of relevant models, and has the lowest standard deviation among the measures discussed above. Therefore, DCG is regarded as the most precise and stable measure. Fig.6 illustrates the average performance of DCG as a function of iteration rounds. For each approach, the most drastic improvement is achieved between the initial search and the second iteration, while the improvement between the third and the fourth iterations is slight. It is apparent from Fig.6 that the performance of our method in the second iteration is more than 0.9, which is an important milestone in retrieval effectiveness. Furthermore, it is a little better than that of SVM in the fourth iteration. In practice, the user is impatient, and wants to find the best possible retrieval results within only a few feedback rounds. Therefore, the proposed SVM active learning algorithm is more suitable for content-based 3D model retrieval.

Figs.1 and 7 are examples of using the SVM active learning algorithms to retrieve the semantically similar models according to the users' semantic knowledge. In Fig.7, a chess-piece (1608 off in PSB) is used as the query model, and there are some other irrelevant objects like snowman, bottle liquid-container, shoe, and two-story home-building retrieved in the nine top-ranked results in the initial search. By marking the relevant and irrelevant models, the first nine models retrieved by the system are all relevant in the first round of relevance feedback.



(a)



(b)

Fig.7 Retrieving a chess-piece model using the SVM active learning algorithm. (a) Initial search; (b) After one iteration

CONCLUSION

In this paper, we proposed a novel SVM active learning algorithm for 3D model retrieval. Compared with the existing relevance feedback schemes, our method combines SVM technique with active learning mechanism. In the proposed approach, two types of the most informative samples are presented, and the active learner obtains maximum information gain learning from the most informative samples rather than the most positive ones. Our method grasps the user's semantic knowledge quickly and accurately with only a few labelled 3D models. Experimental results show that the proposed algorithm significantly improves the retrieval effectiveness. Compared with four state-of-the-art query refinement schemes for 3D model retrieval, it provides superior retrieval performance after no more than two rounds of relevance feedback.

In the future, we will focus on acquiring a semantic space from users' relevance feedback or other related techniques for 3D model retrieval, and will study the possibility of incorporating the approaches proposed by (Zhou and Huang, 2002; He *et al*., 2003) to further improve the retrieval performance of the 3D model retrieval system ModelSeek.

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