Indexing and Retrieval of 3D Models Aided by Active Learning

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ABSTRACT

We demonstrate a system for indexing and retrieval of 3D models aided by active learning. We propose a new set of region-based features for 3D models. Each model is treated as a solid volume with a uniform density. Features such as the volume-surface ratio, the moment invariants and the Fourier transform coefficients are efficiently calculated from the mesh model directly. Comparable retrieval performance is achieved with other features such as the cord histogram, the 3D shape spectrum, etc. To further improve the performance, we incorporate hidden annotation into our system. We propose to use active learning to improve the annotation efficiency. We show that with active learning, the system can perform better than random annotation, and the retrieval result improves rapidly with the number of annotated samples. Moreover, relevance feedback is included in the system and combined with active learning, which provides better user-adaptive retrieval results.

Categories and Subject Descriptors

H.3.3 [**Information Storage and Retrieval**]: Information Search and Retrieval – *query formulation, relevance feedback, retrieval models.*

General Terms

Algorithms, Human Factors.

Keywords

Information retrieval, 3D model retrieval, feature extraction, active learning, semantic distance.

1. SYSTEM TECHNICAL DESCRIPTION

3D scene/object browsing is becoming more and more popular as it engages people with much richer experiences than 2D images. While it is easy to build 3D models from real scenes/objects today, the growing size of available 3D models makes 3D model retrieval very important.

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Work has been done to retrieve similar models from a database. 3D shape has been included in MPEG-7 as part of the experimentation model, and the shape spectrum was proposed as an intrinsic shape description for 3D models. However, the 3D surface description of a model is not unique given an object. Different ways of triangulization may lead to different 3D surfaces, which might in turn significantly change the surface features. In our system, we explore some different features that can be robust for different triangulization processes.

We have been developing a 3D model retrieval system. Around 1700 3D models are collected over the Internet [1][2][3][4]. We study some features with respect to the solid model of a 3D object in this project. Each model is treated as a solid volume with a uniform density. Multiple features are extracted from the solid model, such as the volume-surface ratio, the moment invariants and the Fourier transform coefficients. To calculate a feature for a mesh, we show that we can first compute it for each elementary shape such as a triangle or a tetrahedron, and then add up all the values for the mesh [5]. The algorithm is computationally efficient. A simple experiment shows that given a query, the system on average retrieves 25% more relevant results with our new features than the cord histogram approach.

To further improve the retrieval performance, we employ hidden annotation in our system. Since manual labeling is expensive, we propose to use active learning to improve the annotation efficiency [6]. As a prior knowledge, our database has about 53 attributes that form a complex attribute tree. Attributes are properties such as airplane, car, body, and so on. For each model in the database, we maintain a list of probabilities, each indicating the probability of this model having one of the attributes. During training, the learning algorithm samples models in the database and presents them to the annotator to assign attributes to. For each sampled model, each probability is set to be one or zero depending on whether or not the corresponding attribute is assigned by the annotator. For models that have not been annotated, the learning algorithm estimates their probabilities based on a potential function. Specifically, models close to an annotated model are likely to have the same attributes as the annotated model, so similar probabilities from the annotated model are given to these models. Using active learning, the algorithm is able to determine, among the models that have not been annotated, which model the system is the most uncertain of, and presents it as the next sample to the annotator to assign attributes to. During retrieval, the list of probabilities works as a feature vector for us to calculate the semantic distance between two models, or between the user query and a model in the database. The overall distance between two models is determined by a weighted sum of the semantic distance and the low-level feature distance. We show that with the proposed algorithm, the retrieval performance of the system improves rapidly with the number of annotated samples. Furthermore, we show that active learning outperforms learning based on random sampling.

Relevance feedback has been shown as a powerful tool for information retrieval. We employ relevance feedback to our system and combine it with the active learning approach. Therefore, an authentic user can use feedback as another tool for hidden annotation.

2. THE USER INTERFACES

In this demo, we will show our 3D model retrieval system aided by the active learning algorithm. Figure 1 shows the user interface of our system. The user can randomly browse the 3D model database by clicking the “Rand” button. The input of the user query is flexible, e.g., a VRML file, some simple 3D primitives such as spheres and cubes, a keyword and so on. On the left hand side of Figure 1 we shows a query 3D model given through a VRML file; on the right hand side are the ranked retrieval results given by the system. The ranking orders are from top-left to bottom-right. Thumbnails are listed to show a representative view of the 3D model. When interested in a specific model, the user can double click the thumbnail and study the 3D model from arbitrary viewpoint. By moving the sliders under each retrieval result, the user can give comments on the retrieval results, for example, highly relevant, relevant, normal, non-relevant, highly non-relevant, and so on. Given the feedback, the system can provide better retrieval results tuned to the specific user query.

Figure 1 The retrieval user interface.

In Figure 2, we show the active learning interface. An attribute tree structure is shown on the left hand side with checkboxes in the front of the attributes. On the right hand side is a 3D model proposed by the system automatically for the annotator to annotate. The annotator teaches the system by checking some attributes that he/she thinks the 3D model has. The annotator then clicks the “Annotate” button and the system will learn the annotation and propose the next object for annotation.

The relevance feedback and active learning can work separately or jointly. In the latter case, the user’s feedback is utilized to change the knowledge of the system, or the hidden annotations.

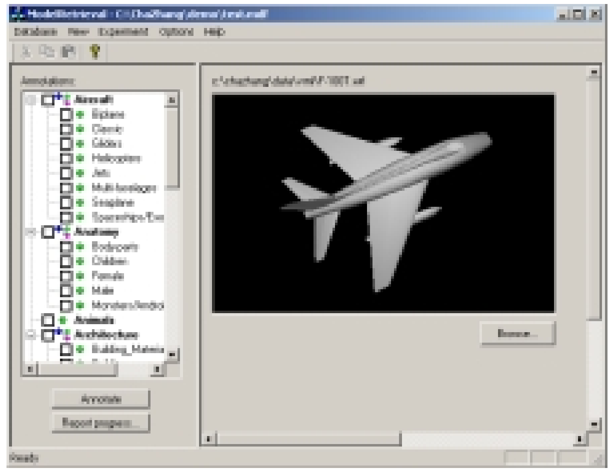

Figure 2 The active learning user interface.

3. CONCLUSIONS

We demonstrated a 3D model retrieval system that has several major contributions. First of all, we proposed region-based features for 3D model retrieval. We explicitly gave the formula of the Fourier transform of a 3D mesh model, which can be used in broad research areas such as shape analysis, object recognition, model matching and so on. Second, we used active learning, an approach typically used in machine learning, to improve the efficiency of hidden annotation in a content-based information retrieval system. The proposed approach, which uses statistical model and allows multiple attribution for learning, hence is also applicable to general machine learning problems.

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