3D Models Retrieval based on Shape-Similarity

Yu Yu Than
University of Computer Studies Mandalay
yuyuthanster@gmail.com

Abstract

Richer types of multimedia such as audio, video and 3D objects are becoming more and more common place. However, current retrieval techniques in these areas are not as sophisticated as textual and 2D image techniques and in many cases rely upon textual searching through associated keywords. The work presented in this paper aims to retrieve similar 3D shapes from the large number of 3D object datasets. Firstly three virtual views, top view, side view and front view, of an object are extracted from 3D objects to perform dimension reduction of 3D model into 2D model. Secondly, we extract the features of the shape by calculating the ratios of virtual views of an object using Euclidean distance. For searching shape similarity, k-nearest neighbor algorithm is applied. To demonstrate the efficiency of proposed system regarding the computational aspects and retrieval performance, we tested the proposed system on NTU 3D model database.

Keywords: 3D Model Retrieval, Shape Similarity, Content-based 3D Models Retrieval, K-nearest neighbor.

1. Introduction

It is a common saying that a picture is worth a thousand words. It is true that visual information is very useful in communicating ideas and certainly humans rely heavily on sight to perceive information regarding the physical world surrounding us. The management of the digital information has always been one of the tasks of computer. In the early decades, when most of the data consisted of text and numbers, relational database handled the storage and searching well. However, with the rapid growth of more complicated data types, such as images, sounds or video. Due to the increasing popularity of 3D graphics in animation and games, the use of 3D geometry models increases dramatically.

The content-based or similarity searching has become a fundamental computational task in variety of application areas, including multimedia information retrieval, data mining, pattern recognition, biomedical databases, computer games and statistical data analysis. The fundamental ingredient of a retrieval system is shape based methods matching, which is the process of the determining how similar two shapes are. Unfortunately, there are some difficulties for 3D shape matching ubiquitously in most of correlative shape retrieval applications, 3D models are not easily retrieved like text documents, but content based 3Dshape retrieval methods that use shape properties of the 3D models to search for similar models usually perform better than text.

This paper presents automatic content-based retrieval of 3D models. Section 2 introduces the related work. Section 3 reviews the content-based retrieval background. Section 4 presents the proposed system. Section 5 presents the experimental results. The paper concludes in Section 6.

2. Related Work

A method for shape similarity comparison of 3D models can be classified by the shape representation it is targeting. Some of the shape comparison algorithms assume well-defined shape representation. Zhang and Chen [1] have described efficient methods to compute global features such as volume; area, statistical moments, and Fourier transform coefficients. Vranic and Saupe [2] have suggested a method in which the feature vector is formed by a complex function on the sphere. Kazhdan et al. [4] have described a reflective symmetry descriptor. Their experimental results show that combining the reflective symmetry descriptor with existing methods provides better results.

Osada et al. [6] have used shape distributions, which measure properties based on distance, angle, area, and volume measurements between random surface points. Similarity between objects is measured with a pseudo-metric that measures distances between distributions. Ohbuchi et al. [7] have devised shape histograms that are discretely parameterized along the principal axes of the inertia of the model. The topology-based approach [3, 5] extract skeletons of a 3D model, and then some graph matching algorithms are used for shape comparison. Although these approaches are flexible and can be used for matching deformable objects, the time consuming nature makes the methods not suitable for real time applications.

This paper presented a method to retrieve 3D models by measuring the similarity between a user query and 2D views generated from 3D models. The basic idea arises from such a fact: engineers usually express their concept of a 3D shape with three 2D views without missing any information.

3. Background

Content-based image retrieval (CBIR), also known as query by image content (QBIC) is the application of computer vision techniques to the image retrieval problem, that is, the problem of searching for digital images in large databases. Content-based means that the search will analyze the actual contents of the image rather than the metadata such as keywords, tags, and/or descriptions associated with the image. The term 'content' in this context might refer to colors, shapes, textures, or any other information that can be derived from the image itself.

3.1. 3D Shape Representation

There are two main methods for representing arbitrary 3D objects. One such method of representing a 3D object is the mesh format. This is a collection of connected polygons forming either part of or the whole surface of an object. Many 3D techniques assume that a mesh is composed of triangles rather than arbitrary sized polygons as this greatly simplifies calculations. A 3D object can be composed of one or more meshes. The other main method of representing a 3D object is by using voxels. A voxel is a volume pixel, the 3D equivalent of a pixel in a 2D image. Unlike the mesh representation which models the surface of the object, a voxel models the whole volume of the object. As with 2D images, increasing the scale of the model can result in blocky edges (pixelation).Often a model will be represented as a mesh and converted to voxels as needed.

3.2. Content-Based 3D Models Retrieval

This section describes a brief description of the content-based 3D model retrieval background. 3D object matching is a growing research area and a wide range of differing techniques have been developed.

3D content-based retrieval typically consists of four stages. There following are: The first stage is to convert the object into a suitable format that is understandable by the rest of the process. This process may also involve re-sampling the object to provide a more even spread of vertices on the mesh. The initial sampling of the object (the creation of the mesh approximation at the time of acquisition or creation) may result in areas of the mesh being more densely populated than other areas.

Typically fatter areas can be represented in a few large faces and much curved areas require many small faces. This process may also try to correct problems in the object, such as holes in the mesh or triangle orientation inconsistencies. This can be done once and the result saved for future use as this process is independent of the Content-Based Retrieval (CBR) algorithm.

The next stage is to normalize the object into a canonical co-ordinate frame; that is to transform each object into a common co-ordinate system. The exact requirements depend on the properties of the algorithm. Stage three is to generate the feature vector for the descriptor from the object mesh. Stage four is to compare the feature vector with other feature vectors of the same type using an appropriate distance metric.

4. Proposed 3D Models Retrieval System

In the content-based 3D retrieval system, serves as a query and similar objects are retrieved from a collection of 3D objects. Content-based 3D model retrieval system is shown in Figure 1.

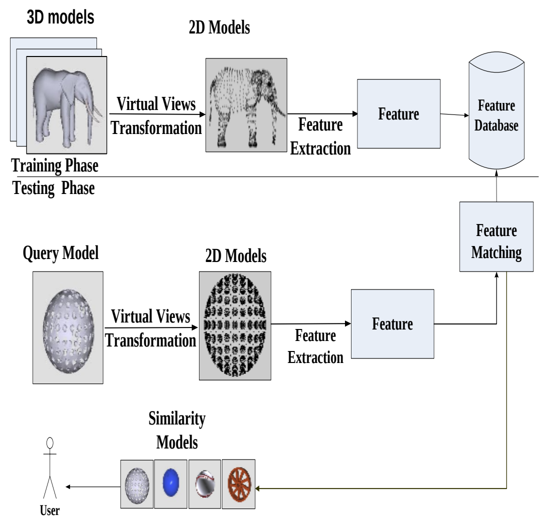

Figure 1: Overview of the System Design

Firstly, load the data file is a query object from the user. The input image takes standard dataset are NTU 3D Model Database. This datasets are (.obj) file format. Object files define the geometry and other properties for objects in Wavefront's Advanced Visualizer. Object files can also be used to transfer geometric data back and forth between the Advanced Visualizer and other applications. Object files can be in ASCII format (.obj) or binary format (.mod). This appendix describes the ASCII format for object files. These files must have the extension .obj. In this release, the .obj file format supports both polygonal objects and free-form objects. Polygonal geometry uses points, lines, and faces to define objects while free-form geometry uses curves and surfaces.

Secondly, this phase is one of the important role phases in this system. Therefore, this phase performs extracting the 3D clouded the points from the data file of this input object and that also this points are change to matrix form and to draw the 3D plot of the object. In third phase is feature extraction phase which is an essential phase all of phases. This phase contains the convert from 3D image to 2D image with their volumes that the 2D image takes three views as the engineering practice. These three views are side view, front view and front view as shown in the Figure 2 and Figure 3.

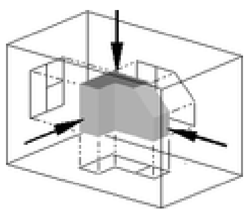

Figure 2: Top View, Side View, and Front View with Engineering Practice

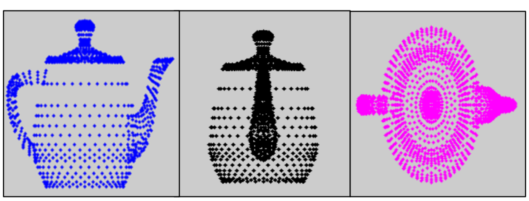

Figure 3: Sample of Teapot's Side View, Front View and Top View

In feature extraction phase: the feature vectors are performed by using geometry parameters ratio of the 2D images. Feature vectors are store in the database as shown in Figure 4. Finally, the shape similarity objects phase that for query result by using k-Nearest Neighbors method.

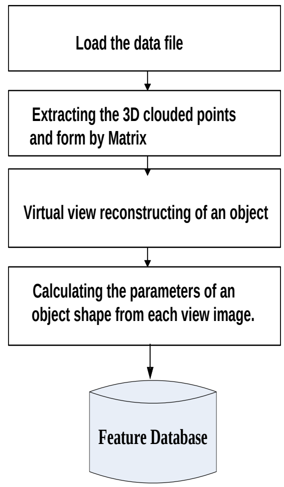

Figure 4: Feature Database Creation

4.1 Feature Extraction

The feature extraction concerns finding shapes in computer images. Shape extraction implies finding their position, their orientation and their size. This feature extraction process can be viewed many basic geometric shapes such as triangles, circles and squares. In this phase, this paper used Euclidean n- space is Euclidean vector. So, **p** and **q** are Euclidean vectors, staring from the origin of the space, and their rips indicate two points. The Euclidean norm, or Euclidean length or magnitude of a vector measures the length of the vector:

$$\|p\| = \sqrt{p_1^2 + p_2^2 + \cdots + p_n^2} = \sqrt{p \cdot p} \quad (1)$$

where the equation 1 involves the dot product. A vector can be described as a directed line segment from the origin of the Euclidean space, to a point in that space.

$$\|q - p\| = \sqrt{(p-q) \cdot (q-p)} \quad (2)$$

which is equivalent to equation 1 and also to:

$$\|p - q\| = \sqrt{\|p\|^2 + \|q\|^2 - 2p \cdot q} \quad (3)$$

The feature extraction considered 2D image. In the Euclidean plane, if p = (p_1, q_1) and q= (q_1, q_2) then the distance is given by

$$d(p,q) = \sqrt{(p_1 - q_1)^2 + (p_2 - q_2)^2}^{\,2} \quad (4)$$

For 2D case: Euclidean distance between point A (x_1, y_1 and point B(x_2,y_2)

$$D = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2} \quad (5)$$

where find the x minimum points A and x maximum points B of the top view and front view of the object. Then, the middle point O is computed. Next, find the y minimum points C and y maximum points D through O. Compute distance of AB, CD, CO and OD by using the Euclidian Distance method in equation (5) as shown in figure 5 with the example of the teapot object. Measuring which are the distance of an object for virtual views from the top view, side view and front view. The size of 2D viewing image is *M* x *N*, it will convert to the column matrix *MN* x 1. Two ratio parameters are computed for each view. The parameter matrix of an object contains at least of the six parameters for three images (top view, side view, front view). Then the data set of an object is (*MN* +6) x 1 matrix. Some of the feature vectors of the ten models are shown in the Table 1. These datasets are stored in the database.

94	64	146	54	48	88	28	24	82	53
64	21	117	48	29	23	35	44	30	4
108	40	147	43	27	81	42	87	45	36
141	67	147	88	61	68	128	92	121	80
64	81	127	83	41	70	56	61	24	61
148	80	144	79	40	90	94	92	60	22

Table 1: Sample of Feature vectors

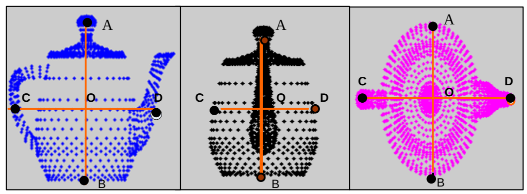

Figure 5: Measurement the distance of Teapot Object

4.2. Shape Matching for Retrieval

After feature extraction, an image is represented as a feature vector of complex valued coefficients. Two from image are determined whether from the same class by comparing the similarity between the corresponding feature vectors. There are need to match the calculated features of images with the store feature vectors to each of object. It is a trivial task for image matching.

In K-nearest neighbor classification method is discussed by no classifier model is built in advance. KNN refers back to the raw training data in the classification of each new sample. Therefore, one can say that the entire training set is the classifier. The basic idea is that the similar tuples most likely belongs to the same class. Based on some pre-selected distance metric, if finds the k most similar or nearest training samples of the sample to be classified and assign the plurality class of those k samples to the new sample. The value for k is the plurality class of those k samples to the new sample. Using relatively larger k may include some not so similar pixels and on the other hand, using very smaller k may exclude some potential candidate pixels. In both cases the classification accuracy will decrease. The optimal value of k depends on the size and nature of the data. The typical value for k is there, five or seven. The steps of the classification process are: (1) Determine a suitable distance metric. (2) Find the k nearest neighbors using the selected distance metric. (3)Find the plurality class of the k-nearest neighbors (voting on the class labels of the NNs). Assign that class to the sample to be classified.

In Figure 6 illustration, two-dimensional feature space produced by the two measures made on each sample, such as measure 1 and measure 2. Each sample gives different values for these measures but the samples of different classes give rise to clusters in the feature space where each cluster is associated with a single class. There are seven samples of two known textures are shown in figure: Class A and Class B depicted by X and O, respectively. A test sample is classified as belonging either to the samples of Class A so it can say that the test appears to be another sample of Class A. Clearly, the clusters will be far apart for measures that have poor discriminatory ability.

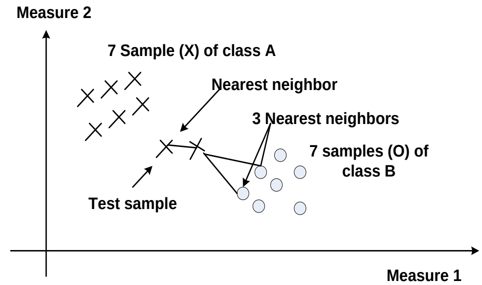

Figure 6: Sample of k-nearest Classification

5. Experimental Results

The success rate of the proposed system evaluates based on NTU3D Model Database.
This system was performed using a data set of 100 models from the NTU Models Database. The performance evaluation of the current approach is proposed based on the classification and the matching accuracy. False accept rate (FAR) and false reject rate (FRR) are usually used to the accuracy of the retrieval system. The FAR is to measure the percentage of incorrect identification and it can be computed since the images are taken from the different datasets. The FRR is to measure the incorrect rejections and it can be computed since images are taken from the same datasets. FAR and FRR can be computed as the following:

$$\mathrm{FAR} = \frac{\text{number of acceptance}}{\text{total number of acceptance by the system}} \times 100\% \quad (6)$$

$$\mathrm{FRR} = \frac{\text{number of rejection}}{\text{total number of rejections by the system}} \times 100\% \quad (7)$$

To evaluate the FAR and FRR, the proposed method is tested 100 models. FRR rate can be computed from the different datasets and the system accepts the false 10 imposters from 100 models. Therefore false acceptance rate is 0.10% by calculating. FRR rate can be computed from same datasets and the system rejects the 20 models from 100 models. Therefore false reject rate is 0.2%. The performance rate shows for identifying the optimum features as well as to increase the overall system accuracy.

$$\text{Accuracy (\%)} = 100 - ((\text{FAR}+\text{FRR})/2) \quad (8)$$

$$\text{Accuracy (\%)} = 100 - ((0.10+0.2)2) = 99.85\% \quad (9)$$

The performance of identification system is obtained by matching each of testing images with all of the training images in the database. The figure 7 shows the retrieval example with the four models. The four models are king, doorknob, person and airplane. The similarity query results are queen, bishop and pwan in the first row and balloon, bulb, light bulb in the second row. The third rows show male, kong, devil and child The last row show same shape similarity of the airplanes.

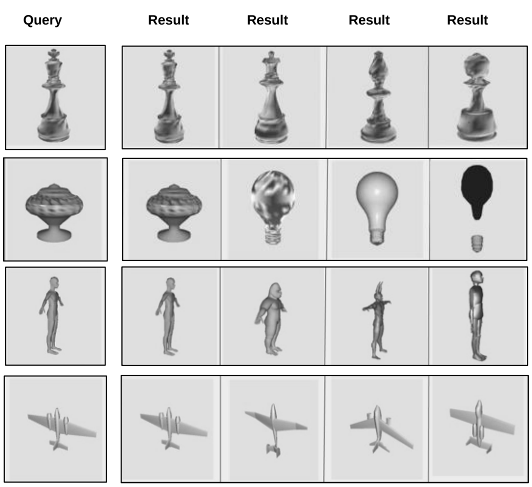

Figure 7: Sample Query and Corresponding Results

6. Conclusion

One of the specific challenges in matching 3D shapes arises from the fact that in many applications, models should be considered to be the same if they differ by a similarity transformation. Thus in order to match two models, a measure of similarity needs to be computed at the optimal translation, scale and rotation. The content-based 3D image retrieval system a model, a polygonal mesh, serves as a query and similar objects are retrieved from a collection of 3D-objects. In this paper, content-based 3D model retrieval system perform quickly well at most of the cases. For a queried model, the ranking for model in the database should be close to human perception. The Euclidian distance method and geometry parameters of the objects are suitable methods to search similarity object in many applications. The outputs results performed ranking of the shape similarity. The system show both the most similar image and nearly similar images among the existing many images. Thus, view based method for feature extraction and geometry moments of objects are suitable methods to search similarity object in many applications.

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