3D Shape Retreival Using Characteristic Level Image

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Abstract—**In this paper a new descriptor for 3D shape retrieval using a characteristics levels images (CLI) has been proposed. For each 3D model we extract a vector descriptor constructed by the coefficients of the Hu moments applied on the set of binary images. To measure the similarity between 3D models we compute the Hausdorff distance between a vectors descriptor. The performance of this new approach is evaluated at set of 3D object of well known database, is a NTU database.**

Keywords-component; 3D shape retrieval; shape descriptor; 3D Zernike moments; Hu moments; caracteristic level images; NTU database.

I. INTRODUCTION

One of the most important research directions in 3D shape retrieval is feature extraction. A variety of methods for characterizing 3D shape have been proposed in recent years. Several surveys of 3D-shape description techniques [2][3] summarize used ideas, without comparing competing methods quantitatively. In [1], 12 different methods for describing shape are compared on the PSB (Princeton Shape Benchmark) set of 3D-objects, presented by the Princeton Shape Retrieval and Analysis Group.

Recent investigations [4] [5][6] illustrate that view-based methods with pose normalization preprocessing get better performance in retrieving rigid models than other approaches and more importantly. In 2D/3D retrieval approach, two serious problems arise: how to characterize 3D model with few 2D views, and how to use these views to retrieve the model from a 3D models collection. Filali et al. [7] proposed a framework for 3D models indexing based on 2D views. The goal of their framework is to provide a method for optimal selection of 2D views from a 3D model, and a probabilistic Bayesian method for 3D models indexing from these views.

In the present paper, inspired by the work presented in [4][7][8][9], we introduce a new descriptor for 3D shape. We generate a set of images given by the intersection of the paralleled, specific plans and the 3D shape. We first normalize this shape to guarantee the invariance of affine transformations, then we extract a number of images called LI (Level Images), after using the x-means method, the number of images is reduced to CLI set (characteristic level images). Each image has been indexed with Hu moments descriptor. The similarity measure between 3D objects returns to measure the similarity between the set of CLI. In the present paper, we will compare the proposed descriptor to two well known descriptors named 3D Zernike moments and 3D surface moments invariants. Then, we will analyze the performance of the proposed descriptor. This paper is organised in the following way. In section 2 and 3 two descriptors are explained in details. In section 4 we present the proposed method for 3D model indexing. In section 5 the results obtained from a collection of 3D models are presented. Finally, the conclusion.

II. 3D ZERNIKE MOMENT DESCRIPTOR

The 3D Zernike functions Z_{nl}^{m} are written in cartesian coordinates [18] using the harmonic polynomials e_l^m:

$$Z_{nl}^{m}(X)=\sum_{p=0}^{k} q_{kl}^{p}\left|X\right|^{2p} e_l^m(X) \tag{1}$$

While restricting l so that $l \le n$ and $(n-l)$ be an even number, $2k = n-1$. And the coefficients q_{kl}^{p} are determined to guarantee the orthonormality. We are now able to define the 3D Zernike moments Ω_{nl}^{m} of a 3D object defined by f as

$$\Omega_{nl}^{m}=\frac{3}{4\pi}\sum_{X} f(X)\overline{Z_{nl}^{m}(X)} \tag{2}$$

not that the coefficients Z_{nl}^{m} can be written in a more compact form as a linear combination of monomials of order up to n

$$Z_{nl}^{m}(X)=\sum_{r+s+t\le n} \chi_{nlm}^{rst}.x^r y^s z^t \tag{3}$$

The value of χ_{nlm}^{rst} is explained in [16]. Finally, the 3D Zernike moments Ω_{nl}^{m} of an object can be written as a linear combination of geometrical moments of order up to n:

$$\Omega_{nl}^{m}=\frac{3}{4\pi}\sum_{r+s+t\le n}\overline{\chi_{nlm}^{rst}}M_{rst} \tag{4}$$

Where M_{rst} denotes the geometrical moment of the object scaled to fit in the unit ball:

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$$M_{rst} := \sum_{|X|\le 1} f(X) x^r y^s z^t \quad (5)$$

Where $X \in \Re^3$ denotes the vector $X = (x, y, z)^t$. The collect of the moments into (2l +1)-dimensional vectors $\Omega_{nl}^{m} = (\Omega_{nl}^{-l}, \Omega_{nl}^{-l+1}, ..., \Omega_{nl}^{l-1}, \Omega_{nl}^{l})$ define the 3D Zernike descriptors F_{nl} as norms of vectors

$$F_{nl} = \left\| \Omega_{nl}^{m} \right\| \quad (6)$$

III. 3D SURFACE MOMENT INVARIANTS DESCRIPTOR

Dong Xu et *al* [10] had used a 3-D surface moment invariants as shape descriptors for the representation of free-form surfaces. We consider a 3D surface triangulation $T = \bigcup_{i \in S} T_i$ consisting of triangles T_i. The $(k+l+m)^{th}$ order 3D surface moments M_{klm} of the T are the accumulated surface moments m_{klm}^{i} of the associated triangles T_i i.e

$$M_{klm} = \sum_{i \in S} m_{klm}^{i} \quad (7)$$

For a general triangle Δ the surface moments are

$$m_{klm} = \iint_{\Delta} x^k y^l z^m \rho(x, y, z) ds \quad (8)$$

with a surface density function ρ. Using a surface parameterization $P(u,v) = (x(u,v), y(u,v), (u,v))$ in $\Re^3$. The moment (8) can be rewritten as

$$m_{klm} = \iint_{D} x^k(u,v) y^l(u,v) z^m(u,v) \rho(P(u,v)) \sqrt{EG - F^2}\, dudv \quad (9)$$

Where $E = x_u^2 + y_u^2 + z_u^2$, $G = x_v^2 + y_v^2 + z_v^2$ and $F = x_u x_v + y_u y_v + z_u z_v$ are the coefficients of the first fundamental form.

The centroid of the 3-D surface can be determined from the zero and the first-order moments by $\bar{x} = \frac{M_{100}}{M_{000}}$, $\bar{y} = \frac{M_{010}}{M_{000}}$, $\bar{z} = \frac{M_{001}}{M_{000}}$ then central moment are defined as

$$M_{klm} = \iint_{\Delta} (x - \bar{x})^k (y - \bar{y})^l (z - \bar{z})^m \rho(x, y, z) ds \quad (10)$$

So the central surface moments are invariant under translation. Then, we normalize the surface moments by $M_{000}^{1+(k+l+m)/2}$, they also became invariant under scaling and can be defined as $\mu_{klm} = \frac{M_{klm}}{M_{000}^{1+(k+l+m)/2}}$. To construct the surface moments invariant under rotation, D. Xu [11] use four geometric primitives for constructing six invariants consist of 3 fourth order, 2 third order and 1 mixed order surface moment invariants.

IV. PROPOSED DESCRIPTOR

We normalize the 3D shape into a canonical coordinate frame, and characterize the shape by a set of characteristic level images noted CLI set. Each one of the CLI set was described by Hu's moments [12]. The final set of moment invariants are used to be the feature vector.

A. Pose normalization

A 3D object is generally given in arbitrary orientation, scale and position in the 3D space. As most of the 2D/3D shape descriptors do not satisfy the geometrical invariance, pose normalization is then necessary before the 3D object feature extraction. To secure translation, rotation and scale invariance of descriptors, 3D-mesh models are normalized [9][13]. Each triangle mesh model is transformed into a canonical coordinate frame by translating (the center of gravity becomes the origin), rotating (using the Continuous Principal Analysis - CPCA), scaling (the average distance of a point on the surface of the model to the origin becomes 1). Complete analytical expressions for transforming a mesh model into canonical coordinates are given in [13]. The CPCA is rather efficient and effective for most categories of 3D-objects.

The covariance matrix is calculated, the first eigenvector of this covariance matrix corresponding to the largest eigenvalue points to the direction of the largest variance along which the rotation is applied. When this step has been done, the model is rotated so that the X-axis maps to the eigenvector with the biggest eigenvalue, the Y-axis maps to the eigenvector with the second biggest eigenvalue and the Z-axis maps to the eigenvector with the smallest eigenvalue.

B. Feature extraction

The method consists on the characterization of 3D objects by a CLI set. Initially, the object 3D has an arbitrary position in the space Figure 1(a), and then has been translated so that its center of mass coincides with the origin, as shown in Figure 1(b), then it is scaled to unit sphere and rotated with the CPCA method Figure 1(c), to alleviate the problem of rotation invariance.

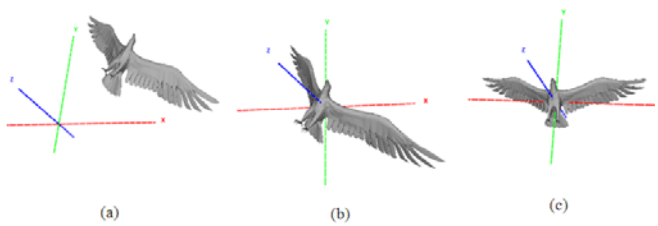

Figure 1. Shape normalization using CCPA

The shape is aligned, Figure 2. (a), so we take 300 perpendicular plans to X-axis, the images generated by the intersection of the shape and this set of plan construct the LI (Level Images) set for a model M of the collection. These plans are equally spaced. For extracting the vector descriptor from these set of images we have to select those that characterize effectively the three dimensional model to avoid the redundancy problem and to reduce the program complexity. We want from to adapt the number of characteristic level images to the geometrical complexity of the 3D model, using *K-means* is not suitable. Dan Pelleg [14] presents a method called *X-means* clustering that avoids the problem of selecting *a priori* the number of clusters K. To avoid the problem of selecting *a priori* the number of characteristic views, we use a range in which we will choose the "optimal" number of characteristic views. In our case, the range will be [1,…,40]. We assume that the maximum number of CLI is 40. This number of views is a good compromise between speed, descriptor size and representation.

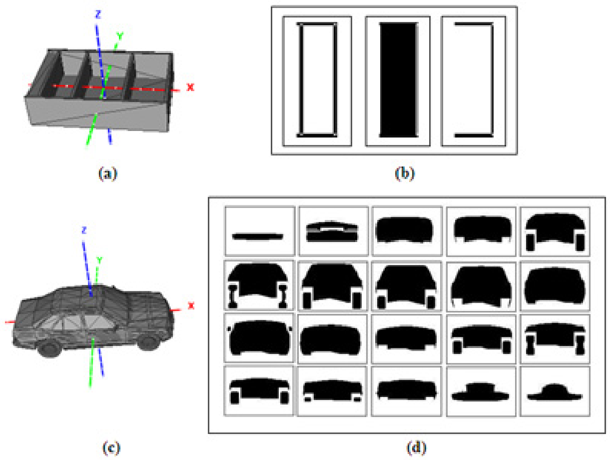

Figure 2. The characteristics level images: (a)(c) the 3D object, (b)(d) its CLI

For each 3D model which are corresponding a number of CLI, the united features of these images also represent the features of the 3D model. The descriptor of the 2D image must be invariant to translation, scaling and rotation. To solve this problem, we use the moments invariant presented by Hu [12]. It is a kind of feature based on region. The 7 moment invariants keep changeless to the translation, rotation and scaling of the object in the images. We can form a feature vector of an image using these 7 moment invariants. The different moments invariants represent different physical meanings.

V. EXPERIMENTS AND RESULTS

A. *Test database*

The Our experiments were performed on a NTU (National Taiwan University) 3D Model Database provides 3D models for research purpose in 3D model retrieval, matching, recognition, classification, clustering and analysis. The database containing 10911 3D models, which are free downloaded from the Internet at [15]. All 3D models are converted into Objet File Format (.off) in the database. In order to evaluate the methods described in this paper, out of these models, 321 were semantically classified into 25 classes, some example of these classes representative are shown in Figure 3.

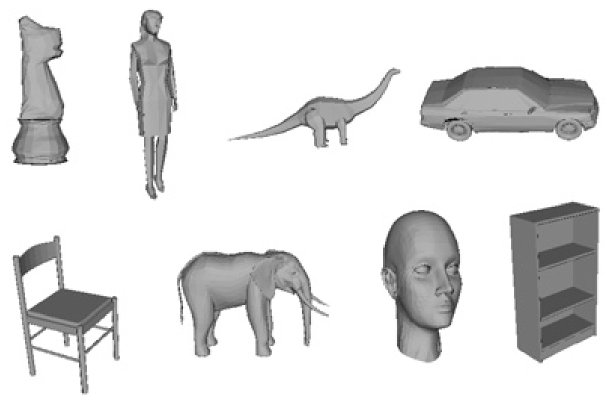

Figure 3. Some classes representatives of the test database

B. *Similarity mesure*

In order to measure how similar two objects are, it is necessary to compute distances between pairs of descriptors using a dissimilarity measure. Although the term similarity is often used, dissimilarity corresponds to the notion of distance: small distances means small dissimilarity, and large similarity. A dissimilarity measure can be formalized by a function defined on pairs of descriptors indicating the degree of their resemblance.

We use a Haudsdorff distance for measuring the similarity between models. Given two shapes represented by two sets of points: $X=(X^1,X^2,...,X^p)$ and $Y=(Y^1,Y^2,...,Y^p)$, as the number of points of the two set X and Y is not correspondent. The Hausdorff distance is defined as:

$$d_H(X,Y)=\max\left\{\max_{X^i\in X}\min_{Y^j\in Y} d(X^i,Y^j);\max_{Y^j\in Y}\min_{X^i\in X} d(X^i,Y^j)\right\} \quad (11)$$

Where d denote the Euclidean distance, is defined as:

$$d(X,Y)=\sqrt{\sum_{i=1}^{p}(X_i-Y_i)^2} \quad (12)$$

Where, X and Y are two vectors in $\Re^p$.

Each model M of the database is characterized by a CLI set noted $I^{CM} = \{I_1^{CM},...,I_N^{CM}\}$. For each image I_i^{CM} corresponding a 2D vector descriptor X_i^M . The vector descriptor of the model is $X^M = (X_1^M,...,X_N^M)$, where

$X_i^M = (X_{i1}^M,...,X_{i7}^M)$ where X_{ik}^M denote to the $k^{ème}$ Hu moment of the image I_i^{CM} .

Let Q and T two two model of the database, the similarity between them is measured as follow:

$$Sim(Q,T) := d_H(X^Q, X^T) \tag{13}$$

$$d_H(X^Q,X^T) = \max\left\{\max_{i\in S^Q}\min_{j\in S^T} d(X_i^Q,Y_j^T); \max_{j\in S^T}\min_{i\in S^{QT}} d(X_i^Q,Y_j^T)\right\} \tag{14}$$

S_M denote to the set of indices of the CLI set of the model M.

C. Results and performance

In order to evaluate the performance of the shape similarity measure, we design experiments performing 3D model retrieval on the test database. Figure 4 shows some of the retrieval examples. We randomly select a model in the database as the query, and then our system returns a list of outputs ranking on the degree of similarity to the input (because the query model in each retrieval test is still from the same test database). We can find that the first several models in the retrieval list are really shape-like to the query model in most cases.

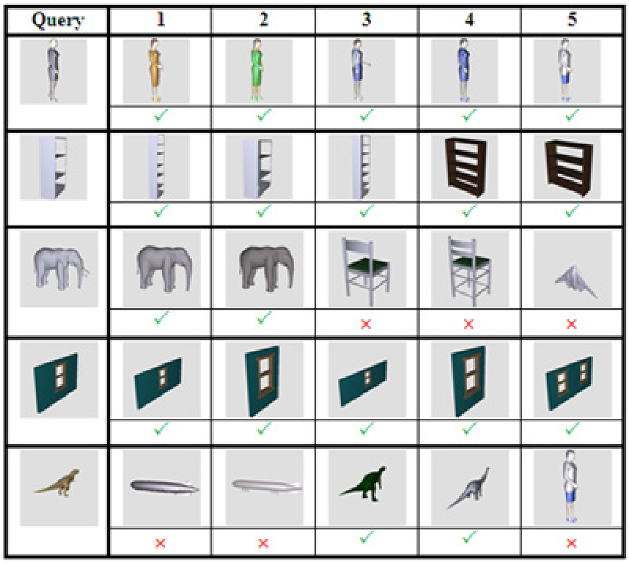

Figure 4. Some retrievals exemples

In order to evaluate the measurement of retrieval performance we examine Recall-Precision diagram for the shape descriptor of 3D objects. "Precision" measures that the ability of the system to retrieve only models that are relevant while "recall" measures the ability of the system to retrieve all models that are relevant. They are defined as:

$$\mathrm{Re}call = \frac{relevant\ correctly\ retrieved}{all\ relevant}$$

$$\mathrm{Pr}ecision = \frac{relevant\ correctly\ retrieved}{all\ retrieved}$$

We compared the classification performance of the proposed method with two well known methods, Zernike moments descriptor [16] and surface moments invariants descriptor by using a six invariants [10]. For each one of the chosen shape categories, we have calculated the average Recall-Precision graph by using all shapes of the test database as a query object Figure 5. We can see that the proposed shape descriptors perform better than the 3D Zernike descriptor and surface moments invariants descriptor.

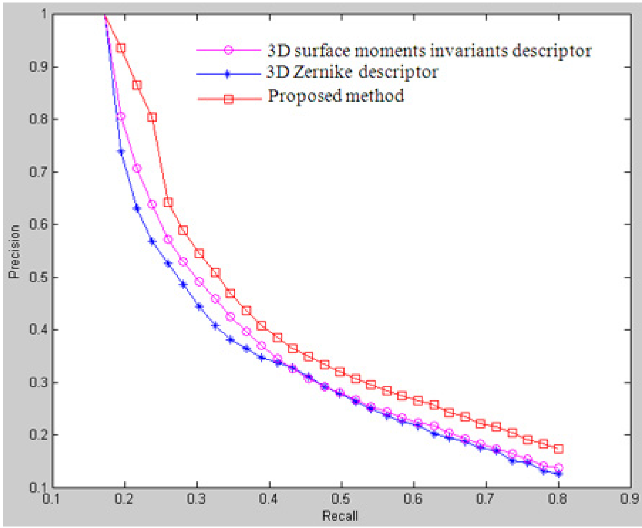

Figure 5. Overall precision-recall graph for all three descriptors

CONCLUSION

In this paper, we present a novel 3D shape descriptor based on characteristic level images. The similarity measure of the descriptor is derived from the Hausdorff and L-2 distance of character function of 3D models, to avoid the redundancy problem and the more calculate we use the x-means technique, the results are promising.

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