

3D Shape Retrieval Using the Characteristics Level Cuts

Mustafa ELKHAL, Abdelaghni LAKEHAL, Khalid SATORI

LIIAN, Department of Mathematics and computer science

Faculty of Sciences, Dhar-Mahraz

Sidi Mohamed Ben Abdellah University

B.P 1796 Atlas- Fez

Morocco.

m.elkhal10@hotmail.com lakehal_abdelghni@yahoo.fr khalidsatorim3i@yahoo.fr

Abstract: -The technological development of 3D modeling leads to the proliferation of a large number of 3D objects databases, which requires a technical to indexing and retrieval these 3D models. In this paper, we propose a method based on binary images extracted from the 3D object called "level cut" LC. These level cut are obtained by the intersection of the 3D object with a set of equidistant parallel plan. We are based on the LC set to extract the vector descriptor using the Hu moment descriptor to index this set. To measure the similarity between the 3D objects we compute the Hausdorff distance between a vectors descriptor. The performance of this method is evaluated with two well known descriptors of 3D object, using the NTU database (national taiwan university).

Keywords: 3D Shape retrieval, X-means Algorithm, Characteristics Level Cut, Vector descriptor, similarity measuring.

1 Introduction

The quantities of 3D models detained by the general or special 3D object databases have increased significantly in recent years. These quantities become gigantic with the rapid advancement of acquisition and modeling technology and involve a need for efficient and rapid methods of 3D objects indexing and retrieval. Many 3D models are now downloadable for free thanks to the internet, as well as the large databases of 3D models have become available in the market.

In this context, we are particularly interested in approach 2D/3D of indexing and retrieval of three dimensional objects, this approach consist to characterize each 3D object by a set of 2D images taken in different views to represent the 3D object. The importance of this technique is the extraction for each image a signature to finally obtained a set of vectors descriptors associated to the 3D object for index it, using a 2D shape descriptor, The Comparison of the 3D objects between them, returns to calculate the similarity measuring using a distance.

To describe the 3D object reliably, it is necessary to extract a large number of images to keep the information on the 3D object, to obtain a new set of these images we introduce a

classification method to eliminate the redundant images.

The different softwares of the 3D modeling provided of 3D objects databases with différents types, formats and sizes, therefore, these 3D objects databases must undergo a certain geometric transformation to render them invariant in rotation, translation and scaling.

The proposed descriptor shows the robustness in terms of response to the query provided by the user and the comparative study between the proposed descriptor and two other descriptors well known of the 3D/3D approach, the 3D Zernike moments[1] and 3D invariant moments[2] shows considerable results.

This study will be organized as follows: in the first part, there will be an overview on previous work of 2D/3D approach. After that, we explain the method we proposed in the second part. Then the experiments and results of our method will be shown in the third part and finally the conclusion of our work.

2 Related Work

The principal objective of the characteristic views is associated to the 3D model a series of multiple projections of viewpoints. This principal is common to all the 2D/3D approaches by view. The problem of this approach is in the choice of:

normalization of the pose, the projection area, the size of image, the nature of the 2D shape descriptors and the size of the signature. The authors [3][4][5][6][7][8] have proposed methods of optimal selection of 2D views to represent a 3D model. Each 3D object is represented by a view set called the characteristic views. The process of selection of views characteristics is based on an adaptive classification algorithm to select the optimal number of views which are calculated from different points of view. These views are represented on the bounding sphere of the 3D object. In [9], each object is associated to 72 views which are structured in a shock graph. The shape retrieval process is based on a shock graph matching algorithm. The major drawback of the method by views is facing the problems of views choice which do not permit to have adaptive methods to the object and the query.

3 Description of Proposed Method

3.1 The Level Cuts

The Triangle meshes that we will use frequently constitute the support of representation of the 3D objects. they are represented the major part of the quantity of information describing the 3D model and are more efficient in the calculation, less expensive and able to represent the 3D object faithfully. Our method consist to extract a set of binary images called Level Cuts (LC) obtained by the intersection of the 3D object with a set of well defined plans. These images used for indexing it and we can construct the 3D object it from these images set. In what follows we are going to give the steps of the LC set extraction.

3.2 Ray-Facet Intersection

Given a triangle PQR and an O origin ray and direction vector \vec{v} as shown in the Fig. 1 below:

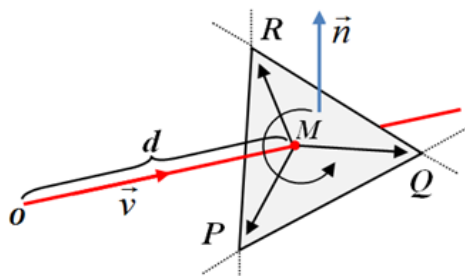


Fig. 1. Ray-facet intersection

Let M the point obtained by the intersection of the ray directed by the \vec{v} vector and the triangle. This point is given by the following relation:

$$\overline{OM} = d.\vec{v} \tag{1}$$

Knowing that M verified the following equation:

$$\overline{OP}.\vec{n} = \overline{OM}.\vec{n} \tag{2}$$

where, \vec{n} that the normal vector to the facet PQR (direct orientation) defined by:

$$\vec{n} = \frac{\overline{PQ} \wedge \overline{PR}}{\|\overline{PQ} \wedge \overline{PR}\|} \tag{3}$$

The Equation 1 permits to calculate the distance d between the ray origin and the M point obtained by intersection with this ray and the surface delimited by the PQR triangle. To verify that the intersection of ray and the triangle is not empty, i.e., the point M is in the delimited surface by the PQR triangle, it is enough that the M point should check the following conditions:

$$\begin{aligned} (\overline{MP} \wedge \overline{MQ}).\vec{n} &> 0, (\overline{MQ} \wedge \overline{MR}).\vec{n} > 0, \\ (\overline{MR} \wedge \overline{MP}).\vec{n} &> 0 \end{aligned} \tag{4}$$

3.3 Level Cut Extraction

To extract the level cut of a 3D object, this latter must submit a preliminary step of normalization as well as its alignment. These preliminary treatments are necessary if we want to index the 3D object, we base on these cuts. To get the cut in a given direction, we move the ray in the associated plan. The Fig. 2 below shows the extraction of the level cut $y = k$ (plan equation $y = k$) in which the ray (color red) moves in the direction \vec{ox} .

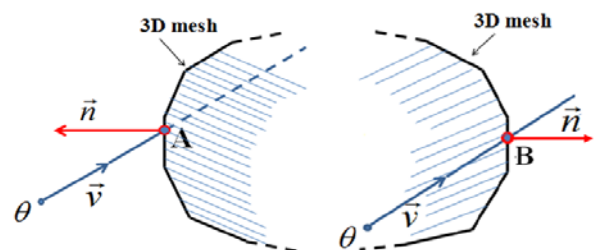


Fig. 2. Test of normal ray with the normal 3D object. A: incoming point belongs to g_{Rin} B: outgoing point belongs to g_{Rout}

The set of the ray intersection points noted (Δ) with the surface of the 3D object O is defined by the following relation:

$$g = \Delta \cap O = g_{Rin} \cup g_{Rout} \tag{5}$$

Knowing that is the subset of g containing the triangles associated with points whose normal

vector is outgoing which is reflected by the following relation in the Fig. 2:

$$\vec{n} \cdot \vec{v} > 0 \tag{6}$$

The same for the g_{Rout} set which is associated to the triangles with the normal vector is incoming checked by the following relation:

$$\vec{n} \cdot \vec{v} < 0 \tag{7}$$

The example in Fig. 3 shows the launch of a ray in the plan $z = k$ in the OY direction.

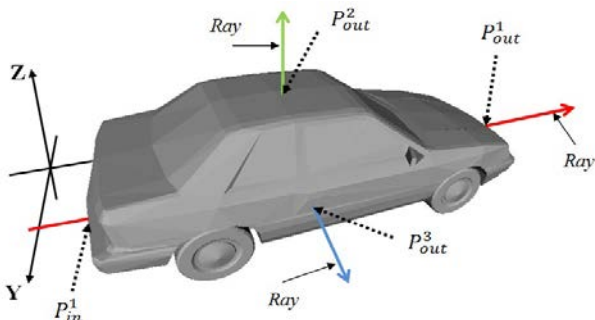


Fig. 3. Ray intersection with the 3D object

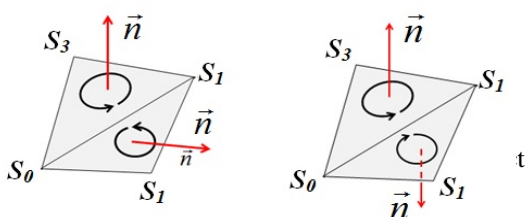
The three points P_{in}^1, P_{in}^2 and P_{in}^3 belong to g_{Rin} set and the three points P_{out}^1, P_{out}^2 and P_{out}^3 belong to the g_{Rout} set. The displacement of ray in the plan defined by the $z = k$ equation in the OY direction, generates a set of intersection points of this ray with the 3D object. Each incoming point of g_{Rin} set corresponds to an outgoing point of g_{Rout} set. The segment connecting these two points is a part of the image constructed by the cut. This algorithm is applied to each pair of the set:

$$g_{Rin} \times g_{Rout} \tag{8}$$

Given a 3D object aligned as shows in Fig. 4.

3.4 3D Model Rigularity

The considered triangular meshes surfaces must comply with certain regularity hypothesis. We are going to introduce some definitions to precise the context mathematically[10][11]. Each facet of the 3D mesh is oriented according to the normal vector which it orthogonal and whose the direction is given by the order of course of the vertices as the example shown in Fig. 4.



A mesh is said adjustable if all facets have the coherent direction in Fig. 4a, i.e., they are oriented in the same direction and the edge common (s1, s2) to two avoisines facets are going in the same direction. The Fig. 4b had shown an example of non-coherent mesh by the opposite directions.

3.5 The founded problems

The method that we proposed need a very specific case study, our interest is to overcome ambiguities and disturbances found, this problem posed because the complexity of 3D objects in well defined areas, which sometimes know hundreds of miles of faces and vertices. That is why, we have proposed techniques to solve the various problems poses in the extraction of these cuts as the example shown in the Fig. 5.

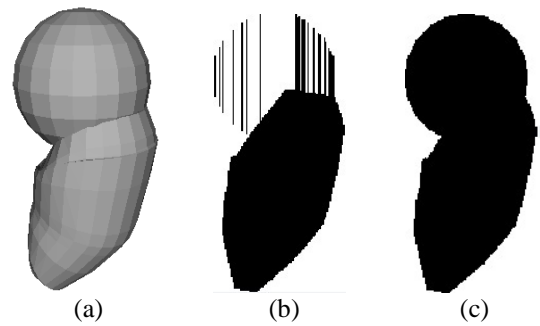


Fig. 5. Exemple of the founded problem in the cut (b)

Before completing the segments between the points obtained by the intersection of the ray with the 3D object, this will lead us to process particular cases to determine the points accept a segment. The example in the Fig. 6 Shows the problem solved of the ray intersection with the 3D object in corners $P_{(Rin,Rout)}$, such as each corner accept two points P_{Rin} and P_{Rout} at the same time.

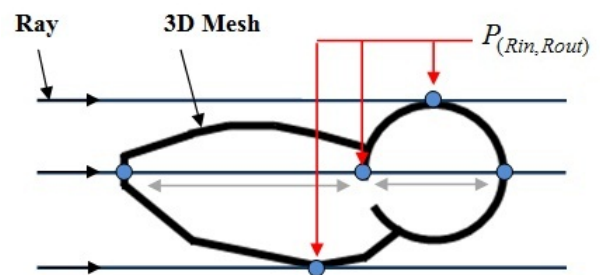


Fig. 6. Case of points accept a segment

The interest to tackle in this problem is undoubtedly a personal conviction to give each 3D object a better representation without losing information, which allows us to increase the value of the search on the most similar models.

3.6 The Discretization Method of the Cut

The principle of cuts extraction needs a discretization method for transform the obtained analog information into digital information. The cut is encoded into memory with a 2D array whose data contains digital values that will be reflected in the colors of pixels on the screen, in our case the cut is black and white where a white pixel is coded with a 1 and a black pixel with a 0. The resolution is therefore the link between the number of pixels of an image and its actual size on a physical support.

The extraction procedure of level cuts follows a step of translation the S set of scatter plots associated with the 3D object towards the positive parts of the mark, which result in the following transformations:

$$\begin{aligned} x_{tr}^p &= x^p - x_{min} \\ \forall p \in S, y_{tr}^p &= y^p - y_{min} \\ z_{tr}^p &= z^p - z_{min} \end{aligned} \tag{9}$$

With x_{min} , y_{min} and z_{min} the coordinates of extreme points of S along the axes ox , oy , oz respectively defined by:

$$\begin{aligned} x_{min} &= \underset{x}{\operatorname{argmin}} \{p(x, y, z) \in S\} \\ y_{min} &= \underset{y}{\operatorname{argmin}} \{p(x, y, z) \in S\} \\ z_{min} &= \underset{z}{\operatorname{argmin}} \{p(x, y, z) \in S\} \end{aligned} \tag{10}$$

The next step is to extract all of the level cut set constructed by the intersection of the 3D object with a set of parallel planes Δ_k equidistant by the distance δ_t with $t \in \{x, y, z\}$ knowing that:

$$I_k = (\Delta_k) \cap \Theta \tag{11}$$

The level cut k obtained by the intersection of the 3D object Θ and the Δ_k plan according to one of the three directions $\overline{ox}, \overline{oy}, \text{ or } \overline{oz}$ with

$$\delta_t = \frac{t_{max}}{n}, t \in \{x, y, z\} \text{ n The number of cuts to extract.}$$

The example below shows the performance and quality of our experience concerning the part applied on different axes.

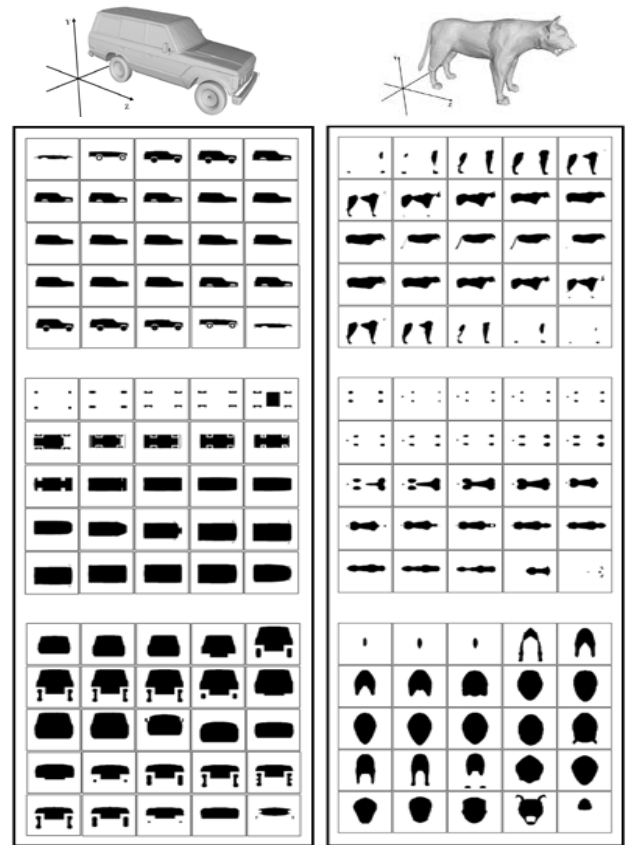


Fig. 7. The level cuts extraction result

Our level cuts extraction result above Fig. 6 shows the accuracy of the quality of the images obtained and the cases that we processed removed the difficulty and problems of density the points in specific parts. This gives us a simplification to process all 3D objects without any problems.

4 The Descriptor Based On The CLC Set And The Similarity Measuring

4.1 The Descriptor Based on the LC Set

The descriptor that we proposed above is based on binary images set called Characteristics Level Cut to indexing the 3D model by using the following steps:

- Normalize the 3D model
- The LC set extraction
- Reduce of the LC set by using the X-means algorithm to extract the CLC set
- Extraction of the signature for each binary image to constructing the vector descriptor of the 3D model

4.2 Normalization of 3D Model

The 3D object is often found in an arbitrary position (scale, position and orientation), which requires a pretreatment step before extracting the vectors descriptors. First, we must make this object invariant to scale space and then using the ACPC [12][13] method to make the 3D model invariant in the orientation.

4.3 The LC Set Extraction

After the step of normalization, the extraction of level cuts sets follows. Often the topology of the surface representing the 3D model contains a lot of information, for this reason, we must extract an important number of cuts to better describe the 3D object as a whole. This number results from the complexity of the 3D object in the precise parts.

4.5 Reduction of LC Set Using the X-Means Algorithm

The increase in the cut number LC is often important for a perfect and accurate description of the 3D object. Unfortunately, this number actually generates of redundant information as shown in Fig. 8.

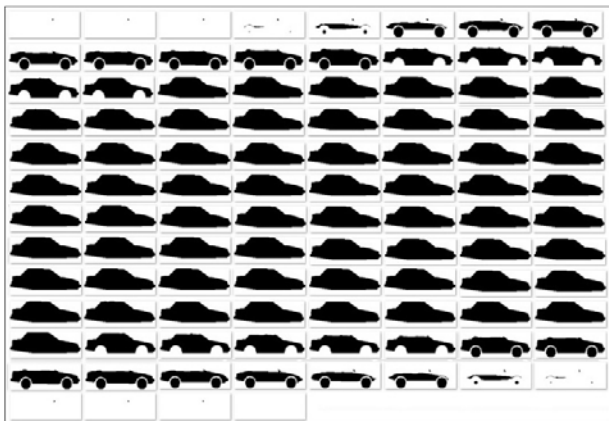


Fig. 8. Extraction of 100 LC set

To avoid this problem, we used the X-means algorithm to classify similar images in a single class[14][15]. We took a representative for each ways of these classes. These representative constructed a new set called the Characteristics Level Cut set (CLC). The Fig. 9 below shows the CLC set of the LC set in (Fig. 8).

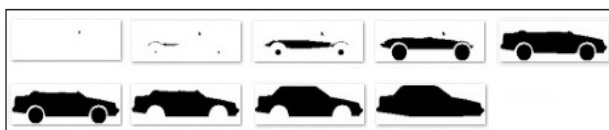


Fig. 9. CLC set obtained by X-means

4.6 Vectors Descriptors Extraction

To construct the vectors descriptors of the 3D model, using a binary image 2D descriptor to extract the signature of each cut of the CLC set. In our case we will use the seven moment's invariants Hu [16], these signatures constructed a set of vectors descriptors associated with the 3D object.

4.7 Similarity Measuring

In order to measure how similar two objects are, it is necessary to compute distances between pairs of their vectors descriptors using a dissimilarity measure. As we are using the X-means to extracting the CLC set, the vectors descriptors do not have the same size for each model, so the Euclidean distance is not valid for our method. There are two distances that could adapt with our descriptors, the hausdorff distance and the Earth Mover Distance (EMD) [17][18]. The EMD seems very expensive in terms of computation, then hausdorff distance is the most adaptable with the proposed vectors descriptors, also, it is the most used in this kind of problem.

The Hausdorff distance between two no empty set A and B noted $d_H(A, B)$ Equation 1, is the maximum of $H(A, B)$ and $H(B, A)$. Thus, it measures the degree of mismatch between two sets by measuring the distance of the point of A that is farthest from any point of B and vice versa. Intuitively, every point of A must be within a distance $d_H(A, B)$ of some point of B and vice versa. Thus, the notion of resemblance encoded by this distance is that each member of A be near some member of B and vice versa. Unlike most methods of comparing vectors, there is no explicit pairing of points of A with points of B (for B). The function $d_H(A, B)$ can be trivially computed in time $O(pq)$ for two point's sets of size p and q, respectively and this can be improved to $O((p+q)\log(p+q))$:

$$d_H(A,B) = \max \{H(A,B), H(B,A)\} = \max \{ \max_{a \in A} \min_{b \in B} d(a,b), \max_{b \in B} \min_{a \in A} d(a,b) \} \tag{12}$$

where, d is the Euclidean distance.

Let M and Q be two models of the database, their vectors descriptors are defined by $X^M = \{X_1^M, \dots, X_K^M\}$ and $X^Q = \{X_1^Q, \dots, X_h^Q\}$ respectively, where K and h represent the number of elements of LI set of the models M and Q respectively. The similarity between M and Q is measured as follow:

$$\text{Sim}(M, Q) = \frac{1}{1 + d_h(X^M, X^Q)} \quad (13)$$

where, $d_h(X^M, X^Q)$ is defined as:

$$d_h(X^M, X^Q) = \max \left\{ \begin{aligned} &\max_{i,j} \text{mind}(X_i^M, X_j^Q); \\ &\max_{i,j} \text{mind}(X_i^M, X_j^Q) \end{aligned} \right\} \quad (14)$$

This similarity function (13) has value in the range [0, 1], if its value is close to 1 for two models, they are assumed to be similar if it is close to 0, they are considered dissimilar.

5 Experiments and results

5.1 Test database

Concerning the experimental side we constructed a test database from the NTU base (National Taiwan University) which offers 10,910 3D models of different kinds. The extracted database is divided into 22 classes which include 133 3D models. Each class contains a number of objects as shown in the Fig. 10 following.



Fig. 10. The representatives of the test database classes

The tests were carried on a computer running Windows 7, with 2GB RAM and a 2 GHz Intel processor using a Java platform. In order to evaluate the performance of the shape similarity measure, we design experiments performing 3D model retrievals on the test database. The first model on the left is considered a query as the example shown in Fig. 11.

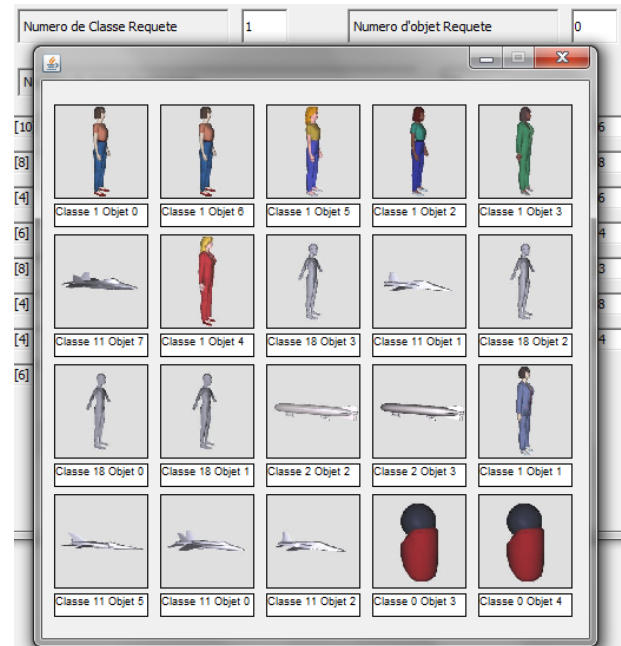


Fig. 11. First twenty shapes retrievals using the CLC set

Our result above shows a search engine that we have built, this system permit to retrieve in the database the most similar 3D objects, such as the 3D object in the top left consider a query, and the 19 3D objects are the nearest neighbors takes an order from left to right and top to down. The comparison between the query 3D object and the others objects in the database returns to compare their vectors descriptors obtained from the cuts set that represent each 3D object.

To test our result, we have organized the database in the classes, each class contains a number of 3D objects, and The Fig. 10 shows the representatives of each class.

5.2 Result and Performance

In order to evaluate the measurement of retrieval performance, we examine the Recall-Precision graph for the shape descriptor proposed. "Precision" Equation15 measures that the ability of the system to retrieve only models that are relevant, while "recall" Equation16 measures the ability of the system to retrieve all models that are relevant. They are defined as:

$$\text{Recall} = \frac{\text{relevant correctly retrieved}}{\text{all relevant}} \quad (15)$$

$$\text{Precesion} = \frac{\text{relevant correctly retrieved}}{\text{all relevants}} \quad (16)$$

We compared the classification performance of the proposed method with two well known methods, that the descriptor of 3D Zernike moments [19] and

descriptor of moments invariants 3D [20]. For each one of the chosen shape categories, we have calculated the average Recall-Precision graph by using all shapes of the test database by a query object Fig. 12.

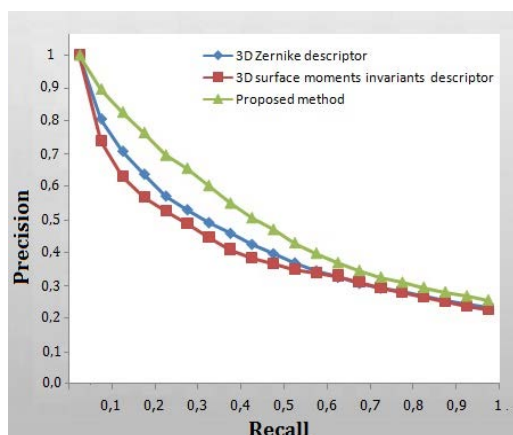


Fig. 12. Precision-Recall graph for all three descriptors

We can see that the proposed shape descriptors perform better than the 3D Zernike descriptor and surface moments invariants descriptor.

6 Conclusion

In this paper, we have presented a method based on the 2D *view-based* approach using 2D images for indexing the 3D models. We use a set of binary images called CLC extracted from the 3D model. These images are indexed with the 2D images descriptor. The similarity between models is calculated by using the Hausdorff. The obtained results show that the proposed descriptor is robust and the comparison with the two well known methods as mentioned above explain good performance. Despite this, some areas in the 3D object pose again the problems during of the extraction which also requires an improvement. The Search on 3D objects by the content of image extracted can be contour based or region based as well as, we can reconstruct the original 3D object from the set of these images extracted.

References

- [1] M. Novotni and R. Klein, "Shape retrieval using 3D Zernike descriptors," *Computer-Aided Design*, vol. 36, no. 11, pp. 1047-1062, Sep. 2004.
- [2] D. Xu & H. Li, "3-d surface moment invariants", *Proceedings of 18th International Conference on Pattern Recognition*, Vol. 4, pp173-176.
- [3] J. Ricard D. Coeurjolly and A. Baskurt, "Generalizations of angular radial transform for 2D and 3D shape retrieval", Volume 26 Issue 14, 15 October 2005 Pages 2174-2186
- [4] H. Sundar, D. Silver, N. Gagvani, and S. Dickinson, "Skeleton based shape matching and retrieval," in *Proceedings of the Shape Modeling International (SMI 2003)*, Seoul, Korea, pp. 130-139, 2003.
- [5] S. Mahmoudi and M. Daoudi, "3D models retrieval by using characteristic views", *Proceedings of the 16th International Conference on Pattern Recognition*, pp. 457-460, Quebec, Canada, 2002.
- [6] J. Ling Shih, C. H. Lee and C.H. Chuang, "A 3D Model Retrieval Approach Based on the Combination of PCA Plane Projections", *Journal of Information Technology and Applications* Vol. 5, No. 2, pp. 46-56 2011
- [7] J. L. Shih, C. H. Lee, and J. T. Wang, "3D object retrieval system based on grid D2," *Electronic Letters*, vol. 41, no. 4, pp. 23-24, Feb. 2005.
- [8] Y. Liu, X. Zhang, Z. Li and H. Li, "3D model feature extraction method based on the projection of principle plane", *Computer-Aided Design and Computer Graphics, 2009 (CAD/Graphics '09)*, Page(s):463 – 469, August 2009.
- [9] C. Cyr and B. Kimia, "3D object recognition using shape similarity-based aspect graph", *Proc. 8th IEEE Int. Conf. Comput. Vision*, Vancouver, BC, Canada, pp. 254–261, 2001.
- [10] J. tseng and Y.H lin, "3D Surface Simplification Based on Extended Shape Operator", *Wseas Transactions On Computers*, Issue 8, Volume 12, August 2013.
- [11] M. Mousa and M-K Hussein, "Adaptive visualization of 3D meshes using localized triangular strips", *Wseas Transactions on Computers*, Issue 4, Volume 11, April 2012.
- [12] D. Vranic, D. Saupe and J. Richter, "Tools for 3D-object retrieval: Karhunen-Loeve transform and spherical harmonics". *Proceedings of the Workshop Multimedia Signal Processing, (MSP' 01)*, Cannes, France, pp: 293-298.
- [13] C. T. Kuo and S. C. Cheng, "3D model retrieval using principal plane analysis and dynamic programming," *Pattern Recognition*, vol. 40, no. 2, pp. 742-755, Feb. 2007.
- [14] R. Tavoli, "Classification and Evaluation of Document Image Retrieval System", *Wseas*

Transactions on Computers, Issue 10, Vol.11, October 2012.

- [15] E. Lebarbier and T. M. huard, “Une introduction au critère BIC: fondements théoriques et interprétation”, journal de la société française de statistique, vol.147, No.1, 2006, pp.39-57.
- [16] R.K. Sabhara, C. Lee² and K. Lim³, “Comparative study of hu moments and zernike moments in object recognition”. Smart Comput. Rev., 3: 166-173.
- [17] Y. Rubner, C. Tomasi and L.G. Guibas, “The earth mover's distance as a metric for image retrieval”, International Journal of Computer Vision 40(2), 99–121, 2000.
- [18] W. Edy, H. Agus, A. M. Arymurthy and E. Winarko, “Improved Real-Time Face Recognition Based On Three Level Wavelet Decomposition-Principal Component Analysis And Mahalanobis Distance”, Volume 10, Issue 5, Pages 844-851.
- [19] A. Sit, J.C Mitchell, G.N. Phillips and S.J Wright, “An extension of 3D zernike moments for shape description and retrieval of maps defined in rectangular solids”, Volume 1, Pages 75–89, ISSN (Online) 2299-3266, 2013.
- [20] T. Suk and J. Flusser, “Tensor method for constructing 3D moment invariants”, Computer Analysis of Images and Patterns, Part II, Volume 6855, 2011, pp 212-219.