# A Bayesian Decision for 3D Object Retrieval and Classification

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**Summary**

This paper presents a Bayesian-based method for classifying 3D objects into a set of pre-determined object classes. The basic idea is to determine a set of most similar three-dimensional objects. The three-dimensional models have to consider spatial properties such as shape. We use curvature as an intuitive and powerful similarity index for three-dimensional objects which consists of a histogram of the principal curvatures of each face of the mesh. An experimental evaluation demonstrates the satisfactory performance of our approach on a fifty three-dimensional models database.

***Key words:***
*3D Object, Bayesian classification, Curvature Index, 3D/3D indexing, 2D/3D Indexing.*

## Introduction

For a few years, we have attended a proliferation of the three-dimensional graphic objects. Many tools of digitized and constructed 3D objects, 3D graphic accelerated hardware, Web3D and so one are getting more and more popular. Therefore, 3D objects can be digitized and modeled easier, faster and less expensive. Also, through the Internet [15], users can download a large number of free 3D models from all over the world. This leads to the necessities of new technique to index, retrieve, cluster and classify 3D object for matching patterns in a straightforward manner.

The problem of 3D model retrieval can be stated as follows: given a 3D model, the retrieval system compares it with all other 3D models from the database, and shows ranked similar models. In short, the problem is to determine the similarity between two given 3D models. Although text-based search engines are ubiquitous today, 3D models usually lacks meaningful description for automatic matching.

A number of different indexing methods have been proposed in the literature. Cord histogram, shape index and some rotation invariant shape descriptors are the commonly used features.

For a large 3D objects database, the research of the closest models to the request object becomes increasingly difficult. An alternative approach is based on categorizing the database. As a result, searching for similar 3D objects reduces to identify the cluster with the closest prototype to a given query feature vector, and then searching only the feature vectors within this cluster to find the nearest neighbors. This approach can provide a much faster response because only a limited subset of 3D objects in the database needs to be considered for the similarity computations.

In this paper, we propose a new probabilistic method for 3D models classification into a set of pre-determined object class. This paper is organized in the following way: First we will give a stat of art of 3D object indexing in section 2. Next in section 3, we present the principal of curvature indexing. In section 4, a probabilistic approach for three-dimensional objects classification is proposed. Finally, the results obtained from a collection of three-dimensional models are presented.

## 1. 2. State of art

In the literature, two families of methods for 3D model retrieval exist: 2D/3D approach, analyze 3D shape that is indirectly represented by various 2D descriptor of different 2D views that are generated from multiple viewpoints, and 3D/3D approach directly characterizes the total shape of the three-dimensional objects described by a set of flat polygons.

In the first approach, two problems arise: how many 2D views to characterize a 3D model, and how to use these views to retrieve the model from a 3D collection.

Abbasi and Mokhtarian [1] propose a method that eliminates the similar views in sense of distance among CSS (Curvature Scale Space) from the outlines of these views. The minimal number of views is selected with an optimization algorithm.

Mahmoudi and Daoudi [2] suggest to use CSS from the outlines of the 3D model extracted views. The CSS is then organized in a tree structure called M-*tree*. Yi and all [c3] propose a method based on a Bayesian probabilistic approach. It means computing a posteriori probability to recognize the model when a certain feature is observed.

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Dorai and Jain [4] use a database consist of ten three-dimensional objects. For each model of this collection, an algorithm allows to generate 320 views. Then, a hierarchical classification, based on a distance measure between curvature histogram from the views, follows.

The latter approach is widely used, because it allows analyzing three-dimensional model shape independently of its position in space or from the observer viewpoint. Several shape descriptors are associated to three-dimensional model by using local invariants describing the local aspect of 3D model such curvatures [5][6]or elementary volumes [7] of the object faces, or global invariants calculated on all the object like the calculation of various statistical moments [8] or the distribution of distance [9], etc.

For example, Zaharia and Prêteux [6] as well as Vandeborre et al. [10] propose to use full three-dimensional information. The three-dimensional objects are represented as mesh surface and curvature descriptors are used for describing local aspect. Osada et al. [9] propose a global index, they used for this end five functions simple to calculate: the angle between three random points on the 3D model surface, the distance between the centroid of the model's and a random point on the surface, the distance between two random points, the square root of the area of the triangle between three random points, and the cube root of the volume of the tetrahedron from four random points.

Liu et al. [11] propose a global descriptor named *Directional Histogram Model* (DHM) invariant with the group of Euclidean transformations. The results obtained show the performances of this descriptor. However, this descriptor doesn't take account the no-rigid transformations.

In this work, we used curvature index to classify our three-dimensional objects into classes. The class composed of objects having similar shape.

## 3. Curvature index

The proposed three-dimensional curvature descriptor aims at providing an intrinsic shape description of three-dimensional mesh models. It exploits some local attributes of the three-dimensional surface. The curvature index, introduced by [12], is defined as a function of the two principal curvatures of the surface. The main advantage of this index is that it gives the possibility to describe the shape of the object at a given point. The drawback is that it loses the information about the amplitude of the surface shape, and that it is also sensitive to noise.

Let *P* be a point on the three-dimensional surface. Let us denote by $k_p^1$ and $k_p^2$ the principal curvatures associated with the point *p*. The curvature value at point *p* is defined as:

$$I_p = \frac{2}{\pi}\frac{k_p^1 + k_p^2}{k_p^1 - k_p^2} \quad \text{With} \quad k_p^1 \geq k_p^2 \qquad (1)$$

The curvature index value belongs to the interval [0, 1] and is not defined for planar surfaces. The curvature spectrum of the three-dimensional mesh is the histogram of the curvature values calculated over the entire mesh. The estimation of the principal curvatures is the key step of the curvature spectrum extraction. Computing these curvatures can be achieved in different ways, each with advantages and drawbacks; [13] proposes five practical methods to compute them. We choose to compute the curvature at each face of the mesh by fitting a quadric to the neighborhood of this face (i.e. the centroid of this face and the centroids of its 1-adjacent faces) using the least-square method. We can then calculate the principal curvatures $k_p^1$ and $k_p^2$ as the eigenvalues of the Weingarten endomorphism:

$$W = I^{-1}.II \qquad (2)$$

Where, I and II are respectively the first and the second fundamental forms [14]. Hence, the curvature index can be computed with $I_p$.

The curvature index provides a scale for representing salient elementary shapes such as convex, concave, rut, ridge and saddle (Figure 1), and is invariant with respect to scale and Euclidean transforms.

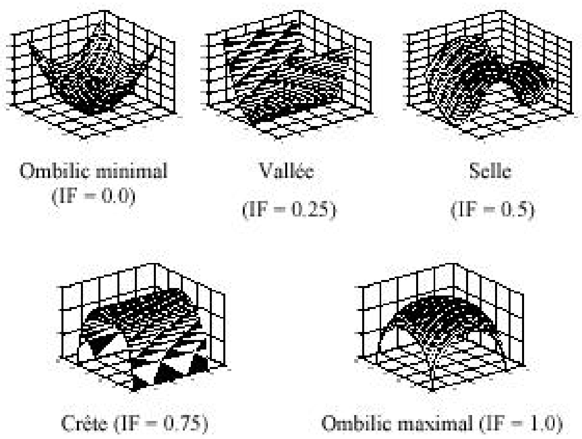


Fig. 1 Elementary shapes and their corresponding shape index.

## 4. Probabilistic approach for 3D object classification

To classify 3D objects into a set of pre-determined object classes, we extend the Bayesian algorithm proposed in [15] to search 3D object. In this end, we exploited the power of curvature descriptor to characterize the three-dimensional objects. (Figure 2) show an example of curvature spectrum of object "vase1" represented in the same figure.


Fig. 2 Curvature histogram of three-dimensional object

The three-dimensional objects database is represented by a set of class $Db = \{C_1, C_2, ..., C_N\}$, with $N$ the number of classes. To each class correspond a set of three-dimensional objects having closest curvatures histograms $C_i = \{M_i^1, M_i^2, ..., M_i^k\}$.

Considering a three-dimensional model request Q, we wish to find the class $C_i$ which its models are closest to the request Q. This class is the one that has the highest probability:

$$\mathrm{P}(\mathrm{C_i}|\mathrm{Q}) = \sum_{j=1}^{k} \mathrm{P}(\mathrm{C_i}, \mathrm{M}_i^j|\mathrm{Q}) \qquad (3)$$

Using the Bayes theorem, we have:

$$\mathrm{P}(\mathrm{C_i}, \mathrm{M_i^j}, \mathrm{Q}) = P(Q, M_i^j|C_i)P(C_i) \qquad (a)$$

$$\mathrm{P}(\mathrm{C_i}, \mathrm{M_i^j}, \mathrm{Q}) = P(C_i, M_i^j|Q)P(Q) \qquad (b)$$

From (a) and (b) we obtain:

$$\mathrm{P}(\mathrm{C_i}, \mathrm{M_i^j}|\mathrm{Q}) = \frac{P(Q, M_i^j|C_i)P(C_i)}{P(Q)} \qquad (4)$$

We also have:

$$P(C_i, M_i^j|Q) = P(Q, M_i^j|C_i)P(M_i^j|C_i)$$

and :

$$P(Q) = \sum_{i=1}^{N}\sum_{j=1}^{K} P(Q, C_i, M_i^j)$$

By integrating this remark, we obtain:

$$\mathrm{P}(\mathrm{C_i}|\mathrm{Q}) = \sum_{j=1}^{k}\left[\frac{P(Q|M_i^j, C_i)P(M_i^j|C_i)P(C_i)}{\sum_{i=1}^{N}\sum_{j=1}^{k} P(Q|M_i^j, C_i)P(M_i^j|C_i)P(C_i)}\right] \qquad (5)$$

With $P(C_i)$ the probability to observe the class $C_i$.

$$P(C_i) = \mu e^{(-\mu(N(M_{C_i})/N(M)))}$$

Where $N(M_{C_i})$ is the number of tree-dimensional objects of the class $C_i$, and $N(M)$ is the number of 3D models in the collection Db. $\mu$ is a parameter to hold the effect of probability $P(C_i)$.

$$P(M_i^j|C_i) = 1 - \nu e^{(-\nu(1/N(M_c)))}$$

Coefficient $\nu$ is introduced to reduce the effect of model probability.

The value $P(Q|M_i^j, C_i)$ is the probability that, knowing that we observe the model $M_i$ of the class $C_i$

$$P(Q|M_i^j, C_i) = e^{(-D_{(Q, M_i^j)})}$$

With $D(Q, M_i^j)$ the Minkowski distance between the curvature histograms of Q and of the model $M_i$ of the class $C_i$.

## 5. Experiments and results

To evaluate our algorithm, described in the previous sections, we use C and Opengl.

We tested on a 3D model database containing 54 models arranged by the judgment of two adults into eight classes. The classes are the following: Avion class -Class A- (8 airplanes objects), Divers class -Class M- (5 misc[1]

[1] The misc class, being considered just as noise in our database, is not a real class. It is therefore meaningless to search for a misc object.

objects), Echec class -Class P- (7 chess pieces objects), Human class -Class H- (8 humans objects), Poisson class -Class F- (6 fishes objects), Quadru class -Class Q- (7 quadrupeds objects), Voiture class -Class C- (8 cars objects) and Vase class -Class V- (6 Vase objects). The first seven classes have been collected from the 3DCafe [16] and the last class is composed of three-dimensional models of Moroccan traditional vases.

The models are simple meshes of approximatively 500 to 25000 faces, without any hierarchical structure. Moreover, it is important to notice that the mesh level of detail is very different from an object to another.

In figure 4, we show the results of the test. We present each request object by a characteristic view, and below each view we give the result class for the request object by our method.

The classification matrix (figure 3) represents the result of using curvature descriptor for the first. The columns correspond to object which has been used as a request for the search engine. Each small square shows how the object of the given row was ranked. The darker the square is, the better the rank.

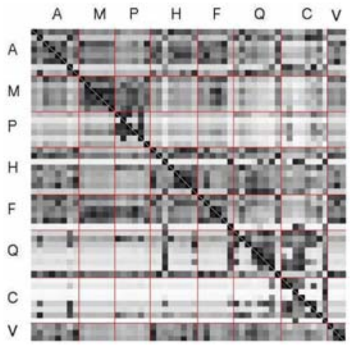


Fig. 3 Classification matrix for the curvature descriptor

The curvature descriptor has no difficulty to classify the airplanes, but has many problems with the car class and fish class. This explains why we get a false class for some request.

To test the performance of our method, we compared the results using our method with the results using fuzzy logic and k-means. Table 1 shows results of comparison.

Table 1: CLASSIFICATION PERFORMANCE

| Method | Bayesian | Fuzzy logic | K-means |
|---|---|---|---|
| Performance | 76.36% | 62.27% | 62.83% |

## 6. Conclusion and future works

In this paper, we have presented a Bayesian probabilistic method to classify three-dimensional objects. This method is independent from the feature used to describe the three-dimensional object.

The evaluation experiments showed that the method gives very satisfactory results.

Currently, we search to generalize our approach to other descriptor like distance descriptor and enrich our descriptors by other geometrical and statistical measurements.

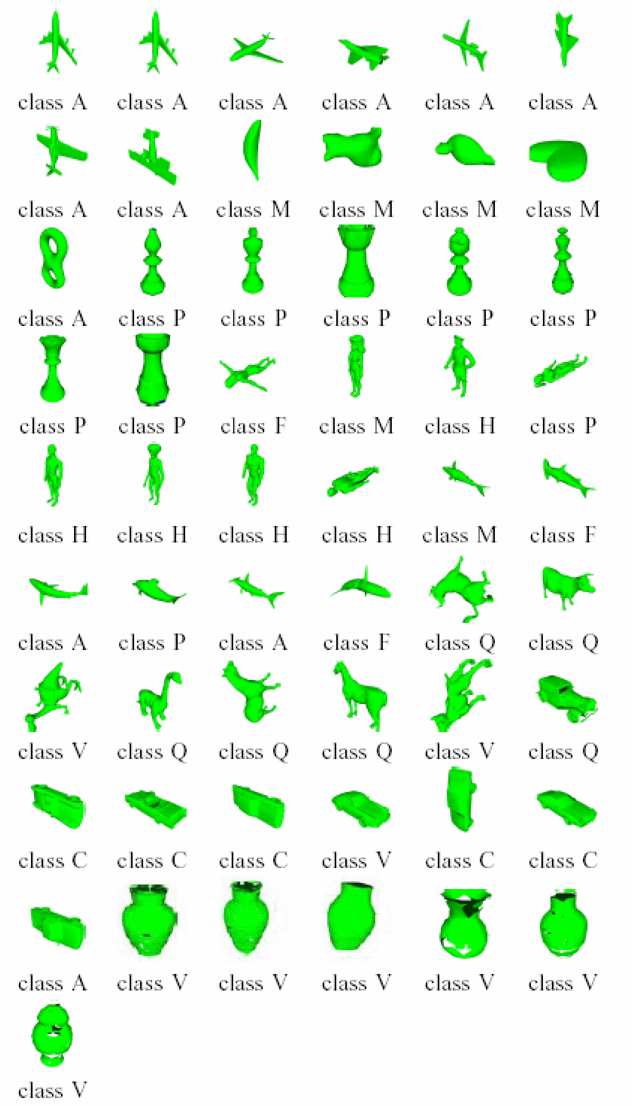


Fig. 4 Test results

## References


[1] S.Abbasi, and F. Mokhtarian "Affine-Similar Shape Retrieval: Application to Multi-View 3D Object Recognition". IEEE Transactions on Image Processing, Volume 10, Number 1, pp. 131-139, 2001.

[2] S.Mahmoudi et M.Daoudi. "Une méthode d'indexation de mod\`{e}les 3D". 13ème Congrès Francophone de Reconnaissance des Formes et Intelligence Artificielle (RFIA 2002), volume 1 pp. 19-28, Angers, France, 8-9Janvier 2002.

[3] J.Ho Yi and D.M.Chelberg. "Model-Based 3D Object Recognition using Bayesian Indexing". Computer vision and image understanding, Vol.69, No. 1, pp.87-105, Janvier, 1998

[4] C.Dorai and Anil K. Jain "Shape Spectrum Based View Grouping and Matching of 3D Free-Form Objects". IEEE Trand. PAMI, Vol. 19, No. 10, pp.1139-1146, 1997.

[5]S.Mahmoudi et M.Daoudi. "Une m\'{e}thode d'indexation de mod\`{e}les 3D". RFIA'02, pages 19-28, Janvier 2002.

[6]T.Zaharia et F.Prêteux. "Indexation de maillages 3D par descripteur de forme". RFIA'02, pages 48-57, Janvier 2002.

[7]C.Zhang and T.Chen. "Efficient feature extraction for 2D/3D objects in mesh representation". ICIP'01, 2001.

[8]T.Muro. "Descriptors of polyhedral data for 3D-shape similarity search". MPEG-7 proposal Evaluation Meeting, p177, Lancaster, UK, Février 1999.

[9]R.Osada, T.Funkhouser, B.Chazells and D.Dobkin. "Matching 3D models with shape distributions". Shape Modeling International, May 2001.

[10]J-P.Vanderborre, M.Daoudi and C.Chaillou. "3D models recognition from a 2D sketch". CESA'98, Nabeul Hammamet,Tunisia April 1998.

[11]Liu, X., et al. Directional Histogram Model for Three-DimensionalShape Similarity. in CVPR. 2003.

[12]Koenderink, J.J. and A.J. van Doorn, "Surface shape and curvature scales". Image and Vision Computing, 1992. 10(8): p. 557-565.

[13]E. M. Stockly and S. Y. Wu. "Surface parametrization and curvature measurment of arbitrary 3D objects: five practical methods". IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(8):833-840, 1992.

[14]M. P. do Carmo. Differential Geometry of Curves and Surfaces. Prentice-Hall, Inc., 1976.

[15]T. F. Ansary, J-P. Vandeborre and M. Daoudi, "A Bayesian Approach for 3D Models Retrieval Based on Characteristic Views," *icpr*, pp. 898-901, 17th International Conference on Pattern Recognition (ICPR'04) - Volume 3, 2004.

[16]www.3dcafe.com