ART Extension for Description, Indexing and Retrieval of a 3D Objects

Julien Ricard, David Coeurjolly, Atilla Baskurt

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Julien Ricard, David Coeurjolly, Atilla Baskurt
LIRIS, FRE 2672 CNRS,
Bat. Nautibus, 43 bd du 11 novembre 1918, 69622 Villeurbanne cedex, France
julien.ricard@liris.cnrs.fr david.coeurjolly@liris.cnrs.fr atilla.baskurt@liris.cnrs.fr

Abstract

This paper presents a new three-dimensional shape descriptor: 3D angular radial transform. It is an extension of the 2D region based shape descriptor proposed by MPEG-7, the Angular Radial Transform (ART). We propose to generalize the ART to index 3D models.

1. Introduction

The technical 3D model databases always grow up since the beginning of the computed-aided design. The engineering laboratories and the design offices always increase the number of 3D solid objects and the current industrial estimates point to the existence of over 30 billion of CAD models [6]. This huge number of models requires a content-based mining with indexing and retrieval processes. The communities have made great strides in image management, but few works exist on 3D data. In the framework of the Semantic-3D national project [1] and in partnership with the car manufacturer, Renault, we investigate the possibilities to make a fast 3D descriptor to index a huge technical database. To guarantee fast answers, the descriptor size and both the indexing and retrieval costs are significant criteria. To index 3D objects, 3D moment approaches exist and the spherical harmonic representation can be cited [3, 4]. On the 2D image field the MPEG-7 standard proposes to index images using a region based shape descriptor, the Angular Radial Transform (ART) [5]. This shape descriptor has many interesting properties: compact size, robustness to noise and scaling, invariance to rotation, ability to describe complex objects.

This paper presents a new 3D shape descriptor, the 3D Angular Radial Transform (3D ART). This descriptor is a generalization of the ART to 3D objects with the willingness to preserve the 2D ART properties. The paper is organized

as follows: section 2 presents a survey of the related work on shape matching, section 3 details the 3D ART descriptor, result and experiment are presented in the last section.

2. Survey of recent methods

The moment based approaches can be defined as projections of the function defining the object onto a set of the moment characteristic functions. These approaches are used in 2D pattern recognition with several 2D moments: geometrical, Legendre, Fourier-Mellin, Zernike, pseudo-Zernike moments [9]. Some of these moments have been extended in 3D: 3D Fourier [2], 3D Wavelet [7], 3D Zernike [1] and a spherical harmonic decomposition, recently described by Vranic and Saupe [10], and Funkhouser et al. [3]. The spherical harmonic analysis decomposes a 3D shapes into irreducible sets of rotation independent components by sampling the three dimensional space with concentric shells, where the shells are defined by equal radial intervals. The spherical functions are decomposed as a sum of its first 16 harmonic components [4], in an analogous way to Fourier decomposition into different frequencies. Using the fact that rotations do not change the norm of the harmonic components, the signature of each spherical function is defined as a list of these 16 norms. Finally, these different signatures are combined to obtain a $32 * 16$ signature vector for the 3D model. During the retrieval step, the similarity of objects is calculated as the Euclidean distance between these vectors. In our experimentation, the proposed descriptor is compared to SH.

3. 3D Angular radial transform

In this section, we generalize the MPEG-7's angular radial transform to 3D space.

3.1. 3D ART definition

First, we suppose the objects to be represented in spherical coordinates where ϕ is the azimuthal angle in the xy-

plane from the x-axis, θ is the polar angle from the z-axis and ρ is the radius from a point to the origin. The 3D ART is a complex unitary transform defined on a unit sphere. The 3D ART coefficients are defined by:

$$F_{nm_\theta m_\phi} = \int_0^{2\pi} \int_0^\pi \int_0^1 V_{nm_\theta m_\phi}(\rho, \theta, \phi) f(\rho, \theta, \phi) \rho d\rho d\theta d\phi \tag{1}$$

where $F_{nm_\theta m_\phi}$ is an ART coefficient of orders n, m_θ and m_ϕ, $f(p, \theta, \phi)$ is a 3D object function in spherical coordinates and $V_{nm_\theta m_\phi}(\rho, \theta, \phi)$ is a 3D ART basis function (BF). The 3D BF are separable along the angular and the two radial directions:

$$V_{nm_\theta m_\phi}(\rho, \theta, \phi) = A_{m_\theta}(\theta) A_{m_\phi}(\phi) R_n(\rho) \tag{2}$$

As in 2D, the radial basis function is defined by a cosine function:

$$R_n(\rho) = \begin{cases} 1 & n = 0 \\ 2\cos(\pi n\rho) & n \neq 0 \end{cases} \tag{3}$$

The angular basis functions are defined by complex exponential functions to achieve rotation invariance and continuity along both θ and ϕ values:

$$\begin{array}{rcl} A_{m_\theta}(\theta) & = & \frac{1}{2\pi} \exp\left(2jm_\theta\theta\right) \\ A_{m_\phi}(\phi) & = & \frac{1}{2\pi} \exp\left(jm_\phi\phi\right) \end{array} \tag{4}$$

The values of the parameters n, m_θ and m_ϕ are trade-offs between efficiency and accuracy. The choice of the values of 3D ART parameters, n, m_θ and m_ϕ, is made by computing of the Recall values for different values of these parameters. For the technical database presented in section 4, we finally choose $n = 3$, $m_\theta = 5$ and $m_\phi = 5$. The real parts of the 3D ART BF are shown in figures 1.

The similarity measure is computed using a L_1 norm by the 3D ART descriptors:

$$d(Q, I) = \sum_{i=1}^{n \cdot m_\theta \cdot m_\phi} \| ART3D_Q[i] - ARRT3D_I[i] \| \tag{5}$$

where Q and I represent respectively a query object and an object of the database and $ART3D$ is the array of 3D ART descriptor values normalized by F_{000}. The choice of the L1 distance is justified by speed preoccupations but of other distances could be used.

3.2. Indexing process

An important property of the 2D ART is the rotation invariance. A rotation representation in polar coordinates can be express as the sum of angular components:

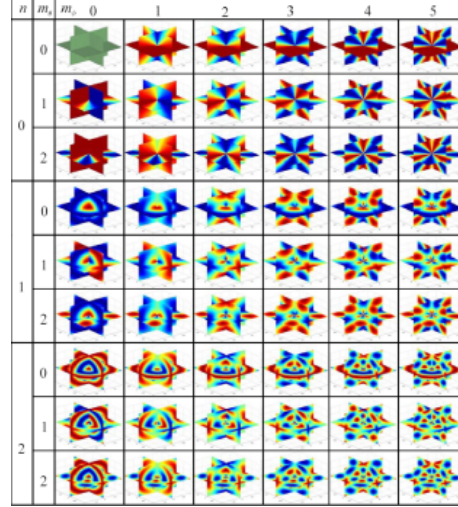$$(\rho, \phi) \xrightarrow{Rot_\alpha} (\rho, \phi + \alpha) \tag{6}$$

Figure 1. Real parts of 3D ART BF.

Thus, that does not modify the norm of the function $A_{m_\theta}(\theta)$ and the ART descriptor. In 3D, unspecified rotations can not be expressed as the sum of constant values on the angular components which modifies the descriptor values. However, if we consider a rotation around the z-axis, the norms of the 3D ART coefficient do not change. Hence, to have a rotation invariance, unspecified rotations must be transformed to rotations along z-axis by alignment according to the first principal direction. A Principal Components Analysis (PCA) is applied to obtain the principal direction of the objects. PCA alignment does not provide a robust normalization when the three principal directions are used. Here, we only aligned the first principal direction along the z-axis and wrong alignments are limited. Fig. 2 shows the indexation process.

Hence, before projecting 3D models onto a BF, the objects are pre-processed as follows: first, they are discretized in a grid such that the voxels are separated into interior and exterior elements of the object. The discretization is used to compute the parameters of centering, scaling and alignment to the z-axis: the 3D object is centered onto the gravity center and scaled up such that its boundaries are touching with the grid boundary. This pre-processing step makes the 3D ART be robust to translations and scaling. Finally, the discretized object is projected into the 3D ART BF to obtain the 3D ART coefficients.

4. Experiments

Two sets of experiments are made on two 3D model databases: the Princeton Shape Benchmark [8] and a Renault database (Fig. 3 shows examples of 3D models). The Renault database is a technical database which contains me-
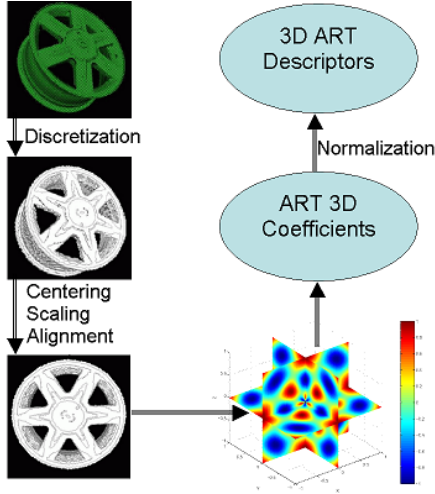
Figure 2. Indexing process.

chanical models. Thus the shapes of the different models in a given class are homogeneous. The Princeton database contains high level semantic classes where the objects of a same class are more heterogeneous.
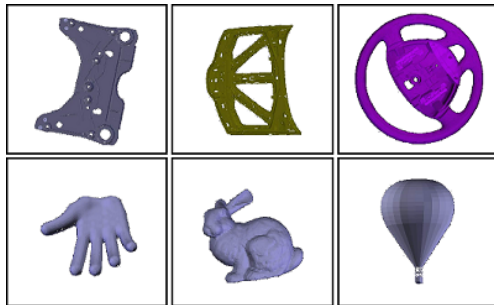

Figure 3. Example of 3D models: first row: Renault database, second row: Princeton Shape Benchmark.

To fix the parameter values, the recall values are compared. Twelve values of the parameters n, m_θ and m_ϕ are evaluated. Fig. 4.a shows that the best results are obtained for $n = 3$ and $m_\theta = m_\phi = 5$. Fig. 4.b presents the same experiment with different sizes of the discretization S. Better results are obtained on the technical database with the parameter value $S = 64$. Thus, we use this value in the rest of this work. This value is also suggested in [4] for the SH computation.

To evaluate the robustness of the process, we distort a 3D object according to scaling, rotation, translation and noise. Table 1 shows the maximum and the mean distance obtained
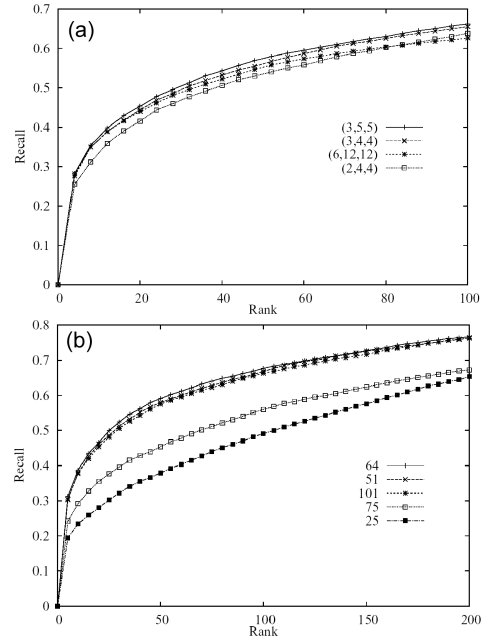

Figure 4. Recall values to set up parameters.

for these four distortions. For each distortion, we create a set of 3D objects and for all the objects we compute the distance with the original ones. The translation has no effect on the distance, because the pre-processing step centers the objects. For the same reasons, the scale distortion has small effects due to artifacts digitization, the maximum distance between the scaled objects are 0.016 when a mean distance between two objects of the same class is around 3. The obtained distances are smaller than intra-class distances and the classification is the same one. The rotation distortion test is a set of rotations around the three axes with random angles and gives a maximum distance of 1.272 and a mean distance of 0.75. The noise distortion is a random move of vertices of the object; each vertex is moved along a random Gaussian vector. This distance is a percentage of the object size. If this distance is higher than 10% the surface of the object is very distorted but the similarity measure is 1.6 and the object are still well classified. Fig. 5 shows distorted objects by the noise distortions.

Distort	Translation	Scale	Rotation	Noise
Max dist.	0	0.016	1.272	2.217
Mean dist.	0	0.003	0.750	1.012

Table 1. Distance obtained for several distortions.

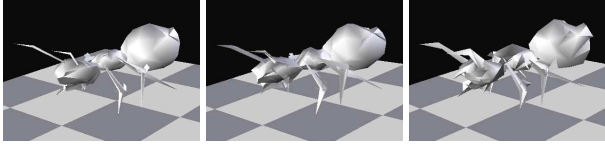A second experiment is set up to compare the 3D ART to

Figure 5. Example of noise distortions for three distance values: 0%, 5% and 10%

	Indexing time	Descriptor size
SH	l0	544
3D ART	4	74

Table 2. Size (in floating numbers) and indexing time (in seconds) comparison between 3D ART and spherical harmonic representation.

the Spherical Harmonic descriptor (SH). This experiment is made on the two model databases. The figures 6.a and 6.b show the recall values for SH and 3D ART descriptors for the two databases. On the Princeton database (Fig. 6.a), the SH method gives a better description than the ART. The results on the Renault database are similar with the two methods (Fig. 6.b). ART description gives better results when the objects of a same class are similar.
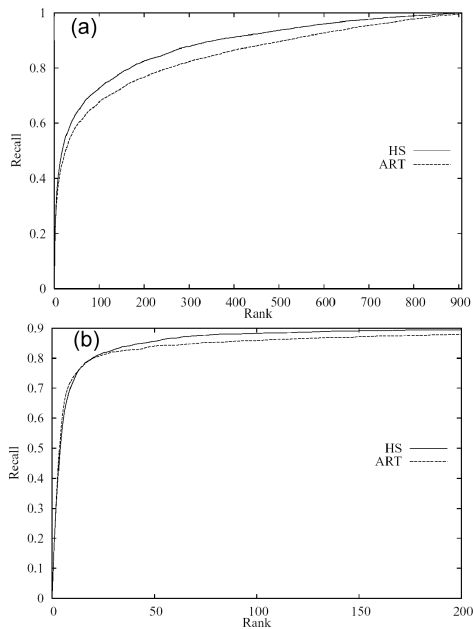

Figure 6. Recall values on Princeton and Renault databases.

The computational cost and the size of the descriptor are significant comparison criteria (Table 2). The 3D ART indexing computation time is 2.5 times less than a SH indexing and the descriptor size and the cost of the similarity measure is approximately 7.8 times less. These differences are due to the fact that the ART BF and the integral calculus are defined in the Euclidian space whereas the SH description is computed using complex frequency transformations.

5. Conclusion

This paper proposes a new 3D shape descriptor, the 3D ART. This 3D transformation and the corresponding indexing process create 3D shape descriptors which are robust to translations, scaling, multi representation (remeshing, weak distortions), noises and 3D rotations. The proposed shape descriptor fulfills the requirements induced by the technical model database analysis: robustness and accuracy of the indexing and retrieval processes and fast similarity computation.

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