A 3-D Search engine based on Fourier series

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Elmustapha Ait Lmaati [a], Ahmed El Oirrak [a,b],
Mohamed Daoudi [c], Driss Aboutajdine [b],
Mohammed Najib Kaddioui [a]

[a] *SIRC, Faculté des sciences Semlalia, Département Informatique, BP 2390 Marrakech, Maroc*

[b] *Faculté des sciences, LEESA-GSCM, BP 1014, Rabat*

[c] *Institut TELECOM ; TELECOM Lille1 ; LIFL UMR USTL/CNRS 8022 Cité Scientifique - Rue Guglielmo Marconi Villeneuve d'Ascq cedex France*

Abstract

The size of 3-D data stored around the Web has become bigger. Therefore the development of recognition applications and retrieval systems of 3-D models is important. In this paper we propose a new scheme to measure similarity between 3-D models. The main idea is to reconstruct a 3-D closed curve that represents a 3-D model given by a polygonal mesh, and to extract a signature from this 3-D closed curve using the Fourier series. The proposed descriptor needs CPCA (Continuous Principal Component Analysis) to align 3-D models into a canonical position. The feature vectors constructed using this method, named FSD (Fourier Series Descriptor) are invariants under rigid transformations composed of translation, rotation, flipping and scale; robust to noise and level of detail. A 3-D polygonal mesh model serves as a query for search by shape similarity in a large collection of 3-D models database using an interactive 3-D search engine.

Key words: 3-D Models; 3-D Curve; Polygonal Mesh; Fourier series; 3-D Search Engine.

⋆ Corresponding author E. Ait Lmaati. Tel. +212(0)44134190.
Email addresses: `lmaatimustapha@yahoo.fr, e.aitlmaati@ucam.ac.ma` (Elmustapha Ait Lmaati), `oirrak@yahoo.fr` (Ahmed El Oirrak), `mohamed.daoudi@telecom-lille1.eu` (Mohamed Daoudi), `aboutaj@fsr.ac.ma` (Driss Aboutajdine), (Mohammed Najib Kaddioui).

1 Introduction

More and more the size of audio-visual data stored around the World Wide Web is growing. Therefore, the description of these data (text, images, audio, video, 3-D models) is the goal of many researchers in multimedia. 3-D model databases appear in various domains like e-commerce, game, communication, medicine, mechanical engineering and education. As the used 3-D models are growing both in size and number, finding desired models from a large collection of 3-D models is becoming important. 3-D model indexing and similarity retrieval application are useful and very promising way to manage this kind of data [3][12]. 3-D similarity retrieval application consists of extracting the most similar models for a given query from a large database. Many methods in this way are developed. The shape spectrum descriptor proposed by Zaharia et al. based on surface geometry, is recommended by MPEG-7 [7]. Filali et al. proposed the descriptor based on 2D views named Adaptive Views Clustering (AVC). It is a probabilistic bayesian method that selects the most interesting views from several views of a 3-D model [1]. Based on the statistics, Osada et al. proposed the descriptor named shape distribution (D2) [9]. Paquet et al. proposed the method of cord histograms [10]. The ratio area/volume is used as a feature vector to describe the 3-D models by Zhang et al. [17]. Even if this descriptor computes the feature vectors easily and quickly, it needs a high quality of mesh. Vranic et al. [15] proposed the method named Ray Based descriptor. It uses the extents obtained from the center of mass of the model to intersection with its surface in directions which are constructed by an icosahedron . This approach is not robust to noise and needs a high dimension of feature vectors, this is why the authors construct the feature vectors from the complex function on a sphere, composed with ray based feature vectors and shading based feature vectors, presented in frequency domain by applying the spherical harmonics [14]. In order to capture the information in the interior of a 3-D model, the authors proposed the descriptor named Layered Depth Spheres [13], where they use the property of spherical harmonics to achieve the rotation invariance.

In this paper, we propose to reconstruct a 3-D closed curve that represent 3-D model and to extract signature from its using Fourier series. The paper is organized as follow. In section 2, we present the method used to reconstruct 3-D closed curve that represent 3-D model. The feature vectors based on Fourier series are proposed in section 3. In section 4, we give the experimental results where we discus our 3-D search engine, tools used to evaluate our retrieval system, comparison with other 3-D descriptors and stability for noise and level of detail. Finally conclusion is presented in section 5.

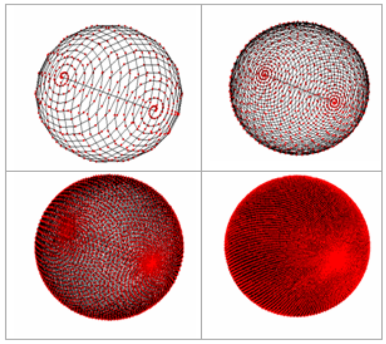


Fig. 1. Spherical Helices Curves with 400 points and q=50, 1000 points and q=70, 4000 points and q=150 and 15000 points and q=200 respectively.

2 3-D Mesh Curve Extraction

What is the main difficulty in comparing shapes of two surfaces? Shape analysis should ideally be invariant to the choice of parameterizations, i.e. one should get the same comparison irrespective of parametrization of the two surfaces. To help understand this issue, consider the problem of analyzing shapes of curves. In this case, there is a fixed ordering of points along the curves that allows their parameterizations. This idea has been used frequently to study shapes of curves. Returning to the problem of comparing surfaces, this problem is made difficult by the fact that there is no natural ordering of points on a surface. Our solution is to impose a natural hierarchy (or ordering) of points on a surface by using the idea of 3-D curve to represent a surface.

Before extracting 3-D curve from 3-D model, CPCA algorithm (Continuous Principal Component Analysis)[16] is applied to each 3-D model. This method consists of a set of transformations applied to a 3-D model on each of its vertices. In order to achieve the translation invariance, we translate the coordinates system to center of mass of the model. The rotation invariance is assured by multiplying the obtained coordinates by the rotation matrix which has the scaled eigenvectors as rows of the covariance matrix after sorting its corresponding eigenvalues in decreasing order. We multiply by the matrix of flipping to determine directions of axes in the new coordinates system, finally we divide by the scale factor equal to the average distance between the center of the model and its surface. These rigid body transformations ϕ are given by the equation (1),

$$\phi(P) = s^{-1}F.V.(P - G), \tag{1}$$

where P is a vertex of a mesh, s is the scale factor, F is the flipping matrix, V is the rotation matrix and G is the center of mass of the object. Note that s, F, V and G are computed using the CPCA technique given in reference [16].

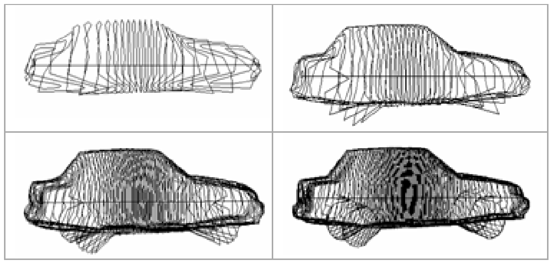


Fig. 2. 3-D Curves with 400 points and q=50, 1000 points and q=70, 4000 points and q=150 and 15000 points and q=200 respectively.

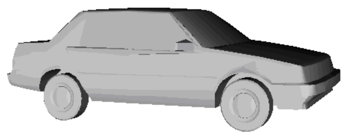


Fig. 3. Car model from the Princeton Shape Benchmark database.

After the alignment of 3-D model in a canonical position using CPCA, we define the corresponding 3-D closed curve such away that is homeomorphic to the spherical Helix curve given by the equation (2). It is a parameterized curve $SH(t)$ on a unit sphere with two parameters q and t . Figure 1 shows that if we increase the number of points of the spherical helix, we can cover the surface of the unit sphere.

$$SH(t) : \begin{cases} x(t) = cos(qt)sin(t) \\ y(t) = sin(qt)sin(t) \ t \in [0, \pi],\ q \in N^* \\ z(t) = cos(t) \end{cases} \tag{2}$$

We are using the ray-casting triangular meshes [2] to calculate the coordinates of points in the surface of model. The used algorithm does not need any preprocessing for triangles and it does not require oriented triangles. So, it is used for any 3-D model not necessarily presented by closed and orientate mesh.

Let $\{u_i, i = 1..N\}$ be a set of N unit vectors constructed by the Spherical Helix with N points and a parameter q, and r_i be the extent of the model from the origin of coordinate in direction u_i.

The farthest vertices from the center of co-ordinate and travelling in directions u_i construct a set of vertices P_i with co-ordinates (x_i, y_i, z_i) equal to the coordinates of the vector $r_i.u_i$,. So as to have a closed curve we set $P_{N+1} = P_1$. As a result the set of points P_i reconstruct a 3D periodic closed curve given by parametric equation $X(t)$(3), where T equal to 2π is the period of X.

$$X(t) = \begin{cases} x(t) \\ y(t) \;\; t \in [0, T] \\ z(t) \end{cases} \tag{3}$$

The Figure 2 shows the 3-D closed curve for the model given in Figure 3.

The proposed curve serves us to define a new representation of 3-D model and to extract feature vectors for any 3-D models given by a triangular mesh since the signature of 3-D closed curve is extracted easily by applying the Fourier series.

3 Fourier series Descriptor for 3-D Model

The main idea of our approach is to reconstruct a 3-D closed curve invariant under translation, rotation, flipping and scale given in last section, and to extract feature vectors from it. In this section we propose to use the method of Fourier series proposed in the literature to define a set of invariants under affine transformation for 2D shape recognition [4] [5].

3.1 Parametrization of 3-D closed curve

In order to compute feature vector for 3-D model presented by 3-D closed curve using Fourier series, the re-parametrization of this curve is necessary. Different parameterizations are proposed in literature. The natural arc length is linearly transformed under similitude. The arc length transforms linearly under translation and rotation. The linearity under affinity is preserved for the affine arc length. In this case nor the problem of starting point nor the problem of invariance to affinities are posed since we align 3-D models using the CPCA. In this condition, we use the natural parametrization that is normalized by equation (4).

$$\tau(t) = \frac{t}{T} \tag{4}$$

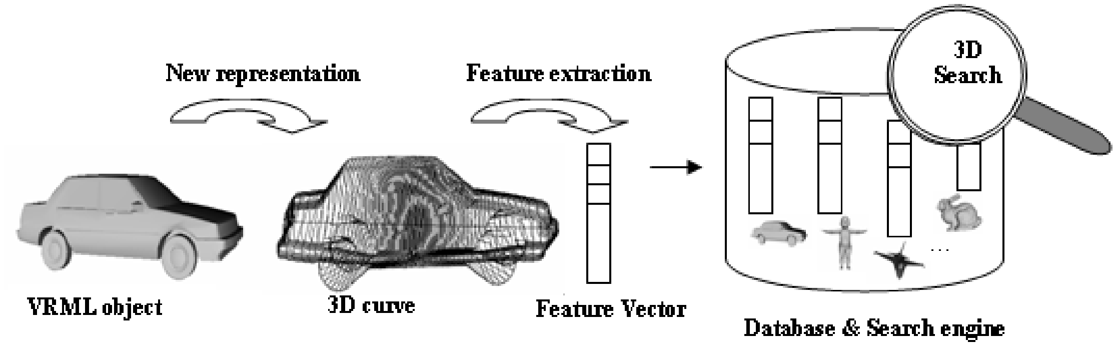


Fig. 4. The process of 3D indexing.

3.2 Features vectors based on Fourier series for 3-D models

In order to extract the feature vectors for 3-D models, we apply the Fourier series to the parameterized function $r(\tau)$ (5) for the reconstructed 3-D closed curve that represent the 3-D model.

$$r(\tau) = \sqrt{x^2(\tau) + y^2(\tau) + z^2(\tau)} \tag{5}$$

where (x, y, z) are the coordinates of points that determine the 3-D curve, and τ is the parameter given in the last section. Thus we have,

$$FS(r(\tau)) = \sum_{n=-\infty}^{+\infty} c_n \exp^{jn2\pi\tau} . \tag{6}$$

We construct the feature vector for any 3-D model by the magnitudes of complexes quantities c_n given in the formula 6.

In practice, we recommend to take the first coefficients because the high frequencies are affected by noise. In our experiment, the dimension of the feature vector taken is 300.

The process of 3D indexing proposed is summarized in Figure 4. For a given 3-D model, we reconstruct its corresponding 3-D closed curve and we extract a set of components as a feature vector. Those feature vectors are stored in order to retrieve the K nearest neighbors using the search engine.

4 Experiment results

A useful method to represent 3-D models is by a set of facets determined by a set of vertices with 3D coordinates. Using this representation, the surface of 3-D model can be textured or colored for visualization in 3D space. Several formats of file describing a 3-D models are used in literature. VRML is the most useful and the standard on the web. It is a scene description language that enables the construction of interactive, animated 3-D models and environments on Web pages. For our test, all 3-D models are represented by polygonal meshes, with triangular facets given in arbitrary orientation. The search engine uses the VRML2.0 in order to visualize the models in 3D space.

Our retrieval system consists of an off-line step. It is the process where we compute the feature vectors for any 3-D model. We are using Java to reconstruct 3-D closed curves for the models, and C/C++ to extract feature vectors. We are developing a local search engine using Hypertext Preprocessor language (PHP), where the Apache Web server, accepts queries and returns the results On-line. All programs used in our retrieval system are compiled and executed under Windows platform using 1.4 Ghz, Celeron M machine with 512 MB memory. The average time to generate 3D closed curve and to compute feature vectors with dimension 300 are 1.5 seconds for a model in the PSB database.

4.1 The 3-D Search Engine

The basic idea of feature vectors based similarity search system is given in figure 5. The off-line step consists of storing the collection of 3-D models and theirs feature vectors. For each 3-D model we generate its 3-D closed curve, after determination of its canonical position, and using Fourier series we extract the feature vectors. From our search engine, we can browse the collection and query by example the system, the search engine computes the distances to other models in the collection, and extract the most similar models to the query model. All models can be visualized in 3D space using the VRML format. Figure 6 shows a screen-shot of our 3-D search engine.

4.2 The Princeton Shape Benchmark

In order to test our 3D descriptor, we use the Princeton Shape Benchmark database (PSB) [11]. It consists of 1814 3-D models given in format OFF (Object File Format), with two sets (test set and train set) of classified 3-D

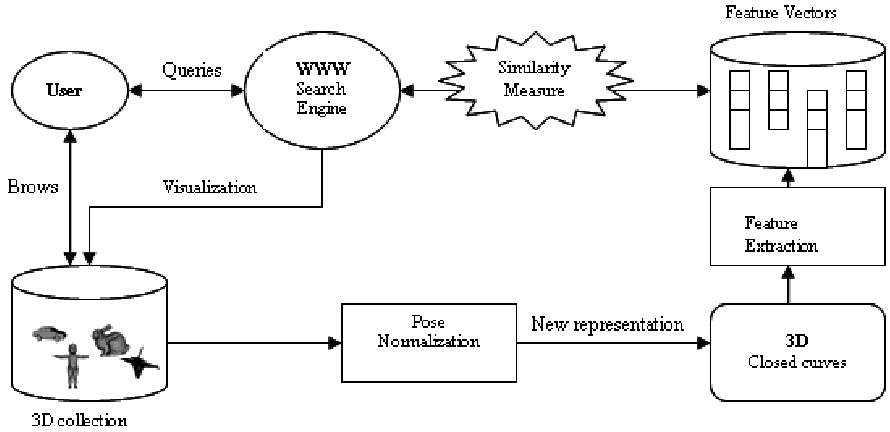


Fig. 5. The retrieval system and search engine.

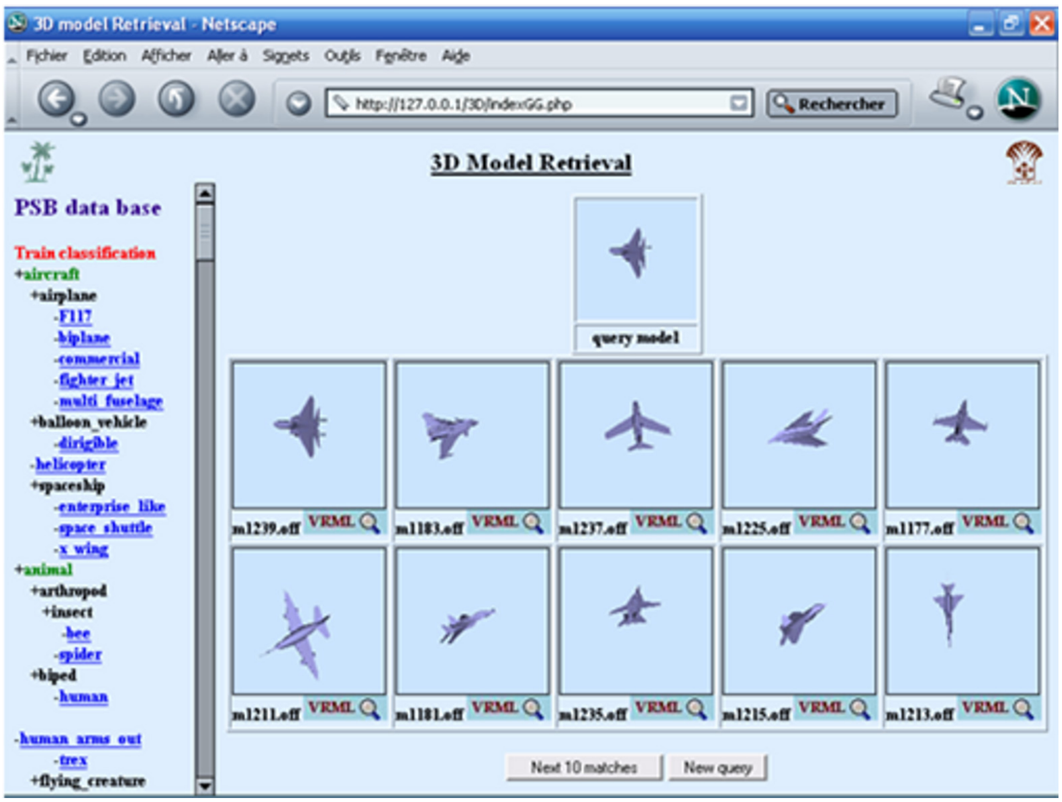


Fig. 6. Screen shot of the 3-D search engine.

models. The test classification consists of 907 models classified into 92 classes. The training classification consists of 907 models classified into 90 classes.

We add some 3-D models to the PSB database, which have been created using QSlim software [6] so as to provide models with different levels of detail. The modified PSB consists of 1889 models reclassified with geometrical aspects, our classification consists of 982 models classified into 93 classes.

4.3 Evaluation criterion

We use the average Precision versus Recall plots and the First Tier (FT), Second Tier (ST), and Nearest Neighbor (NN) quantities widely used in shape retrieval community to evaluate the performance of the descriptors. For a given query Q in a class C with n models, let Rk be the number of correctly retrieved models among the K best matches. The recall is defined as a ratio of relevant models Rk to (n-1), and the precision is the ratio of the relevant results and returned results K, given by the following formulas.

$Recall = Rk/(n-1).$

$Precision = Rk/K.$

The First Tier is the same as precision value when K is equal to n-1, the Second Tier is also the same as precision value when K is equal to 2(n-1) and the Nearest Neighbor measure is the percentage of the closest matches that belong to the same class as the query. Obviously, an ideal score is 100%, and higher scores represent better results.

Now that we have defined a Fourier descriptor for each 3-D curve as real valued components. For a given feature vectors F_1 and F_2 with p components each one, we use the Manhattan metric d_1, the Euclidean metric d_2 and the maximum metric d_{max} given by the following formulas.

$$d_1(F_1, F_2) = \sum_{i=1}^{p} |F_{1i} - F_{2i}|,$$

$$d_2(F_1, F_2) = (\sum_{i=1}^{p} (F_{1i} - F_{2i})^2)^{1/2},$$

$$d_{max}(F_1, F_2) = \max_{1=<i<=p} |F_{1i} - F_{2i}|,$$

to compute the distance between them.

We experimentally found that the d_2 distance is the most effective for ranking the models for our method using curves with 15000 points. Figure 6 is the result of similarity query in a 3-D model database. The shown models represent the nearest neighbors retrieved by the search engine for the model m1239 from the PSB database. We give the Precision versus Recall curve for our approach in figure 7 using different classifications from the PSB database.

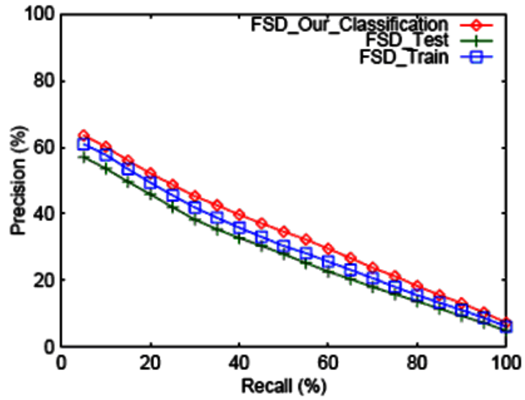


Fig. 7. Precision versus Recall plots for our classification, test classification and train classification using PSB database.

4.4 Comparison with other 3D descriptors

We compare our approach to the descriptor named Ray based with Spherical Harmonic (RSH), proposed by Vranic et al.[15]. In order to extract the feature vector for a 3-D model the authors use the continuous principal component analysis to align the model into the canonical position. Then they extract the maximal extents from the center of mass of the model to its surface, finally the spherical harmonic is applied to represent these rays in the frequency domain.

The second descriptor used in comparison is the silhouette based feature vectors (SIL), proposed by Heczko et al. [8]. This approach aligns models using the CPCA, capture shape characteristics of models in three monochromes images. Then the authors extract the three contours and for each contours they apply the discrete Fourier transform in order to present feature vectors in spectral domain.

The third descriptor used in the comparison is the descriptor named Depth Buffer (DBD), it is an efficient image-based descriptor proposed by Heczko et al. [8]. It needs the CPCA to align the model in a canonical position and scale into the canonical unit cube. Six grey-scale images are rendered using parallel projection. Then the authors apply 2D Fourier Transform, and their features vectors are composed in the low frequency coefficients. The figure 8 shows the average Precision versus Recall plots comparing the four descriptors, where the dimension of the DBD, SIL, FSD and RSH are 438, 300, 300 and 136 respectively. Table 1 provides comparative performance measures of the different descriptors (DBD, SIL). It is clear from Table 1 that the proposed approach gives lower performance than DBD and SIL. However, it is worth mentioning that DBD and SIL methods are 2-D view based approaches. The proposed approach is a 3D object based method and a fair comparison can only be made against RSH and our approach gives a better performance.

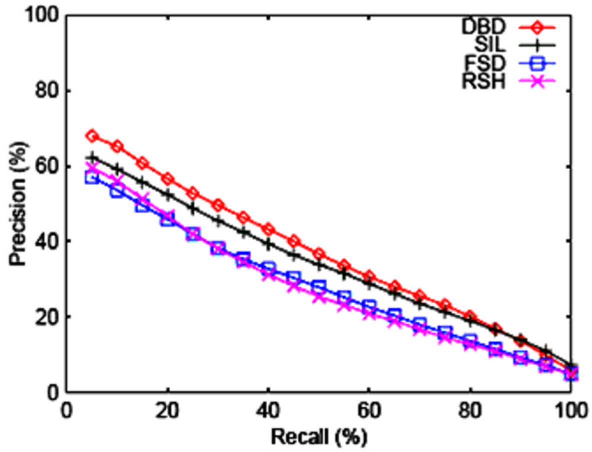


Fig. 8. Precision versus Recall plots comparing FSD method to RSH, SIL and DBD using PSB database.

	FT	ST	NN
DBD	44.7%	34.2%	61.3%
SIL	43.6%	32.6%	55.7%
FSD	38.9%	28.4%	52.3%
RSH	38.4%	27.8%	53.3%

Table 1
Comparison of measurements: NN, FT and ST for different methods using PSB database.

4.5 Robustness to noise and level of detail

We test the robustness of our approach to noise by applying perturbation on each vertex and facet. We translate randomly the facets, adding a random value to coordinates of each vertices for any models. We give Precision versus Recall plots with different levels of noise (5%, 15%, 20%) in Figure 10(c), fig. 10(d) and 10(e) using PSB database, training classification.

The Precision versus Recall plots were computed for each value of noise and for decimation for the DBD, SIL, FSD and RSH. The figure 11 shows the effect of decimation and noise addition for different values 5%, 15% and 20% on 3D-model. Notice that the deleted facets from the model appear in black. Precision versus Recall plots were computed for each value of noise and decimation (fig. 11). From Figure 11(a), we can learn that the decimation does not affect strongly the FSD which mean that it is more stable than the other approaches (e.g for 20% of recall, the precision of DBD, SIL, FSD and RSH decreases respectivly by 9%, 4%, 6% and 16%). From Figures 11(b,c,d), even if 15% and 20% are high noise addition Precision versus Recall plots (fig. 11)

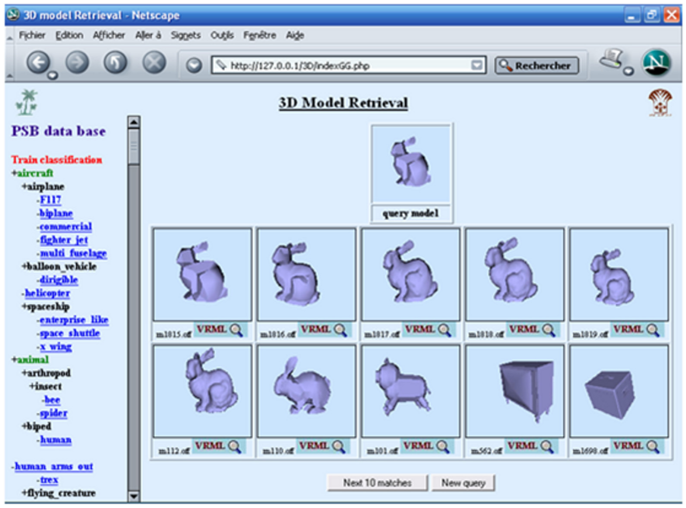
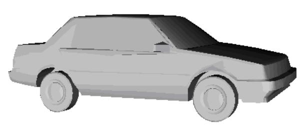


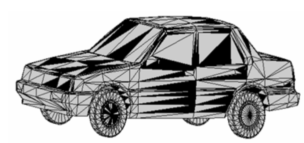
Fig. 9. Query for a rabbit model from the modified PSB database.

shows that our approach remains quite robust. From these results, it can be observed that the robustness of the FSD approach to the noise is better than RSH which is a 3D object based method and becomes comparable to DBD and SIL which are 2-D view based approaches, when the value of noise is high.

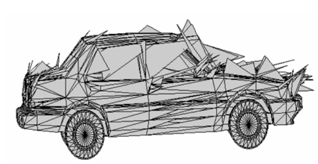
The stability of our approach to the level of detail is achieved using a query from rabbit class that contains 7 different representations of the Stanford bunny model in different levels of detail. Figure 9 shows the result of a query with a car model from the modified PSB database.



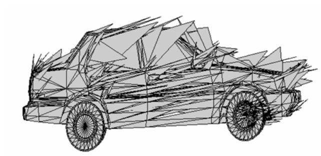
(a) Original 3-D-model



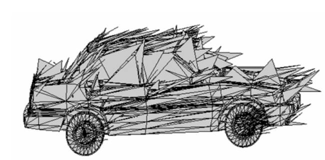
(b) Model with decimation



(c) Model with 5% noise

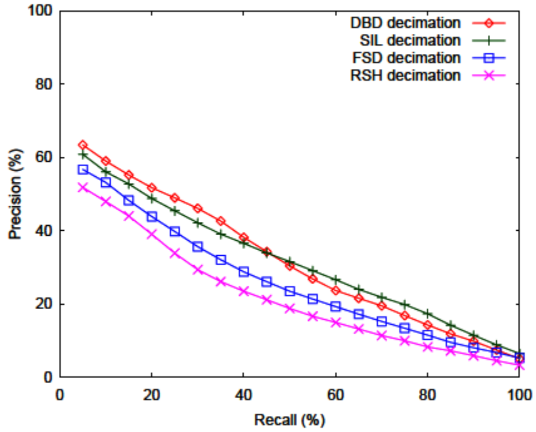


(d) Model with 15% noise

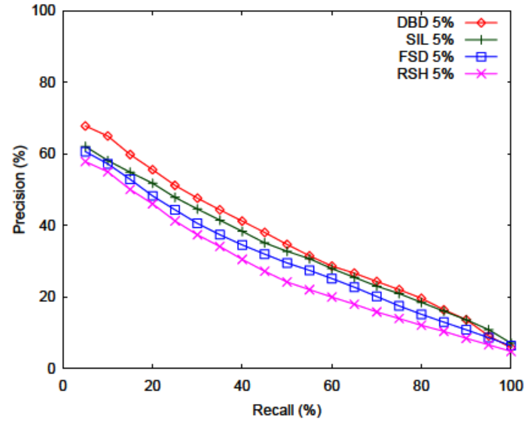


(e) Model with 20% noise

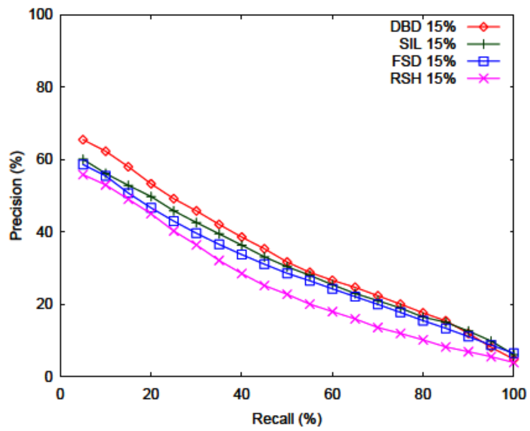
Fig. 10. Robustness evaluation of noise and decimation from a 3-D-model.



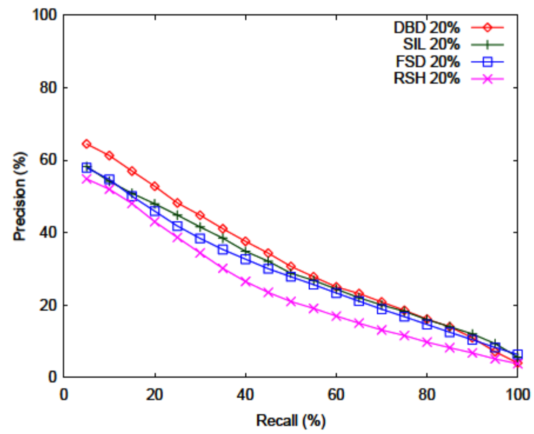
(a)



(b)



(c)



(d)

Fig. 11. Precision versus Recall on PSB database with deformation effects (a)decimation (b) 5% (c) 15% (d) 20%

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5 Conclusion

A 3-D model retrieval based on Fourier series is proposed. We reconstruct a 3-D closed curve representing the 3-D model in order to extract feature vectors for any 3-D model using Fourier series. The proposed descriptor is robust to noise and level of detail. FSD is compared to descriptors named Depth Buffer, Silhouette and Ray with Spherical Harmonic. Our approach shows retrieval performances comparable with Ray with spherical harmonic descriptor. It is easy to implement and shows promising results. A 3D search engine based on FSD descriptor has been proposed.

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