An Experimental Comparison of Feature-Based 3D Retrieval Methods

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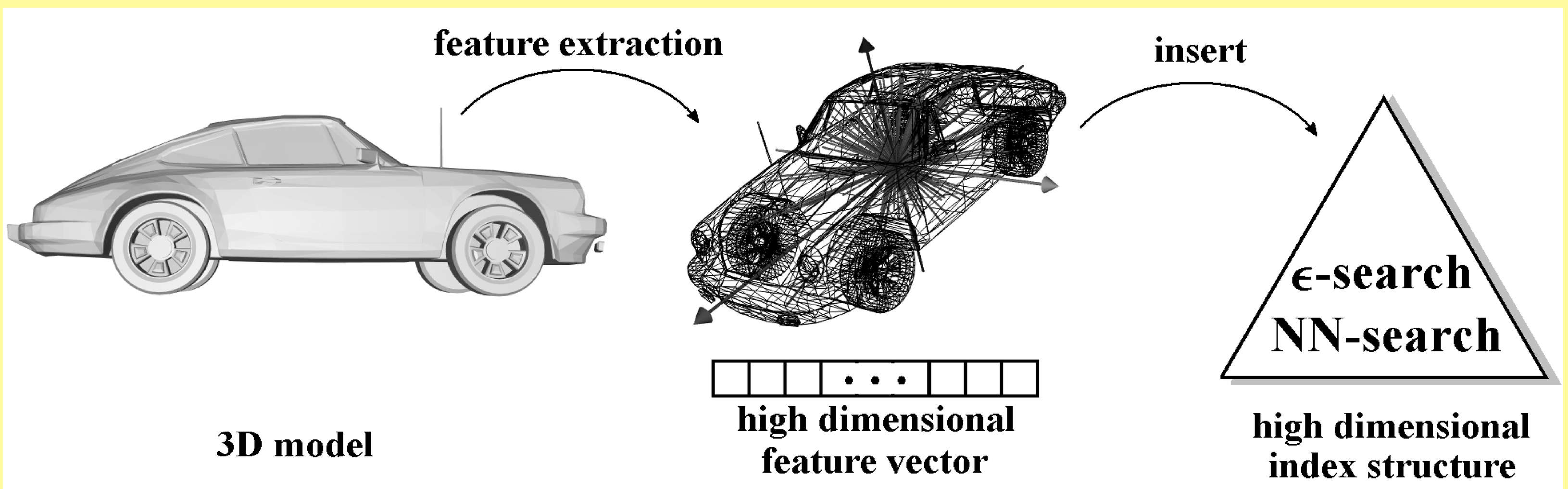
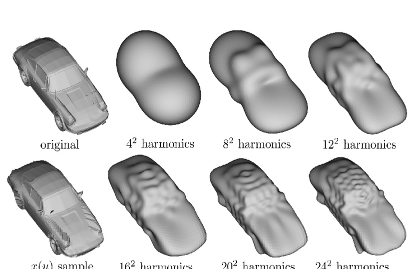
Similarity search of 3D objects



Given that it is not clear how to use geometry directly for similarity search, in many methods for retrieval of 3D models the data is transformed in some way to obtain a numerical description for indexing and distance calculation, also referred to as feature vectors. The basic idea is to extract numeric values that describe the objects under a certain geometric aspect, and to infer the similarity of the models from the distance of these feature vectors in some vector space.

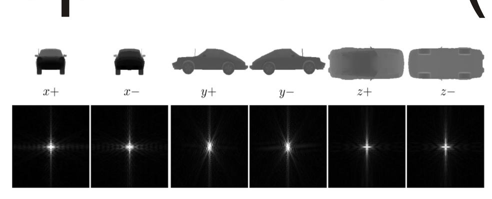
Implemented feature vectors

Sph.Harm.-based



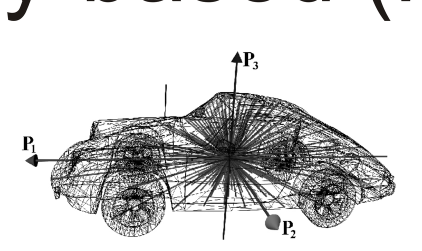
The spherical harmonics transform may be applied to obtain an embedded multiresolution description of samples of functions defined on the sphere. To obtain 3D feature vectors, we engage the Ray-based sampling scheme (RS), the scalar product of the ray direction vector and the intersected triangle's normal vector (SH), or the combination of both measures in a complex number(CP), respectively. The magnitudes of certain low-frequency spharm coefficients give the components of this feature vector.

Depth Buffer (DB)



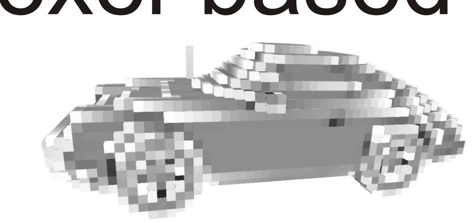
The depth buffer feature vector renders six gray-scale images using parallel projections, each two for one of the principal axes. A pixel attribute represents the distance between the object and the viewing plane measured along a corresponding direction that is perpendicular to the viewing plane. These images correspond to the concept of z- or depth-buffers in computer graphics. After rendering the six images are transformed using the standard 2D Fourier transform, and the magnitudes of low-frequency coefficients of each image contribute to the depth buffer feature vector.

Ray-based (RA)



This method is based on taking samples from a 3D object by means of rays emitted from the center of mass of the object in uniformly distributed directions. For all such rays, the last intersection point with a polygon of the object is found. Then, the distance between the center of mass and this point is computed. These distances values make up the components of the feature vector.

Voxel-based (VX)



The voxel feature vector is obtained by first subdividing the bounding cube of an object, after pose normalization, into equally sized voxel cells. Each of these cells stores the fraction of the 3D object surface area that lies in the corresponding voxel. The voxel cell occupancies constitute the feature vector. Another possibility is to apply the Fourier transform on these values, using a number of low-frequency coefficient magnitudes as the values of the feature vector's coordinates.

Harm. 3D (H3D)

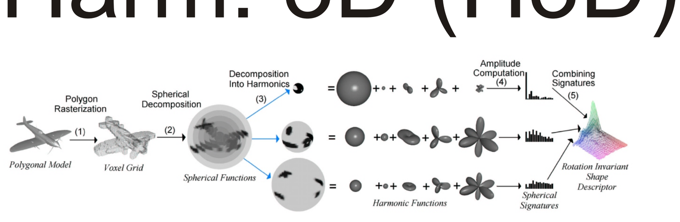


Illustration taken from

This feature vector considers the spherical harmonics representation of multiple spherical functions defined on the binary rasterization of model surface into the voxel grid. The models are normalized for scale and translation, while rotational invariance is achieved by considering low frequency band energies from the spherical harmonics transform as the components for this descriptor.

Other Methods

- Silhouette DFT (SL)
- 3DDFT of Voxelization (DF)
- Motofumi Suzuki's 90-Degree Rotation Invariant (RI)
- Shape Distribution D2 (SD)
- Moments based on Ray-Samples (RM)
- Moments based on triangle centroids (MO)
- Eric Paquet's Cords(CO)
- Artificial volume partitions (VO)
- MPEG-7 Shape Spectrum (SS)

References

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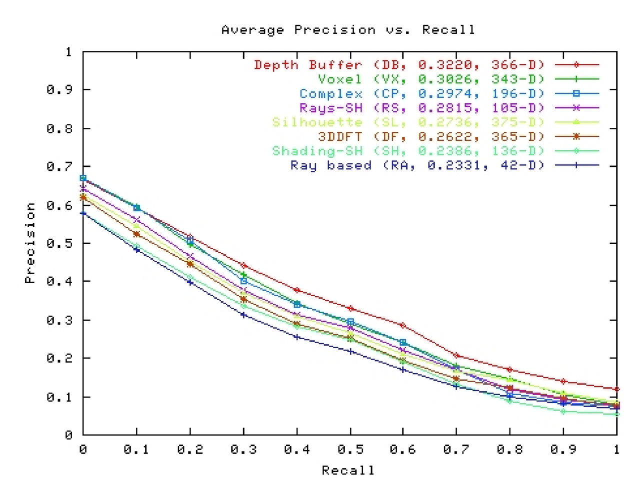
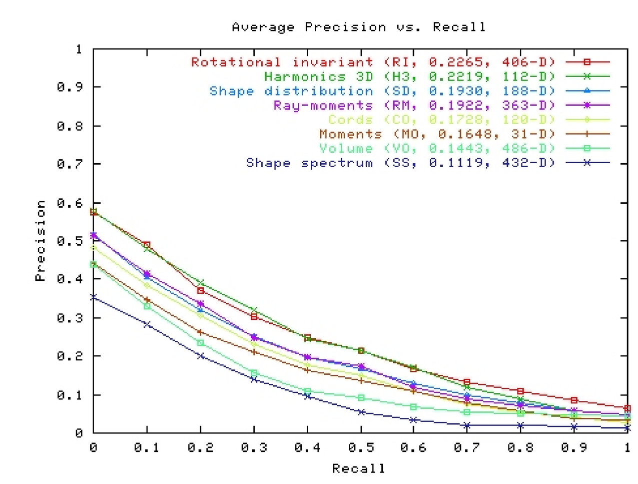
Extensions

- A priori estimation of individual feature vector performance based on entropy impurity.
- Query processor based on query-dependent characteristics.
- Selection, weighting, and combination of several feature vectors for improved search effectiveness.

Experimental results

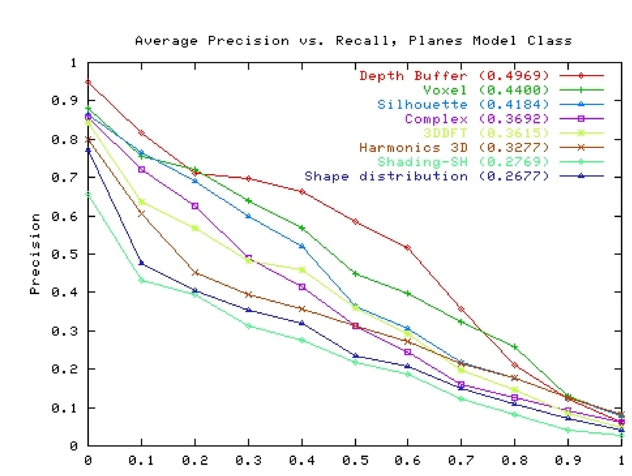
Average precision vs. recall

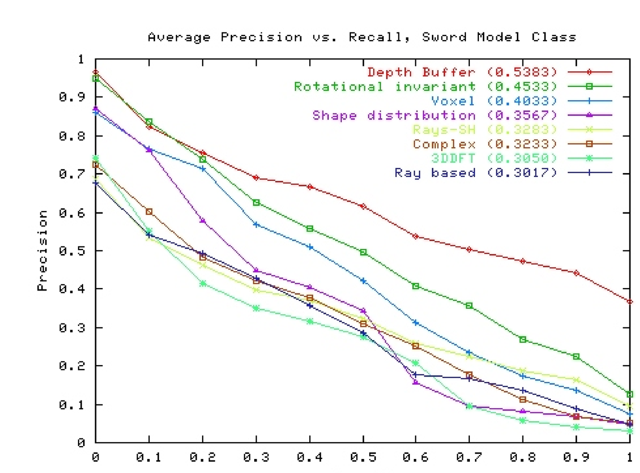




The charts show that the most effective method is the depth buffer. The difference of the average R-precision values between the best performing methods is small. As a contrast, the effectiveness difference between the best and the worst feature vector is significant, up to a factor of 3. We observed that feature vectors that rely on consistent polygon orientation exhibit low retrieval rates in our database.

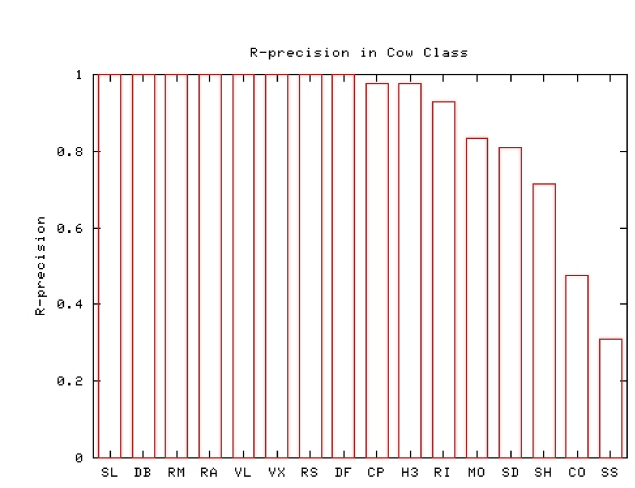
Precision vs. recall in model classes

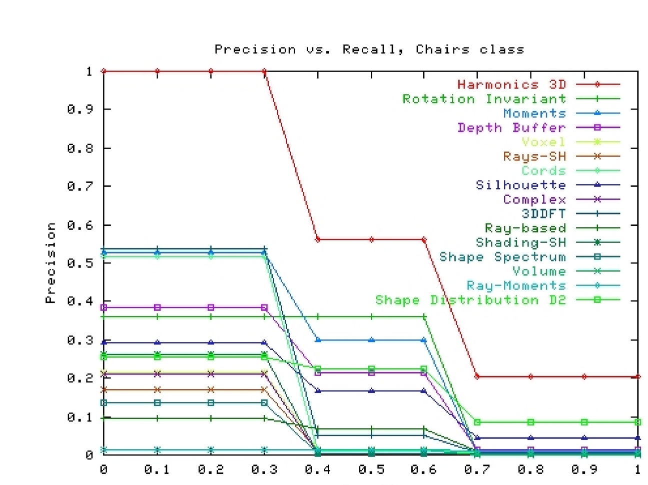




A substantial fraction of the individual query classes from our database reflects the effectiveness ranking obtained in the database average, while certain deviations in the class-specific rankings are possible.

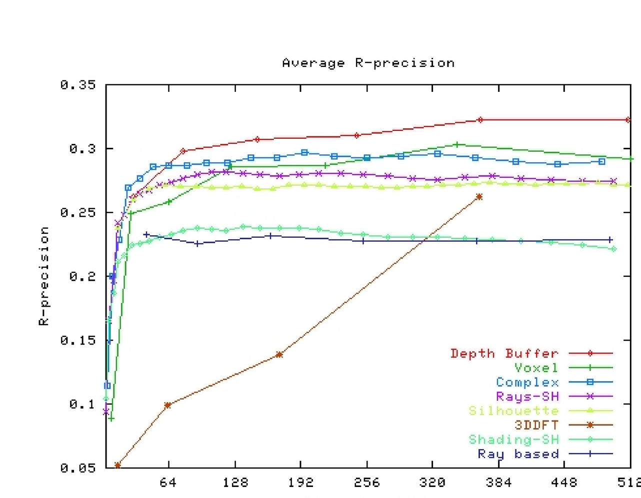
Robustness and PCA invariance

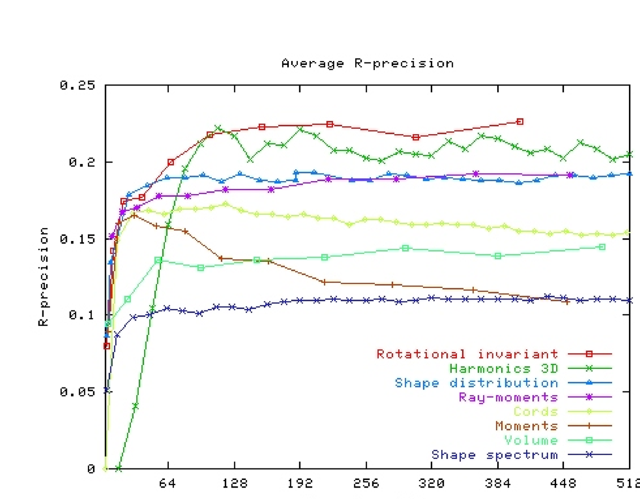




We tested robustness with respect to level-of-detail, using a query class that contains 7 different versions of the same 3D object, in varying levels of resolutions. Almost all feature vectors achieved good to perfect retrieval results.

Dimensionality vs. R-precision





Feature vector effectiveness first increases in dimensionality, but the improvement rate diminishes quickly for roughly more than 64 dimensions. It is interesting to note that the saturation effect is reached for most feature vectors at the same dimensionality level.