Computer Visualization of 3D objects using Feature Vector Based Methods

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ABSTRACT
Recent development in the techniques for digitizing and visualizing 3D objects has led to an explosion the number of available of models on the internet and in domain specific databases. Various 3D objects have different styles and use different units so that desired properties of feature vector are invariance with respect to translation, rotation, reflection and scaling, robustness with respect to level-of-detail of a model and changeable dimension. A feature vector based methods are used for multimedia retrieval. In this paper we review recent methods for feature vector retrieval of 3D objects.

Keywords
real-value component, contours, 2D projections.

1. INTRODUCTION
For visualization of 3D objects, the 3D object is transformed in some way to obtain a numerical description for indexing and retrieval, which is referred to as Feature Vector [FV]. The basic idea is to extract numeric values that describe the model under a certain geometric form, and to find the similarity of the objects from the distance of these feature vectors in some vector space. Features are represented by vectors with real-valued components and such descriptors are regarded as FV. Descriptors should be defined in such a way that similar 3D models are attributed FVs that are close in search space. Feature vector can be applied on any multimedia databases. The usage of feature vectors (FVs) is the standard approach for multimedia retrieval proposed by Faloutsos[6]. The feature-based approach is general and can be applied on any multimedia database.

Each 3D model is attributed a FV, which is represented in an appropriate way and is used for retrieving the nearest neighbors or all 3D objects whose FVs are within a given search from a query. A 3D model, in an appropriate 3D file format, serves as a query and the contents are automatically extracted and used as points in search space. The feature extraction of 3D model retrieval consists of a file storing a 3D model. It needs to be parsed and then geometry and topology are considered.

This paper reviews recent methods for feature vector retrieval of 3D objects. Information about normal vectors, triangles, vertices and also considered a polygonal mesh. An overview a detailed description of many individual methods, sorted according to classification.

2. FEATURE VECTOR CAN BE CLASSIFIED AS
- Image based feature vector
- Statistical based feature vector
- 3D-geometry-based feature vector
- Volume-based feature vector
- Voxel-based feature vector
- Functions on a sphere-based feature vector

2.1 Image-Based Feature Vector
3D similarity object can be reduced to an image, similarity by comparing 2D projections rendered from the 3D models. Projections are usually rasterized into rectangular 2D-images. The number of projections of a model depends on the definition of a feature vector. Rectangular 2D-images of the model, generated from different viewpoints, represent silhouettes, depth-buffer. One advantage of image based feature vector retrieval methods is a straightforward to design query interfaces where user apply 2D sketch which is then input to the search algorithm. [1,2]

2.1.1 Silhouette-Based Feature Vector
This approach to capture shape characteristics of objects in 2D-images is to analyze silhouettes (contours). According to [3] , the word silhouette indicated the region of a 2D-image of an object, which contains the projections of the visible points of that object. A silhouette can also be defined as an outline of a solid object. A contour as a collection of boundary points of a silhouette. In [4] a contour is approximated by a polygonal line whose vertices are either points of extreme curvature or points which are added to refine the polygonal approximation. The obtained polygonal lines can be used for both global and local similarity search.
Figure 1 shows from left to right, the viewing direction is parallel to the first, second and third principal axes of the model. Equidistant sampling points are marked along the contour.

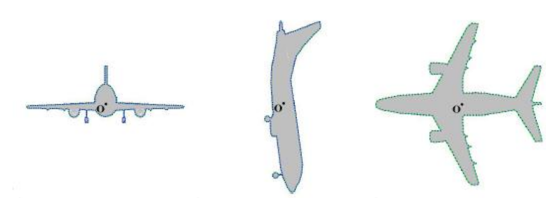

Fig: 1. Silhouettes of a 3D models.

2.1.2 Depth Buffer Feature Vector
Another image-based descriptor was proposed in [5] and further discussed in Vranic[7] . Depth buffer feature vector starts with the same as the silhouette feature vector, the model is oriented and scaled into the canonical unti cube. Instead of three silhouettes, six grey-scale images are rendered using parallel

projection, two each for principal axes. Each pixel encodes in an 8-bit grey value the distance from the viewing plane of the object. These images correspond to the concept of z-buffer of depth buffer in computer graphics.

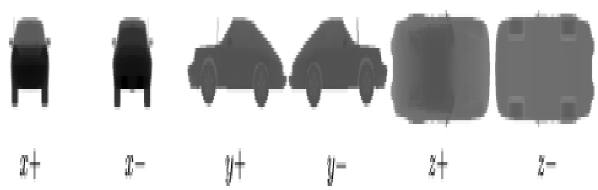

Fig: 2. Depth buffer-based feature vector.

2.2 Statistical Based Feature Vector

Features that are derived from several randomly selected points on the mesh, such that a distance between two randomly selected points is purely statistical. Histogram is the most prominent tool for representing randomized features[9,10].

2.2.1 Simple statistics

Bounding volume, object orientation, and object volume density feature vector are probably the most basic shape descriptors and this simple statistics are widely used in the CAD domain. The authors [11] review several possible simple shape descriptors. The bounding volume (BV) is given by the volume of the minimal rectangular box that encloses a 3D object. The orientation of this bounding box is usually specified parallel to either the coordinate frame or parallel to the principal axes of the respective object.

2.2.2 Parameterized Statistics

A statistical feature vector which is composed of three measures taken from the partitioning of a model into slices orthogonal to its three principal axes is proposed by Ohbuchi [12]. The FV consists of $3 * 3 * (n - 1)$ components, where n is the number of equally-sized bins along the principal axes.

2.2.3 Geometric 3D Moment

Moments have been used in feature vectors for 3D object retrieval. The moments are not invariant with respect to translation, rotation, and scale of the considered distribution, appropriate normalization should be applied before moment calculation. When given as a polygon mesh, candidates for input to moment calculation are the mesh vertices, the centers of mass of triangles, or other object points sampled by some scheme. A FV can then be constructed by concatenating several moments. Studies that employ moments as descriptors for 3D retrieval include Vranic and Saupe [13] where moments are calculated for object points sampled uniformly with a ray-based scheme , and Paquet [11] where moments are calculated from the centers of mass (centroids) of all object faces. Another publication that proposed the usage of moments for 3D retrieval is Elad et al. [14]. A user performs an initial query using a feature vector of several moments under the Euclidean norm and iterate through this process until a satisfactory result is obtained. The authors conclude that this process is suited to improve search effectiveness.

2.2.4 Shape Distribution

Osada [10] propose describing the shape of a 3D object as a probability distribution sampled from a shape function, which reflects geometric properties of the object. The algorithm calculates histograms called shape distributions and estimates similarity between two shapes by any metric that measures distances between distributions (e.g., Minkowski distances). Depending on the shape function employed, shape distributions possess rigid transformation invariance, robustness against small model distortions, independence of object representation, and efficient computation.

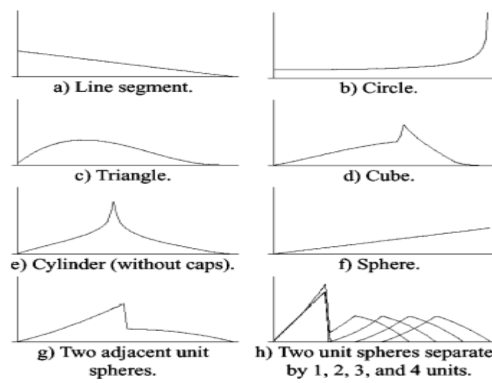

Fig: 3. D2 distance histograms for some example objects. (adapted from Osada [12]).

2.2.5 Cords-Based Feature Vector

Paquet [11] present a descriptor that combines information about the spatial extent and orientation of a 3D object. The authors define a cord as a vector that runs from an object's center of mass to the centroid of a face of the object. For all object faces, such a cord is constructed. The descriptor consists of three histograms, namely, for the angles between the cords and the object's first two principal axes, and for the distribution of the cord length, measuring spatial extension. The three histograms are normalized by the number of cords. Using the principal axes for reference, the descriptor is invariant to rotation and translation. It is also invariant to scale as the length distribution is binned to the same number of bins for all objects. It can be inferred that the descriptor is not invariant to nonuniform tessellation changes.

2.3 3d Geometry Based Feature Vector

To present 3D geometry that are based on object surface measures. These surface measures include surface curvature measures as well as the distribution of surface normal vectors.

2.3.1 Surface Normal Directions

Paquet and Rioux [11] consider histograms of the angles enclosed between each of the first two principal axes and the face normals of all object polygons. It is possible to construct either one unifying histogram, or two separate histograms for the distribution with respect to each of the two first principal axes, or a bivariate histogram which reflects the dependency between the angles. The bidimensional distribution contains the relevant information. Still, such histograms are sensitive to the level of detail by which the model is represented.

2.3.2 Surface Curvature

Zaharia and Preteux [15] present a FV for 3D retrieval proposed within the MPEG-7 framework for multimedia content description. The feature vector reflects curvature properties of 3D objects. The shape spectrum FV is defined as the distribution of the shape index for points on the surface of a 3D object which is a function of the two principal curvatures.

The shape index is a scaled version of the angular coordinate of a polar representation of the principal curvature vector, and it is invariant with respect to rotation, translation and scale by construction.

2.3.3 Extended Gaussian Image

The distribution of the normals of the polygons that form a 3D object can be used to describe its global shape. To represent this distribution is using the Extended Gaussian Image (EGI) by Horn at el.[16]. The EGI is a mapping from the 3D object to the Gaussian sphere (Figure 4). To compute the EGI of a 3D object , the normal vectors of all polygons of the 3D objects are mapped onto the respective point of the Gaussian sphere that has the same normal as the polygon. Retrieval performance studies were performed by Kazhdan [8].

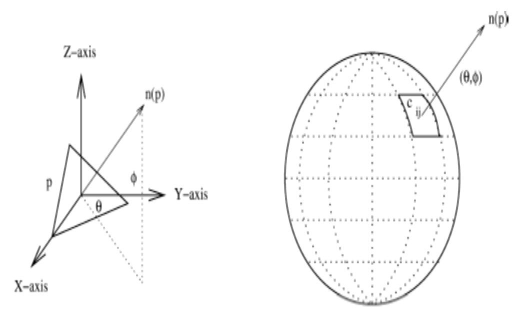

Fig: 4. Mapping from object normals to the Gaussian sphere. [Horn at el.]

2.4 Volume-Based Feature Vector

The volume based feature vector posses many desirable properties like translation, rotation, scale and reflection invariance, robustness with respect to level-of-detail,different tessellations and multiresolution feature representation.

2.4.1 Discretized Model Volume

A class encompassing several 3D Feature vector that are all derived from some form of volumetric discretization of the models is reviewed next. Here, the basic idea is to construct a feature vector from a model by partitioning the space in which it resides, and then aggregating the model content that is located in the respective partitioning segments to form the components of feature vectors. One method is the shell model which partitions the space into shells concentric to the object's center of mass, keeping radii intervals constant.

The sector model decomposition uses equally-sized segments obtained by forming Voronoi partitions around rays emitted from the model origin and pointing to the vertices of an enclosing regular polyhedron. A combined model uses the intersection of shells and sectors, see Figure 5 for an illustration.

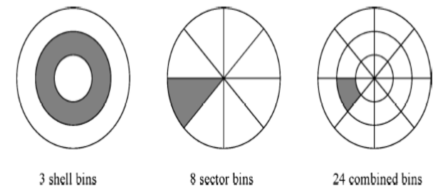

Fig:5. Combination of Shells and sectors.

2.5 Voxel Based Feature Vector

Vrani´c and Saupe [13] present a FV, based on the rasterization of a model into a voxel grid structure and experimentally evaluate the representation of this FV in both the spatial and the frequency domain The voxel descriptor is obtained by first subdividing the bounding cube of an object (after PCA-based rotation normalization) into n × n × n equally-sized voxel cells.

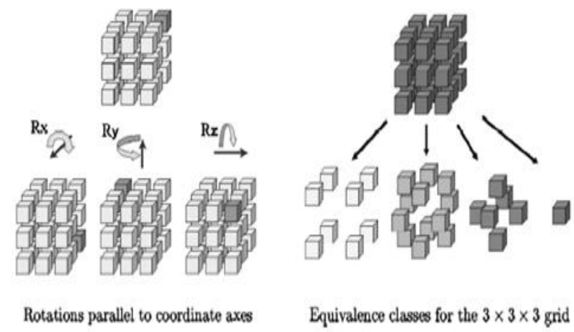

Fig: 6. Feature-vector based similarity search in 3D objects databases.

The object's voxel cell occupancies constitute the FV of dimension n3. For similarity estimation with this FV, a metric can be defined in the spatial domain (voxel), or after a 3D Fourier-transform in the frequency domain (3DFFT). Then, magnitudes of certain k low-frequency coefficients are used for description, enabling multiresolution search. The voxel-based feature vector compares occupancy fractions of voxelized models in the spatial or frequency domain.

2.6 Functions on the Sphere-Based Feature Vector

A 3D mesh model can be projected on an enclosing sphere. A point on the sphere is attributed a value, which can be a distance, surface area curvature index.

2.6.1 Ray-Based Sampling with SphericHarmonics Representation

Vrani´c and saupe [7,13] proposed a feature vector framework that is based on taking samples from a PCA-normalized 3D object by probing the polygonal mesh along regularly spaced directional unit vectors uij as defined and visualized in Figure. The samples can be regarded as values of a function on a sphere (||uij || = 1). The so-called ray-based feature vector measures the extent of the object from its center of gravity O in directions uij .The extent r(uij) = ||P(uij) − O|| in direction uij is determined by finding the furthest intersection point P(uij) between the mesh and the ray emitted from the origin O in the direction uij . If the mesh is not intersected by the ray, then the extent is set to zero, r(uij) = 0. The number of samples, 4B2 (Figure), should be large enough (e.g., B ≥ 32) so that sufficient information about the object can be captured. The samples obtained can be considered components of a feature vector in the spatial domain.

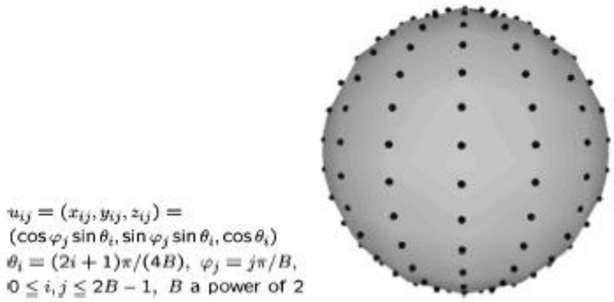

Fig: 7. The number of samples using spherical harmonics .

In order to characterize many samples of a function on a sphere by just a few parameters, spherical harmonics by Healy [17] are proposed as a suitable tool. The magnitudes of complex coefficients, which are obtained by applying the fast Fourier transform on the sphere (SFFT) to the samples, are regarded as vector components. Thus, the ray-based feature vector is represented in the spectral domain where each vector component is formed by taking into account all original samples.

3. CONCLUSION

This survey paper described a variety of recently proposed feature vector based techniques visualizing 3D objects, The feature vector approach maps 3D objects to a vector of real values that can be used for distance calculation. Further it is applicable for the multimedia indexing techniques.

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