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3D OBJECTS RETRIEVAL USING SPHERICAL HARMONICS FEATURE VECTOR METHOD

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Abstract- As the amount of new information generated in the world rapidly increases, efficient search in collections of structured data, texts and multimedia objects. 3D objects are an important type of multimedia data with many applications. The approach is based on feature vector 3D methods for searching and using algorithm for content based retrieval of 3D objects. The feature vector is obtained by forming a complex function on the given object. Apply the Fast Fourier Transform (FFT) on the object and obtain Fourier coefficients for spherical harmonics. Retrieval efficiency of the new approach is evaluated by constructing precision/recall diagrams and using 3D model databases.

Introduction

Recent advances in the area of computer visualization and 3D retrieval techniques have rapidly growing amount of 3D object databases. The www is enabling access to 3D models constructed by the people all over the world. 3D objects will be an important part of digital libraries in the future. An important issue is how to search for 3D objects like text, images, audio and video. Automatic content based methods for similarity estimation of multimedia objects are required. Search methods for 3D objects have some problem to achieve desirable properties. They have to select similar object for their characteristics. A feature-vector (FV) is used for approach multimedia retrieval. Feature-vector can be applied on any multimedia databases. We will use it from the perspective of 3D object databases.

There are many feature vectors which are considered to represent 3D model shape, such as Shape histogram by Mihael et al.[11], Geometry images by Hamid et al. [7], Aspect graph by Christopher and Benjamin [5], Visual similarity by Chen et al.[4], Skeleton based similarity by Sundar et al.[13], 3D Fourier transform based descriptor by Vranic [15], Topology matching by Masaki et al.[9], Physical Moment by Michael et al.[10] and cube based 3D similarity by Wang et al.[16].

Success of implementation of this model highly depends on the category of the shape of the model. It is applicable for the wide area of multimedia indexing techniques which have been researched by Bohm et al.[3].

Retrieval systems may also have been researched for semi interactive query enhancement methods, like relevance feedback by Elad et al.[6], annotation information proposed by Zhang and Chen [17], or feature selection and combination techniques by Bustos et al.[2].

For each model, feature vectors are automatically extracted and stored. 3D objects in searching nearest neighbors in the feature vector space. The feature vector is obtained by forming a complex function on the sphere then we apply the Fast Fourier coefficients for spherical harmonics. Retrieval efficiency of the new approach is evaluated by constructing precision/recall diagram and using 3D object databases. 3D objects are used in many application domains, different from for object representation; manipulation and presentation have been developed. The most widely used representation is to approximate a 3D object by a mesh of polygons.

Content based 3D retrieval system requires following

2.1 Normalization

3D models are given in arbitrary units of measurement and in unpredictable positions and orientations in 3D shape. The normalization step transforms model into a canonical coordinate frame. The goal of this procedure is that if one can chose a different scaled, translated, rotated or flipped model, then the representation in the canonical coordinate frame would be the same. Moreover, since objects may have different levels-of-detail, their normalized representations should be the same as much as possible.

2.2 Feature vector extraction

The features of 3D models are stored as vectors with real-valued components and fixed dimension. Varnic and Saupe[14] proposed feature range from simple bounding box parameters to complex image-based representations. There is a trade off between the required storage, computational complexity and the resulting retrieval performance.

2.3 Calculating the distance between feature vector
All models from an available database are compared to a query object by calculating distance between selected type of feature vectors. The feature vectors are considered as points in the search space and the best match is the nearest neighbor. The L1 and L2 norms are conventionally used to calculate distances in the feature space.

Normalization
The normalization step is needed to insure the invariance requirement for most of the 3D-shape descriptors. By normalization, finding a canonical coordinate frame taken from Vranic et al.[15]

3.1 Algorithm for normalization

1. Given a triangle mesh as consisting of a set of triangles $T=\{T_{1,.......,}T_m\}, T_i \subset R^3$.
2. Given a set of vertices $P=\{p_1,....., p_n\}$, $\left(p_i=(x_i, y_i, z_i)\in R^3\right)$
3. $I=\bigcup_{i=1,.......m} T_i$ is the point set of all triangles of given object.
4. To derive an linear transformation (affine map) $\tau : R^3 \to R^3$ in such way that for an arbitrary concatenation σ of translations, rotations, reflections, and scaling the desired invariance property of τ, i.e. $P' = \tau(P) = \tau(\sigma(P))$.
5. Let S_i be the surface area of triangle $T_i, i = 1,......,m$.
6. The surface area of the whole object is given by $S := S_1 + ...+ S_m = \int\int_I ds$.
7. The translation invariance is accomplished by finding the center of gravity of a model $c = S^{-1}\int\int_I v ds(v \in I)$ and forming the point set $I^{'} = \{u \mid u = v - c, v \in I\}$.
8. To secure the rotation invariance we apply the "continous" PCA on the set $I^{'}$. First, calculate the covariance matrix C(type 3x3) by $C = S^{-1}\int\int_I u.u^T ds(u \in I')$
   (i) Matrix C is a symmetric real matrix, therefore, its eigenvalues are positive real numbers.
   (ii) Then, sort the eigenvalues in the non-increasing order and find the corresponding eigenvectors. The eigenvectors are scaled to the Euclidean unit length.
   (iii) To Form the rotation matrix R, this has the scaled eigenvectors as rows. Rotate all the points of $I^{'}$ and form the new point set $I^{''} = \{w = (w_x, w_y, w_z) \mid w = R.u, u \in I^{'}\}$.
9. The scaling invariance is obtained using the matrix $F = diag(sign(f_x), sign(f_y), sign(f_z))$ where $f_x = S^{-1}\int\int_{I''} sign(w_x) w_x^2 ds$ (f_y, f_z analogously).
10. The scaling invariance is provided by the scaling factor $s = \sqrt{\left(s_x^2 + s_y^2 + s_z^2\right)/3}$, where $s_x, s_y,$ and s_z represent average distances of points $w \in I^{''}$ from the origin along x,y and z axes, respectively. These distances are calculated by $s_x = S^{-1}\int\int_{I''} |w_x| ds$ (s_y, s_z analogously).
11. Putting all the above together, the linear transformation affine map τ is defined by $\tau(p) = s^{-1}.F.R.(p - c)$.
    The canonical coordinate are obtained by applying τ to the initial point set I. In practice, transform only the set of vertices P into the canonical coordinate P ', because the topology remains the same.

Using this algorithm for normalizing 3D model, and then apply the feature vector extraction for improving the retrieval performance.

Feature Vector Extraction
Most of the feature vectors are extracted in the canonical co-ordinate frame of a 3D-model. Feature extraction follows after the complete normalization.

4.1 Spherical harmonics with complex function
The sphere $S^2 \subset R^3$ is a sphere of an arbitrary radius with the center at the origin. For example a normalized model I define a function f on the sphere S^2,

$$f : S^2 \to K$$
$$u \to f(u)$$

where $K = \{0,1\}$, $K \equiv R$ or $K \equiv C$. This function $f(u)$ measures a property of the object in the directions given by

$$u = u(\theta, \phi) =$$
$$(\cos\phi \sin\theta, \sin\phi \sin\theta, \cos\theta) \in S^2,$$
$$0 \le \theta \le \pi,\ 0 \le \phi \le 2\pi$$

Hence, f depends only on angular co-ordinates θ and ϕ. This angle θ is measured down from the z-axis, while ϕ is measured counterclockwise of the x-axis.

An algorithm for defining 3D-shape descriptors based on a function on the sphere S^2 is extracted by the following steps:

1. Define a function $f(u)$ on the S^2.
2. Sample f at $4B^2$ points u_{ab} defined , $B \in \{32,64,128,256,512\}$;
3. Perform the SFFT to obtain B^2 complex coefficients $\hat{f}_{l,m}(|m| \le l < B)$;
4. Find the magnitudes | $\hat{f}_{l,m}$ | of the obtained coefficients

$$
\begin{array}{ccccccc}
 & & & |\hat{f}_{0,0}| & & & \\
 & & |\hat{f}_{1,-1}| & |\hat{f}_{1,0}| & |\hat{f}_{1,1}| & & \\
 & |\hat{f}_{2,-2}| & |\hat{f}_{2,-1}| & |\hat{f}_{2,0}| & |\hat{f}_{2,1}| & |\hat{f}_{2,2}| & \\
|\hat{f}_{3,-3}| & |\hat{f}_{3,-2}| & |\hat{f}_{3,-1}| & |\hat{f}_{3,0}| & |\hat{f}_{3,1}| & |\hat{f}_{3,2}| & |\hat{f}_{3,3}|
\end{array}
$$

5. If f is a complex-valued function, then take the magnitudes $|\hat{f}_{l,m}|$ from the first k rows of coefficients $(|m| \le l \le k)$ as components of the feature vector f.

$$f = \left(|\hat{f}_{0,0}|, |\hat{f}_{1,-1}|, |\hat{f}_{1,0}|, |\hat{f}_{1,1}|, \ldots\ldots\ldots, |\hat{f}_{k-1,-k+1}|, \ldots\ldots\ldots, |\hat{f}_{k-1,0}|, \ldots\ldots\ldots, |\hat{f}_{k-1,k-1}|\right)$$

$$\Rightarrow \dim(f) = k^2$$

6. If f is a real-valued function, then the symmetry exists. The feature vector f is composed by taking the magnitudes $|\hat{f}_{l,m}|$ with positive values of the index m and half of the magnitudes $|\hat{f}_{1,0}|$ from the first k rows of the obtained coefficients($l < k$);

$$f = \left(|\hat{f}_{0,0}|/2, |\hat{f}_{1,0}|/2, |\hat{f}_{1,1}|, \ldots\ldots |\hat{f}_{k-1,0}|/2, \ldots\ldots, |\hat{f}_{k-1,k-1}|\right)$$

$$\Rightarrow \dim(f) = k(k+1)/2.$$

That a feature vector formed either using step 5 or step 6 contains all feature vectors of the same type of smaller dimension, providing an embedded multi-resolution representation for 3D shape feature vector.

The use of Spharmonic kit by Healy et al.[8] should correct the normalization problem that exists. After the SFFT, the obtained co-efficients $\hat{f}_{l,m}$ should be scaled as follows:

$$\hat{f}_{l,m} \leftarrow 2\sqrt{\pi}\,\hat{f}_{l,m} \quad , \quad \hat{f}_{l,0} \leftarrow \sqrt{2\pi}\,\hat{f}_{l,0} \quad ,$$

$l \le |m| \le l$, $0 \le l \le B$

The inverse scaling should be performed before the inverse transform. Note that feature vector derived in this way contain all feature vectors of the same type of smaller dimensions. Therefore, an embedded multi-resolution feature representation is provided.

4.2 Tools for Evaluation of Retrieval Effectiveness

Baiza and Ribeiro [1] proposed common tools from information retrieval theory. The tools are based on precision and recall values. The precision recall diagrams are use to compare competing feature vectors.

4.3 Distance between two feature vector

We also examined how the choice of distance metric (l_1, l_2, $l-\max$,ScaledL1) affects the retrieval. Apply all distances presented above. Test the application of the L1 distance to rescaled feature vector. Compute the distance between two feature vectors FV1 and FV2 Since 3D-shape descriptors are usually represented as N-dimensional vectors with real-valued components, a natural way to compute distances between feature vectors is to use a vector norm.

Let

$$f' = (f'_1, \ldots\ldots\ldots, f'_N),\ f'' = (f'', \ldots\ldots f''_N) \in R^N$$

be two feature vectors. The l_p distance between f' and f'' is defined by

$$d_p(f', f'') = \|f' - f''\|_p = \left(\sum_{i=1}^{N} |f_i' - f_i''|^p\right)^{1/p}, \ p = 1,2,\ldots\ldots\ldots$$

(1)

For $p = 1$, then the l_1 norm,

$$d_1(f', f'') = \|f' - f''\|_1 = \sum_{i=1}^{N} |f_i' - f_i''| \tag{2}$$

while for p =2, then the l_2 norm of the difference $f' - f''$, which is called Euclidean metric

$$d_2(f', f'') = \|f' - f''\|_2 = \sqrt{\sum_{i=1}^{N} (f_i' - f_i'')^2} \tag{3}$$

When $p \to \infty$, the $l-$infinity (or l_∞ or $l-\max$) norm,

$$d_1(f', f'') = \|f' - f''\|_\infty = \max_{1 \le i \le N} |f_i' - f_i''| \tag{4}$$

The l_p norm is usually ineffective as the distance metric of features in the spatial domain. The definition of the l_p norm, that the component-wise differences $f' - f''$ are equally important. According to eq. (1), it is assumed that the individual components of the feature vector are independent of each other.

Scaled l_1 // The l_1 norm of each FV is normalized to 1 first, and then the l_1, distance is computed.

The database used for retrieval experiments contains 1800 3D objects downloaded from Internet. In this set, 292 objects were classified by shape into 25 different model classes and rests of them were unclassified. Classified set of 3D object database shown in table. Each classified object was used as a query object, and the objects belonging to the same model class, excluding the query were considered relevant to it. All three classifications of 3D models, which are used in experiments, are shown in table 1.

Experimental result of spherical harmonic feature vector representation

In this section , we evaluated the spherical harmonic using the first k rows of Fourier coefficients, obtaining the feature vector of dimension dim=k(k+1)/2. To demonstrate the results, we selected precision-recall curves of three classifications Train datasets, Test datasets and AllModels.

We suggest sampling the extent function r at 128^2 points defined by applying the Fourier transform on the sphere. We used distance L1, L2, Lmax and Scaled L1 length of each feature vector. Scaled L1 perform the best result.

Conclusion

The entire implemented feature vector showed good robustness with respect to the level of detail of the 3D objects. We also observed significant variance with respect to the effectiveness of retrieval when comparing the results for classes of models and unclassified models. For different classes of models, a feature vector was the most effective one. The reported feature vector extraction method presents the important achievements in the search for general purpose, fast retrieval algorithm for 3D object databases.

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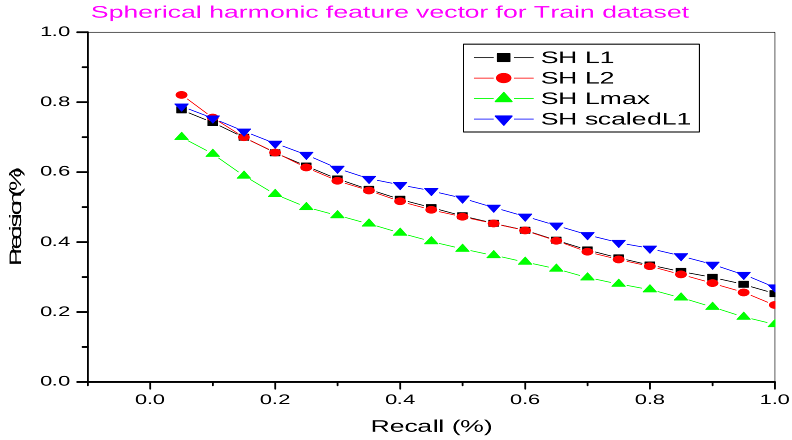
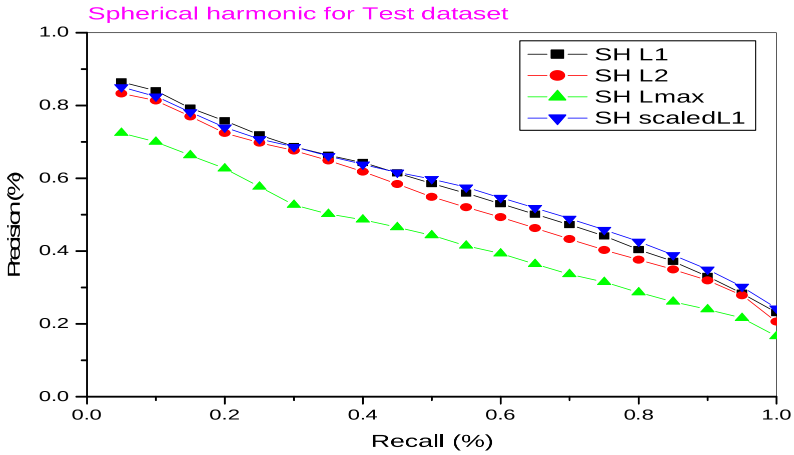
Table 1-Classifications of 3D models

Classification	Training data set	Test data set	All Models
Number of models	907	907	1840
Number of classified Models	907	907	170
Number of unclassified Models	0	0	1680
Average number of vertices	4071	4373	5660
Average number of triangles	7326	7960	10304





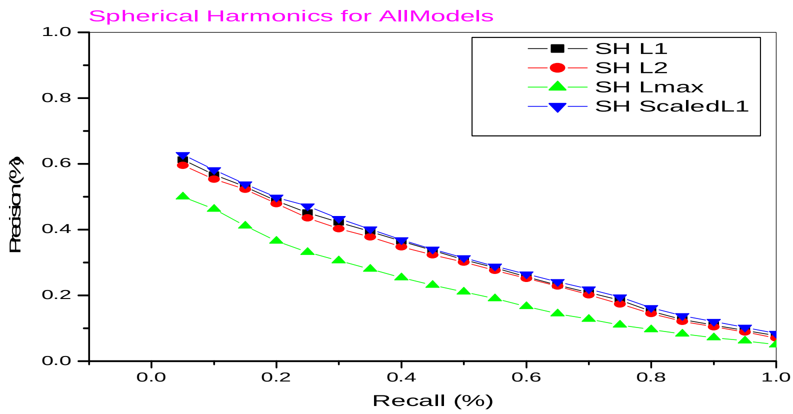


Fig. 1