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3D Object Retrieval via Range Image Queries based on SIFT descriptors on Panoramic Views

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Abstract

The increasing availability of low-cost 3D scanners is resulting in the creation of large repositories of 3D models. Low-cost 3D range scanners in particular can also be used to capture partial views of real 3D objects which can then act as queries over 3D object repositories. This paper concerns a new methodology for 3D object retrieval based on range image queries which represent partial views of 3D objects. SIFT descriptors based on panoramic views are used to address this problem. The proposed method is evaluated against state-of-the-art works on a standard dataset.

Categories and Subject Descriptors (according to ACM CCS): I.3.8 [Computer Graphics]: Applications—I.3.7 [Computer Graphics]: Three-Dimensional Graphics and Realism—I.4.8 [Image Processing and Computer Vision]: Scene Analysis—Range Data

1. Introduction

3D model retrieval has now considerably matured and a number of very accurate and robust descriptors have been proposed by our team [PPTP09, SPT11] and others [CSTO03, KFR03, Vra05]. These methodologies use a 3D object query to search a database of 3D models in a content-based manner. However, in practical situations, it is often difficult to come up with a suitable 3D object query in the first place: this has either to be found or built, a random and time-consuming action respectively. Nowadays, 3D scanners that typically produce range images are becoming common place and cheap, e.g. Microsoft Kinect [SFC*11]. It would thus, be beneficial, to use as query the range scan of a real object. Realizing this trend, a special track of the SHREC competition [DGA*,DGC*] was set up for this purpose.

A number of challenges exist. First, a range scan only represents a partial object. Second, range scans can be rough and noisy. Third, it is not straightforward how to bridge the gap between the 3D model representation and the range scan, i.e. how to produce descriptors that can be relatively invariant to these two representations. The problem with the partial data that a range scan represents is that it is not possible to effectively match them against a full 3D model representation, since most of it may be missing. The representation gap makes it difficult to extract a signature that will be (at least partially) similar when presented with a full, clean 3D model and when presented with a partial and noisy range scan of a similar query object.

We have addressed the above challenges by using a sequence of 3 steps to extract our descriptor, both for full 3D models as well as for range scan queries. First we compute a number of panoramic views on axes, which are perpendicular to the faces of a dodecahedron. Each axis defines three panoramic view cylinders (one for the axis itself and two more for any two axes that, along with the first one, make up an orthonormal basis). In the second step we use the corner detection algorithm of He and Yung [HY08] in order to create a set of candidate points that are independent of the orientation of a panoramic view. Finally in the third step, we apply the SIFT algorithm to the points given by the corner detector.

The remainder of the paper is structured as follows. In Section 2, recent work in 3D model retrieval based on range image queries is discussed. Section 3 details the proposed method and Section 4 presents experimental results achieved

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in the course of the method's evaluation. Finally, conclusions are drawn in Section 5.

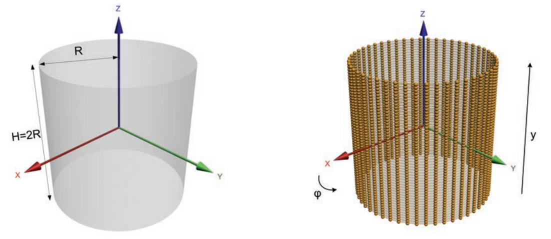
2. Related Work

Over the last few years, the number of works addressing the problem of multimodal 3D model retrieval, and more specifically the retrieval of 3D models based on range scan queries, have increased significantly. Although this task still remains non-trivial, the quality of the works presented shows that important steps have been made in the field. The works presented in the sequel have either directly used captured range scans (i.e. from a 3D range scanner) or artificially produced them from the complete 3D models.

A significant number of works use real range scans, or artificially produced range images. This choice was made because, until recently, there was no standard dataset for testing, or the existing datasets were not always suitable for the specific properties of the task (e.g. occlusions existence, single or multiple objects etc). Hetzel et al. [HLLS01] explore a view based approach for the recognition of free-form objects in range images. They combine a set of local features (pixel depth, surface normal and curvature metrics) in a multidimensional histogram in order to achieve classification. Chen and Bhanu [CB07] introduce a local surface descriptor for 3D model recognition. This descriptor is computed on feature points of a 3D surface, where large shape variations occur. The local surface descriptor is characterized by its centroid, its local surface type and a 2D histogram which shows the frequency of occurrence of shape index values vs. the angles between the normal of reference feature point and that of its neighbors. Adan et al. [AMS11] explore the use of Depth Gradient Image (DGI) models for the recognition of 3D models. The DGI representation synthesizes both surface and contour information, for a specific viewpoint, by mapping the distance between each contour point and the edge of the viewpoint image in terms of internal and external object pixels. This measure is computed for the entire model, taken from the nodes of a tessellated sphere. Ohbuchi et al. [ONT03] proposed the Multiple Orientation Depth Fourier Transform (MODFT) descriptor where the model is projected from 42 viewpoints to cover all possible view aspects. Each depth buffer is then transformed to the $r-\theta$ domain and the Fourier transform is applied. To compare two models, all possible pairs of coefficients are compared which inevitably increases comparison time.

Another subset of presented works use range images from standard 3D model datasets like the Princeton Shape Benchmark (PSB) [SMKF04] and the SHREC datasets. Stavropoulos et al. [SMM*10] present a retrieval method based on the matching of salient features between the 3D models and query range images. Salient points extracted from vertices that exhibit local maxima in terms of protrusion mapping for a specific window on the surface of the model. A hierarchical matching scheme based is used for the matching. The authors experimented on range images acquired from the SHREC'07 *Watertight models* [GBP07] and the PSB standard datasets. Chaouch and Verroust-Blondet [CVB06] present a 2D/3D shape descriptor which is based on either silhouette or depth-buffer images. For each 3D model a set of six projections in calculated both silhouette and depth-buffers. The 2D Fourier transform is then computed on the projection. Furthermore, they compute a relevance index measure which indicates the density of information contained in each 2D view. The same authors in [CVB07] propose a method where a 3D model is projected to the faces of its bounding box giving 6 depth buffers. Each depth buffer is then decomposed into a set of horizontal and vertical depth lines that are converted to state sequences which describe the change in depth at neighboring pixels. Experimentations were conducted on range images artificially acquired from the PSB dataset. Shih et al. [SLW07] proposed the elevation descriptor where six depth buffers (elevations) are computed from the faces of the 3D model's bounding box and each buffer is described by a set of concentric circular areas that give the sum of pixel values within the corresponding areas. The models were selected from the standard PSB dataset.

Finally, an increasing number of works, use the datasets of the SHREC'09 *Querying with Partial Models* [DGA*] and SHREC'10 *Range Scan Retrieval* [DGC*] datasets, that aim at evaluating methods that retrieve full 3D models from range image queries, which have been acquired by range scanned real 3D objects, similar to those in the target dataset. Experimenting on the SHREC'09 dataset, Daras and Axenopoulos in [DA09] present a view-based approach for 3D model retrieval. The 3D model is initially pose normalized and a set of binary (silhouette) and range images are extracted from predefined views on a 32-hedron. The set of features computed on the views are the Polar-Fourier transform, Zernike moments and Krawtchouk moments. Each query image is compared to all the extracted views of each model of the dataset. Ohbuchi et al. [OOFB08] extract features from 2D range images of the model viewed from uniformly sampled locations on a view sphere. For every range image a set of multi-scale 2D visual features are computed using the Scale Invariant Feature Transform (SIFT) [Low99]. Finally, the features are integrated into a histogram using the Bag-of-Features approach [GEW06]. The same authors enhanced their approach by pre-processing the range images, in order to minimize interfere caused by any existing occlusions, and also and by refining the positioning of SIFT interest points, so that higher resolution images are favored [FO09, OF09]. Their works have experimented on and competed on both corresponding SHREC'09 and SHREC'10 datasets. Wahl et al. [WHH03] propose a four-dimensional feature that parameterizes the intrinsic geometrical relation of an oriented surface point pair (surflets). For a 3D model a set of surflet pairs is computed over a number of uniformly sampled viewing directions on the surrounding sphere. This work was one of



(a) (b)

Figure 1: (a) A projection cylinder for the acquisition of a 3D model's panoramic view and (b) the corresponding discretization of its lateral surface to the set of points $s(\phi_u, y_v)$

the two contestants of the SHREC'10 *Range Scan Retrieval* track.

3. Methodology

3D object retrieval via range image queries is performed as follows: (i) extract shape descriptors from the full 3D models of the dataset (off-line), (ii) extract a shape descriptor from the range image query (potentially on-line) and (iii) compare the query descriptor against the dataset descriptors.

In the case of the full 3D models of the dataset, a number of panoramic views of each model are extracted on axes that are defined by the axes of a dodecahedron, thus extending the PANORAMA [PPTP09] method to multiple axes. Each axis defines three panoramic view cylinders (one for the axis itself and two more for any two axes that, along with the first one, make up an orthonormal basis). To obtain a panoramic view, we project the model to the lateral surface of a cylinder of radius R and height $H = 2R$, centered at the origin with its axis parallel to one of the coordinate axes (see Fig. 1a). We set the value of R to $2 * d_{max}$ where d_{max} is the maximum distance of the model's surface from its centroid. In the following, we parameterize the lateral surface of the cylinder using a set of points $s(\phi, y)$ where $\phi \in [0, 2\pi]$ is the angle in the xy plane, $y \in [0, H]$ and we sample the ϕ and y coordinates at rates B and $2B$, respectively (we set $B = 540$). Thus we obtain the set of points $s(\phi_u, y_v)$ where $\phi_u = u * 2\pi/(B)$, $y_v = v * H/(2B)$, $u \in [0, B-1]$ and $v \in [0, 2B-1]$. These points are shown in Fig. 1b.

The next step is to determine the value at each point $s(\phi_u, y_v)$. The computation is carried out iteratively for $v = 0, 1, ..., B-1$, each time considering the set of coplanar $s(\phi_u, y_v)$ points i.e. a cross section of the cylinder at height y_v and for each cross section we cast rays from its center c_v in the ϕ_u directions. To capture the position of the model's surface, for each cross section at height y_v we compute the distances from c_v to the intersections of the model's surface with the rays at each direction ϕ_u.

Let $pos(\phi_u, y_v)$ denote the distance of the furthest from c_v point of intersection between the ray emanating from c_v in the ϕ_u direction and the model's surface; then $s(\phi_u, y_v) = pos(\phi_u, y_v)$. Thus the value of a point $s(\phi_u, y_v)$ lies in the range $[0, R]$, where R denotes the radius of the cylinder.

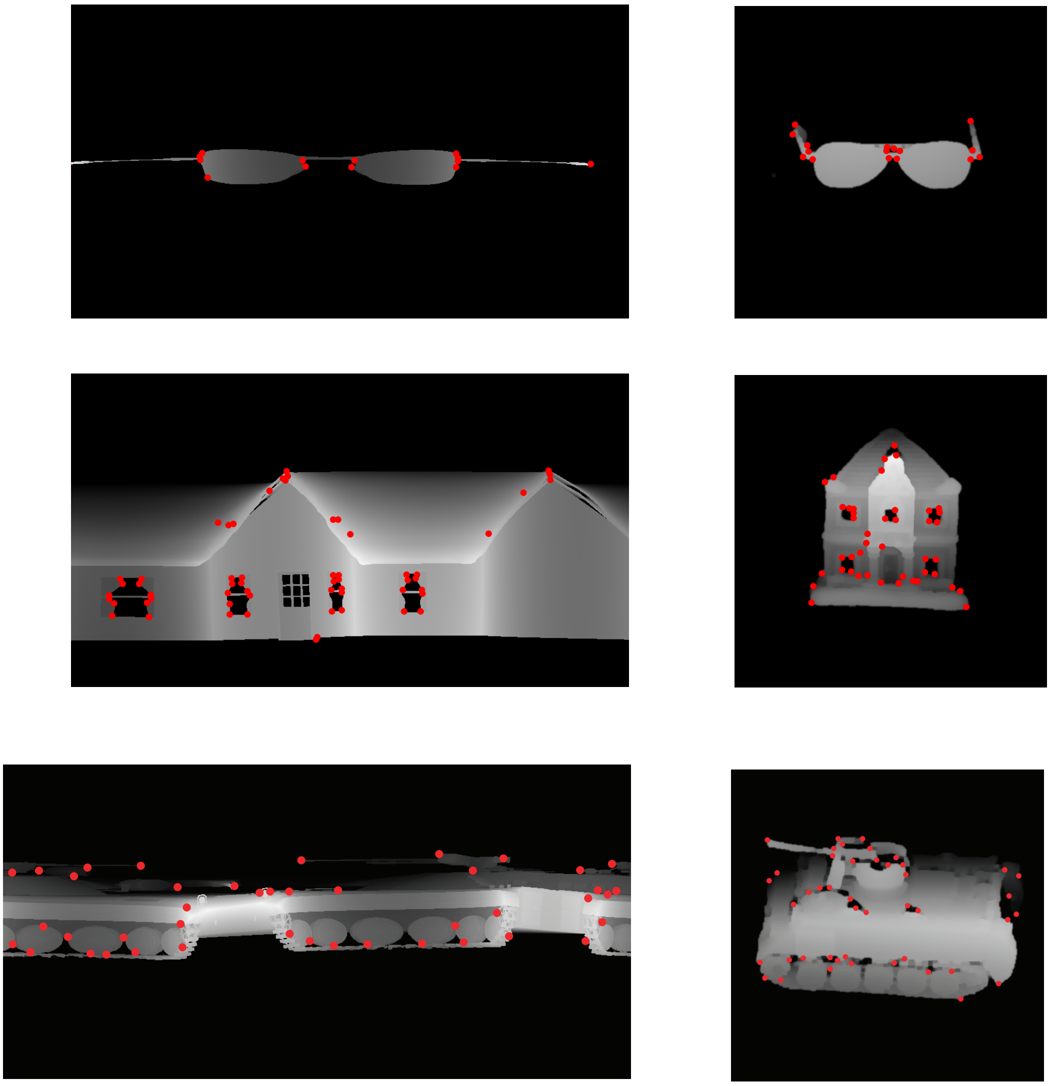
A cylindrical projection can be viewed as a 2D gray-scale image where pixels correspond to the $s(\phi_u, y_v)$ intersection points in a manner reminiscent of cylindrical texture mapping [TPPP07] and their values are mapped to the [0,1] range. In Fig. 2a, we show an example 3D model and in Fig. 2b the unfolded visual representation of its corresponding cylindrical projection $s(\phi_u, y_v)$.

Once the panoramic views have been extracted, the SIFT [Low99] descriptor is calculated on the cylindrical depth images. The first step of the SIFT computation, is the extraction of a number of interest points, where the SIFT descriptors are calculated on. The original implementation by Lowe, calculates these interest points through the Difference of Gaussians (DoG) method, which is geared towards high frequency information. In our approach we have chosen a method that detects both fine and coarse feature points, such as corners and surfaces of high curvature, on the extracted depth images; this is the corner detector described by He and Young in [HY08], which is an attractive alternative to the celebrated Harris corner detector [HS88]. Once the computation of the SIFT on the selected N ($N \leq 40$) corner points is complete, the resulting $N \times 128$-dimensional descriptor is stored as the full 3D model's signature. Fig. 3a shows sample interest points calculated on panoramic views of three sample 3D models of the classes *Glasses, SingleHouse* and *MilitaryVehicle*.

In the case of the range image query, the SIFT descriptor is computed directly on the 540×540 sampled range im-

(a) (b)

Figure 2: (a) An example 3D model and (b) its corresponding cylindrical projection on the z-axis.



(a) (b)

Figure 3: (a) Interest points computed on panoramic views of full 3D models that belong to the *Glasses, SingleHouse* and *MilitaryVehicle* classes. (b) Interest points on the query objects' depth images for the same objects.

age, in a similar manner. Since the query range image originates from *real* scanned data, a number of preprocessing steps are needed, for the elimination of noise and for closing any holes that may exist. These are achieved by: (i) Gaussian filtering of the range images, with $\sigma = 1$, (ii) dilation and morphological closing of the images. Steps (ii) are sequentially performed by using disk shaped morphological structuring elements (STREL) of size 3. Once the preprocessing is complete, the SIFT descriptor is computed on the N interest points defined by the corner detector and the result is stored as the query's signature. Fig. 3b shows sample interest points calculated on the range images of query objects of the classes *Glasses, SingleHouse* and *MilitaryVehicle*.

Finally the query descriptor must be matched against the 3D model dataset descriptors. To this end, every SIFT point of the range image is compared against every SIFT point of a 3D model's panoramic views. This comparison is performed by calculating the $L2$ distance, similarly to Lowe [Low99]. For each interest point of the range image, the least distance to the corresponding interest point of the 3D model's panoramic views is kept. The mean of these least distances is stored as the final distance of the query and the target model.

4. Evaluation

In this section we show the performance results of the proposed 3D model retrieval method on the SHREC'10 *Range Scan Retrieval* dataset. We compared against the variations of the BF-DSIFT-E method proposed by Ohbouchi and Furuya [OF09] and the variations of the SURFLET method proposed by Hillebrand et al. [WHH03].

According to the SHREC'10 classification scheme, the target subset is composed of 800 full 3D objects, classified into 40 classes, each of which contains 20 objects. The query set is composed of 120 partial 3D models of various corresponding classes.

Our experimental evaluation is based on Precision-Recall plots and five quantitative measures: Nearest Neighbor (NN), First Tier (FT), Second Tier (ST), E-measure (E) and Discounted Cumulative Gain (DCG) [SMKF04] for the classes of the corresponding datasets. For every query model that belongs to a class C, recall denotes the percentage of models of class C that are retrieved and precision denotes the proportion of retrieved models that belong to class C over the total number of retrieved models. The best score is 100% for both quantities. Nearest Neighbor (NN) indicates the percentage of queries where the closest match belongs to the query class. First Tier (FT) and Second Tier (ST) statistics, measure the recall value for the $(D-1)$ and $2(D-1)$ closest matches respectively, where D is the cardinality of the query's class. E-measure combines precision and recall metrics into a single number and the DCG statistic gives a sense of how well the overall retrieval would be viewed by a human [JK02]: similar shapes near the front of the list are more likely to appear at the top of the list.

In Figure 4, using the experimental results given in [DGC*], we illustrate the P-R scores for the complete SHREC'10 *Range Scan Retrieval* dataset for the proposed 3D model retrieval method and the methods by Ohbouchi and Hillebrand. Table 1 shows the corresponding five quantitative measures for the same methods.

Both the P-R scores, as well as the five quantitative measure of Table 1 clearly illustrate that the proposed method outperforms the SURFLET retrieval system and is competitive against the BF-DSIFT-E retrieval system. At this point we must note that the method proposed by Ohbuchi and Furuya requires a training stage, using the bag-of-words model [GEW06], while the proposed method is fully unsupervised, producing results relying only on the model descriptors.

The proposed method was tested on a Core2Quad 2.5 GHz system, with 6 GB of RAM, running Matlab R2010b. The system was developed in a hybrid Matlab/C++/OpenGL architecture, which resulted in very low computational times. The average descriptor extraction time for an 80,000 face 3D model is about 2 seconds.

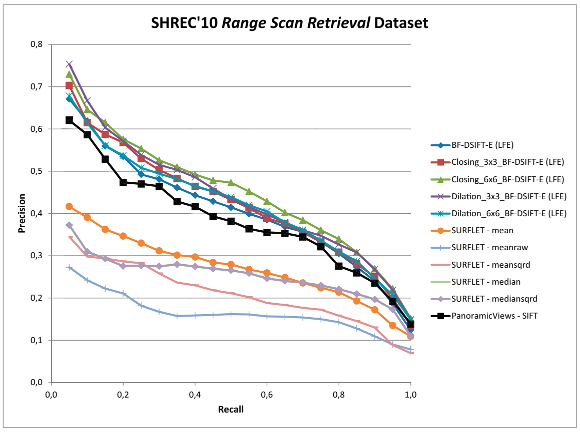


Figure 4: Average P-R scores for the SHREC'10 *Range Scan Retrieval* dataset. Illustrated methods are the proposed 3D object retrieval method, the variations of the BF-DSIFT-E method and the variations of the SURFLET method.

5. Conclusions

We have presented a new method for 3D object retrieval based on range image queries, by combining the properties of panoramic views and SIFT descriptors. The results outperform the SURFLET 3D object retrieval system and are competitive against the BF-DSIFT-E retrieval system on the SHREC'10 dataset, noting that the proposed method is fully unsupervised whereas BF-DSIFT-E uses the bag-of-words model, which requires training. Future work consists of improving the matching procedure to better reflect the properties of the panoramic views and the addition of a training step (similar to BF-DSIFT-E) to increase performance.

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Table 1: Comparison between the proposed 3D object retrieval system based on range images queries and the competitive methods presented on the on the SHREC'10 *Range Scan Retrieval* track using five quantitative measures. All measures are normalized.

Method	NN	FT	ST	E	DCG
BF-DSIFT-E (LFE)	0.573	0.380	0.524	0.367	0.683
Closing_3x3_BF-DSIFT-E (LFE)	0.598	0.393	0.535	0.382	0.696
Closing_6x6_BF-DSIFT-E (LFE)	0.650	0.424	0.569	0.398	0.713
Dilation_3x3_BF-DSIFT-E (LFE)	0.675	0.405	0.557	0.392	0.713
Dilation_6x6_BF-DSIFT-E (LFE)	0.547	0.395	0.550	0.386	0.696
SURFLET - mean	0.325	0.244	0.363	0.252	0.556
SURFLET - meanraw	0.171	0.153	0.242	0.163	0.462
SURFLET - meansqrd	0.231	0.197	0.322	0.213	0.513
SURFLET - median	0.282	0.226	0.325	0.224	0.528
SURFLET - mediansqrd	0.282	0.226	0.325	0.224	0.528
PanoramicViews - SIFT	0.512	0.374	0.466	0.256	0.598

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