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SHREC'12 Track: Sketch-Based 3D Shape Retrieval

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Abstract

Sketch-based 3D shape retrieval has become an important research topic in content-based 3D object retrieval. The aim of this track is to measure and compare the performance of sketch-based 3D shape retrieval methods implemented by different participants over the world. The track is based on a new sketch-based 3D shape benchmark, which contains two types of sketch queries and two versions of target 3D models. In this track, 7 runs have been submitted by 5 groups and their retrieval accuracies were evaluated using 7 commonly used retrieval performance metrics. We hope that the benchmark, its corresponding evaluation code, and the comparative evaluation results of the state-of-the-art sketch-based 3D model retrieval algorithms will contribute to the progress of this research direction for the 3D model retrieval community.

Categories and Subject Descriptors (according to ACM CCS): H.3.3 [Computer Graphics]: Information Systems—Information Search and Retrieval

1. Introduction

Sketch-based 3D model retrieval is to retrieve 3D models using a 2D sketch as input. This scheme is intuitive and convenient for users to search for relevant 3D models and also important for several applications including sketch-based modeling and sketch-based shape recognition. However, most existing 3D model retrieval algorithms target the Query-by-Model framework, that is, using existing 3D models as queries. Much less research work has been done regarding the Query-by-Sketch framework. In addition, until now there is no comprehensive evaluation or comparison for available sketch-based retrieval algorithms. Considering of this, we organize this track to foster this challenging research area by providing a common sketch-based retrieval benchmark and soliciting retrieval results from current state-of-the-art retrieval methods for comparison. We will also provide corresponding evaluation code for computing a set of performance metrics similar to those used in the Query-by-Model retrieval technique.

The objective of this track is to evaluate the performance of different sketch-based 3D model retrieval algorithms using both hand-drawn and standard line drawings sketch queries on a watertight 3D model dataset. Every participant will perform the queries and send us their retrieval results. We will then do the performance assessment.

In this paper, we report the results of five 3D retrieval algorithms tested in the Sketch-Based 3D Shape Retrieval track of SHREC 2012, held in conjunction with the fifth Eurographics Workshop on 3D Object Retrieval.

2. Data Collection

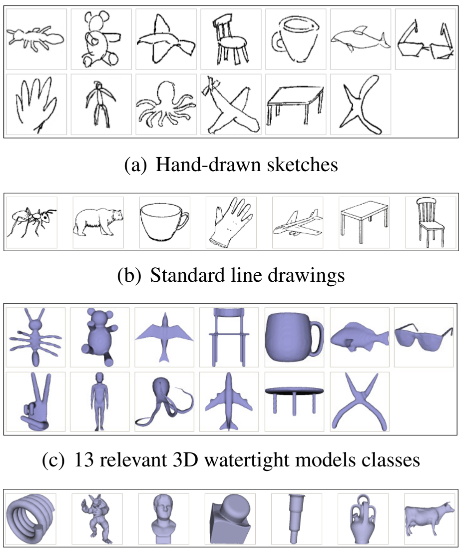
2.1. 3D Target Dataset

Our 3D benchmark dataset is built based on the Watertight Model Benchmark (WMB) dataset [VtH07] which has 400 watertight models, divided into 20 classes, with 20 models each. The 3D target dataset contains two versions: Basic and Extended. The **Basic version** comprises 13 selected classes from the WMB dataset with each 20 models (in summary, 260 models). In the basic version, all 13 classes are considered relevant for the retrieval challenge. Figure 1 (c) shows one typical example for each class of the basic benchmark. The **Extended version** adds to the basic version all remaining 7 classes of the WMB dataset (each 20 models). These additional classes, however, are not considered relevant for the retrieval challenge but added to increase the retrieval difficulty of the basic version. Figure 1 (d) illustrates typical examples for these remaining 7 irrelevant classes. The Extended version is utilized to test the robustness performance of a sketch-based retrieval algorithm.

2.2. 2D Query Set

The 2D query set comprises two subsets, falling into two different types.

- **Hand-drawn sketches** We utilize the hand-drawn sketch data compiled by TU Darmstadt and Fraunhofer IGD [YSSK10]. It contains 250 hand-drawn sketches, divided into 13 classes. One typical example for each class is shown in Figure 1 (a).
- **Standard line drawings** We also select 12 relevant sketches from the Snograss and Vanderwart's standard line drawings dataset [SV]. Some examples are shown in Figure 1 (b).
  In this track, the two subsets will be tested separately. However, users can also form a query set by combining these two to form a query set which contains diverse types of sketches.



(a) Hand-drawn sketches

(b) Standard line drawings

(c) 13 relevant 3D watertight models classes

(d) 7 irrelevant 3D watertight models classes

Figure 1: *Typical 3D model and 2D sketch for each class of Yoon et al.'s [YSSK10] benchmark.*

3. Evaluation

All the sketches and models are already categorized according to the classification of the WMB dataset, which contains 20 classes, as shown in Figure 1 (c) and (d). They are ant, teddy, bird, chair, cup, fish, glasses, hand, human, octopus, airplane, table, plier, spring, armadillo, bust, mechanic, bearing, vase and four legs, respectively.

To have a comprehensive evaluation of the retrieval algorithms, we employ seven commonly adopted performance metrics in 3D model retrieval technique. They are Precision-Recall plot (PR), Nearest Neighbor (NN), First Tier (FT), Second Tier (ST), E-Measures (E), Discounted Cumulated Gain (DCG) [SMKF04] and Average Precision (AP). We also have developed the code [SBR] to compute them.

4. Participants

Five groups have participated in SHREC'12 track on Sketch-Based 3D Shape Retrieval. Totally, seven rank list results (runs) for different methods have been submitted. The participants and their runs are listed as follows:

- *BOF-SBR* submitted by Mathias Eitz, Ronald Richter, Tamy Boubekeur, Kristian Hildebrand and Marc Alexa from TU Berlin, Germany and Telecom ParisTech/CNRS, France
- *SBR-2D-3D* submitted by Bo Li and Henry Johan from Nanyang Technological University, Singapore
- *HKO-KASD* submitted by Jose M. Saavedra, Benjamin Bustos, Tobias Schreck and Sang Min Yoon from University of Chile, Chile; University of Konstanz, Germany; and Yonsei University, Korea
- *Orig_DG1SIFT* and *Dilated_DG1SIFT* submitted by Tomohiro Yanagimachi, Jipeng Chen, Songhua Huang, Takahiko Furuya and Ryutarou Ohbuchi from University of Yamanashi and Nisca Corp., Japan
- *HOG-DTF* and *HOG-SC* submitted by Sang Min Yoon, Maximilian Scherer, Gang Joon Yoon, Tobias Shreck and Arjan Kuijper from Yonsei University, Korea; National Institute for Mathematical Science, Korea; GRIS, TU Darmstadt, Germany; University of Konstanz, Germany; and Fraunhofer IGD, Germany

5. Methods

5.1. Bag-of-Features Sketch-Based 3D Shape Retrieval, by Mathias Eitz, Ronald Richter, Tamy Boubekeur, Kristian Hildebrand and Marc Alexa [EHBA10]

The method employs a bag-of-features based approach for sketch-based shape retrieval [EHBA10] and uses non-photorealistic rendering (NPR) algorithms to extract important feature lines from a mesh. Recent research on such feature lines indicates that people agree on similar lines when asked to depict a certain model [CGL*08]. Additionally, the

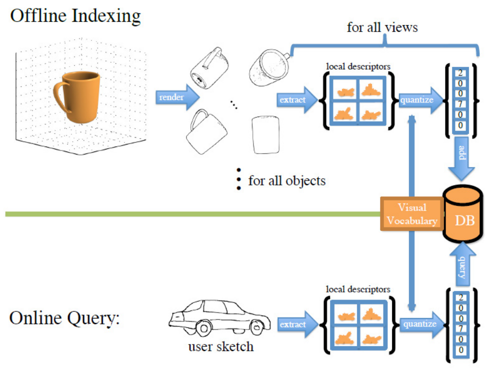


Figure 2: *System overview of BoF-SBR approach.*

set of feature lines generated by recent NPR methods is often sufficient to convey the shape of an object [CSD*09]. Building on those insights, an image-based approach is employed to 3D shape retrieval to exploit the similarity of human sketches and the results of current line drawing algorithms. The system takes a binary sketch of the desired model drawn by a user as the input and compares this sketch to a set of line drawings automatically generated for each of the models in the collection, see Figure 2.

5.1.1. Approach

In the approach, the 3D retrieval problem is mapped to a simpler image retrieval problem such that matching a user sketch to an NPR rendered view of a mesh is needed. However, this is still an extremely challenging problem due to two reasons:

- User sketches are typically extremely abstract with strong local and global distortions with respect to the original
- Retrieval should be fast as we can expect to see a growth in the size of future shape collection and it is roughly similar to the growth we have seen for image collections during the last decade

To account for those challenges, an engine is built upon a bag-of-features model. Robustness against deformations as well as translation invariance are achieved by using quantized local features. Retrieval is fast, as inverted indices are employed during a query.

1) Generating Views: A set of 102 views per model are generated by uniformly sampling from the bounding sphere of the model. Each point on the bounding sphere defines a camera position and is used as input for view-dependent line drawing algorithms. Specifically, occluding and suggestive contours [DFRS03] are extracted.

2) Local Descriptor: The method relies on a histogram of oriented gradients extracted from small local regions as previously employed for sketch-based image retrieval [EHBA11]. It uses 4x4 spatial bins and 4 orientational bins, resulting in 64-dimensional local descriptor. Each local feature is quadratic and covers 15% of the area of the view image, resulting in a large overlap between all features.

3) Histogram of Visual Words: Each view is represented using 1000 local features that do not carry any spatial information. A histogram of visual words is learned from a subset of those features using k-means clustering with 1000 clusters, and represent each view by its specific distribution of "visual words" using hard quantization.

4) Retrieval: To query a collection, the approach computes the histogram of visual words of the query image and returns those models with most similar views to the query. This process is accelerated by using inverted indices. As a result, only views that have at least one visual word in common with the query need to be compared and the query is extremely quick.

5.2. Sketch-Based 3D Model Retrieval by Incorporating 2D-3D Alignment, by B. Li and H. Johan [LJ12]

The algorithm [LJ12] consists of two stages which are precomputation and retrieval. The retrieval stage is divided into 2D-3D alignment utilizing a 3D model feature named View Context [LJ10] and 2D-3D matching based on relative shape context matching [BMP02]. The 2D-3D alignment step reduces the search space from many densely sampled views to only a set of candidate views, thus avoiding a directly brute-force matching between the sketch and many sample views. Its main idea is as follows: a sample view is replaced with the sketch and if its new View Context is very similar to the original one, then it is regarded as a candidate view.

1) Feature Extraction: Silhouette and outline feature views are generated for both 2D sketches and 3D models to effectively and efficiently measure the differences among them. Two examples are shown in Figure 3.

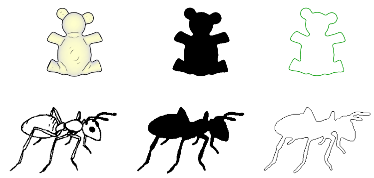


Figure 3: *The feature views of a 3D teddy model and a 2D ant standard line drawing sketch. For each row, from left to right: model/sketch, silhouette view; outline view.*

2) Feature Distance: A computationally efficient integrated image descriptor named *ZFEC* is adopted for View Context computation. It contains a region-based Zernike moments feature Z for the silhouette view and a contour-based Fourier descriptor feature F for the outline view. Additionally, eccentricity feature E and circularity feature C are also utilized to extract the geometric feature of the outline view. To more accurately measure the difference between the sketch and each candidate view, the relative shape context matching method [BMP02] is adopted.

3) Sketch's View Context Feature Extraction: The integrated image descriptor distances between the sketch and all the base views of the target model are computed and the resulting distance vector D^k=<d_1,d_2,...,d_m> is named sketch's View Context.

4) 2D-3D Alignment: To align the 2D sketch and a 3D model, some candidate views are shortlisted by keeping a certain percentage (e.g. 20% or 16 sample views for the track) of the sample views with top View Context similarities as the sketch, in terms of correlation similarity S_i,

$$S_i = \frac{D_i^s \cdot D^k}{\|D_i^s\| \, \|D^k\|}. \quad (1)$$

where, D_i^s and D^k are the View Contexts of the i^{th} sample view V_i^s of the 3D model and the 2D sketch, respectively.

5) Sketch-Model Distance Computation: Comparing the sketch with every candidate outline view using the relative shape context matching and regarding the minimum relative shape context distance obtained as the sketch-model distance.

6) Ranking and Output: Sorting all the sketch-model distances between the sketch and the models in an ascending order and listing the retrieved models accordingly.

5.3. HKO-KASD: Histogram of Keyshape Orientations - Keyshape Angular Spatial Descriptor, by J. M. Saavedra, B. Bustos, T. Shreck and S. Yoon [SBSY12]

To compare a hand-drawn image with a set of 3D models, the method transforms each 3D model into a set of projections that are computed using 14 suggestive contour (SC) images as specified by Yoon et al. [YSSK10].

The approach [SBSY12] comprises two stages. First, a global descriptor is used to determine the most appropriate SC for each 3D model having a query sketch as input. Next, it uses a local descriptor exploiting both structural and locality information provided by sketches or suggestive contour images.

5.3.1. Getting Keyshapes

First, let I be an edge map representation of a sketch or SC image. I is represented by a set of strokes $I = \{S_1, S_2, \ldots, S_{N_s}\}$. Second, for getting *keyshapes*, the method takes each stroke S to be approximated by a set of straight lines leading to define $I = l_1, l_2, \ldots, l_n$, where n is the total number of detected lines or *keyshapes*. Finally, *keyshapes* are classified as horizontal line (H), vertical line (V), diagonal line with slope 1 (D_1), or diagonal line with slope -1 (D_2).

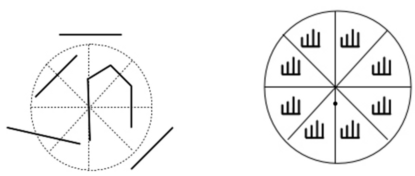
5.3.2. Global Approach: Histogram of Keyshape Orientations (HKO)

Unlike gradient-based global methods [DT05, SB10], the approach takes into account the information given by *keyshapes*. In this way, it computes a histogram of *keyshape* orientations (HKO) made up with the orientation of lines detected previously. It quantizes $\theta(L_i) \in [0, \pi]$ $(i = 1 \ldots n)$ into 8 bins. In this way, each HKO bin b represents the number of lines with orientation quantized as b, $b = 1, \ldots, 8$. The final descriptor is the corresponding unitary version of the HKO descriptor.

For each 3D model, the method chooses the suggestive contour image with the smallest distance to the input in terms of the HKO descriptor. It uses L_1 metric (Manhattan distance) as distance function.

5.3.3. Local Approach: Keyshape Angular Spatial Descriptor (KASD)

Let L_R be a referent *keyshape*, the approach defines a circular local region around L_R. In addition, the local region is divided in angular partitions (slices). An example of a local region and its partitions is depicted in Figure 4 (a).



(a) (b)

Figure 4: *(a) Local region around a referent* keyshape. *(b) Local descriptor and its 4-bin histogram for each slice.*

It proceeds to compute a 4-bin histogram for each partition (see Figure 4 (b)). This histogram represents the distribution of *keyshape* types around L_R computed for each edge pixel. Each bin corresponds to a *keyshape* type (H, V, D_1, D_2). The local descriptor is the unitary version of the juxtaposition of the eight histograms.

For matching a sketch S and a suggestive contour image C, the method solves an instance of the bipartite graph problem using the well known Hungarian Method [Kuh10] between sets of descriptors of the same class belonging to S and C. The final cost is the average match cost normalized by the number of matches. It uses as cost function the well known Manhattan distance.

5.4. Visual Features on Silhouettes for Sketch-Based 3D Model Retrieval, by T. Yanagimachi, J. Chen, S. Huang, T. Furuya and R. Ohbuchi [OF09]

The algorithm turns both query sketch and 3D model into silhouette images for image-based comparison. Its processing

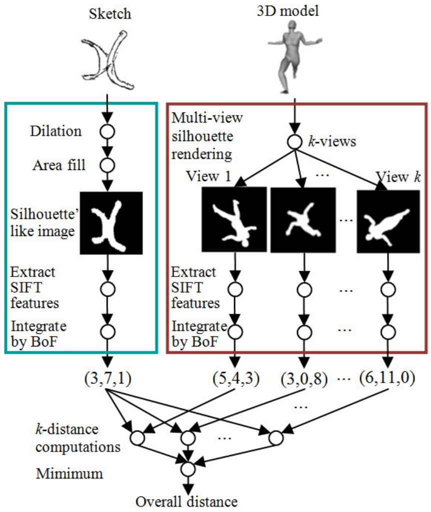


Figure 5: *Overview of the sketch-based 3D model query algorithm.*

pipeline (Figure 5) is quite similar to the one employed for the partial view 3D model retrieval track in SHREC 2009 [OF09]. Most of the code are the same between the two. However, scale weighting described in [OF09] was not employed for this track.

To make a filled, silhouette-like image from a sketch image with possible gaps in curcumference, the algorithm first applies dilation. Then, after most of the gaps are closed, area filling is done to turn majority of sketches into silhouette-like images. Inevitably, some of the sketches are left as non-silhouette drawings, possibly impacting retrieval performance. Each 3D model in the database is rendered from multiple (i.e., 42) viewpoints into silhouette images.

After both query and database models are turned into a set of silhouette images, their similarities are compared by using visual features. The method employs the same three features as the Generic 3D track, that are, set of local features Dense SIFT (DSIFT) and Grid SIFT (GSIFT), plus a global feature One SIFT (1SIFT). (Please refer to [FO09] and [LGA*12] for details on these features and their distance computation algorithms.) In sketch-based retrieval, a view of 3D model is compared against a sketch. Thus, for GSIFT and DSIFT, Bag-of-Features integration is performed per view, to produce feature vector per view. (For 3D-model-to-3D-model comparison of Generic 3D track, all the SIFT features from 42 views of a 3D model are integrated into a feature vector for the 3D model.) To have a reasonably well-populated histogram per view for DSIFT and GSIFT, the number of SIFT samples per view is increased from about 300 in [LGA*12] to about 1,200 for this track.

For each of the three features, 42 distances from a sketch to 42 views of a 3D model are computed. Minimum of the 42 distance values becomes the distance from the sketch to the 3D model. Three distances derived from three features are combined, after normalization, by using linear combination to become an overall distance from a sketch to a 3D model. Note that, unlike the Generic 3D track, the method does not use distance metric learning based on Manifold Ranking for this track.

5.5. Sketch-Based 3D Model Retrieval Using Histogram of Oriented Gradient in Diffusion Tensor Fields, by S.M. Yoon, M. Sherer, T. Shreck and A. Kuijper [YSSK10]

A new approach is proposed for content based 3D model retrieval by hand-drawn sketch images. This approach to retrieve visually similar mesh models from a large database consists of three major steps: (1) suggestive contour renderings from different viewpoints to compare against the user drawn sketches; (2) descriptor computation by analyzing diffusion tensor fields of suggestive contour images, or the query sketch respectively; (3) similarity measurement to retrieve the models and the most probable view-point from which a model was sketched.

This approach for 3D model retrieval using hand-drawn sketch images evaluates the similarity by comparing the query image to 14 projected views of the model by following the approach of Yoon et al. [YSSK10]. For each such image, it extracts a histogram of orientation from the corresponding diffusion tensor field.

1) Suggestive Contour Extraction from Different Viewpoints: To find the most similar features of the user-drawn sketches, it extracts the Suggestive Contours [DFRS03] to construct descriptors from different viewpoints. It closely resembles the way most people sketch three dimensional objects. To be able to compare 3D models and user sketches, it renders the suggestive contour of each model from 14 different, equally spaced viewpoints.

2) Feature Analysis in Diffusion Tensor Fields: To extract a feature vector from each suggestive contour image and the query image itself, the method analyzes its properties in the space of diffusion tensor fields [YG09].

3) Similarity Measure: The similarity between the query image I_c and one projected view image of a 3D model I_s, $S(I_c,I_s)$ is then given by the following equation:

$$S(I_c, I_s) = \frac{H_c \cdot H_s}{\|H_c\| \, \|H_s\|} \tag{2}$$

For user-drawn sketch based 3D model retrieval, the method projected the 3D model into 14 different viewpoints. The similarity measure between a query image and a 3D model is determined by extracting the $max|S(I_c,I_s)|$ from the 14 similarity values. In the track, this algorithm is denoted as HOG-DTF.

5.6. Sketch-Based 3D Model Retrieval Using Sparse Coding, by S.M. Yoon, G. J. Yoon and T. Shreck

The performance of any content-based 3D object retrieval system crucially depends on the availability of effective descriptors and similarity measures for this kind of data. An improved approach of Section 5.5 is presented for supporting 3D object retrieval by optimizing the appropriate gradient descriptor using a sparse coding approach, which is denoted as HOG-SC. It performs encompassing experiments, the results of which show that the retrieval quality outperforms existing state-of-the-art methods and is therefore recommended for sketch-based 3D object retrieval.

1) HOG-DTF Feature Descriptor: The same approach as *1)* and *2)* of Section 5.5.

2) Feature Optimization Using Sparse Coding: Used for feature optimization, sparse coding, which is well known to be powerful for retrieving similar 3D objects using a dramatically smaller trained dictionary, is regarded as a suitable technique for optimally representing an input HOG-DTF in terms of a linear combination of items in an overcomplete trained dictionary of basis vectors, with sparse coefficients that are sufficient for preserving specific features. Sparse coding is the method of finding the optimal representation of input data using a linear combination of an overcomplete trained dictionary basis with sparse coefficients for extracting or preserving specific features [CDS99,DE]. Sparse coding has become considerably popular to save or retrieve observed data using a dramatically small quantity of the preassigned dictionary of basis vectors (which consists of feature descriptors in some contexts). It uses the sparse coding algorithm proposed by Lee et al. [LBRN07].

6. Results

In this section, we perform a comparative evaluation of the results of the 7 runs submitted by the 5 groups. To have a comprehensive comparison, we measure the retrieval performance based on the 7 metrics mentioned in Section 3: *PR*, *NN*, *FT*, *ST*, *E*, *DCG* and *AP*.

As described in Section 2, there are two versions of target dataset: Basic and Extended. There are also two sets of sketch queries: hand-drawn sketches and standard line drawings, which will be tested separately. Thus, there are four combinations: (1) Hand-drawn sketch queries and Basic version of target dataset; (2) Standard line drawing queries and Basic version of target dataset; (3) Hand-drawn sketch queries and Extended version of target dataset; (4) Standard line drawing queries and Extended version of target dataset. Comparisons of the participating methods for the above four cases are respectively shown in Figure 6 and Table 1; Figure 7 and Table 2; Figure 8 and Table 3; and Figure 9 and Table 4. For some cases, results are not provided for certain group(s), while each group submit results for the first case, which is the most preliminary experiment.

First, we start with the overall performance evaluation. As shown in the aforementioned figures and tables, Li's SBR-2D-3D apparently performs the best, followed by Eitz's BOF-SBR. While, the performances of other remained three groups are comparable and the disparity among them is relatively small.

Second, we look into different types of queries. Compared to hand-drawn sketches queries, standard line drawing queries usually achieve superior performance. One reason is that the number of the standard line drawings for each class is limited, which is because of the essential property of this type of queries: standardization. Thus it does not have the diversity issues of the hand-drawn sketch queries. On the other hand, the standard line drawings also posses most important salient features of a typical class of object, which also explains its relatively higher retrieval accuracy.

Last but not least, we evaluate the robustness of different methods based on the provided results. Table 5 lists the percentage of performance decrease based on the hand-drawn sketch queries and the two versions of target dataset. Similarly, we can find that Li's SBR-2D-3D is the most robust, followed by Eitz's BOF-SBR. Compared to these two approaches, other three methods show more decrease in the retrieval performance when adding the irrelevant models to the target dataset. The conclusion also applies on the standard line drawing sketch queries.

In addition, we classify the five participants into different types based on different standards. Three groups (Eitz, Saavedra and Yoon) utilize suggestive contours to extract 3D model features. Two groups (Etiz and Yanagimachi) adopt the Bag-of-Words framework. Three groups (Eitz, Saavedra and Yanagimachi) employ local features while other two groups (Li and Yoon) perform global feature matching. Therefore, diverse approaches can be employed for the sketch-based 3D shape retrieval task and shape illustration techniques, Bag-of-Words approach and local/global shape matching methods are often utilized and promising in achieving better performance.

7. Conclusions

In this paper, we first present the motivation of the organization of this sketch-based 3D shape retrieval track. Then, we introduce our approach to build the benchmark including both target 3D models and 2D sketch queries. Next, we briefly introduce our evaluation method, followed by the short descriptions of the 6 methods (7 runs) submitted by 5 groups. Finally, a comprehensively comparative evaluation has been conducted in terms of accuracy, robustness and query types. Based on all the above comparisons, Li's SBR-2D-3D method performs the best, followed by Eitz's BOF-SBR approach while broadly speaking the other three groups are comparable in terms of overall performance.

This sketch-based retrieval track is the first attempt to in-

Table 1: *Other Performance metrics for the performance comparison on the Hand-drawn sketch queries and Basic version of target dataset*

Participant	Method	NN	FT	ST	E	DCG	AP
Eitz	BOF-SBR	0.532	0.339	0.497	0.338	0.662	0.450
Li	SBR-2D-3D	0.688	0.415	0.581	0.411	0.731	0.556
Saavedra	HKO-KASD	0.248	0.150	0.258	0.166	0.503	0.254
Yanagimachi	Orig_DG1SIFT	0.172	0.152	0.253	0.167	0.490	0.290
Yanagimachi	Dilated_DG1SIFT	0.212	0.168	0.276	0.183	0.503	0.302
Yoon	HOG-DTF	0.220	0.167	0.286	0.182	0.513	0.292
Yoon	HOG-SC	0.312	0.215	0.335	0.225	0.554	0.331

Table 2: *Other Performance metrics for the performance comparison on the Standard line drawing queries and Basic version of target dataset*

Participant	Method	NN	FT	ST	E	DCG	AP
Li	SBR-2D-3D	0.750	0.542	0.700	0.516	0.807	0.675
Saavedra	HKO-KASD	0.083	0.146	0.263	0.164	0.463	0.243
Yanagimachi	Orig_DG1SIFT	0.250	0.192	0.321	0.205	0.518	0.328
Yanagimachi	Dilated_DG1SIFT	0.333	0.225	0.363	0.240	0.567	0.373
Yoon	HOG-DTF	0.417	0.192	0.313	0.212	0.549	0.335
Yoon	HOG-SC	0.583	0.183	0.242	0.170	0.551	0.307

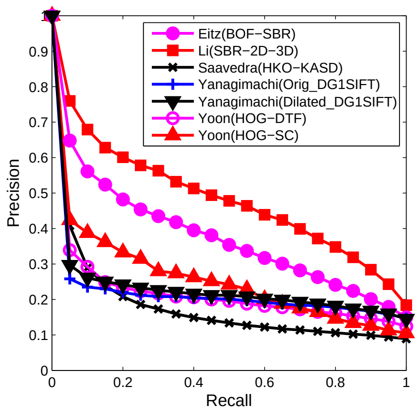


Figure 6: *Precision-Recall plot performance comparison on the Hand-drawn sketch queries and Basic version of target dataset.*

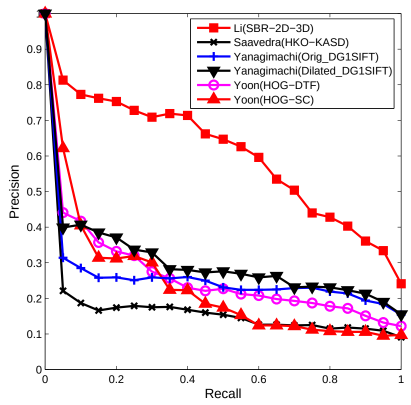


Figure 7: *Precision-Recall plot performance comparison on the Standard line drawing queries and Basic version of target dataset.*

clude this topic in SHREC in order to foster this challenging and interesting research direction. Even though it is the first time, we already have 5 groups who have successfully participated into the newly proposed track. In fact, the most important is that we provide a common platform (the benchmark) to solicit current latest sketch-based 3D model retrieval ap-

Table 3: *Other Performance metrics for the performance comparison on the Hand-drawn sketch queries and Extended version of target dataset*

Participant	Method	NN	FT	ST	E	DCG	AP
Eitz	BOF-SBR	0.460	0.278	0.412	0.281	0.614	0.383
Li	SBR-2D-3D	0.628	0.371	0.520	0.364	0.692	0.498
Yanagimachi	Orig_DG1SIFT	0.100	0.092	0.158	0.100	0.426	0.224
Yanagimachi	Dilated_DG1SIFT	0.168	0.120	0.212	0.137	0.462	0.254

Table 4: *Other Performance metrics for the performance comparison on the Standard line drawing queries and Extended version of target dataset*

Participant	Method	NN	FT	ST	E	DCG	AP
Li	SBR-2D-3D	0.750	0.454	0.625	0.442	0.750	0.574
Yanagimachi	Orig_DG1SIFT	0.083	0.100	0.163	0.106	0.426	0.224
Yanagimachi	Dilated_DG1SIFT	0.167	0.133	0.229	0.144	0.465	0.264

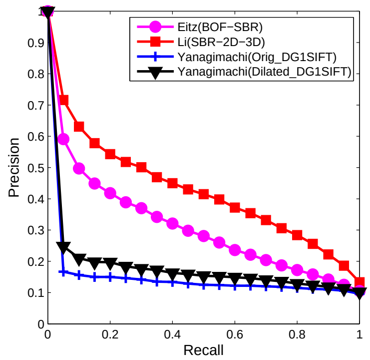


Figure 8: *Precision-Recall plot performance comparison on the Hand-drawn sketch queries and Extended version of target dataset.*

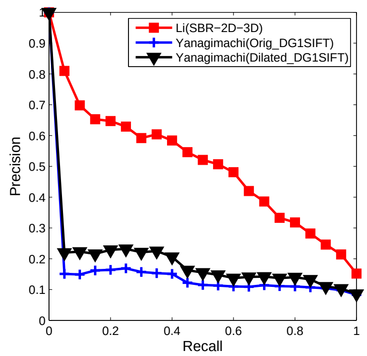


Figure 9: *Precision-Recall plot performance comparison on the Standard line drawings queries and Extended version of target dataset.*

proaches to help us to identify the current research progress and existing status that can be reached in terms of retrieval performance. We also hope that the sketch retrieval benchmark together with the evaluation code will become a good reference for researchers in this community.

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Table 5: *Robustness performance comparison in terms of performance decrease (%) on the Hand-drawn sketch queries.*

Participant	Method	NN	FT	ST	E	DCG	AP
Eitz	BOF-SBR	13.5	18.0	17.1	16.9	7.3	14.9
Li	SBR-2D-3D	8.7	10.6	10.5	11.4	5.3	10.4
Saavedra	HKO-KASD	53.2	40.0	36.8	38.6	14.5	22.0
Yanagimachi	Orig_DG1SIFT	41.9	39.5	37.5	40.1	13.1	22.8
Yanagimachi	Dilated_DG1SIFT	20.8	28.6	23.2	25.1	8.2	15.9

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