# Sketch/Image-Based 3D Scene Retrieval: Benchmark, Algorithm, Evaluation

Hameed Abdul-Rashid<sup>1</sup>, Juefei Yuan<sup>1</sup>, Bo Li<sup>1</sup>, Yijuan Lu<sup>2</sup>

<sup>1</sup>University of Southern Mississippi, <sup>2</sup>Texas State University

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- Related Work
- Benchmark
- Method
- Evaluation
- Conclusions and Future Work

### Introduction

- 2D Scene Sketch/Image-Based 3D Scene Retrieval (Scene\_SBR\_IBR) focuses on retrieving relevant 3D scene models using scene sketches/image(s) as input Motivation:
- - Vast applications: 3D scene reconstruction, autonomous driving cars, 3D geometry video retrieval, and 3D AR/VR Entertainment
- Challenges
  - 2D sketches/images lack 3D scene information they are supposed to present
  - Semantic gap between 2D scene iconic sketches or realistic images and accurate 3D scene models

2D Scene Sketch/Image-based 3D Scene retrieval (Scene\_SBR\_IBR) focuses on retrieving relevant 3D scene models using scene sketch(es)/image(s) as input.

# The Motivation of the Scene\_SBR\_IBR is that:

 It has vast applications such as 3D scene reconstruction, autonomous driving cars, 3D geometry video retrieval, and 3D AR/VR Entertainment

### Introduction

- Challenges contd.
  - o Brand new research topic in the field of sketch/image-based 3D object retrieval (Scene\_SBR\_IBR)
    - √ A query sketch/image contains <u>several</u> objects
    - ✓ Objects may overlap with each other
    - √ Relative context configurations among the objects
- To promote this challenging research direction, we built the most comprehensive and largest 2D scene sketch/image-based benchmark 3D scene retrieval benchmark Scene\_SBR\_IBR.

# But there are some existing challenges with 2D sketch/image-based 3D Scene Retrieval, which are:

- Firstly, 2D sketches/images lack 3D scene information they are supposed represent
- Secondly, there is still a semantic gap between 2D scene sketches/images and accurate 3D scene models
- Finally, it is a brand new research topic in the field of sketch/image-based 3D object retrieval:
  - $\checkmark$  A query image contains <u>several</u> objects
  - √ Objects may <u>overlap</u> with each other
  - ✓ There existing relative <u>context</u> configurations among the objects in a scene image/model

Considering the above, we built the most comprehensive and largest 2D scene

sketch/image-based benchmark 3D scene retrieval benchmark, **Scene\_SBR\_IBR.** 

### Outline

- Introduction
- Related Work
- Benchmark
- Method
- Evaluation
- Conclusions and Future Work

### Related Work

3D Scene Retrieval



3D Scene Retrieval

o Fisher and Hanrahan proposed context-based 3D model retrieval [1]

 Xu et. al proposed Sketch2Scene, a system for automatic 2D sketch-based 3D scene composition repu [2]

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[1] M. Fisher and P. Hanrahun. Context-based search for 3D models. ACM Trans. Graph., 29:182:1-182:10, 2011.

[2] B. Li and et al. A comparison of 3D shape retrieval methods based on a large-scale benchmark supporting multimodal queries, Computer Vision and Image Understanding, 131:1-27, 2015.

Fisher and Hanrahan proposed context-based 3D model retrieval, which retrieves models according to their spatial context in a 3D scene. They first locate the position of the model by drawing a 3D box and then searching relevant 3D models based on the dimensionality and context information.

Xu et. al proposed Sketch2Scene for automatic 2D sketch-based 3D scene composition by representing 3D scene objects' functional and spatial relationships based on structural groups.

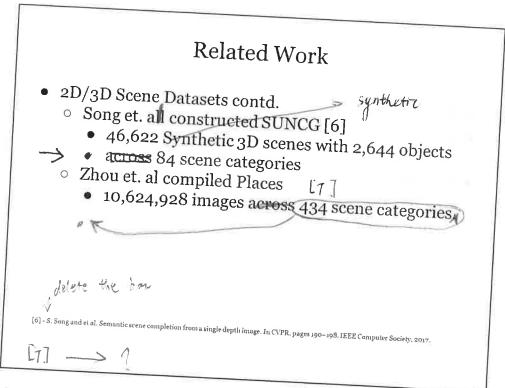
### Related Work

- 2D/3D Scene Datasets
  - o Xiao et. al built Scene UNderstanding (SUN) datacis
    - 130,519 images across 899 scene categories [3]
    - Expanded to 908 classes [4]
  - o Xiao et. al created SUN3D [5]
    - RGB-D video database with camera pose and object labelsx

delete the lars [4] -J. Xiao and et al. SUN database: Exploring a large collection of scene categories. International Journal of Computer Vision, 119(1):3-22, 2016 [5] J. Xiao and et al. SUN3D: A database of big spaces reconstructed using SM and object labels. In ICCV, pages 1625–1632, 2013.

Xiao et. al built SUN and introduced 130,519 images across 899 scene categories. This was later extended to include 908 scenes classes.

Xiao et. al also built SUN3D RGB-D video database that captures the full extent of 3D scenes with camera pose and object labels. Videos were used for partial 3D reconstruction and propagated labels between frames. Labels were then used to refine the final partial reconstruction.

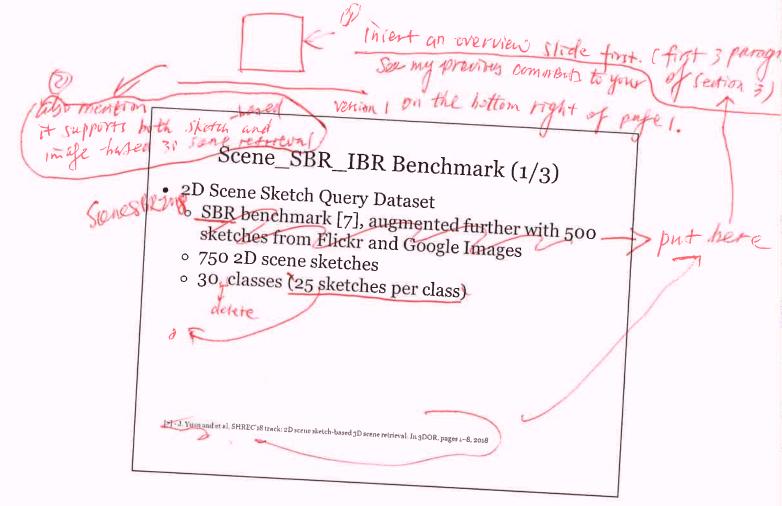


Song et. al constructed SUNCG, a database of synthetic 3D scenes with manually labelled voxel occupancy and semantic labels. SUNCG is categories.

Zhou et. al compiled Places, a database of 10,624,928 scene images across 434 scene categories. While, Places does not provide annotations at the object level, it provides the most diverse scene composition.

### Outline

- Introduction
- Related Work
- Benchmark
- Method
- Evaluation
- Conclusions and Future Work



The 2D Scene Sketch Query Dataset utilizes the 2D scene images in SBR benchmark further extends with sketches from Flickr and Google images.

• The 2D Scene Sketch Query Dataset utilizes the 2D scene images in Google (Contain)

 The 2D Scene Sketch Query Dataset 750 2D scene images categorized into 30 classes, each with 25 sketches each

# Scene\_SBR\_IBR Benchmark (1/3)

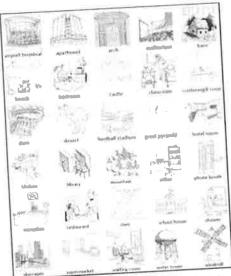
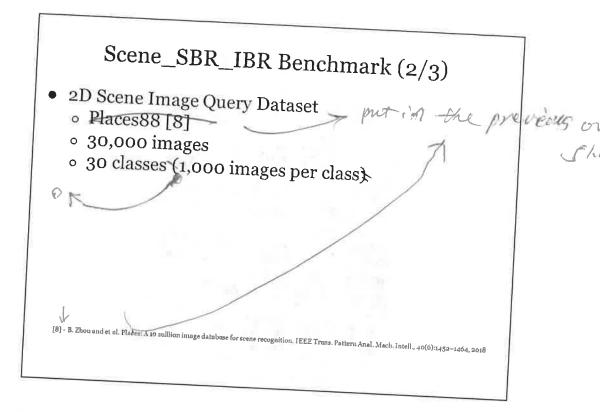


Fig. 1 Example 2D sketches (1 per class)



The 2D Scene Image Query Dataset utilizes the 2D scene images in Places 88 as its 2D scene image dataset

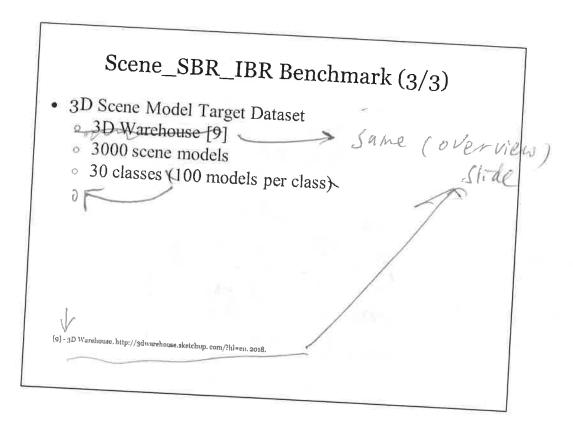
• The Places88 scene images contain 30,000 2D scene images categorized into 30 classes, each with 1,000 images each

Isome one not coming from places, we only use categornes information of places)

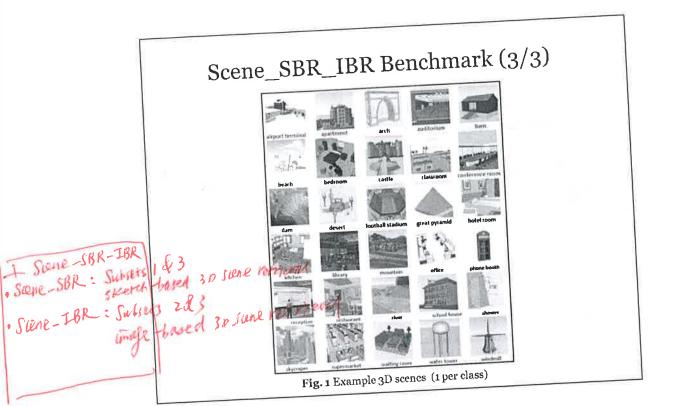
# Scene\_SBR\_IBR Benchmark (2/3)



Fig. 1 Example 2D scenes (1 per class)



oThe 3D scene dataset contains 3000 3D scene models collected from the 3D Warehouse. Similarly, they are categorized into the same 30 classes, but each having 100 models.



Testing 2- for tearning lased
Training

### Evaluation

- Seven commonly adopted performance metrics in 3D model retrieval technique [10, 11]:
  - o Precision-Recall plot (PR)
  - o Nearest Neighbor (NN)
  - First Tier (FT)
  - Second Tier (ST)
  - o E-Measures (E)
  - o Discounted Cumulated Gain (DCG)
  - Average Precision (AP)
- We also have developed the code to compute them
  - o http://orca.st.usm.edu/~bli/Scene SBR IBR/data.html

[10] -H. Abdul-Rashid and et al. SHREC'18 track: 2D scene image-based 3D scene retrieval. In 3DOR, pages 1-8, 2018.
[11] -J. Yuan and et al. SHREC'18 track: 2D scene sketch-based 3D scene retrieval. In 3DOR, pages 1-8, 2018.

There are seven commonly adopted performance metrics in 3D model retrieval technique, which are PR, NN, FT, ST, E, DCG and AP.

We also have developed the code to compute them, and the code can be downloaded from the provided link.

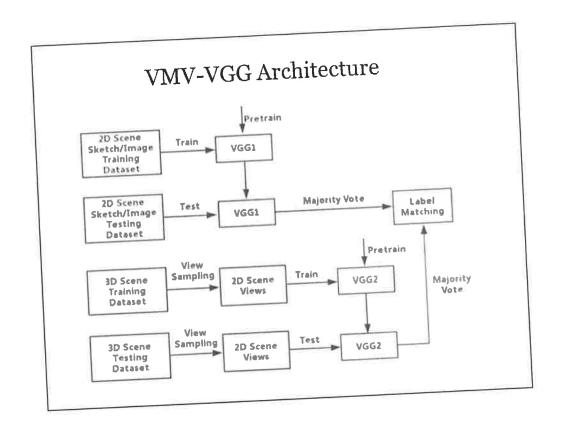
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- Introduction
- Related Work
- Benchmark
- Method
- Evaluation
- Conclusions and Future Work

Our Retrieval Algorithm VMV-VGG

Create an overview stide based on the list partagraph of Section 4.

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#### VMV-VGG

- Incorporates two different VGG-16 based models [12] (VGG1 and
- (1) 3D Scene view sampling
- (2) Data Augmentation on each training Batch
- (3) Pre-Training and Training on VGG1 and VGG2
- (4) Fine-tuning
- (5) Sketch/Image/View Scene Classification
- (6) Majority vote-based label matching



[12] - K. Simonyan and A. Zisserman. Very deep convolutional networks for large-scale image recognition. CoRR, abs/1409.1556, 2014.

- (1) Scene view sampling
  - Automate sample through QMacro script
  - ii. Uniformly sample 12 views along the equator of the sphere and 1 top-down view, for 13 views in total.
- (2) Data Augmentation
  - Perform random rotations, reflections or translations to augment each batch size per epoch.
- o (3) Pre-Training and Training on VGG1 and VGG2 Simplify sentency

- i. For the sketch-based retrieval
  - 1. VGG1 is pre-trained only on the TU-Berlin dataset [7] for 500 epochs
  - 2. VGG2 is pre-trained on only the Places data set for just 100 epochs
- ii. For the image-based retrieval
  - VGG1 and VGG2 is pre-trained on only the Places data set for just 100 epochs

### iii. For Training

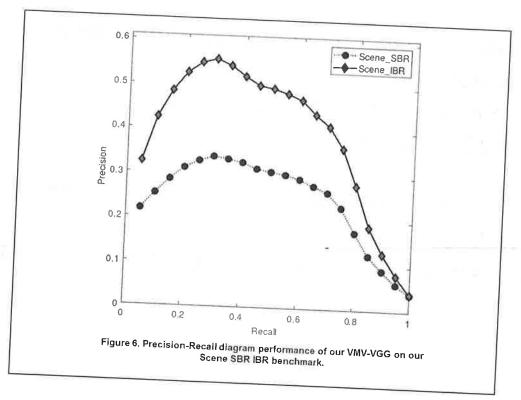
- VGG1 is trained on the 2D Scene Sketch/Image Query Dataset for 100 epochs
- VGG2 is trained on 2D views of the
   3D scene models for 50 epochs
- (4) Fine-tuning
  - i. Fine-tune the pre-trained VGG1/VGG2 models each 100/50 epochs
- 5) Sketch/Image/View Classification
  - i. We feed the well-trained model
     (VGG1/VGG2) alongside its
     corresponding testing query
     sketch/image or target scene view to
     obtain two classification vectors.

- (6) Majority vote-based label matching
  - i. We generate a rank list for each query by using a majority vote-based label matching method based on the query's classification vector and the target 3D scene's 13 classification vectors.

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- Introduction
- Related Work
- Benchmark
- Method
- Evaluation • Conclusions and Future Work



We have found that compared with the performance that has been achieved

in our two SHREC'18 tracks [21, 2] which used a much

smaller benchmark containing only 10 classes, in contrast to

the current 30 classes available in our new benchmark, the

overall performance dropped significantly for either type of

retrieval. For example, Li's MMD-VGG method, which

also utilizes VGG, has achieved an excellent overall per-

formance in terms of DCG (0.856) or AP (0.685) on the

SceneSBR benchmark, while they drop to DCG (0.533)

and AP (0.244) respectively based on our VMV-VGG.

Results: Performance Metrics

Benchmark	NN	FT	CYPE			
Scene_SBR	2.000		ST	$\mathbf{E}$	DCG	AP
	0.081	0.281	0.369	0.280		
Scene IBR	0.122	0.458	0.573		0.533	0.244
		01-100	0.3/3	0.452	0.644	0.392

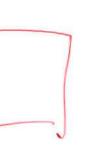
Performance metrics generated by running our VMV-VGG on our Scene SBR IBR benchmark.

This performance decrease should be a direct and natural result after a substantial increase in the comprehensiveness and

challenge level that exist in Scene SBR IBR after we incorporate much more scene categories.

The addition of more classes will

cause more ambiguities during the retrieval process and the retrieval algorithm may fail to properly distinguish between classes that share certain similarities.



Add a stide based on Section 5 and paragraph, to ellustrate

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- Introduction
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- Evaluation
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### Conclusions & Future Work

- Objective: To foster this challenging and interesting research direction: Scene Sketch/Image-Based 3D Scene Retrieval
- Dataset: Build the current largest 2D Scene sketch/image 3D scene retrieval benchmark
- Method: Baseline performance has been provided by VMV-VGG
- Evaluation: Performed a comparative evaluation on the accuracy



Sketch/Image-based 3D scene retrieval are research topics with a lot of application potentials. There is extremely limited preliminary work in this field, which allows us to explore many promising ideas and interesting results. In this paper, the currently

largest 3D scene retrieval benchmark Scene SBR IBR is

proposed with the hope to advance this research direction. To assist other interested researchers, the baseline

performance on the benchmark has been provided by conducting evaluation based on a proposed CNN classifier-based 3D scene retrieval algorithm VMV-VGG. Our future goals include: (1) building a large-scale and/or multimodal 2D scene sketch/image-based 3D scene retrieval

benchmark; (2) semantics-driven 2D scene sketch/image-based 3D scene retrieval.

## Conclusions & Future Work

- Build a large-scale and/or multimodal 2D scene-based 3D scene
- Semantics-driven 2D scene image-based 3D scene retrieval
- Impact: Provided the largest and most comprehensive common platform for evaluating 2D scene sketch/image-based 3D scene
- Build a large-scale and/or multimodal 2D scene-based 3D scene retrieval benchmark
- Semantics-driven 2D scene image-based 3D scene retrieval



Sketch/Image-based 3D scene retrieval are research topics with a lot of application potentials. There is extremely limited preliminary work in this field, which allows us to explore many promising ideas and interesting results. In this paper, the currently

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### References

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- [3] -J. Xiuo and et al. SUN database: Large-scale scene recognition from abbey to 200. In CVPR, pages 3485-3492, IEEE Computer Society,
- [4] J. Xiao and et al. SUN database: Exploring a large collection of scene categories. International Journal of Computer Vision, 119(1):3-22,
- [5] J. Niao and et al. SUN3D: A database of big spaces reconstructed using SIM and object lakels. In ICCV, pages 1625–1632, 2013. [6] - S. Song and et al. Semantic scene completion from a single depth image. In CVPR, pages 190–198. IEEE Computer Society, 2017.
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- [8] B. Zhou and et al. Places: A 10 million image database for scene recognition. IEEE Trans. Pattern Anal. Mach. intell., 40(6):3452-1464,
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Thank you!

Q&A?
E-mail: bo.li@usm.edu