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Perception and Computer Vision Lab.

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Surface IR Reflectance Estimation and Material Recognition using ToF Camera

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Introduction

Material Recognition

fabric

foliage

glass

leather

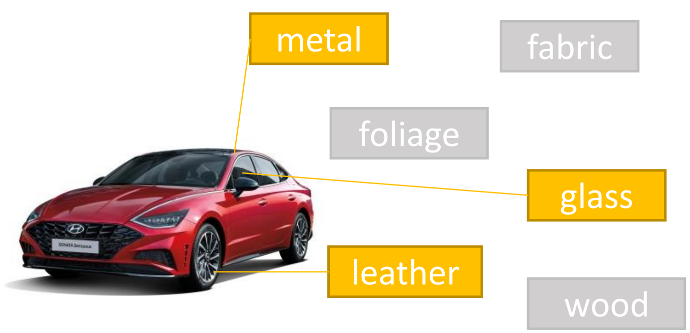
metal

. . .

Provides HIGH-LEVEL information to understand objects
that were not provided by <u>conventional features</u>

Color, Shape

Weak correlation between object and its visual features



Understanding material components helps to understand object itself.

Previous work

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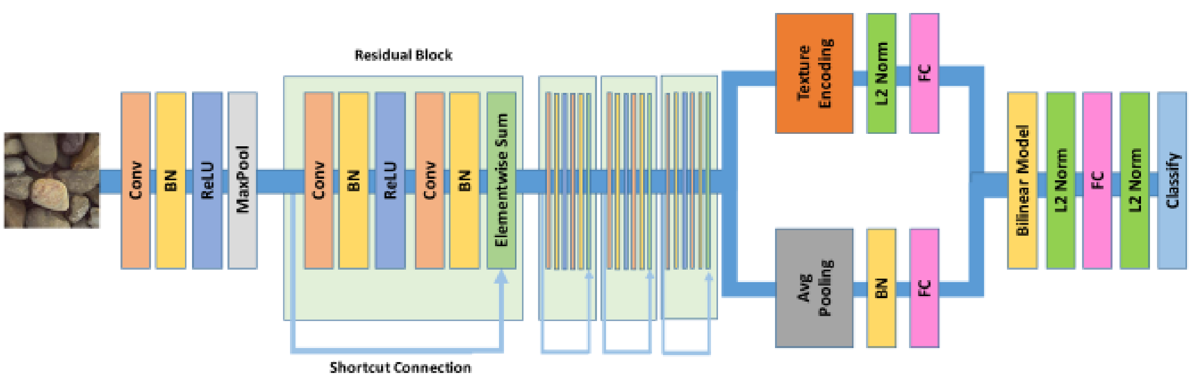
Material recognition in the wild with the materials in context databases

Bell et al. 2015 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)

- Context information based material classification
- *Golden-standard* dataset with 23 material classes

Deep Texture Manifold for Ground Terrain Recognition

Xue et al. 2018 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)



- Shows state-of-the-art performance with MINC dataset while using only color features

Previous work

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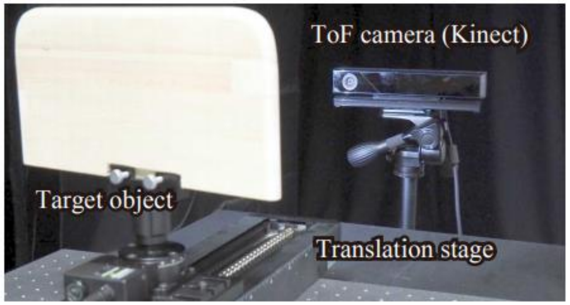
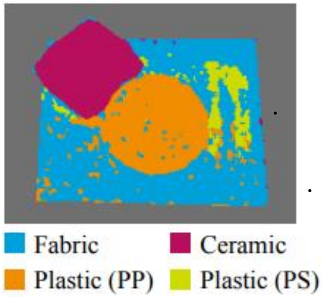
Material classification using frequency and depth-dependent time-of-flight distortion

Tanaka et al. 2017 IEEE Conference on Computer Vision and Pattern Recognition(CVPR)



(a) The scene of white utensils



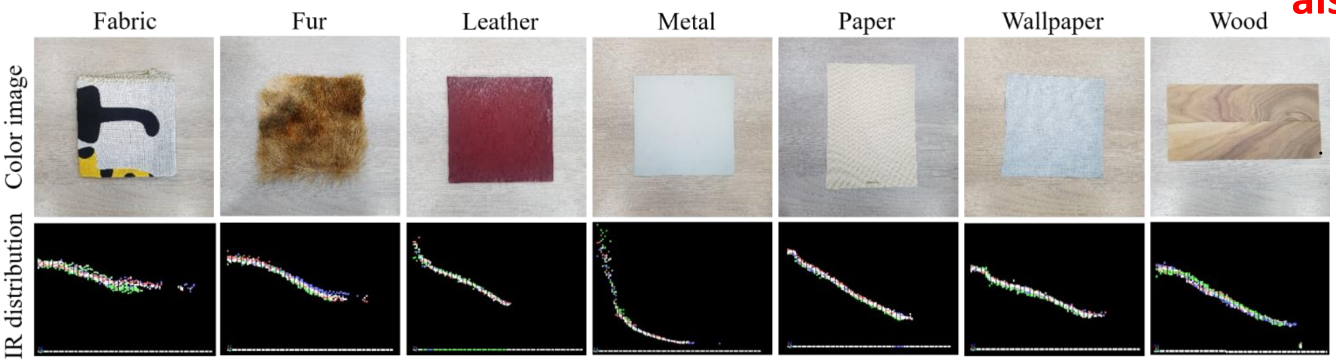
(b) Classification result

- Object translation required
- Restricted environment

IR Surface Reflectance Estimation and Material Type Recognition using Two-stream Net and Kinect Camera

Lee et al. 2019 ACM SIGGRAPH

This Color-IR data pairs were also used in our experiment



- Restricted Environment
- Limited Performance

Proposed work

1. Verification on Color-feature based Material Recognition

2. Surface Reflectance Estimation with practical environment

3. 3D Segment-wise Material Recognition

4. Two-stream Material Recognition Network with Gradual CNN

Proposed work

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1. Verification on Color-feature based Material Recognition

- MINC-2500: A subset of MINC with balanced class distribution (2500 samples / class)
- MINC-NEW: Another subset of MINC (same patch extraction rules with MINC-2500).
- OUR-NEW: A dataset collected from online (google) and offline(IKEA showroom), shares context information with MINC-2500.

Proposed work

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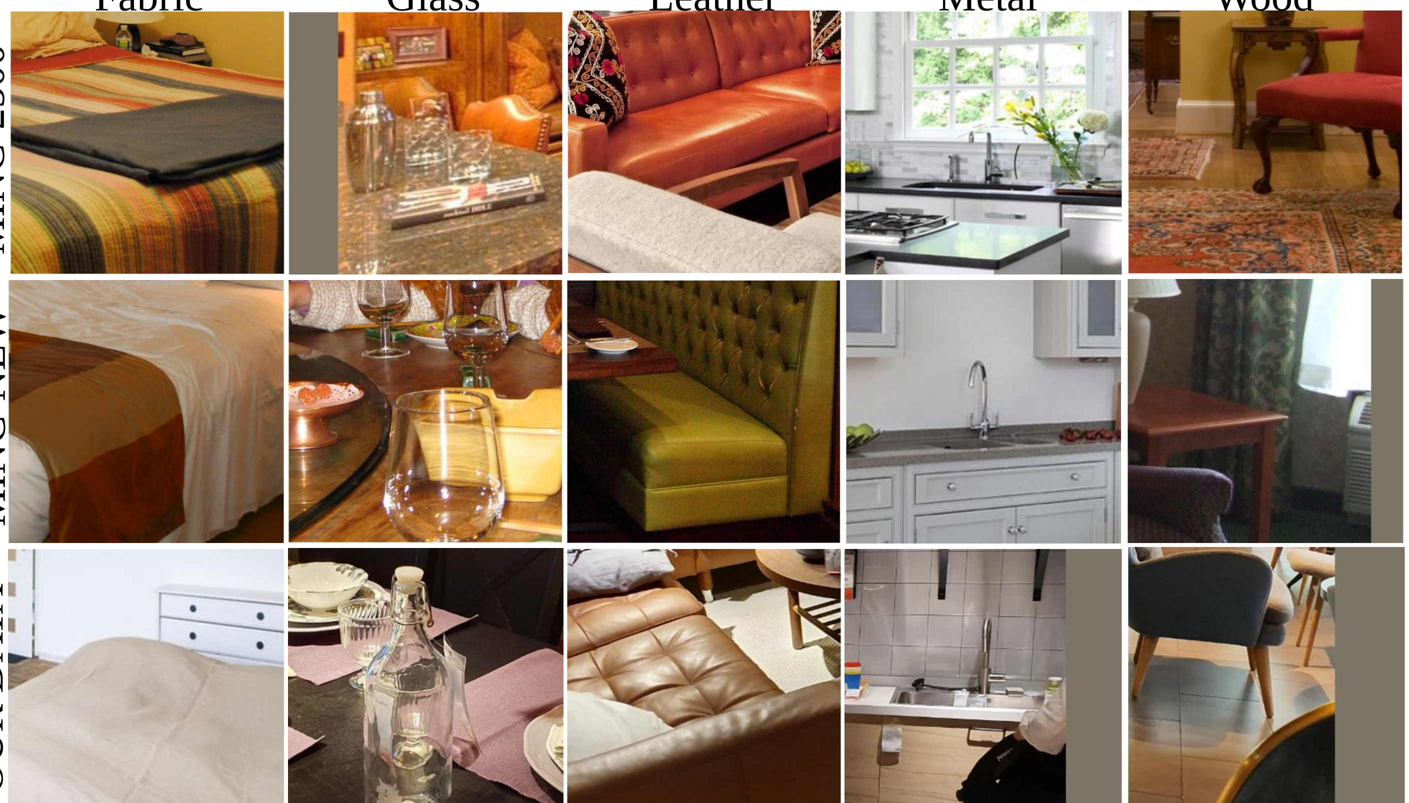

Proposed work

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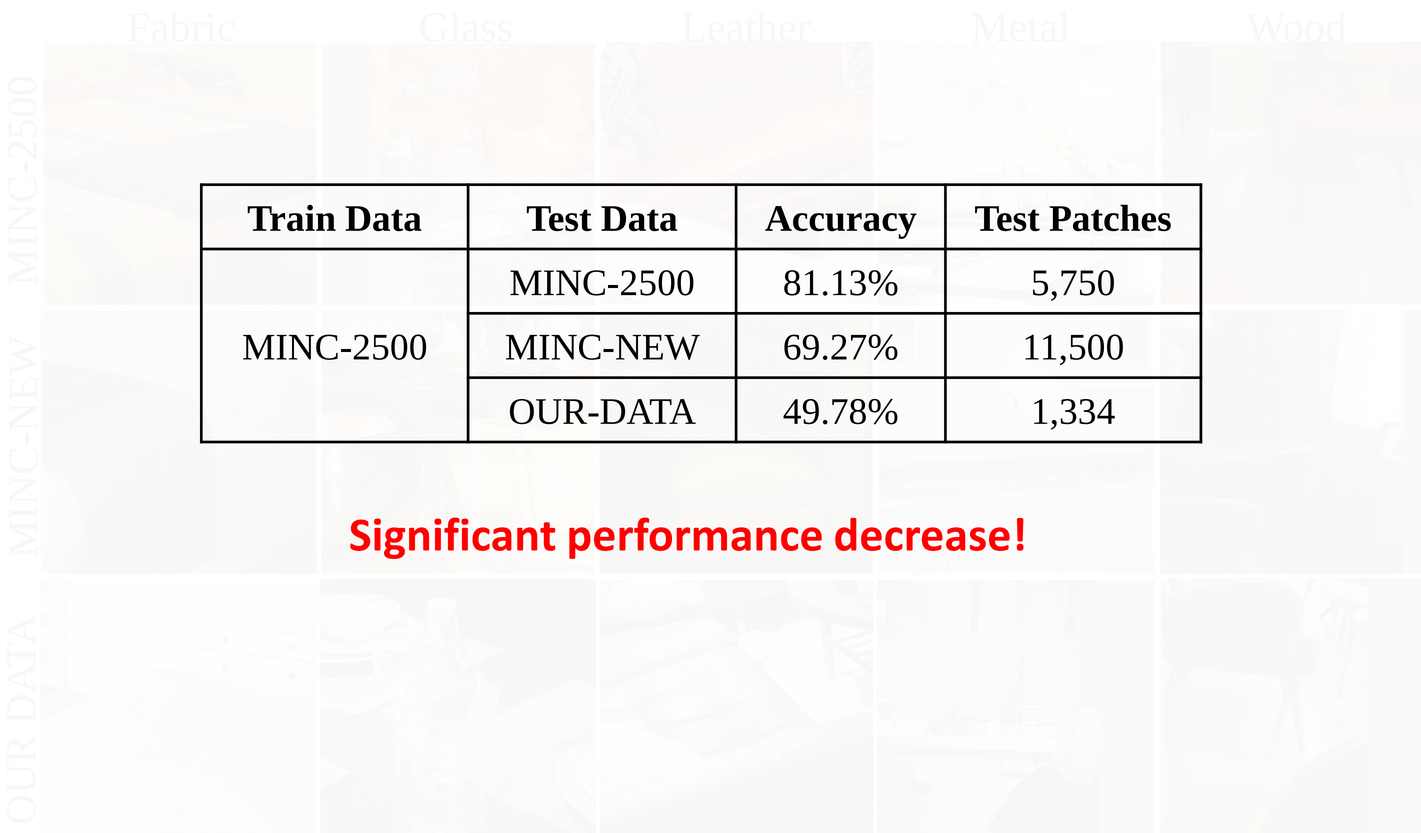
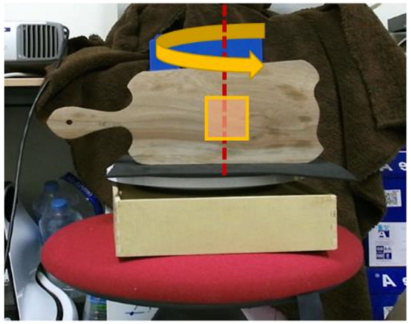


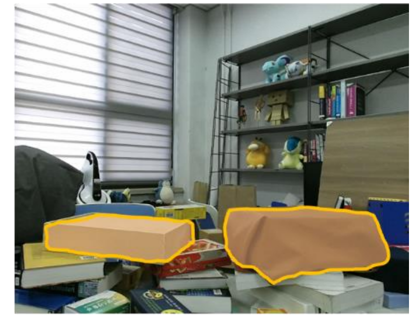
Train Data	Test Data	Accuracy	Test Patches
MINC-2500	MINC-2500	81.13%	5,750
	MINC-NEW	69.27%	11,500
	OUR-DATA	49.78%	1,334

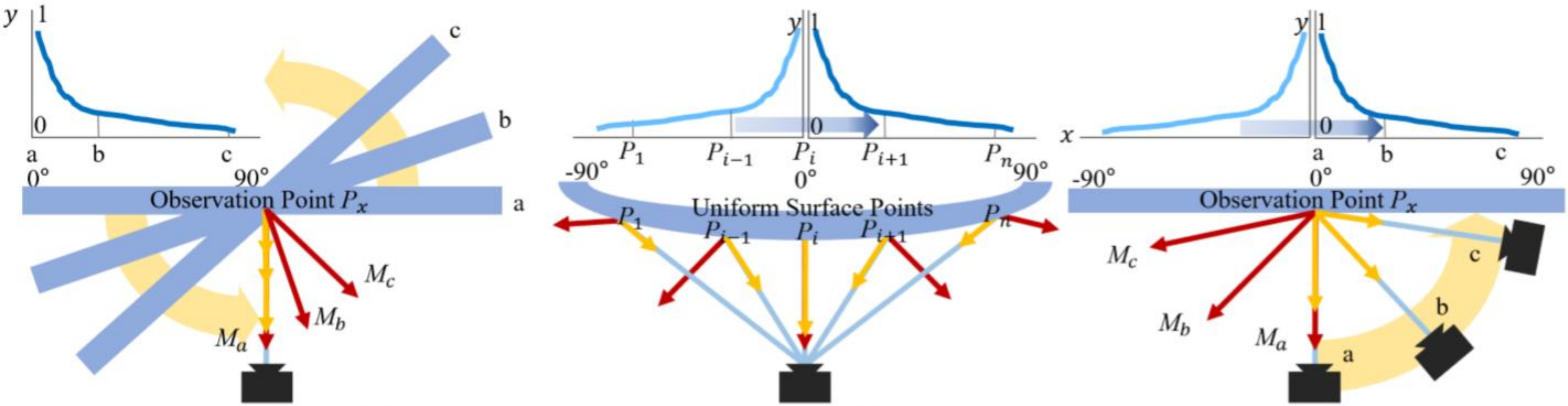
Significant performance decrease!

Proposed work

2. Surface Reflectance Estimation with practical environment







(a) Object-rotation acquisition (b) One-shot acquisition (c) Camera-rotation acquisition

Emitted IR ray direction
Obtained IR intensity at θ
Maximum reflected IR ray ($M_{position}$)

x Incidence angle
y Reflected IR intensity

	Isotropicity	Uniform Surface	Incidence Angle Range	Required Frame
(a)	isotropic	X	~35°	many
(b)	isotropic	O	~80°	1
(c)	anisotropic	X	~80°	many

(d) Experimental condition for each acquisition method

Proposed work

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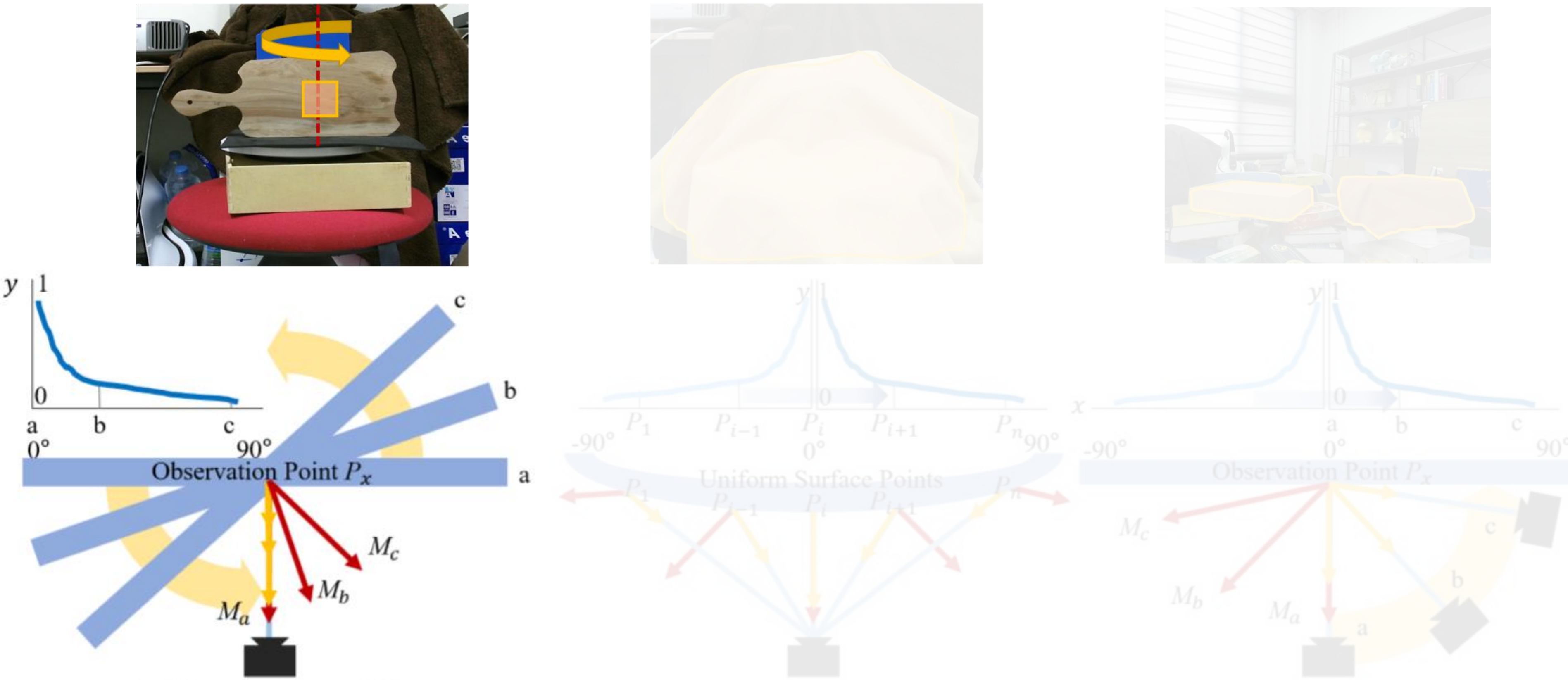
2. Surface Reflectance Estimation with practical environment



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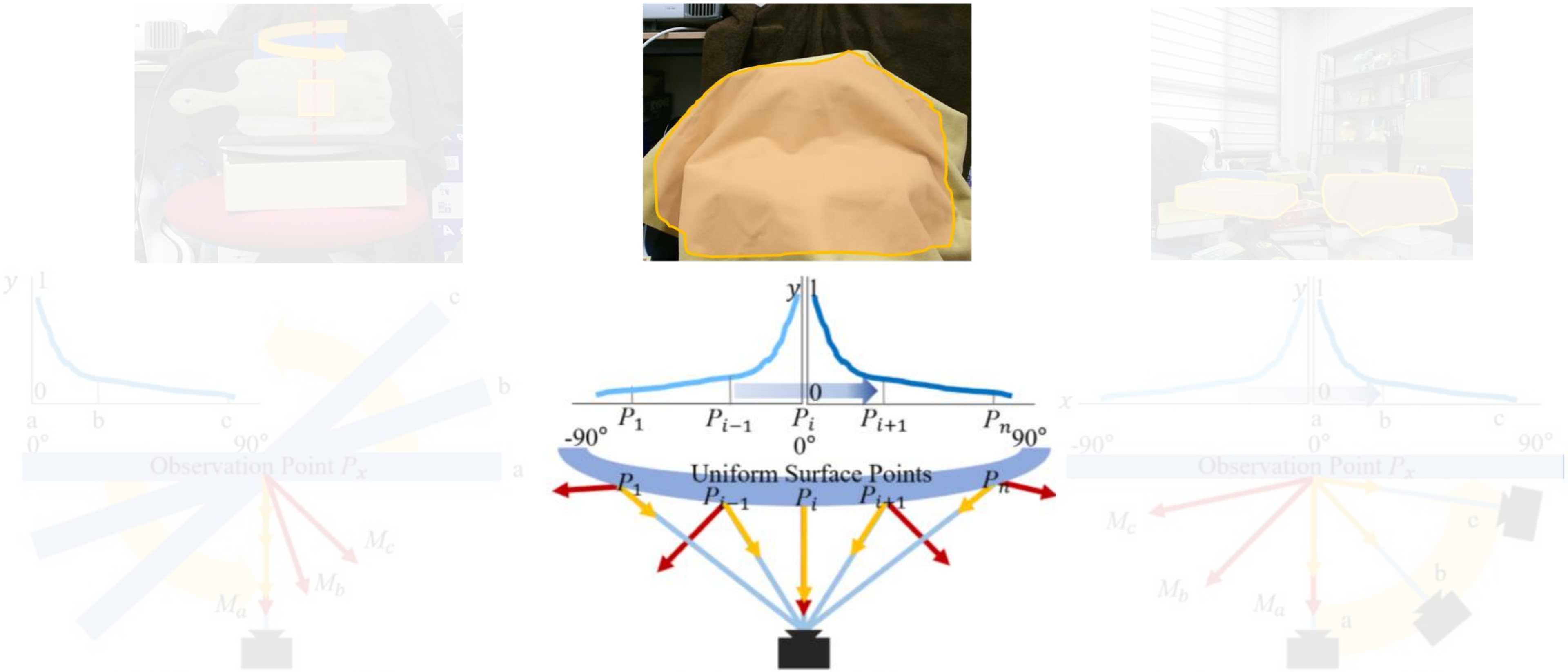

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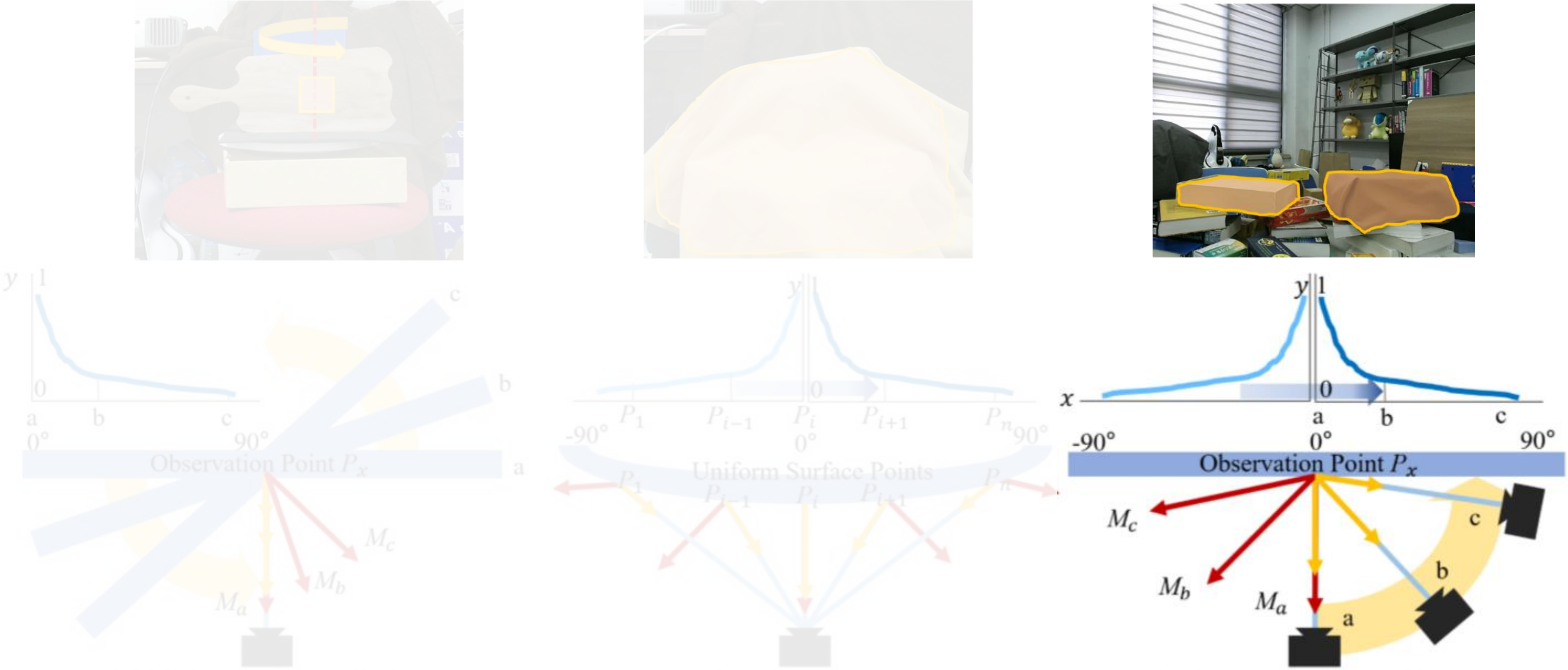

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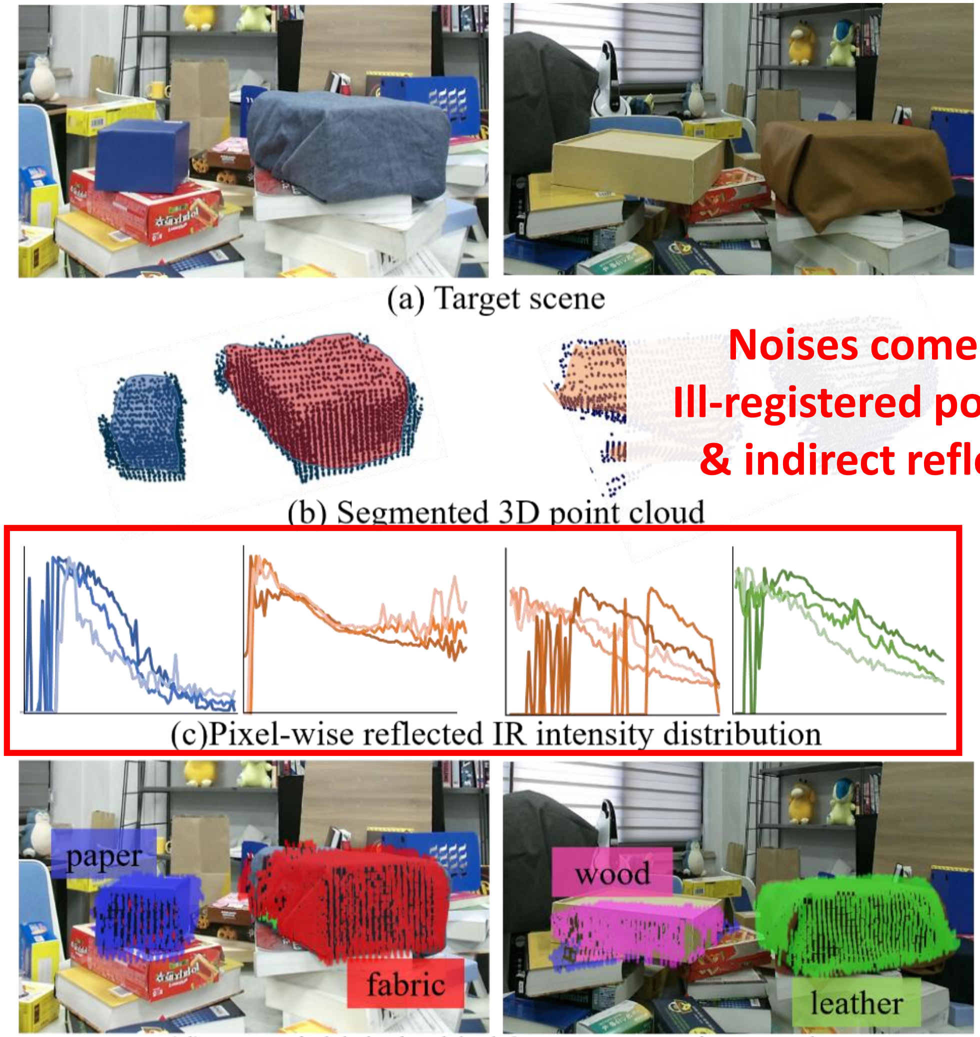
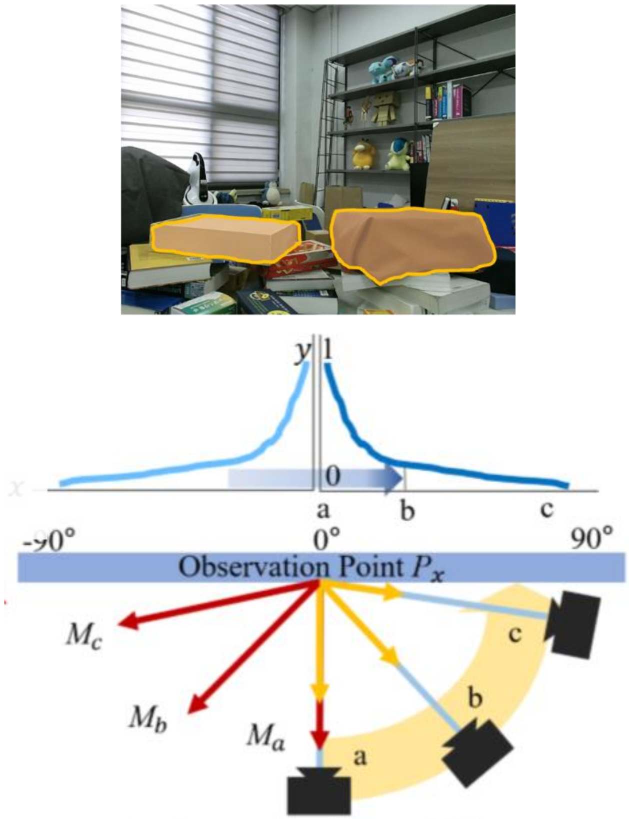


(a) Target scene
(b) Segmented 3D point cloud
(c)Pixel-wise reflected IR intensity distribution
(d) Material label added 3D segmentation result

Noises comes from Ill-registered point cloud & indirect reflections!



(c) Camera-rotation acquisition

Proposed work

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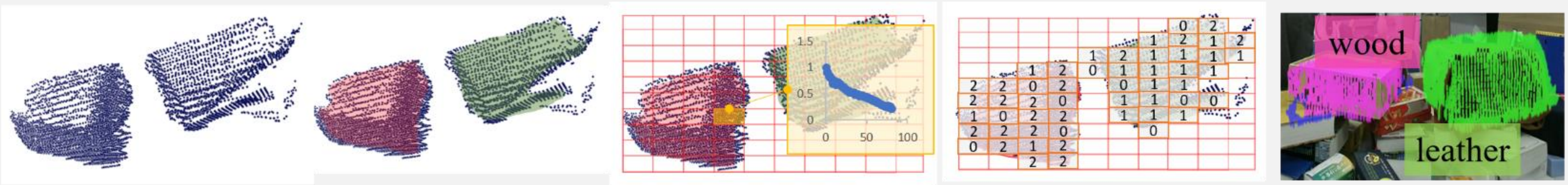
3. 3D Segment-wise Material Recognition

scene1

scene2

<Camera-rotation acquisition process(scene1)>



Registration output | Normal-based segmentation | Grid-wise reflectance merging | Find dominant label inside cluster | Material labeled segment

>>Requires scene registration, large number of frames & experimental cost..

Proposed work

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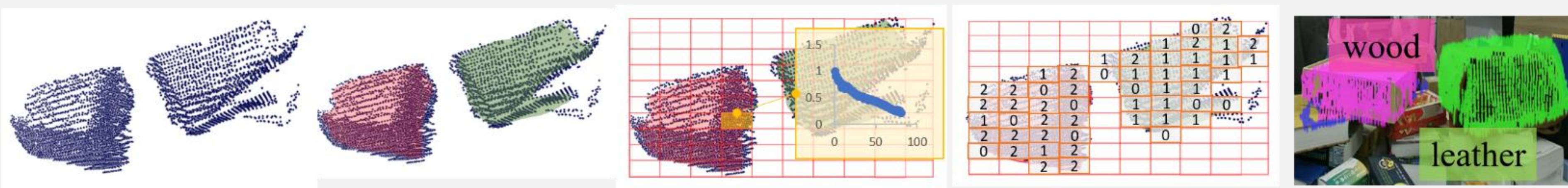
3. 3D Segment-wise Material Recognition

scene1

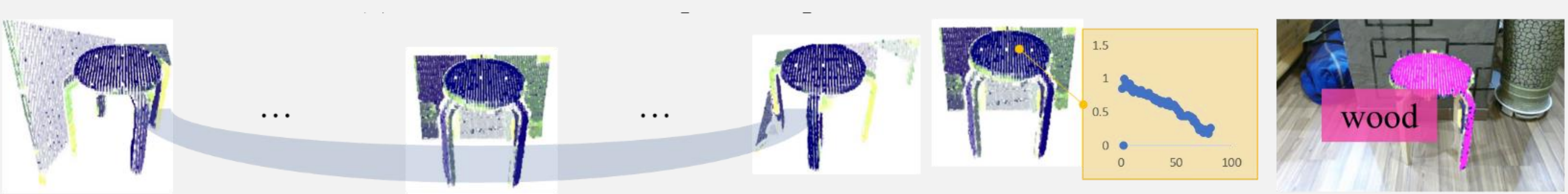
scene2

<Camera-rotation acquisition process(scene1)>



Registration output | Normal-based segmentation | Grid-wise reflectance merging | Find dominant label inside cluster | Material labeled segment

<Multi-viewed acquisition process without point cloud registration(scene2)>



7 different camera viewing direction with corresponding normal-based segmentation | Cluster-wise reflectance merging | Material labeled segment

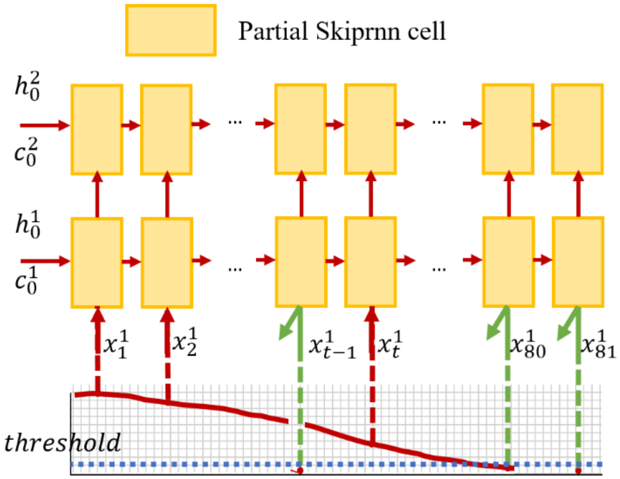
Uniform Surface Assumption!

Proposed work

4. Two-stream Material Recognition Network with Gradual CNN

RNN structure with conditional update gate

Feature vector concatenation



(a) Partial Skiprnn (Lee et al.)

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4. Two-stream Material Recognition Network with Gradual CNN

RNN structure with conditional update gate

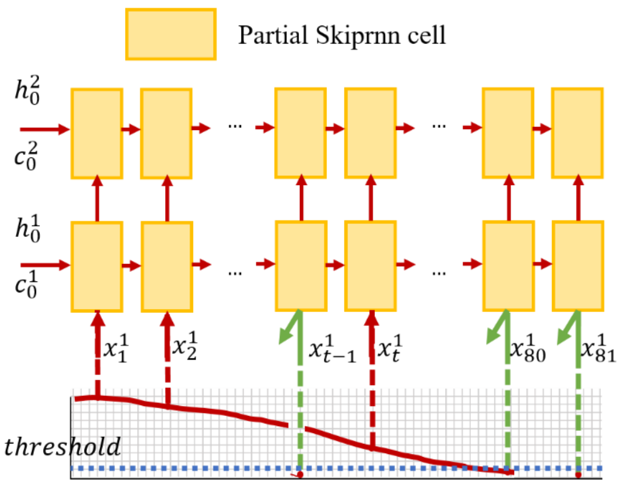
CNN structure with gradually increasing kernel size

Feature vector concatenation

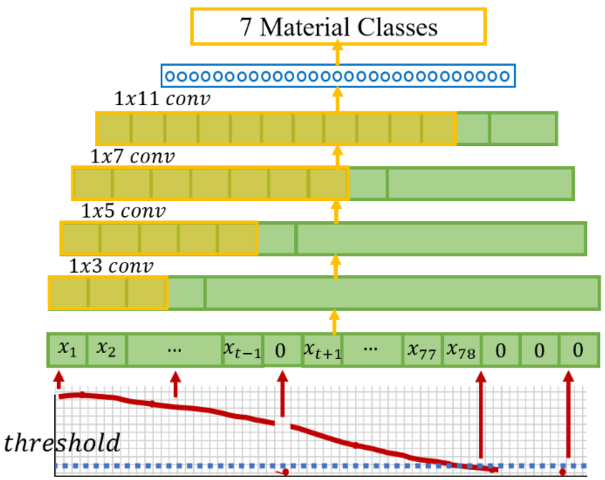
Feature vector multiplication

Wavenet: A generative model for raw audio
Oord et al. 2016 Deep-Mind

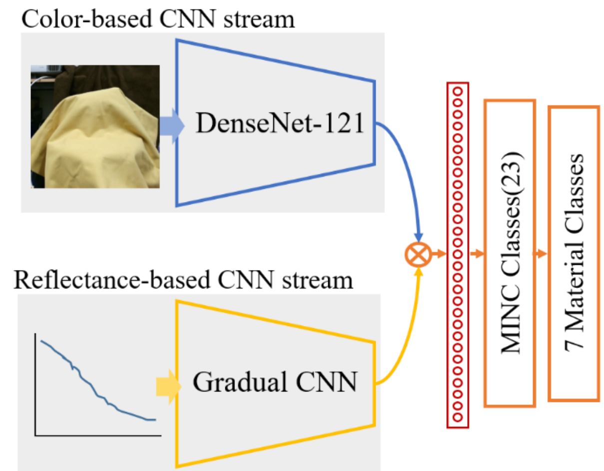
Bilinear cnn models for fine-grained visual recognition
Lin et al. 2015 International Conference on Computer Vision(ICCV)



(a) Partial Skiprnn (Lee et al.)



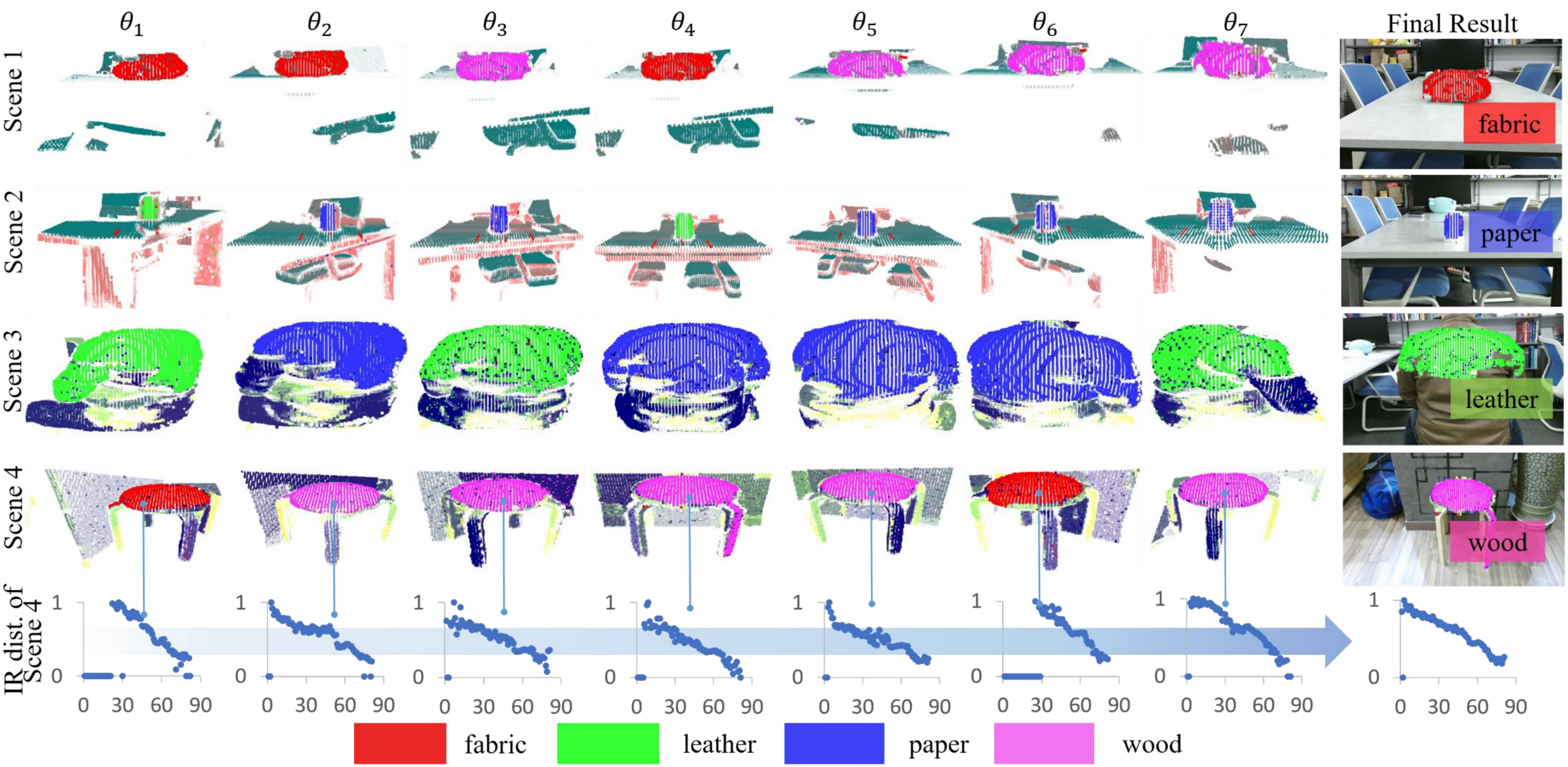
(b) Gradual Increasing CNN (Ours)



(c) Two-stream network structure (Ours)

Result

3D Segment-wise Material Recognition



Result

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Two-stream Material Recognition Network with Gradual CNN

<Performance Growth>

Reflectance-only	64.67%
Color + Reflectance	76.00%

Network	Fusion Method	Data	Top-5 Accuracy
SkipRNN [25]	-	Ref.	$62.67_{\pm 5.5}$
Partial SkipRNN [25]	-	Ref.	$64.67_{\pm 1.8}$
Gradual 1D CNN	-	Ref.	$\mathbf{72.66}_{\pm 1.5}$
Dilated 1D CNN	-	Ref.	$68.67_{\pm 1.8}$
SkipRNN + DenseNet-121 [25]	Concat.	Ref. + Color	$74.67_{\pm 3.0}$
Partial SkipRNN + DenseNet-121 [25]	Concat.	Ref. + Color	$76.00_{\pm 4.9}$
Partial SkipRNN + DenseNet-121	Outer product	Ref. + Color	$83.34_{\pm 4.7}$
Gradual 1D CNN + DenseNet-121	Outer product	Ref. + Color	$\mathbf{86.00}_{\pm 4.3}$
Dilated 1D CNN + DenseNet-121	Outer product	Ref. + Color	$83.33_{\pm 5.3}$

Result

Two-stream Material Recognition Network with Gradual CNN

<Performance Growth>

Up to 10% of performance growth

Reflectance-only	64.67%	➡	72.66%
Color + Reflectance	76.00%	➡	86.00%

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Q & A