Surface IR Reflectance Estimation and Material Recognition using ToF Camera

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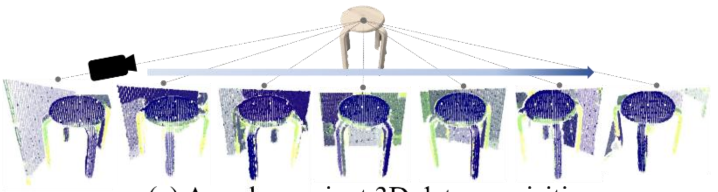
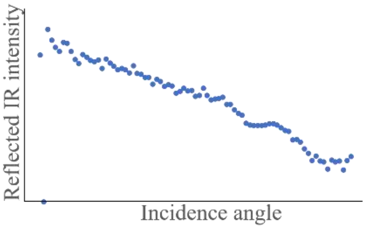
Problem

Recently, various material recognition methods uses single color or light field camera have been proposed, which focuses on color and texture information of an object. However, material type can be characterized better by surface reflectance, visual appearance rather than its color and textures. Some of the previous works which uses reflectance feature has limitation in its practicality. In this paper,

- We experimentally prove that color feature is insufficient for material classification.
- We propose ToF (*time-of-flight*) camera based surface IR reflectance acquisition in a purpose of material type recognition.
- We propose two-stream material recognition network which uses both color and IR reflectance feature.



(a) Angular-variant 3D data acquisition



(b) Surface IR reflectance

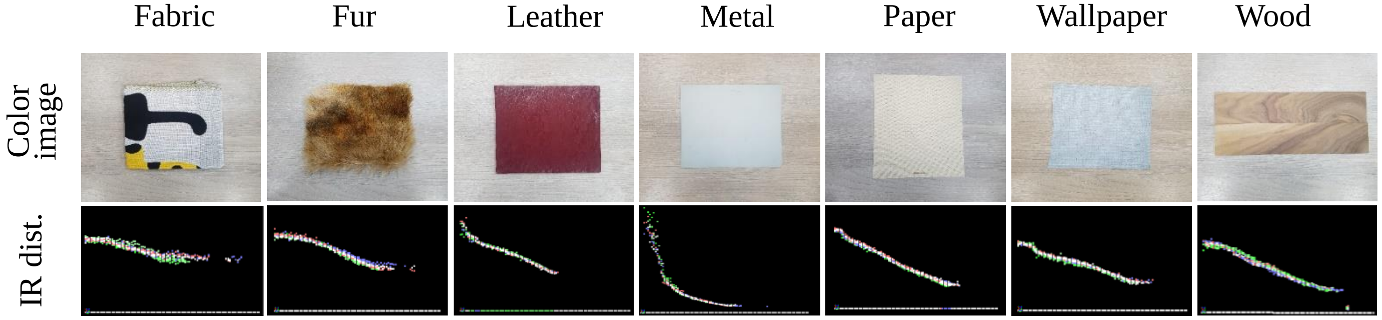
(c) Material-labeled 3D data

(1)

Physically-motivated feature based material recognition in real-world environment!

Previous Work

- Lee et al.[5] suggest an IR Reflectance feature for material recognition with their Color-IR Material dataset (figure (2)).
- Tanaka et al.[3] propose a exemplar-based material classification using distortion of a ToF camera as a feature.
- DEP-Net[2] shows *state-of-the-art* performance with MINC [1] dataset while using only color features.



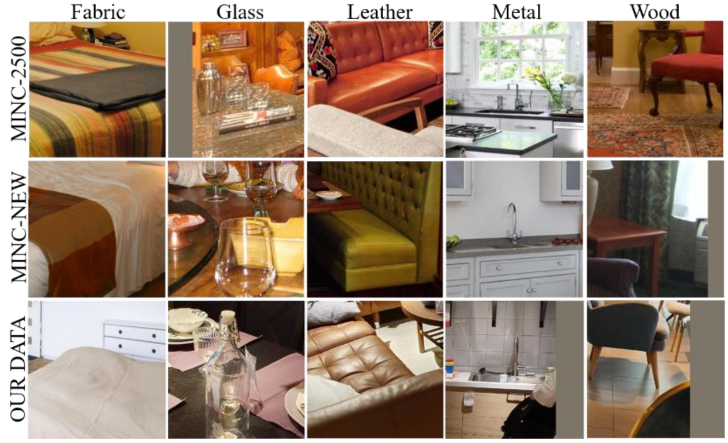
(2)

*** Same Color-IR data pairs were used in our experiment for comparison**

1. Cross-data Verification on Color-feature based Material Recognition

We have collected two MINC-like dataset named MINC-NEW and OUR-NEW (figure (3)). A model trained with MINC-2500 shows significant performance decrease(table (4)) with our dataset despite the similarities.

- **MINC(Materials IN Context)**[1]: One of the *golden-standard* dataset in the fields, consists of 23 material classes.
- **MINC-2500** [1]: A subset of MINC database with balanced class distribution (2500 samples per class)
- **MINC-NEW**: Another subset of MINC database (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.

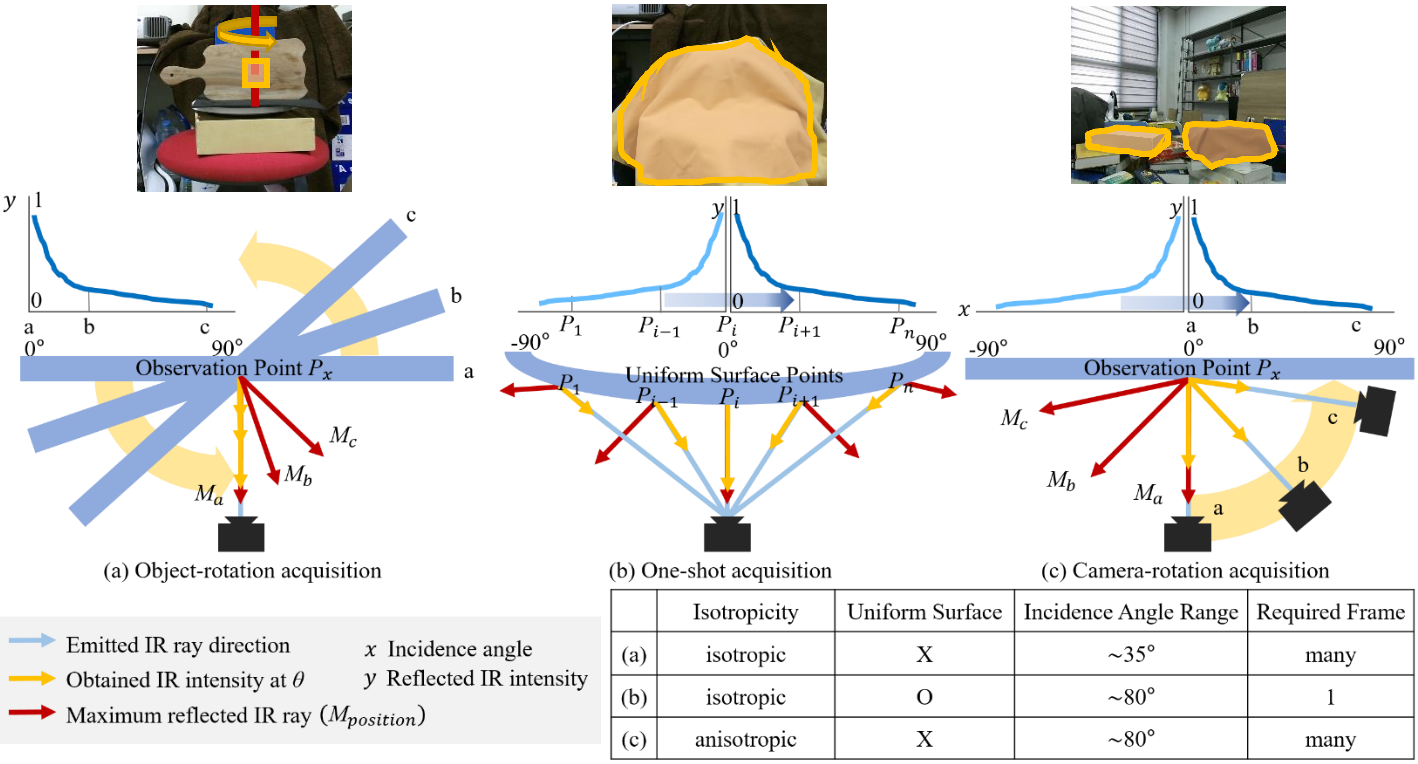


(3)

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

(4)

2-1. Material Surface Estimation



(a) Object-rotation acquisition

(b) One-shot acquisition

(c) Camera-rotation acquisition

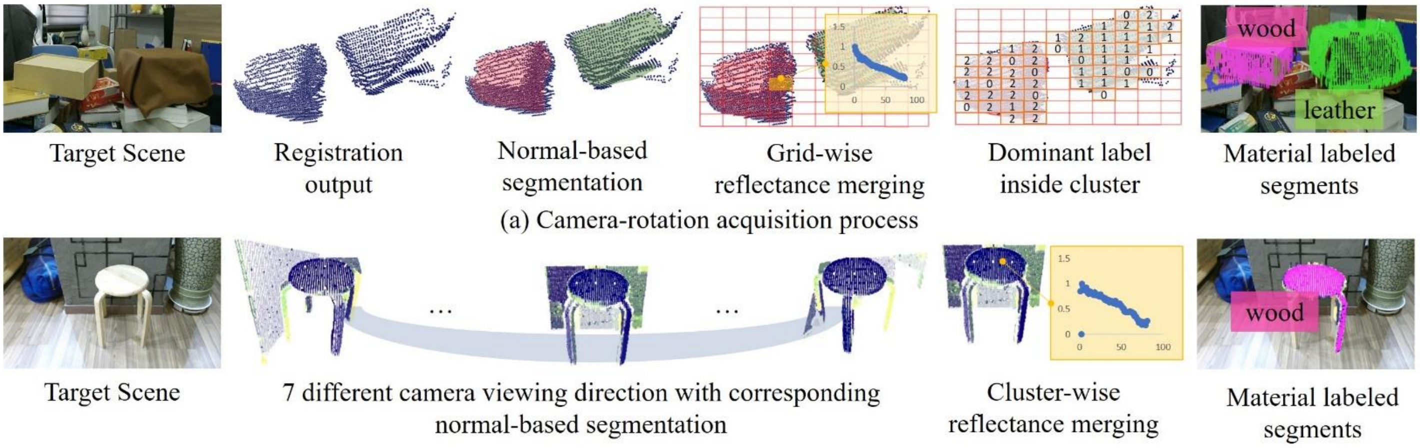
	Isotropicity	Uniform Surface	Incidence Angle Range	Required Frame
(a)	isotropic	X	~35°	many
(b)	isotropic	O	~80°	1
(c)	anisotropic	X	~80°	many

(d) Experimental condition for each acquisition method

(5)

- **(5)-(a)**: A fixed camera acquires reflected IR intensities while rotating target surface.
- **(5)-(b)**: With an curved surface object, reflectance feature can be acquired for one shot.
- **(5)-(c)**: Acquires pixel-wise reflected IR intensity distribution using point cloud registration. Includes errors comes from registration noises and occlusions yet most practical.

2-2. 3D Segment-wise Material Classification



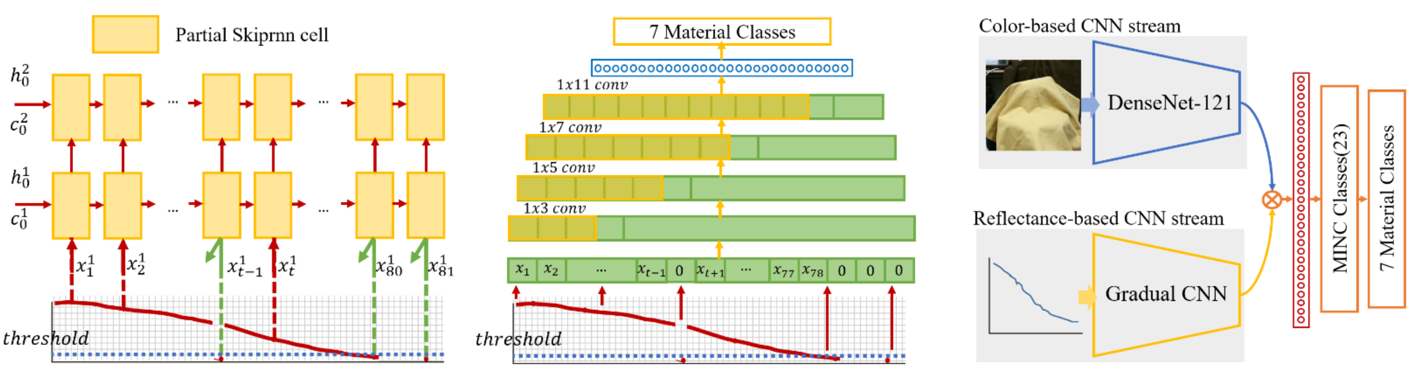
(b) Multi-viewed acquisition process without point cloud registration

(6)

- (6)-(a): In order to get robust yet point-wise reflectance feature, the segmentation outputs were divided into 10 x 10 grid and merged separately. Requires frame registration and multiple input frames.
- (6)-(b): Total 7 reflectance feature from 7 different viewing directions were collected and merged for single segment-wise reflectance feature (uniform surface assumption). A several functional units of our framework include ICP registration and normal-based segmentation are based on publicly available library, PCL [8].

<Multi-viewed Acquisition Process>
Required Frame: Many -> 7 (or less)
Environment: X Frame Registration, X Environmental Restriction

3. Two-stream Material Recognition Network



(a) Partial Skiprnn (Lee et al.) (b) Gradual CNN (Ours) (c) Two-stream network structure (Ours)

(7)

- LSTM based approaches [6] ((7)-(a)) can somehow propagates errors from points to points despite the noise cancellation.
- Figure (7)-(b) illustrates our gradient-based noise cancellation method and *Gradual* CNN, which has gradually increasing 1-dimentional kernels to cover sequential relations.
- Figure (7)-(c) shows our two-stream material recognition network structure which uses outer product based feature fusion, instead of feature concatenation that cannot guarantee contribution of each modality feature.

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4. Final Results & Conclusion

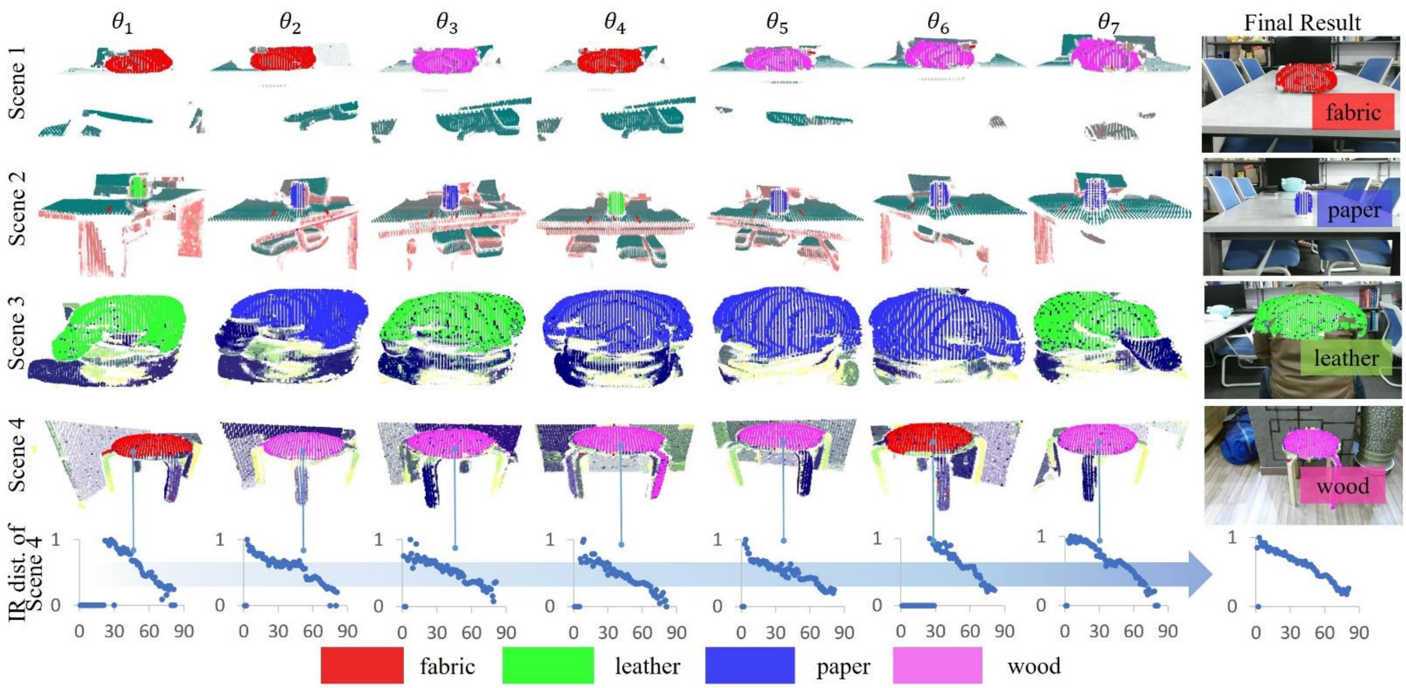
Figure (8) shows comparison between previous work [5] and our baseline network and its variation. Our network shows up to 10% of performance growth compares to previous work.

Up to 10% of Performance Growth!

Network	Fusion Method	Data	Top-5 Accuracy
SkipRNN [28]	-	Ref.	$62.67_{\pm 5.5}$
Partial SkipRNN [28]	-	Ref.	$64.67_{\pm 1.8}$
Gradual 1D CNN	-	Ref.	**$72.66_{\pm 1.5}$**
Dilated 1D CNN	-	Ref.	$68.67_{\pm 1.8}$
SkipRNN + DenseNet-121 [28]	Concat.	Ref. + Color	$74.67_{\pm 3.0}$
Partial SkipRNN + DenseNet-121 [28]	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	**$86.00_{\pm 4.3}$**
Dilated 1D CNN + DenseNet-121	Outer product	Ref. + Color	$83.33_{\pm 5.3}$

(8)

Figure (9) shows our 3D segment-wise material classification result. Final classification result is based on the merged reflectance that is obtained from 7 merged reflectance of respective views.



(9)

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