Deep Hyperspectral-Depth Reconstruction Using Single Color-Dot Projection

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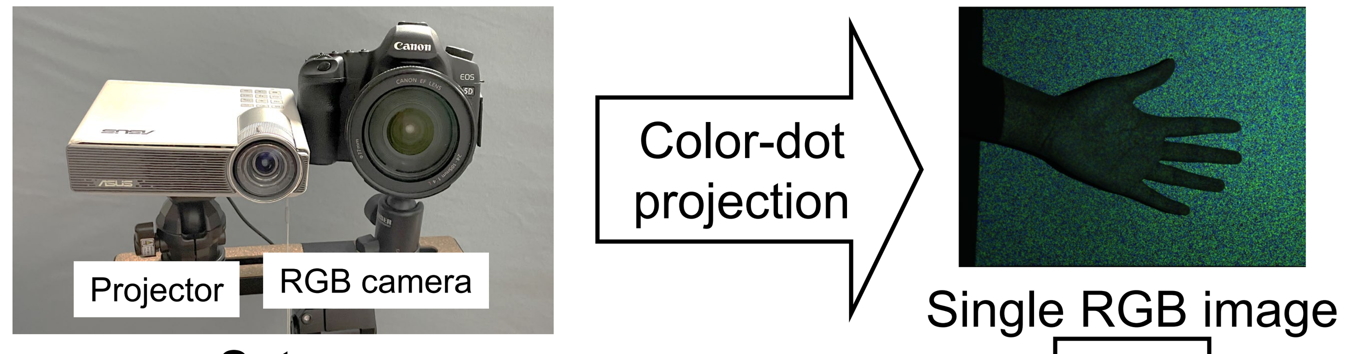
Introduction

Single-shot reconstruction of depth and spectral reflectance using an **off-the-shelf** RGB camera and projector.



Setup

Single RGB image

CNN

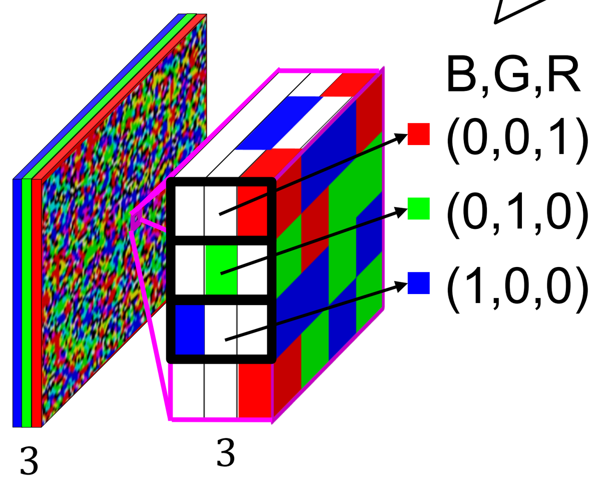
Estimated depth

Estimated spectral reflectance

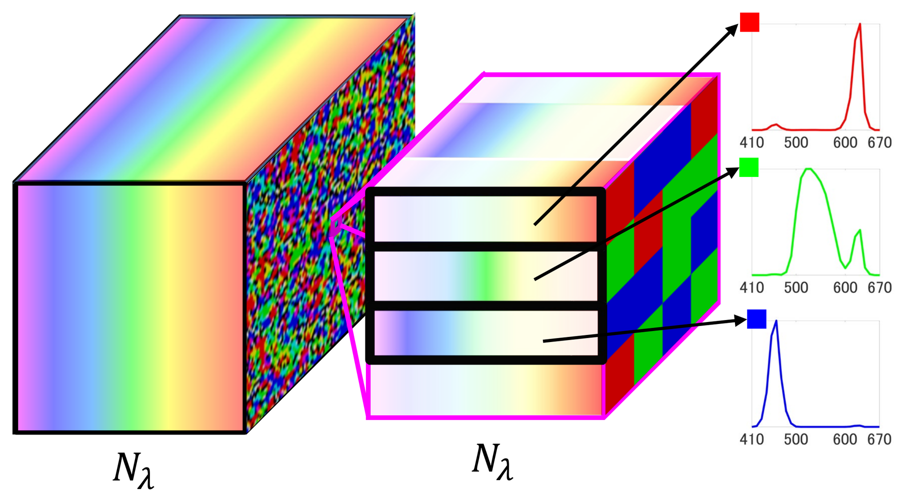
Random Color-Dot Projection

The random pattern provides **locally unique codes** for establishing correspondences.

3 illuminations × 3 camera channels = **9 bands** for hyperspectral reconstruction

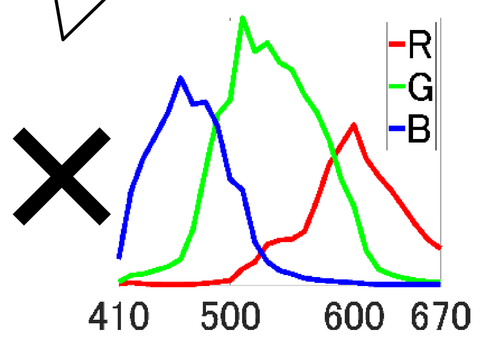


Color-dot pattern $\boldsymbol{P}$



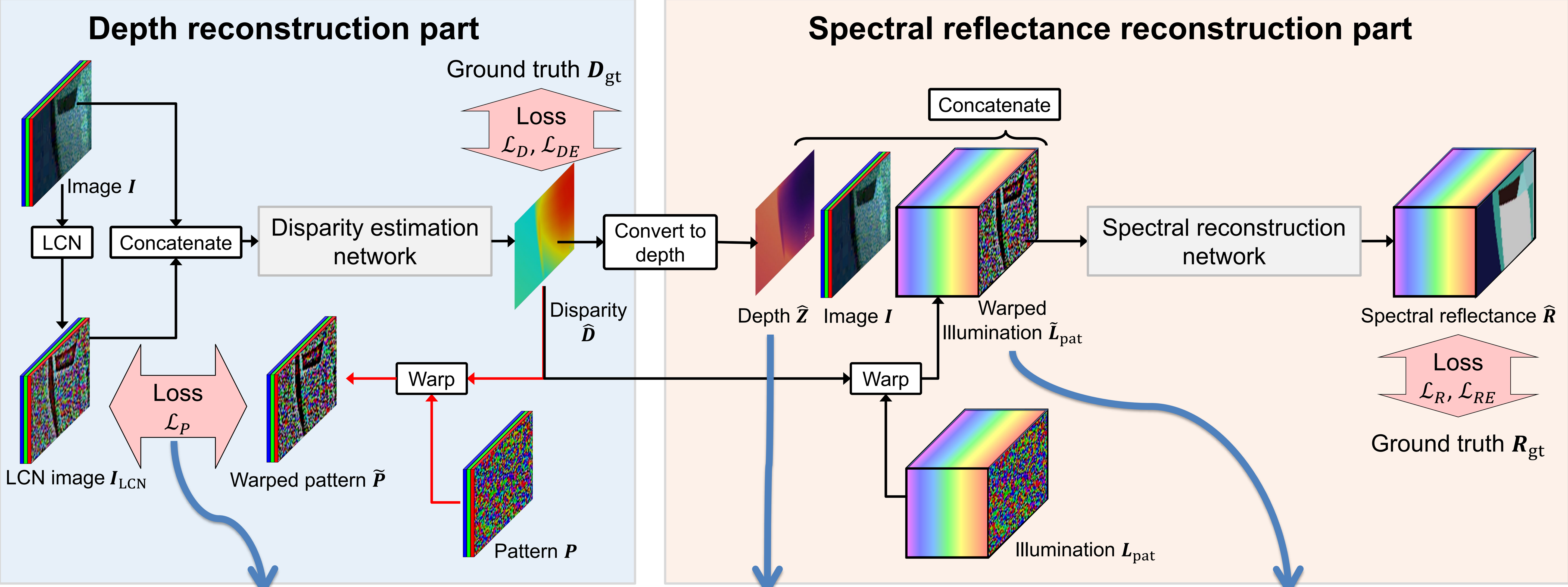
Illumination spectrum $\boldsymbol{L}_{\rm pat}$

×



Camera sensitivity

Proposed End-to-End Network



Pattern loss:
Structured-light supervision for geometry

Using depth as input:
Considering the effect of shading

Warping illumination:
Benefitting both disparity and spectrum via end-to-end training

Loss functions:

Pattern loss:

$$\mathcal{L}_P = \sum_{u,v \in \mathcal{V}} \| \boldsymbol{I}_{LCN} - \widetilde{\boldsymbol{P}} \|_C$$

Census transform

Pixel set which is not in cast shadow

Disparity loss:

$$\mathcal{L}_D = \sum_{u,v \in \mathcal{V}} \| \widehat{\boldsymbol{D}}(u,v) - \boldsymbol{D}_{\rm gt}(u,v) \|^2$$

Disparity edge loss (gradient loss):

$$\mathcal{L}_{DE} = \sum_{u,v \in \mathcal{V}} \| \widehat{\boldsymbol{D}}'(u,v) - \boldsymbol{D}'_{\rm gt}(u,v) \|^2$$

Reflectance loss:

$$\mathcal{L}_R = \sum_{u,v \in \mathcal{V}} \| \widehat{\boldsymbol{R}}(u,v,\lambda) - \boldsymbol{R}_{\rm gt}(u,v,\lambda) \|^2$$

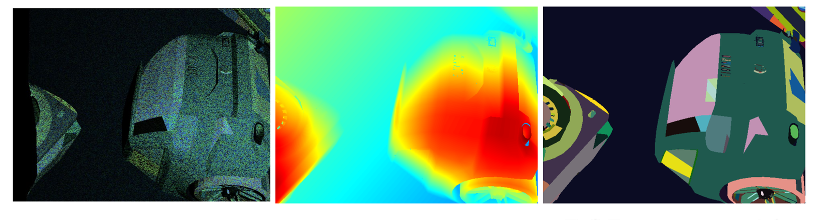
Reflectance edge loss (gradient loss):

$$\mathcal{L}_{RE} = \sum_{u,v \in \mathcal{V}} \| \widehat{\boldsymbol{R}}'(u,v,\lambda) - \boldsymbol{R}'_{\rm gt}(u,v,\lambda) \|^2$$

Experimental Results

Hyperspectral-Depth Dataset Generation

	Object	Reflectance	Scene number
Training data	Chair and car models in ShapeNet [1]	1,269 Munsell color chips [2]	8,192
Testing data	Camera, airplane, and watercraft models in ShapeNet [1]	X-Rite colorchart (24 patches)	256

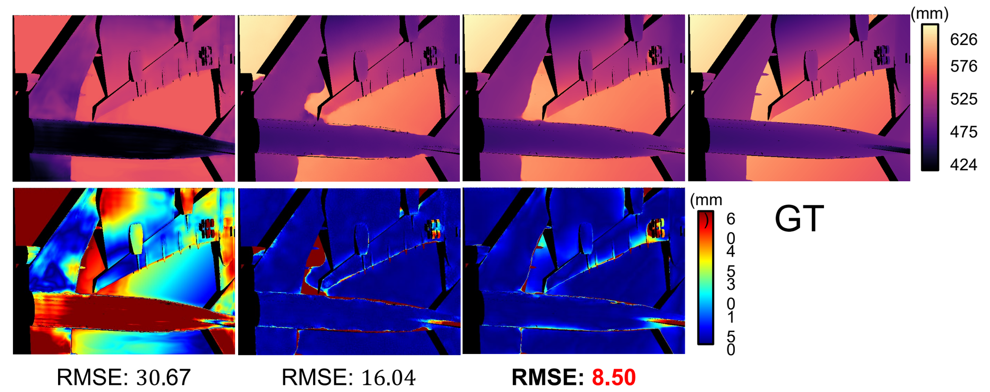


Color-dot image　Disparity map　sRGB converted from spectral reflectances.

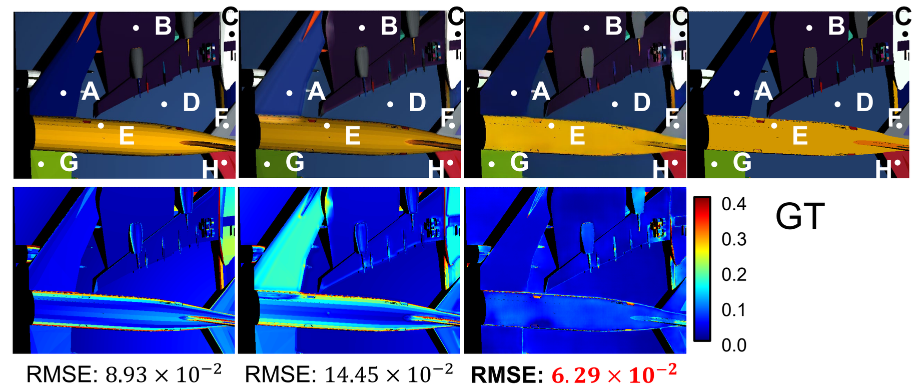
Spectral rendering examples

Whole dataset can be downloaded from project homepage.

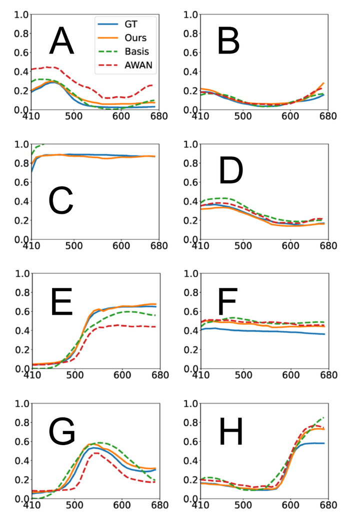
Evaluation on Synthetic Data



Depth results and visualized errors



Spectral reflectance results and visualized errors



Spectral reflectance results on 8 samples

Quantitative Evaluation

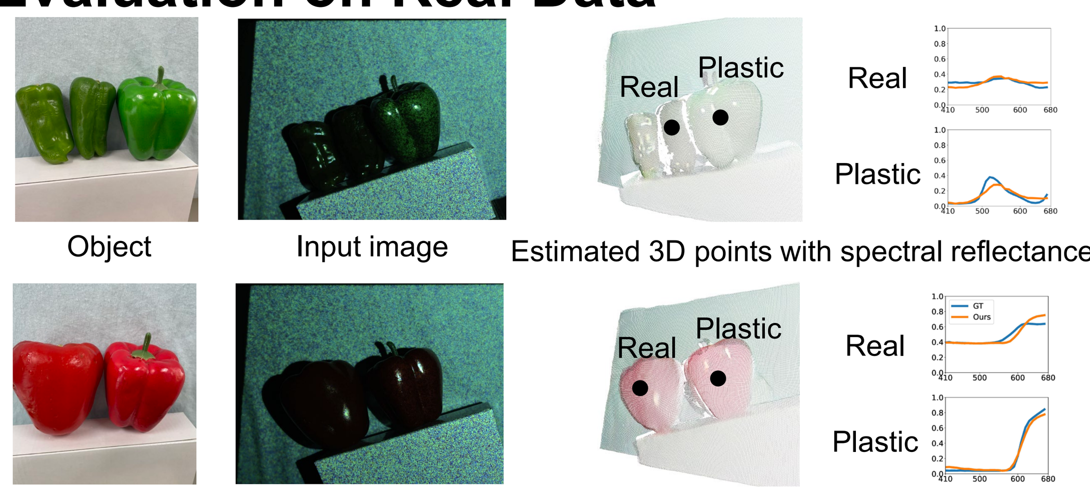
Comparison with the state-of-the-art methods on all the test scenes

	Depth RMSE	Reflectance RMSE ($\times 10^{-2}$)
AdaBins [3]	24.60	-
Connecting [4]	8.83	-
Basis [5]	-	8.02
AWAN [6]	-	7.93
Ours	**6.10**	**5.31**

Effectiveness of joint training

		Depth RMSE	Reflectance RMSE ($\times 10^{-2}$)
Disparity estim. network		6.80	-
Spectral recon. network		-	5.79
Joint	w/o depth input	6.24	5.69
	w/o illumination input	6.32	5.75
	full model	**6.10**	**5.31**

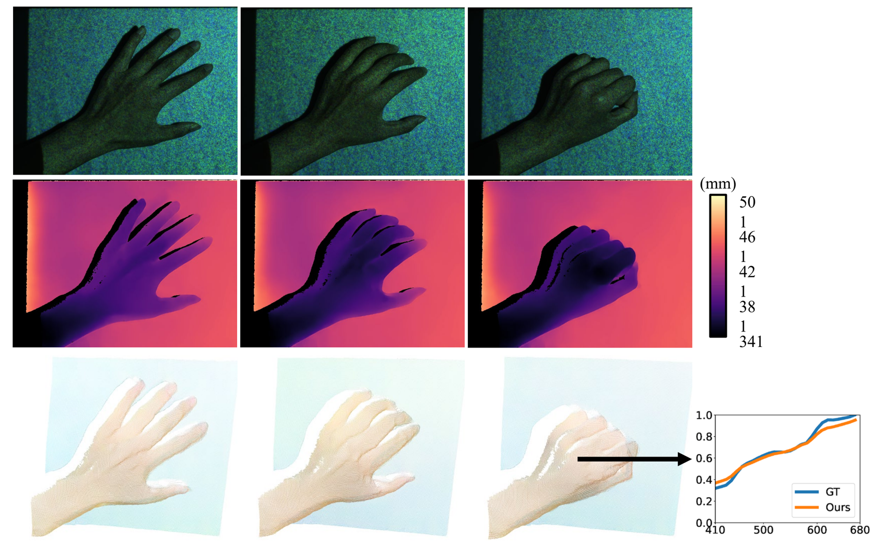
Evaluation on Real Data



Object　Input image　Estimated 3D points with spectral reflectance

Object　Input image　Estimated 3D points with spectral reflectance

Which is real?



The reconstruction results for a dynamic scene

Reference

[1] Angel X Chang , et al. "ShapeNet: An information-rich 3D model repository". arXiv, 2015.
[2] Munsell colors matt: https://sites.uef.fi/spectral/munsell-colors-matt-spectrofotometer-measured/
[3] Shariq Farooq Bhat, et al. "Adabins: Depth estimation using adaptive bins", *CVPR*, 2021.
[4] Gernot Riegler, et al. "Connecting the dots: Learning representations for active monocular depth estimation". *CVPR*, 2019.
[5] Shuai Han, et al. "Fast spectral reflectance recovery using DLP projector", *IJCV*, 2014.
[6] Jiaojiao Li , et al. "Adaptive weighted attention network with camera spectral sensitivity prior for spectral reconstruction from RGB Images", *CVPRW*, 2020

Project Homepage

http://www.ok.sc.e.titech.ac.jp/res/DHD/