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Technische Universität München

Depth Super-Resolution Meets Uncalibrated Photometric Stereo

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ICCV 2017 Color and Photometry in Computer Vision Workshop

Outline

1 Introduction

2 Background

3 Methodology

4 Evaluation and Results

5 Conclusion

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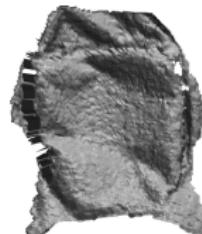
5 Conclusion

Problem Statement

Example: RGB-D data from ASUS Xtion Pro Live



Input RGB image



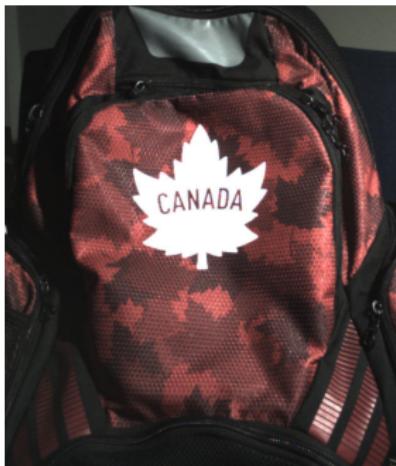
Input depth

- + Good quality
- + High resolution

- Noisy & missing areas
- Low resolution



Goal



Input RGB image



Input depth



Refined depth

Objective:

Use high-resolution photometric clues in the RGB image to turn the low-resolution depth maps into a refined, high resolution one

Contribution

Propose a novel variational model to:

- disambiguate depth super-resolution through high-resolution photometric clues;
- disambiguate uncalibrated photometric stereo through low-resolution depth cues.

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Background

Depth Super-Resolution

$$\mathbf{z}_0^i = K\mathbf{z} + \varepsilon_{\mathbf{z}}^i, \quad \forall i \in \{1, \dots, n\}$$

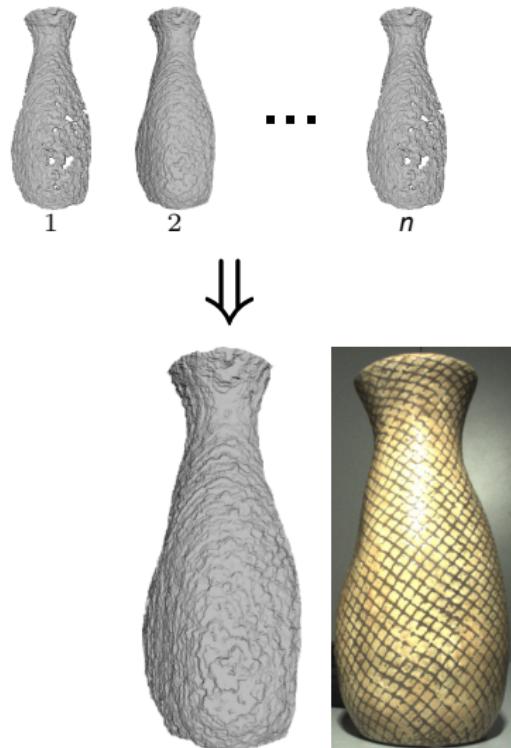
\mathbf{z}_0^i : input LR depth maps

\mathbf{z} : output HR depth map

K : down-sampling kernel

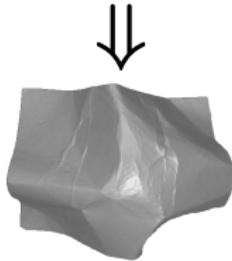
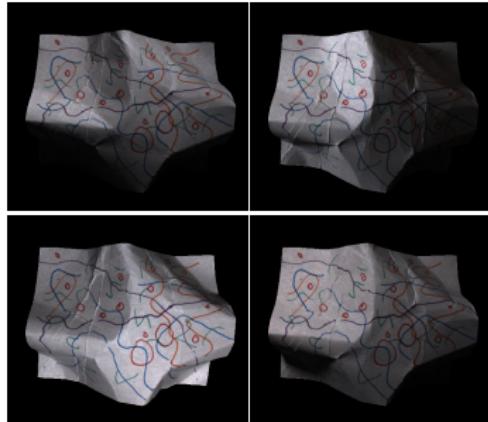
$\varepsilon_{\mathbf{z}}^i$: noise $\sim \mathcal{N}(0, \sigma_z^2)$

$$\min_{\mathbf{z}} \mathcal{R}_{\mathbf{z}}(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \|K\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2$$



Background

[Grosse et al., ICCV 2009]



Photometric Stereo

$$I^i = \rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} + \varepsilon_I^i, \quad \forall i \in \{1, \dots, n\}$$

I^i : images under various lightings

\mathbf{l}^i : lighting vector \mathbb{R}^4

ρ : albedo / reflectance

$\mathbf{n}(\mathbf{z})$: surface normal

$$\min_{\mathbf{z}} \mathcal{R}_I(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \| \rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} - I^i \|_{\ell^2}^2$$

Background

Depth Super-Resolution

$$\mathbf{z}_0^i = K\mathbf{z} + \varepsilon_{\mathbf{z}}^i, \quad \forall i \in \{1, \dots, n\}$$

\mathbf{z}_0^i : input LR depths

\mathbf{z} : output HR depth

K : down-sampling kernal

$\varepsilon_{\mathbf{z}}^i$: noise $\sim \mathcal{N}(0, \sigma_z^2)$

$$\min_{\mathbf{z}} \mathcal{R}_{\mathbf{z}}(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \|K\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2$$

Photometric Stereo

$$I^i = \rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} + \varepsilon_I^i, \quad \forall i \in \{1, \dots, n\}$$

I^i : images under various lightings

\mathbf{l}^i : lighting vector \mathbb{R}^4

ρ : albedo / reflectance

$\mathbf{n}(\mathbf{z})$: surface normal

$$\min_{\mathbf{z}} \mathcal{R}_I(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \|\rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} - I^i\|_{\ell^2}^2$$

Background

Depth Super-Resolution

$$\mathbf{z}_0^i = K\mathbf{z} + \varepsilon_{\mathbf{z}}^i, \quad \forall i \in \{1, \dots, n\}$$

\mathbf{z}_0^i : input LR depths

\mathbf{z} : output HR depth

K : down-sampling kernal

$\varepsilon_{\mathbf{z}}^i$: noise $\sim \mathcal{N}(0, \sigma_z^2)$

$$\min_{\mathbf{z}} \mathcal{R}_z(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \|K\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2$$

Proposed Model: $\min_{\mathbf{z}} \frac{1}{2n} \sum_{i=1}^n \left\{ \|K\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2 + \lambda \|\rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} - I^i\|_{\ell^2}^2 \right\}$

Photometric Stereo

$$I^i = \rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} + \varepsilon_I^i, \quad \forall i \in \{1, \dots, n\}$$

I^i : images under various lightings

\mathbf{l}^i : lighting vector \mathbb{R}^4

ρ : albedo / reflectance

$\mathbf{n}(\mathbf{z})$: surface normal

$$\min_{\mathbf{z}} \mathcal{R}_I(\mathbf{z}) + \frac{1}{2n} \sum_{i=1}^n \|\rho \mathbf{l}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{z}) \\ 1 \end{bmatrix} - I^i\|_{\ell^2}^2$$

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Methodology

With (i, \star, p) the indices of images, channel and pixel,

$$I_{\star}^i(\mathbf{p}) = \rho_{\star}(\mathbf{p}) \mathbf{l}_{\star}^i \cdot \begin{bmatrix} \mathbf{n}(\mathbf{p}) \\ 1 \end{bmatrix} + \varepsilon_{\star}^i(\mathbf{p})$$

Methodology

With (i, \star, p) the indices of images, channel and pixel,

$$\left. \begin{aligned} I_\star^i(p) &= \rho_\star(p) l_\star^i \cdot \begin{bmatrix} n(p) \\ 1 \end{bmatrix} + \varepsilon_\star^i(p) \\ n(p) &= \frac{1}{d(z)(p)} \begin{bmatrix} f \nabla z(p) \\ -z(p) - \nabla z(p) \cdot (p - p^0) \end{bmatrix} \end{aligned} \right\}$$

f : focal length

p^0 : principal point

$d(z)$: normalizer

Methodology

With (i, \star, p) the indices of images, channel and pixel,

$$\left. \begin{aligned} I_\star^i(p) &= \rho_\star(p) l_\star^i \cdot \begin{bmatrix} n(p) \\ 1 \end{bmatrix} + \varepsilon_\star^i(p) \\ n(p) &= \frac{1}{d(z)(p)} \begin{bmatrix} f \nabla z(p) \\ -z(p) - \nabla z(p) \cdot (p - p^0) \end{bmatrix} \end{aligned} \right\} A^i(z, \rho, l^i)^\top \begin{bmatrix} \nabla z \\ z \end{bmatrix} = b^i(\rho, l^i) + \varepsilon^i$$

f : focal length

p^0 : principal point

$d(z)$: normalizer

Proposed Variational Model

Here we have:

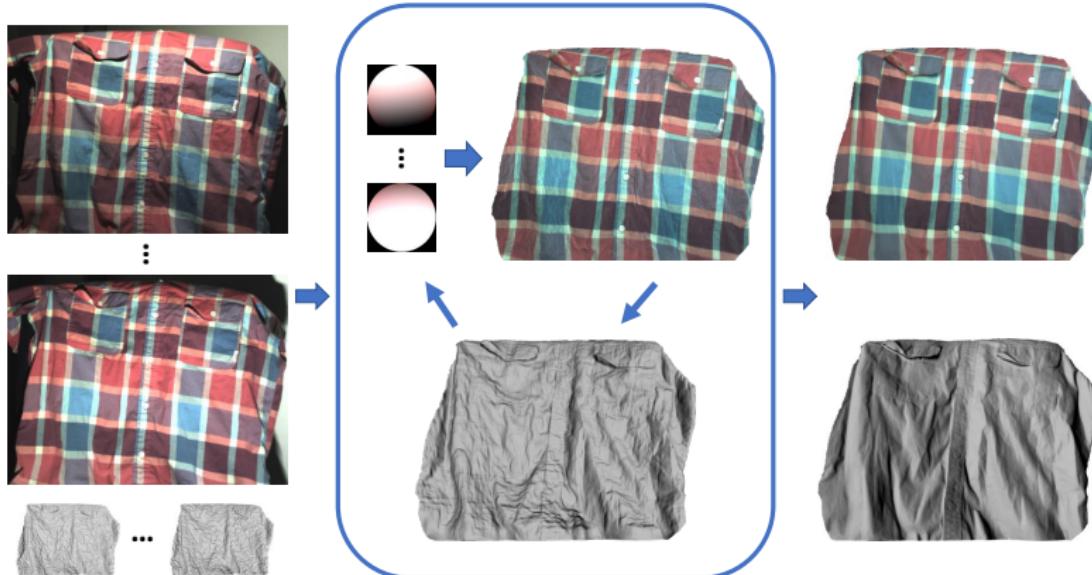
- depth super-resolution cue: $\mathbf{z}_0^i = K\mathbf{z} + \varepsilon_{\mathbf{z}}^i, \forall i \in \{1, \dots, n\}$
- photometric stereo cue: $\mathbf{A}^i(\mathbf{z}, \rho, \mathbf{l}^i)^\top \begin{bmatrix} \nabla \mathbf{z} \\ \mathbf{z} \end{bmatrix} = \mathbf{b}^i(\rho, \mathbf{l}^i) + \varepsilon^i$

The final variational model is acquired from maximum likelihood:

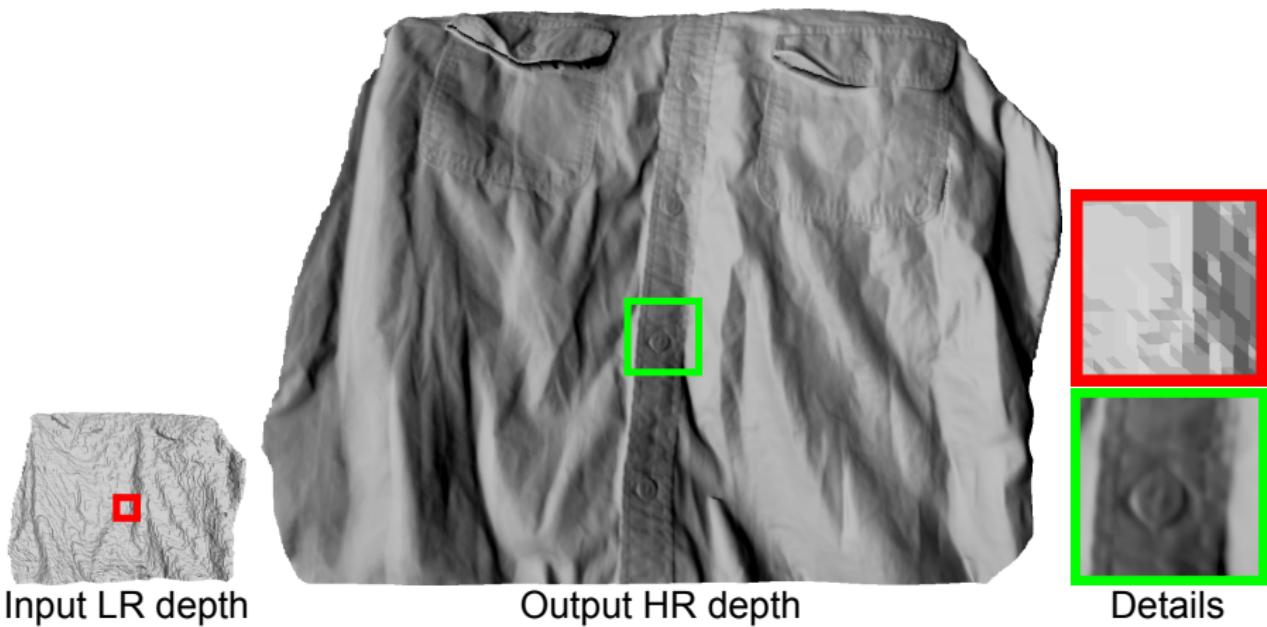
$$\min_{\mathbf{z}, \rho, \{\mathbf{l}^i\}_i} \left\{ \sum_{i=1}^n \|K\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2 + \lambda \sum_{i=1}^n \left\| \mathbf{A}^i(\mathbf{z}, \rho, \mathbf{l}^i)^\top \begin{bmatrix} \nabla \mathbf{z} \\ \mathbf{z} \end{bmatrix} - \mathbf{b}^i(\rho, \mathbf{l}^i) \right\|_{\ell^2}^2 \right\}$$

Alternating Optimization Workflow

$$\min_{\mathbf{z}, \boldsymbol{\rho}, \{\mathbf{l}^i\}_i} \left\{ \sum_{i=1}^n \|\mathbf{K}\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2 + \lambda \sum_{i=1}^n \left\| \mathbf{A}^i(\mathbf{z}, \boldsymbol{\rho}, \mathbf{l}^i)^\top \begin{bmatrix} \nabla \mathbf{z} \\ \mathbf{z} \end{bmatrix} - \mathbf{b}^i(\boldsymbol{\rho}, \mathbf{l}^i) \right\|_{\ell^2}^2 \right\}$$



Alternating Optimization Workflow



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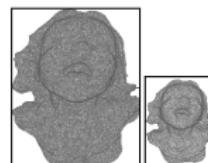
Synthetic Data



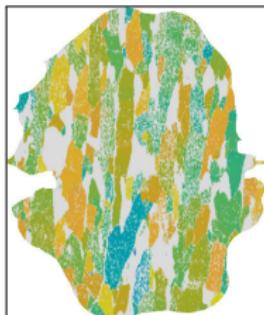
3D shape



Ground truth HR depth



LR noisy depth

HR albedo map¹

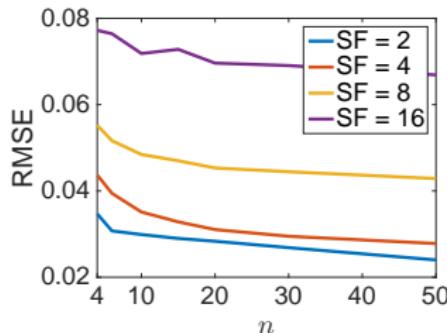
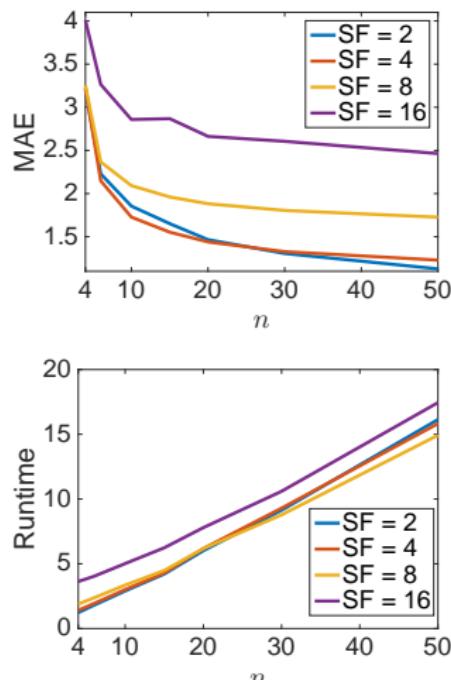
HR photometric stereo images



¹Source: <https://mtex-toolbox.github.io/files/doc/EBSDSpatialPlots.html>

Quantitative Evaluation

Number of images

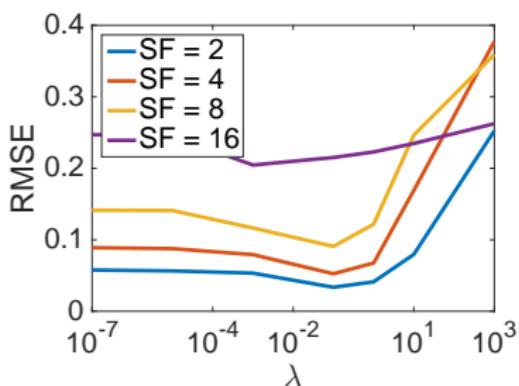
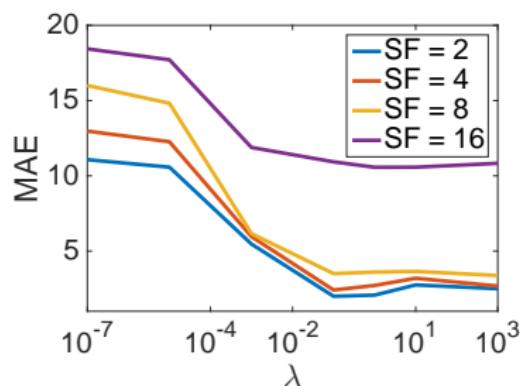


$n \in [10, 30]$ is a good compromise between accuracy and speed

Quantitative Evaluation

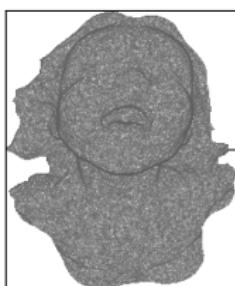
Parameter tuning

$$\min_{\mathbf{z}, \boldsymbol{\rho}, \{\mathbf{l}^i\}_i} \left\{ \sum_{i=1}^n \|\mathbf{K}\mathbf{z} - \mathbf{z}_0^i\|_{\ell^2}^2 + \lambda \sum_{i=1}^n \left\| \mathbf{A}^i(\mathbf{z}, \boldsymbol{\rho}, \mathbf{l}^i)^\top \begin{bmatrix} \nabla \mathbf{z} \\ \mathbf{z} \end{bmatrix} - \mathbf{b}^i(\boldsymbol{\rho}, \mathbf{l}^i) \right\|_{\ell^2}^2 \right\}$$



$\lambda \in [10^{-2}, 10^1]$ provide satisfactory results

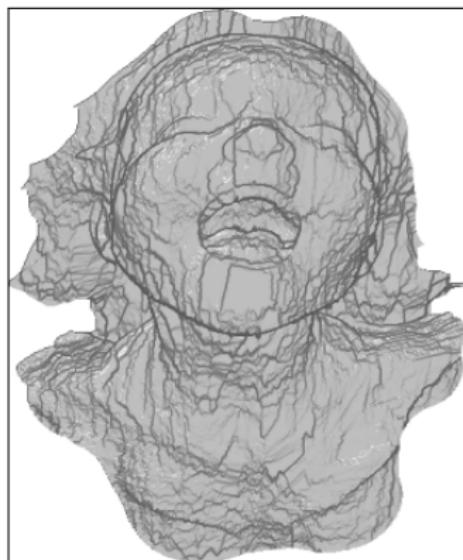
Quantitative Evaluation



RMSE = 0.0579

MAE = 65.7150

Input depth

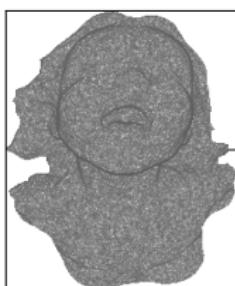


RMSE = 0.0728

MAE = 34.4129

Depth super-resolution with TV

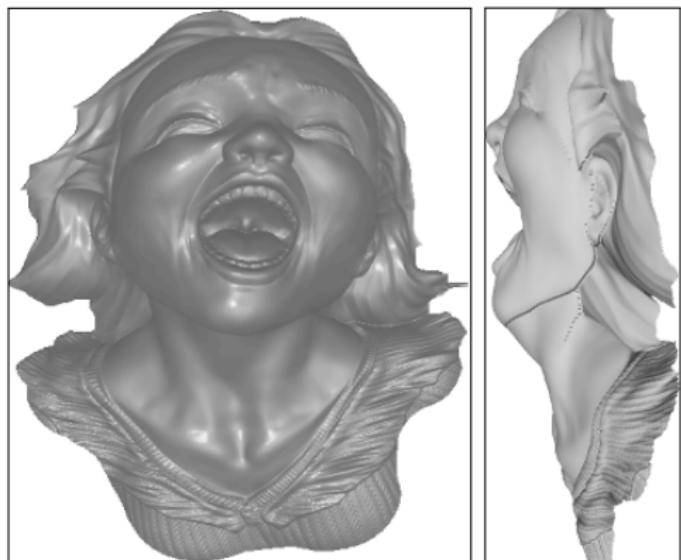
Quantitative Evaluation



RMSE = 0.0579

MAE = 65.7150

Input depth

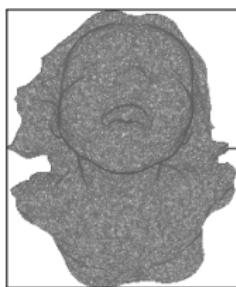


RMSE = 0.9199

MAE = 41.8041

LDR Photometric Stereo
[Papadhimitri and Favaro, IJCV 2014]

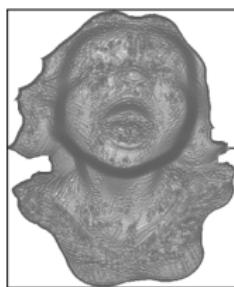
Quantitative Evaluation



RMSE = 0.0579

MAE = 65.7150

Input depth



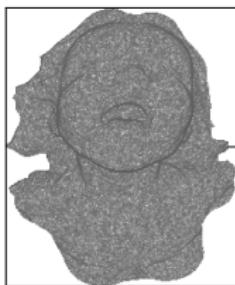
RMSE = 0.1655

MAE = 38.9316

RGBD-Fusion

[Or-El et al., CVPR 2015]

Quantitative Evaluation



RMSE = 0.0579

MAE = 65.7150

Input depth



RMSE = **0.0314**

MAE = **1.45280**

Ours

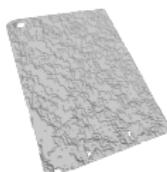
Quantitative Evaluation

	RMSE	MAE
Input	0.0579	65.7150
Depth SR	0.0728	34.4129
LDR PS	0.0919	41.8041
RGBD-Fusion	0.1655	38.9316
Ours	0.0314	1.45280

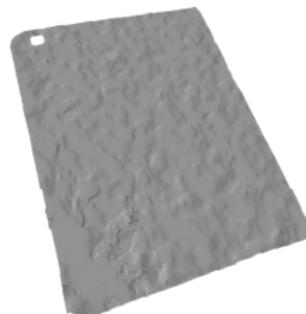
Qualitative Evaluation



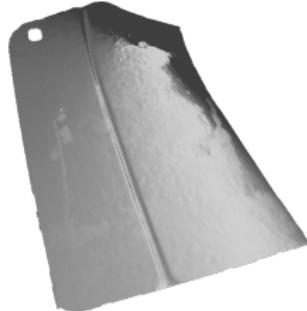
Input RGB image



Input depth



Depth SR



LDR-PS



RGBD-Fusion



Ours

Qualitative Evaluation



Input RGB image



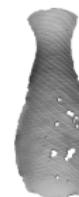
Input depth



Depth SR



LDR-PS



RGBD-Fusion



Ours

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Conclusions and Future work

- We proposed a novel variational framework for joint depth super-resolution and reflectance/light estimation
- Our method can be used out-of-the-box with common devices
- Theoretical analysis of this approach will be the next step

Data and codes are available on
<https://github.com/pengsongyou/SRmeetsPS>



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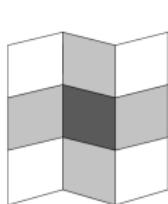
Computer Vision Group

Technical University of Munich

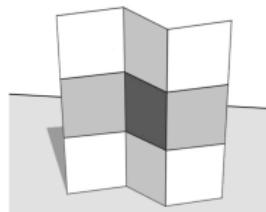


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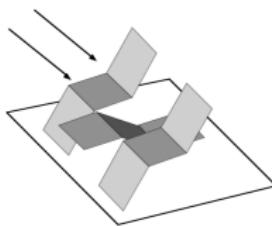
Shape from shading ambiguity



(a) An image

(b) A possible expla-
nation

(c) painter's



(d) sculptor's

(e) Lighting
designer's

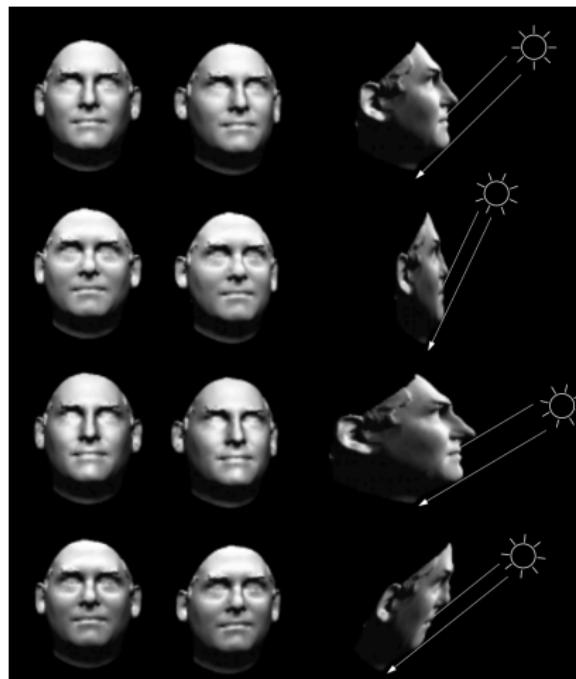
[Adelson and Pentland, 1996]



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Generalized Bas-Relief (GBR)



[belhumeur et al., IJCV 99]