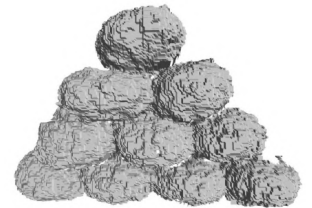


Fight Ill-Posedness with Ill-Posedness: Single-Shot Variational Depth Super-Resolution from Shading

Bjoern Haefner, Yvain Quéau, Thomas Möllenhoff, and Daniel Cremers, 2018 IEEE/CVF
Conference on Computer Vision and Pattern Recognition

Presentation by Paul Rötzer

06. Oktober 2020

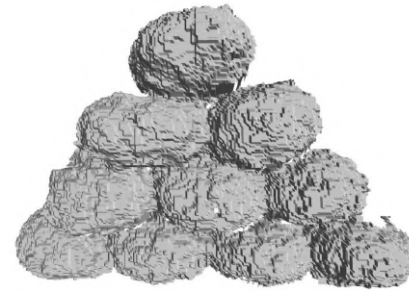


What are we trying to do?

One High Resolution Image



One Low Resolution Depth Map

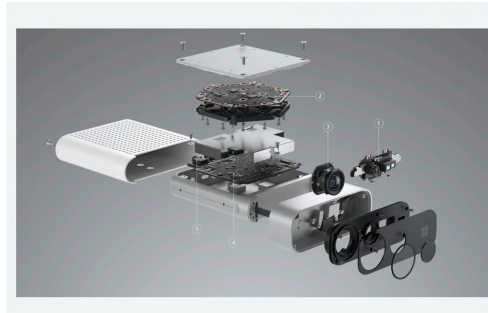


High Resolution Depth Map



Why High Res Image and Low Res Depth Map?

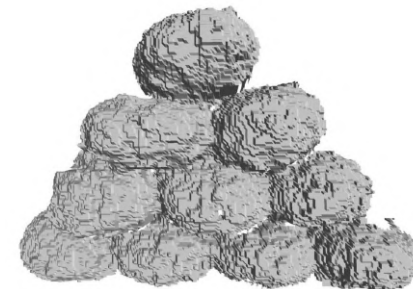
RGB-D Sensors



High Resolution Image

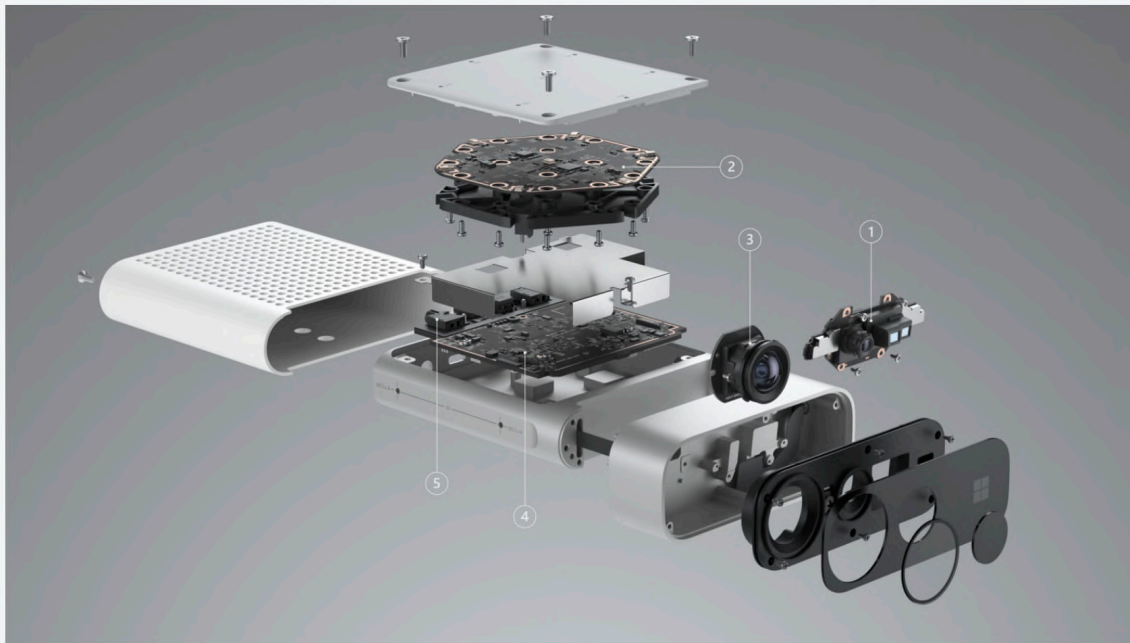


Low Resolution Depth Map



RGB-D Sensors

What's inside the Azure Kinect DK



1 1-MP depth sensor with wide and narrow field-of-view (FOV) options that help you optimize for your application

2 7-microphone array for far-field speech and sound capture

3 12-MP RGB video camera for an additional color stream that's aligned to the depth stream

4 Accelerometer and gyroscope (IMU) for sensor orientation and spatial tracking

5 External sync pins to easily synchronize sensor streams from multiple Kinect devices

<https://azure.microsoft.com/en-us/services/kinect-dk/#industries>

RGB-D Sensors

- Low Cost
- Consumer Hardware (e.g. Xbox Kinect)
- Mobile
- Small
- Lightweight

Agenda

Related Work

Fundamentals

Analytical Derivation

Numerical Solution

Numerical Examples

Conclusion

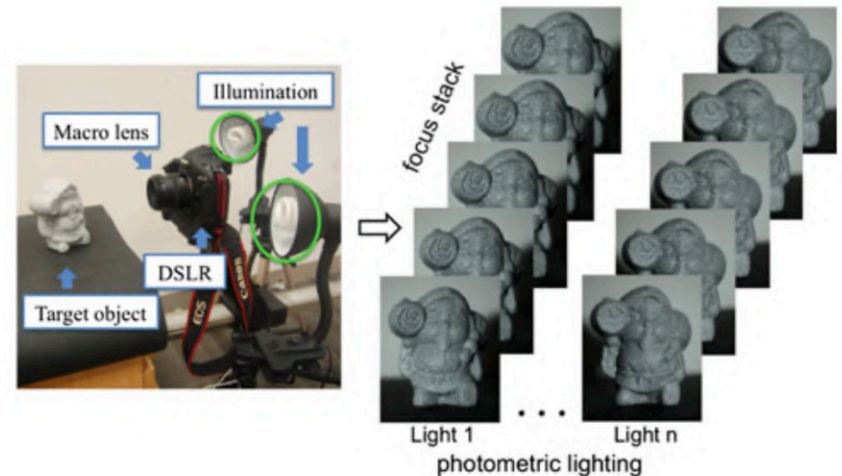
Related Work

Multiple Images



Multiple View Super-Resolution Depth Map

[Goldluecke, 2018]



Multiple Lighting Super-Resolution Depth Map

[Lu, 2013]

Single RGB-D Images

[Han, 2013]

- Input: single RGB-D image
- Constant albedo
=> Computation time: ~ 20 min



(a)



(b)

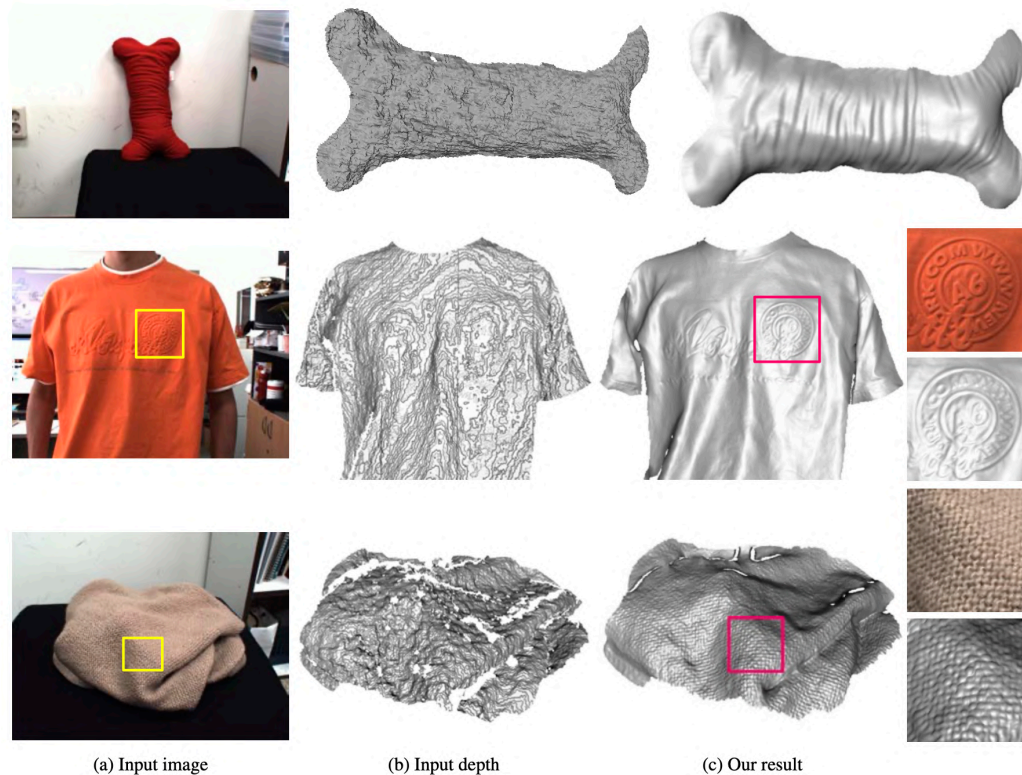


(c)



(d)

Single RGB-D Images



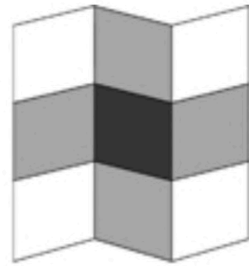
(a) Input image
[Han, 2013]

(b) Input depth

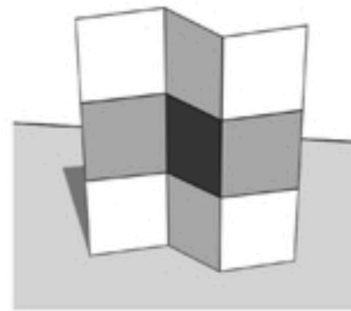
(c) Our result

Fundamentals: Ill-Posedness in 3D Reconstruction (Single-Shot)

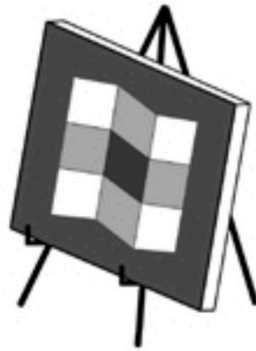
How do physical objects look which produce an image?



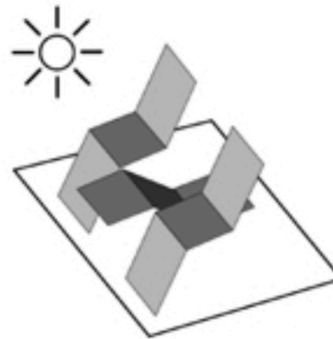
(a) an image



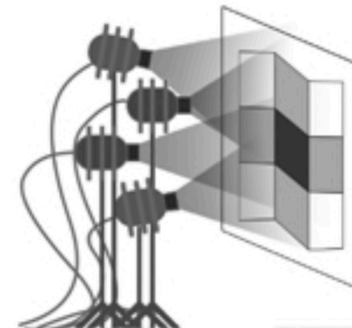
(b) a likely explanation



(c) painter's explanation



(d) sculptor's explanation



(e) gaffer's explanation

[Adelson, 1996]


How do physical objects look which produce an image?

- Ill-Posed Problem
- Humans address this problem with priors
 - Depends on the individual Background (e.g. Painter, Sculptor)
- RGB-D sensors
 - Provide an initial guess
- Different Approaches
 - Shape from Shading
 - Single Depth Super-Resolution

Ill-Posedness in **Shape** from **Shading**



Ill-Posedness in **Shape from Shading**

$$I = \mathcal{R}(z|l, \rho) + \eta_I$$


I : Image
 $\mathcal{R}(z|l, \rho)$: Scene
z : Depth Map
l : Lighting
 ρ : Surface Reflectance
 η_I : Noise

Ill-Posedness in **Shape from Shading**

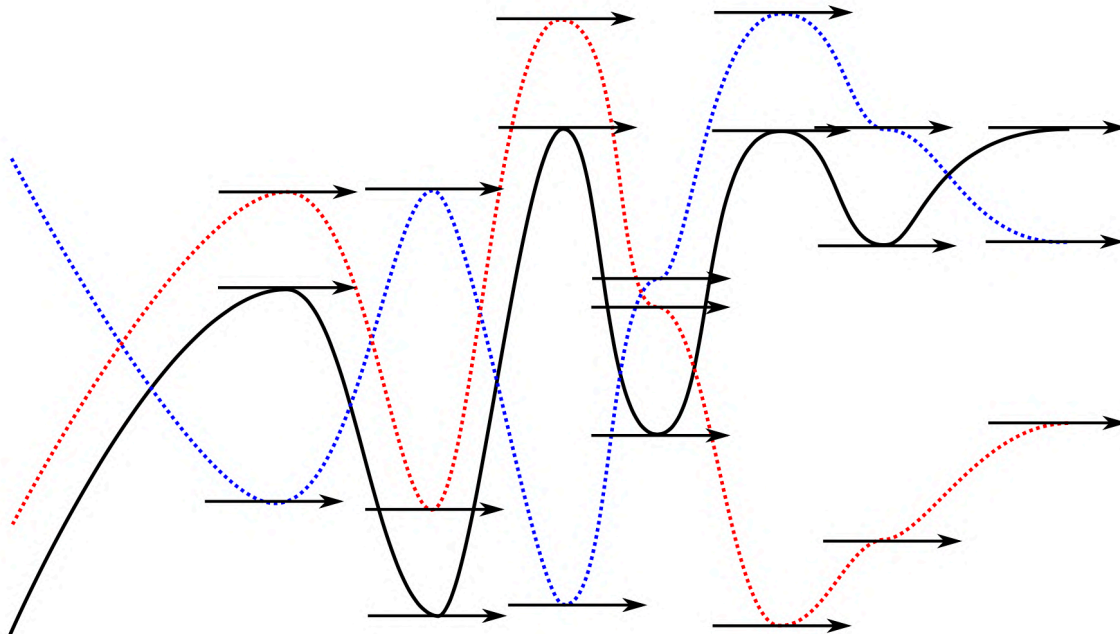
$$I = \mathcal{R}(z|l, \rho) + \eta_I$$

Solution provides only magnitude of depth gradient and not direction

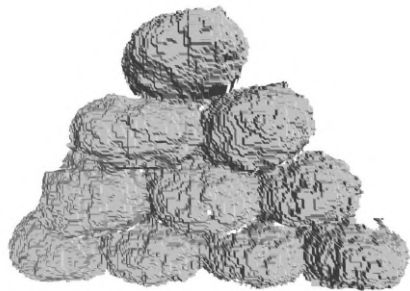
I : Image
 $\mathcal{R}(z|l, \rho)$: Scene
z : Depth Map
l : Lighting
 ρ : Surface Reflectance
 η_I : Noise

Ill-Posedness in **Shape from Shading**

Solution provides only magnitude of depth gradient and not direction



Ill-posedness in **Single Depth Image Super-Resolution**



Ill-posedness in **Single Depth Image Super-Resolution**

$$z_0 = Kz + \eta_z$$



z_0 : *Depth Map (low res)*
 z : *Depth Map (high res)*
 K : *Warping, Blurring, Downsampling*
 η_z : *Noise*

Ill-posedness in **Single Depth Image Super-Resolution**

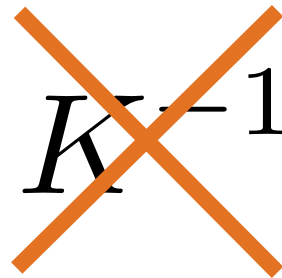
$$z_0 = Kz + \eta_z$$

$$z_0 = Kz + \eta_z$$

z_0 : Depth Map (low res)
 z : Depth Map (high res)
 K : Warping, Blurring, Downsampling
 η_z : Noise

Ill-posedness in **Single Depth Image Super-Resolution**

$$z_0 = Kz + \eta_z$$


$$~~K^{-1}~~$$

K not square \blacktriangleright K not invertible

z_0 : Depth Map (low res)
 z : Depth Map (high res)
 K : Warping, Blurring, Downsampling
 η_z : Noise

Fight Ill-Posedness with Ill-Posedness: **Derivation** of the Variational Approach

Derivation of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I)$$

z_0 : *Depth Map (low res)*

I : *Image*

z : *Depth Map (high res)*

ρ : *Surface Reflectance*

l : *Lighting*

Derivation of the Variational Approach

$$\mathcal{P}(z, \rho, l | z_0, I) = \frac{\mathcal{P}(z_0, I | z, \rho, l) \mathcal{P}(z, \rho, l)}{\mathcal{P}(z_0, I)}$$
$$\propto \underbrace{\mathcal{P}(z_0, I | z, \rho, l)}_{\text{likelihood}} \underbrace{\mathcal{P}(z, \rho, l)}_{\text{prior}}$$

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) = -\min_{z, \rho, l} \log (\mathcal{P}(z, \rho, l | z_0, I))$$

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

$$\mathcal{P}(z, \rho, l | z_0, I) = \frac{\mathcal{P}(z_0, I | z, \rho, l) \mathcal{P}(z, \rho, l)}{\mathcal{P}(z_0, I)}$$
$$\propto \mathcal{P}(z_0, I | z, \rho, l) \mathcal{P}(z, \rho, l)$$

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) = -\min_{z, \rho, l} \log (\mathcal{P}(z, \rho, l | z_0, I))$$



z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

$$\mathcal{P}(z, \rho, l | z_0, I) = \frac{\mathcal{P}(z_0, I | z, \rho, l) \mathcal{P}(z, \rho, l)}{\mathcal{P}(z_0, I)}$$

$$\propto \mathcal{P}(z_0, I | z, \rho, l) \mathcal{P}(z, \rho, l)$$

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) = -\min_{z, \rho, l} \log (\mathcal{P}(z, \rho, l | z_0, I))$$



$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) = -\min_{z, \rho, l} \log (\mathcal{P}(z_0, I | z, \rho, l)) + \log (\mathcal{P}(z, \rho, l))$$

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

Assumptions

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

- RGB-D Sensors: Image and Depth measurement are independent (by construction)

$$\mathcal{P}(z_0, I | z, \rho, l) = \mathcal{P}(z_0 | z) \mathcal{P}(I | z, \rho, l)$$

- Depth is independent from reflectance and lighting

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

- RGB-D Sensors: Image and Depth measurement are independent (by construction)

$$\mathcal{P}(z_0, I | z, \rho, l) = \mathcal{P}(z_0 | z) \mathcal{P}(I | z, \rho, l)$$

- Depth is independent from reflectance and lighting

- Independence of Depth, Reflectance and Lighting

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z) \mathcal{P}(\rho) \mathcal{P}(l)$$

- Lambertian Surfaces
- Distant-Light

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z_0, I | z, \rho, l) = \mathcal{P}(z_0 | z) \mathcal{P}(I | z, \rho, l)$$

z_0 : *Depth Map (low res)*

I : *Image*

z : *Depth Map (high res)*

ρ : *Surface Reflectance*

l : *Lighting*

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z_0, I | z, \rho, l) = \mathcal{P}(z_0 | z) \mathcal{P}(I | z, \rho, l)$$



Homoskedastic, zero-mean Gaussian noise

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z_0, I | z, \rho, l) = \mathcal{P}(z_0 | z) \mathcal{P}(I | z, \rho, l)$$

Homoskedastic, zero-mean Gaussian noise

Achromatic lighting, first-order spherical harmonics, homoskedastic, zero-mean Gaussian noise

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\mathcal{P}(l)$$

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\mathcal{P}(l)$$



Minimal surface

- Robustness

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\mathcal{P}(l)$$

Minimal surface

- Robustness

Piecewise constant

- Reflectance must fit this prior

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

Assumptions

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\mathcal{P}(l)$$

Minimal surface
• Robustness

Piecewise constant
• Reflectance
must fit this prior

constant

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

$$\mathcal{P}(z_0, I|z, \rho, l) = \mathcal{P}(z_0|z)\mathcal{P}(I|z, \rho, l)$$

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\mathcal{P}(l)$$

constant



z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

$$\mathcal{P}(z_0, I|z, \rho, l) = \mathcal{P}(z_0|z)\mathcal{P}(I|z, \rho, l)$$

$$\mathcal{P}(z, \rho, l) = \mathcal{P}(z)\mathcal{P}(\rho)\overset{\text{constant}}{\cancel{\mathcal{P}(l)}}$$



$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l|z_0, I) =$$

$$- \min_{z, \rho, l} \log(\mathcal{P}(I|z, \rho, l)) + \log(\mathcal{P}(z_0|z)) + \log(\mathcal{P}(z)) + \log(\mathcal{P}(\rho))$$

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Derivation of the Variational Approach

$$\mathcal{P}(z_0, I|z, \rho, l) = \overbrace{\mathcal{P}(z_0|z)}^{\text{single depth super-resolution}} \underbrace{\mathcal{P}(I|z, \rho, l)}_{\text{shape from shading}}$$

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Derivation of the Variational Approach

$$\mathcal{P}(z_0, I|z, \rho, l) = \overbrace{\mathcal{P}(z_0|z)}^{\text{single depth super-resolution}} \underbrace{\mathcal{P}(I|z, \rho, l)}_{\text{shape from shading}}$$

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l|z_0, I) =$$

$$- \min_{z, \rho, l} \underbrace{\log(\mathcal{P}(I|z, \rho, l))}_{\text{shape from shading}} + \overbrace{\log(\mathcal{P}(z_0|z))}^{\text{single depth super-resolution}} + \log(\mathcal{P}(z)) + \log(\mathcal{P}(\rho))$$

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ρ : Surface Reflectance
 l : Lighting

Fighting Ill-Posedness with Ill-Posedness: **Numerical Solution** of the Variational Approach

Numerical Solution of the Variational Approach

Alternating Direction Method of Multipliers (ADMM)

Numerical Solution of the Variational Approach

Alternating Direction Method of Multipliers (ADMM)

Problem

$$\min f(x) + g(z)$$
$$\text{s.t. } x = z$$

Numerical Solution of the Variational Approach

Alternating Direction Method of Multipliers (ADMM)

Problem $\min f(x) + g(z)$

s.t. $x = z$

Lagrangian

$$\mathcal{L}_\rho(x, z, y) = f(x) + g(x) + u^T (Ax - z) + \frac{\rho}{2} \|Ax - z\|_2^2$$

Numerical Solution of the Variational Approach

Alternating Direction Method of Multipliers (ADMM)

Problem $\min f(x) + g(z)$

s.t. $x = z$

Lagrangian

$$\mathcal{L}_\rho(x, z, y) = f(x) + g(x) + u^T (Ax - z) + \frac{\rho}{2} \|Ax - z\|_2^2$$

Iterations

$$x^{k+1} := \operatorname{argmin}_x \mathcal{L}_\rho(x, z^k, y^k)$$

$$z^{k+1} := \operatorname{argmin}_z \mathcal{L}_\rho(x^{k+1}, z, y^k)$$

$$u^{k+1} := u^k + x^{k+1} - z^{k+1}$$

[Boyd, 2010]

Numerical Solution of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) =$$
$$- \min_{z, \rho, l} \log(\mathcal{P}(I | z, \rho, l)) + \log(\mathcal{P}(z_0 | z)) + \log(\mathcal{P}(z)) + \log(\mathcal{P}(\rho))$$

z_0 : *Depth Map (low res)*
 I : *Image*
 z : *Depth Map (high res)*
 ρ : *Surface Reflectance*
 l : *Lighting*

Numerical Solution of the Variational Approach

$$\begin{aligned}
 \max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) = \\
 - \min_{z, \rho, l} \underbrace{\log(\mathcal{P}(I | z, \rho, l))}_{:= -f(z, \nabla z, \rho, l)} + \underbrace{\log(\mathcal{P}(z_0 | z))}_{:= -\mu g(z)} + \underbrace{\log(\mathcal{P}(z))}_{:= -\nu h(z, \nabla z)} + \underbrace{\log(\mathcal{P}(\rho))}_{:= -\lambda p(\rho)}
 \end{aligned}$$

z_0 : Depth Map (low res)
 I : Image
 z : Depth Map (high res)
 ∇z : Gradient of Depth Map
 ρ : Surface Reflectance
 l : Lighting
 μ, ν, λ : Weights

Numerical Solution of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) =$$

$$\min_{z, \rho, l} f(z, \nabla z, \rho, l) + \mu g(z) + \nu h(z, \nabla z) + \lambda p(\rho)$$

z : Depth Map (high res)

∇z : Gradient of Depth Map

ρ : Surface Reflectance

l : Lighting

μ, ν, λ : Weights

Numerical Solution of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) =$$
$$\min_{z, \rho, l} f(z, \nabla z, \rho, l) + \mu g(z) + \nu h(z, \nabla z) + \lambda p(\rho)$$

Introducing

$$\theta := (z, \nabla z)$$

z : Depth Map (high res)
 ∇z : Gradient of Depth Map
 ρ : Surface Reflectance
 l : Lighting
 μ, ν, λ : Weights

Numerical Solution of the Variational Approach

$$\max_{z, \rho, l} \mathcal{P}(z, \rho, l | z_0, I) =$$

$$\min_{z, \rho, l} f(z, \nabla z, \rho, l) + \mu g(z) + \nu h(z, \nabla z) + \lambda p(\rho)$$

Introducing

$$\theta := (z, \nabla z)$$

To obtain

$$\min_{z, \rho, l, \theta} f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho)$$

$$\text{s.t. } \theta = (z, \nabla z)$$

z : Depth Map (high res)
∇z : Gradient of Depth Map
ρ : Surface Reflectance
l : Lighting
μ, ν, λ : Weights

Numerical Solution of the Variational Approach

$$\min_{z, \rho, l, \theta} f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho)$$

s.t. $\theta = (z, \nabla z)$

z : Depth Map (high res)
∇z : Gradient of Depth Map
ρ : Surface Reflectance
l : Lighting
μ, ν, λ : Weights
u : Lagrange Multiplier
κ : Step Size

Numerical Solution of the Variational Approach

$$\min_{z, \rho, l, \theta} f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho)$$

s.t. $\theta = (z, \nabla z)$

$$\mathcal{L}_\kappa(z, \rho, l, \theta, u) = f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho) \\ + u^T (\theta - (z, \nabla z)) + \frac{\kappa}{2} \|\theta - (z, \nabla z)\|_2^2$$

z : Depth Map (high res)
 ∇z : Gradient of Depth Map
 ρ : Surface Reflectance
 l : Lighting
 μ, ν, λ : Weights
 u : Lagrange Multiplier
 κ : Step Size

Numerical Solution of the Variational Approach

$$\begin{aligned} \mathcal{L}_\kappa(z, \rho, l, \theta, u) = & f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho) \\ & + u^\top (\theta - (z, \nabla z)) + \frac{\kappa}{2} \|\theta - (z, \nabla z)\|_2^2 \end{aligned}$$

$$\rho^{(k+1)} = \operatorname{argmin}_\rho f(\theta^{(k)}, \rho, l^{(k)}) + \lambda p(\rho)$$

$$l^{(k+1)} = \operatorname{argmin}_l f(\theta^{(k)}, \rho^{(k+1)}, l)$$

$$\theta^{(k+1)} = \operatorname{argmin}_\theta f(\theta, \rho^{(k+1)}, l^{(k+1)}) + \nu h(\theta) + \frac{\kappa}{2} \|\theta - (z^{(k)}, \nabla z^{(k)}) + u^{(k)}\|_2^2$$

$$z^{(k+1)} = \operatorname{argmin}_z \mu g(z) + \frac{\kappa}{2} \|\theta^{(k+1)} - (z, \nabla z) + u^{(k)}\|_2^2$$

$$u^{(k+1)} = u^{(k)} + \theta^{(k+1)} - (z^{(k+1)}, \nabla z^{(k+1)})$$

z : Depth Map (high res)
 ∇z : Gradient of Depth Map
 ρ : Surface Reflectance
 l : Lighting
 μ, ν, λ : Weights
 u : Lagrange Multiplier
 κ : Step Size

Numerical Solution of the Variational Approach

$$\min_{z, \rho, l, \theta} f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho)$$

$$\text{s.t. } \theta = (z, \nabla z)$$

$$\rho^{(k+1)} = \underset{\rho}{\operatorname{argmin}} f(\theta^{(k)}, \rho, l^{(k)}) + \lambda p(\rho)$$

$$l^{(k+1)} = \underset{l}{\operatorname{argmin}} f(\theta^{(k)}, \rho^{(k+1)}, l)$$

$$\theta^{(k+1)} = \underset{\theta}{\operatorname{argmin}} f(\theta, \rho^{(k+1)}, l^{(k+1)}) + \nu h(\theta) + \frac{\kappa}{2} \|\theta - (z^{(k)}, \nabla z^{(k)}) + u^{(k)}\|_2^2$$

$$z^{(k+1)} = \underset{z}{\operatorname{argmin}} \mu g(z) + \frac{\kappa}{2} \|\theta^{(k+1)} - (z, \nabla z) + u^{(k)}\|_2^2$$

$$u^{(k+1)} = u^{(k)} + \theta^{(k+1)} - (z^{(k+1)}, \nabla z^{(k+1)})$$

z : Depth Map (high res)
 ∇z : Gradient of Depth Map
 ρ : Surface Reflectance
 l : Lighting
 μ, ν, λ : Weights
 u : Lagrange Multiplier
 κ : Step Size

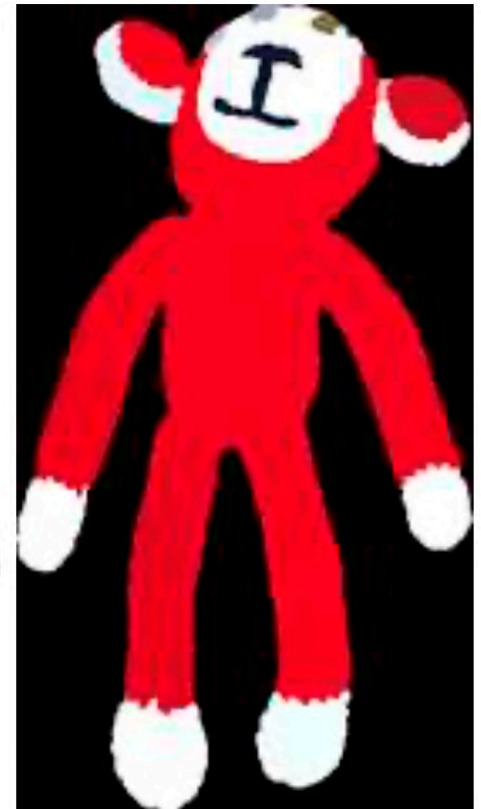
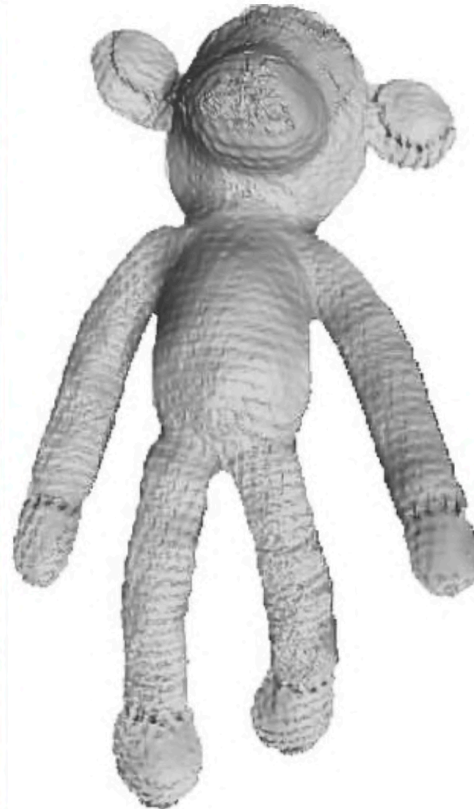
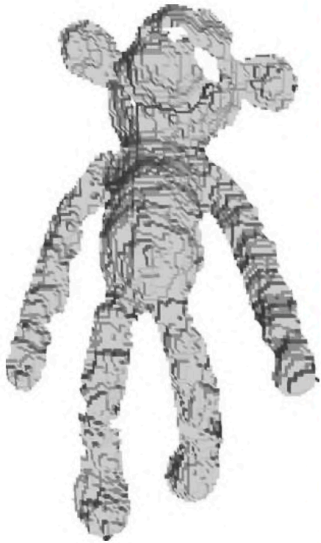
Convergence

$$\begin{aligned} \min_{z, \rho, l, \theta} & f(\theta, \rho, l) + \mu g(z) + \nu h(\theta) + \lambda p(\rho) \\ \text{s.t. } & \theta = (z, \nabla z) \end{aligned}$$

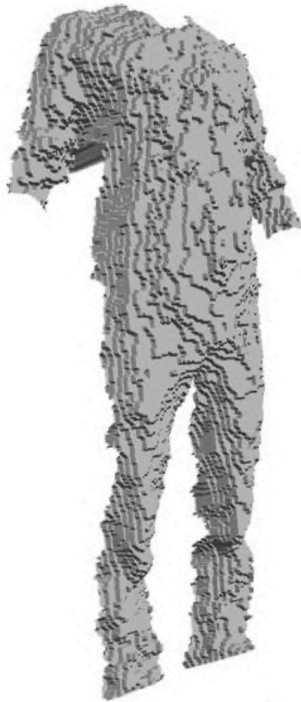
- Non-convex optimization problem
- No convergence can be imposed
- In “Fight Ill-Posedness with Ill-Posedness”:
Always Convergence after 10-20 iterations
- Computation time: ~ 2 minutes

Numerical Examples

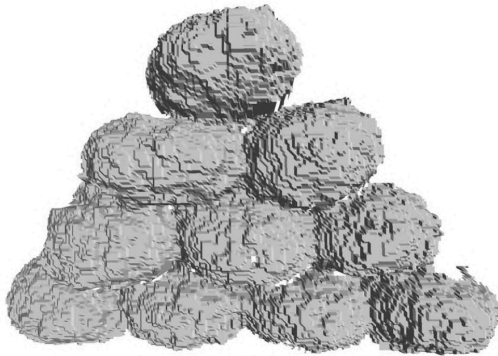
Real World Examples



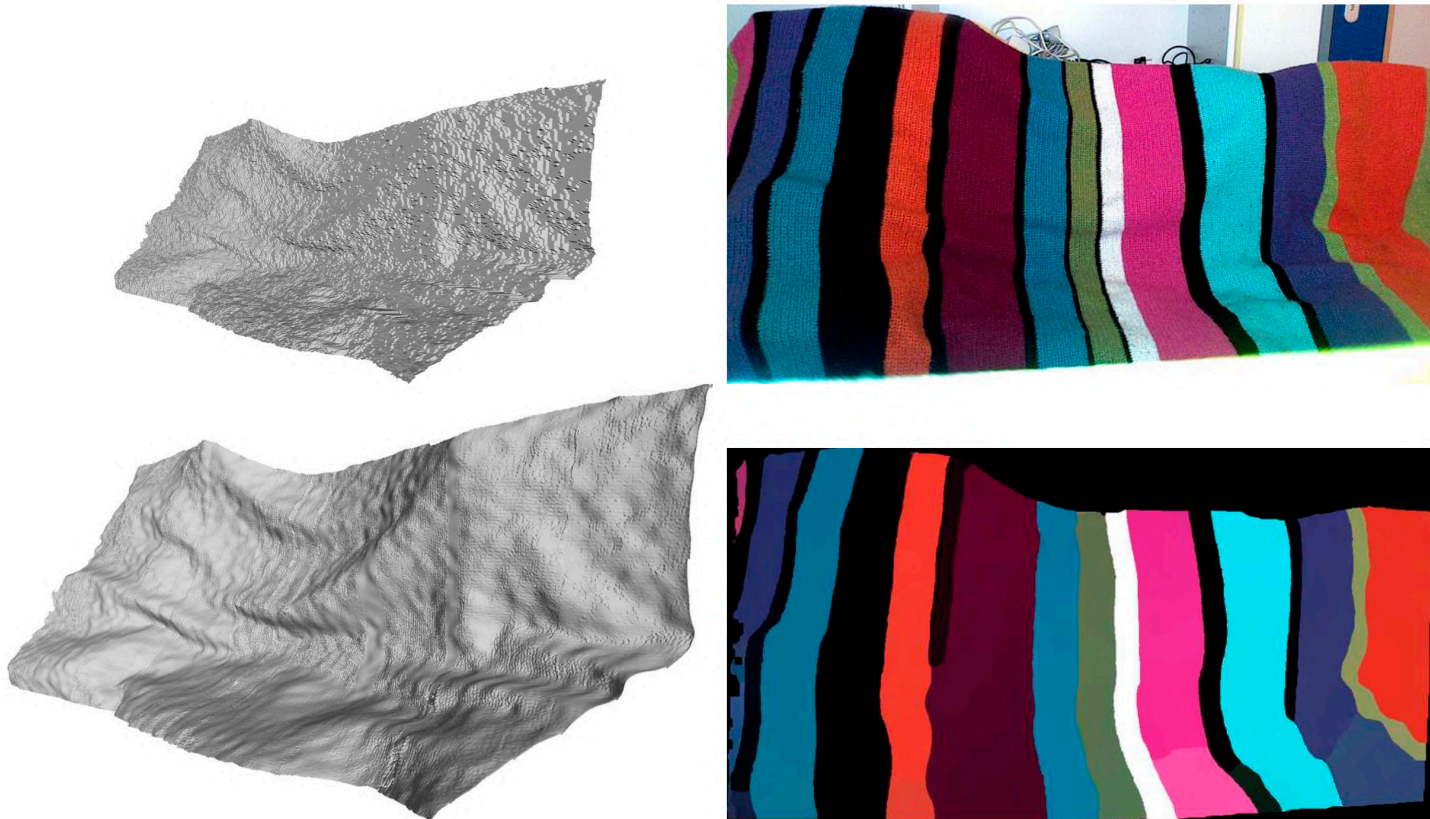
Real World Examples



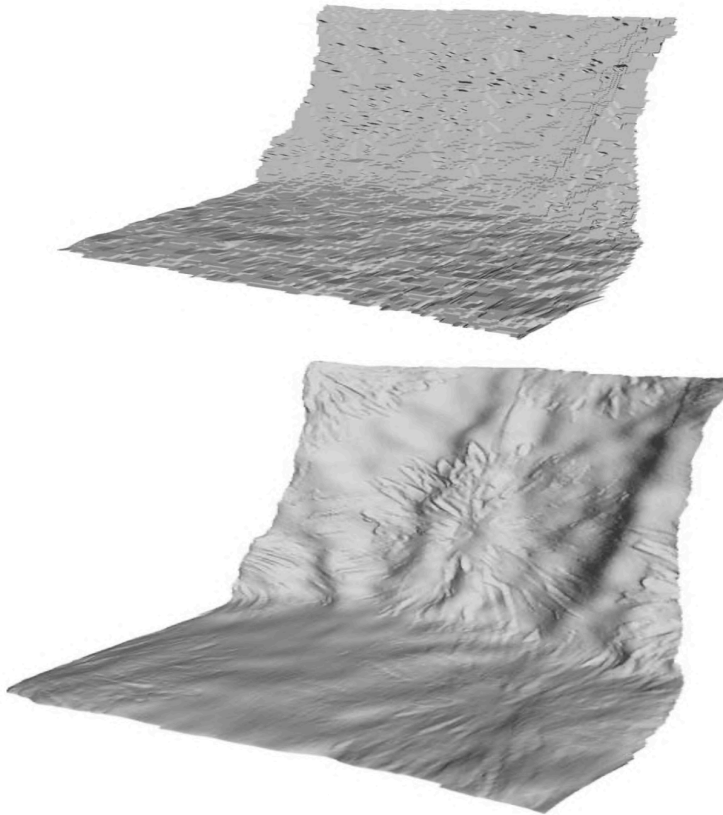
Real World Examples: Saturated Colors



Real World Examples: Black Areas



Real World Examples: Not Piecewise Constant Reflectance



Conclusion

Conclusion

- Ill-posedness in shape from shading and single depth map super-resolution
- Variational model to construct high resolution depth map from a single RGB-D image
- Corresponding numerical solution
- Numerical examples with this approach were discussed

- Relatively Fast Approach
- Requires little data (one image + one low resolution depth map)
- Extension: non-piecewise constant reflectance assumption
- Extension: Application to single-class problems (e.g. reconstructing faces)

Sources

Sources

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Thanks for your Attention! 😊

Homoscedasticity

In [statistics](#), a [sequence](#) (or a vector) of [random variables](#) is **homoscedastic** [/ˌhɒmɒsˌkɛˈdæstɪk/](#) if all its random variables have the same finite [variance](#). This is also known as **homogeneity of variance**.

<https://en.wikipedia.org/wiki/Homoscedasticity>

Azure Kinect Resolution Modes and Framerate

Color camera supported operating modes

Azure Kinect DK includes an OV12A10 12MP CMOS sensor rolling shutter sensor. The native operating modes are listed below:

RGB Camera Resolution (HxV)	Aspect Ratio	Format Options	Frame Rates (FPS)	Nominal FOV (HxV)(post-processed)
3840x2160	16:9	MJPEG	0, 5, 15, 30	90°x59°
2560x1440	16:9	MJPEG	0, 5, 15, 30	90°x59°
1920x1080	16:9	MJPEG	0, 5, 15, 30	90°x59°
1280x720	16:9	MJPEG/YUY2/NV12	0, 5, 15, 30	90°x59°
4096x3072	4:3	MJPEG	0, 5, 15	90°x74.3°
2048x1536	4:3	MJPEG	0, 5, 15, 30	90°x74.3°

<https://docs.microsoft.com/de-de/azure/kinect-dk/hardware-specification>