

Depth Extraction from Video Using Non- parametric Sampling

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Problem Statement

Given an image/video, estimate distance from the camera

No parallax necessary Camera motion OK Scene motion OK

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No parallax necessary

Camera motion OK

Scene motion OK

Input

Estimated depth



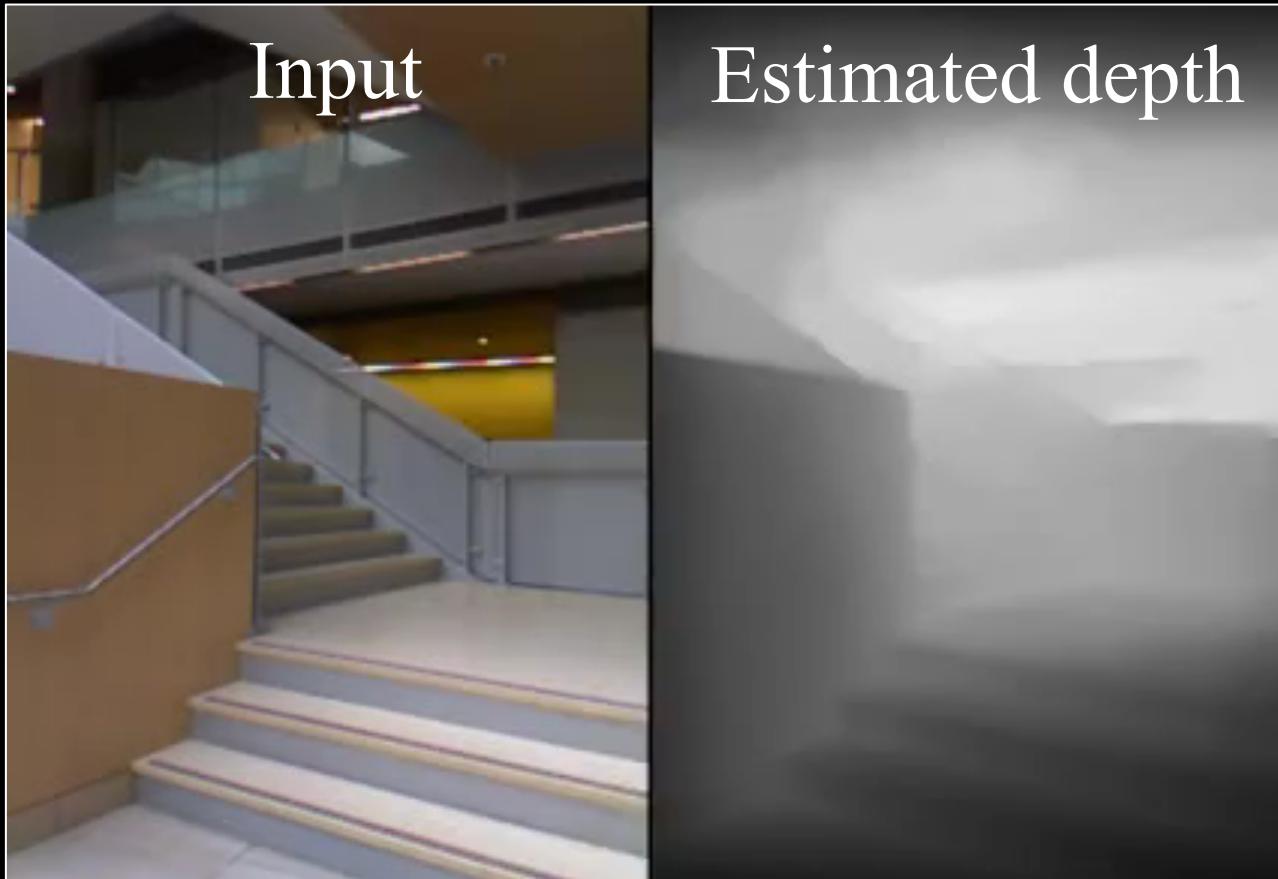
Problem Statement

Given an image/video, estimate distance from the camera

No parallax necessary

Camera motion OK

Scene motion OK



Related Work



[Zhang et al. '09]

Multiview reconstruction

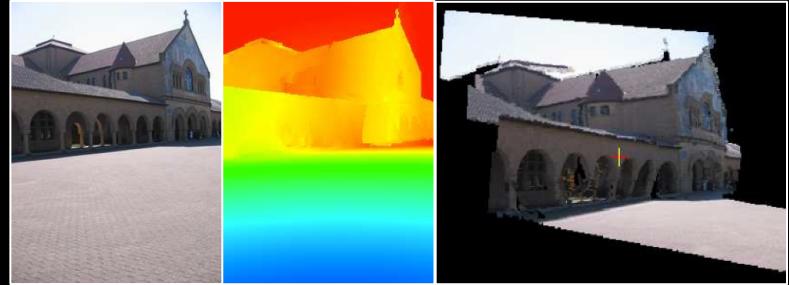
- Very accurate for videos with moving camera
- May fail for dynamic scenes

[Newcombe and Davidson '10]

[Furukawa and Ponce '09]

[Zhang et al. '09]

...



[Liu et al. '10]

Parametric learning

- Works well for single images
- No literature on extending to video

[Liu et al. '10]

[Saxena et al. '09]

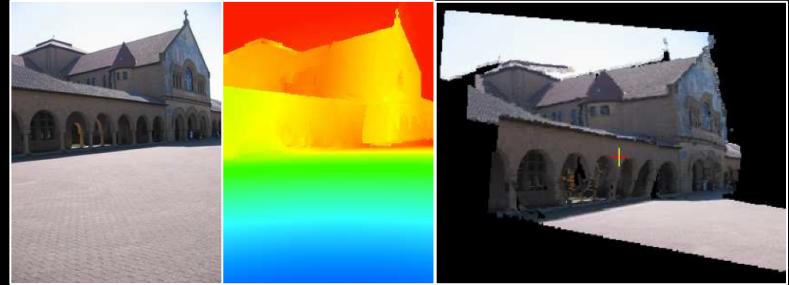
[Hoiem et al. '05]

...

Related Work



[Zhang et al. '09]



[Liu et al. '10]

Multiview reconstruction

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Parametric learning

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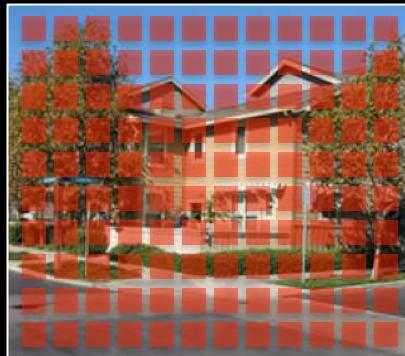
[Saxena et al. '09]

[Hoiem et al. '05]

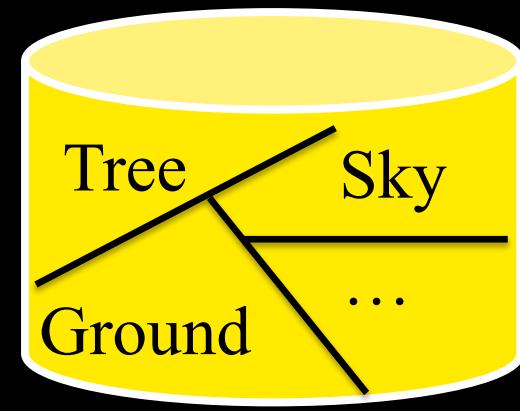
...

Training set

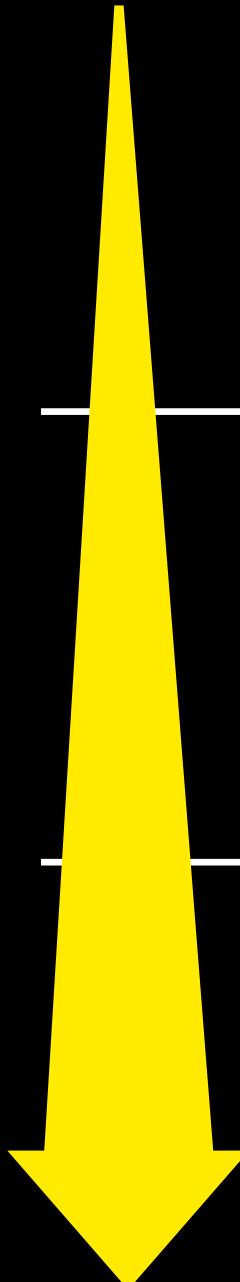
Pixel level [Saxena et al. '05]



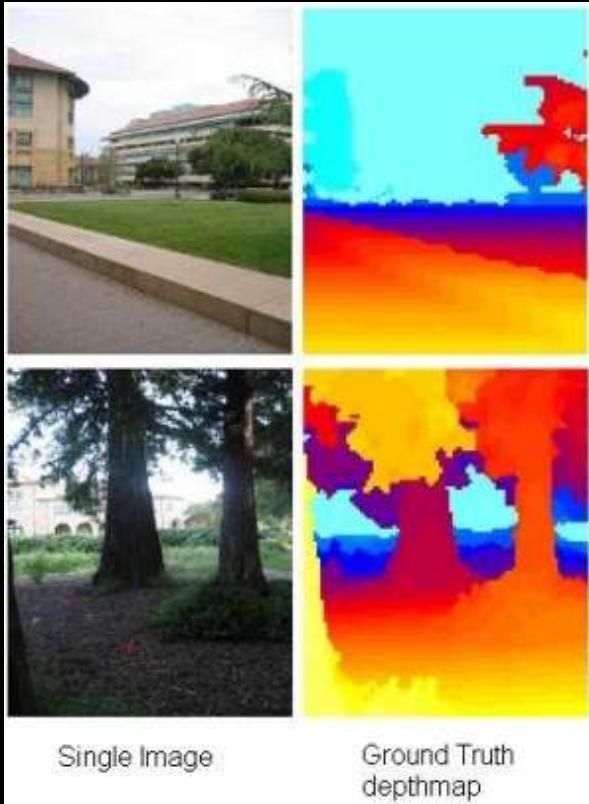
Object level [Lui et al. '10]



Scene level (ours)



RGBD Datasets



Laser rangefinder
Outdoor scenes
[Saxena et al.]



MSR-V3D
Indoor scenes
(Ours)

SIFT Flow Refresher

- Optical flow using dense SIFT features
 - Larger search window
 - Modified smoothness constraints
- Scenes rearranged so semantics are matched

Ψ
Warping operator



A

B

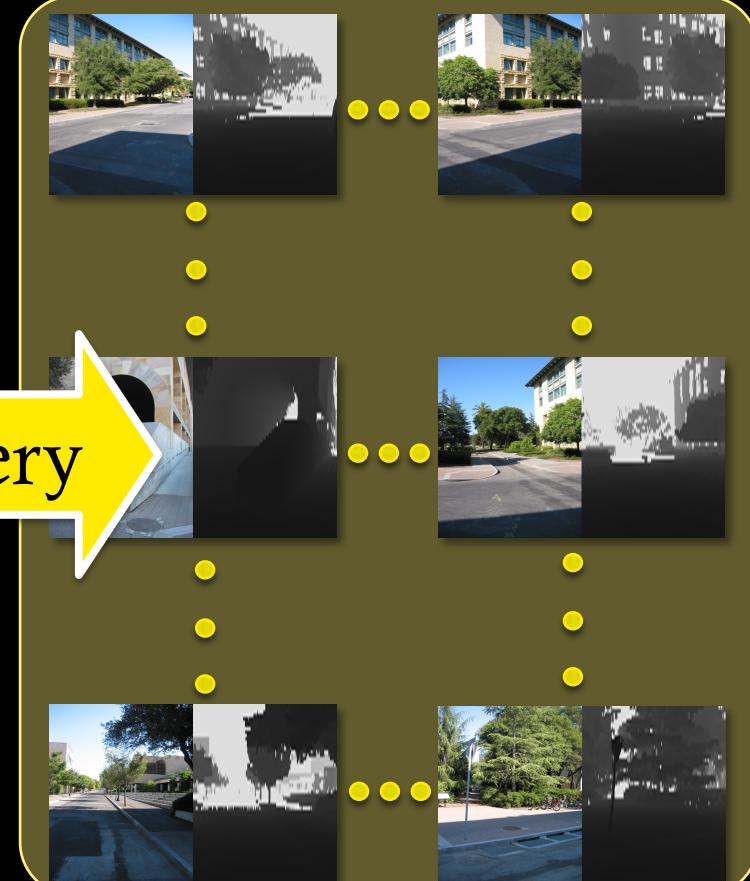
[Liu et al. '08, '09]

Algorithm

Input image



RGBD Database



Algorithm

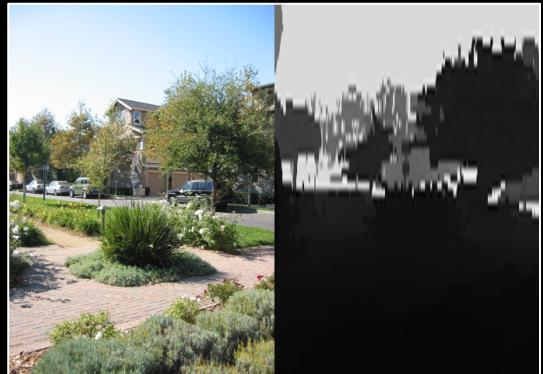
Input



Candidates

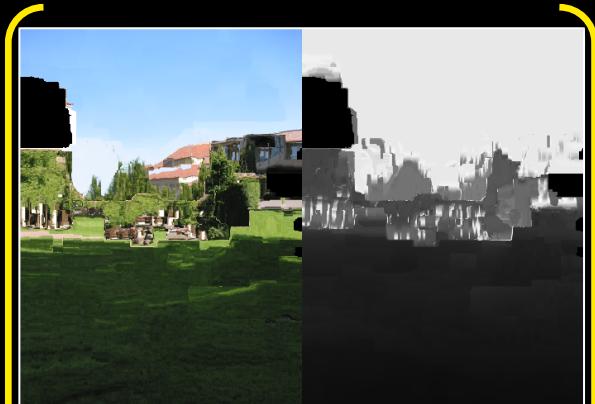


⋮



SIFT
flow

Warped candidates



⋮

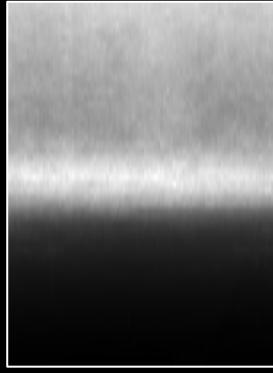


Algorithm

Input



Prior



Warped candidates



Depth
inference

Inferred depth



Inference

$$\operatorname{argmin}_D E(D) = \text{Enforce depth to match candidates}$$
$$\sum_{i \in \text{pixels}} \left[\underbrace{\sum_{C \in \text{candidates}} w_i (|D_i - C_i|_1 + \gamma |\nabla D_i - \nabla C_i|_1)}_{\text{Spatial smoothness}} + \underbrace{\alpha s_i |\nabla D_i|_1 + \beta |D_i - \text{prior}_i|_1}_{\text{Match to database mean}} \right]$$

D : inferred depth
 C : warped candidate depth
 w : depth confidence
 s : image-based weights
 α, β, γ : constant weights

- Both *absolute* and *relative* depth are transferred
- Regularize with smoothness and prior

Inference

$$\operatorname{argmin}_D E(D) = \text{Enforce depth to match candidates}$$
$$\sum_{i \in \text{pixels}} \left[\sum_{C \in \text{candidates}} w_i (|D_i - C_i|_1 + \gamma |\nabla D_i - \nabla C_i|_1) \right]$$

Not a discrete MRF!

D : inferred depth

C : warped
candidate depth

w : depth confidence

S : image-based
weights

α, β, γ : constant
weights

Spatial
smoothness

Match to
database mean

- Both *absolute* and *relative* depth are transferred
- Regularize with smoothness and prior

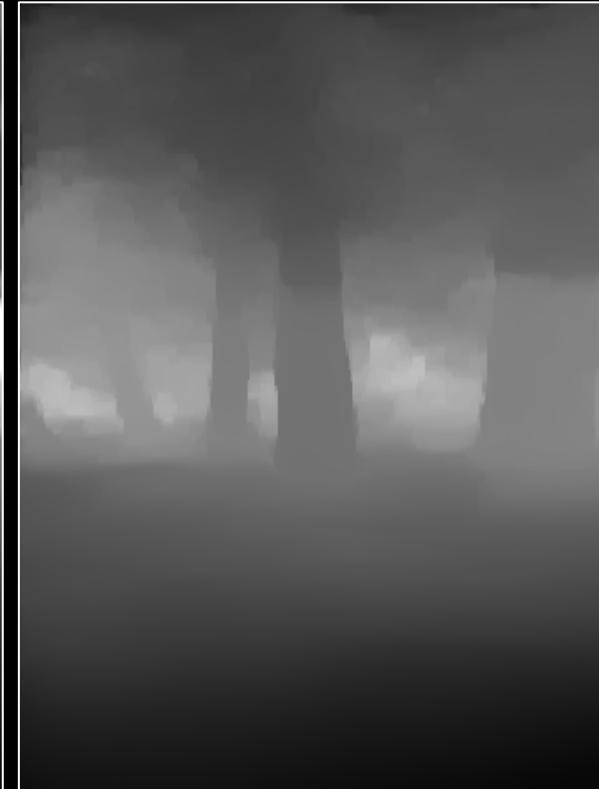
Input

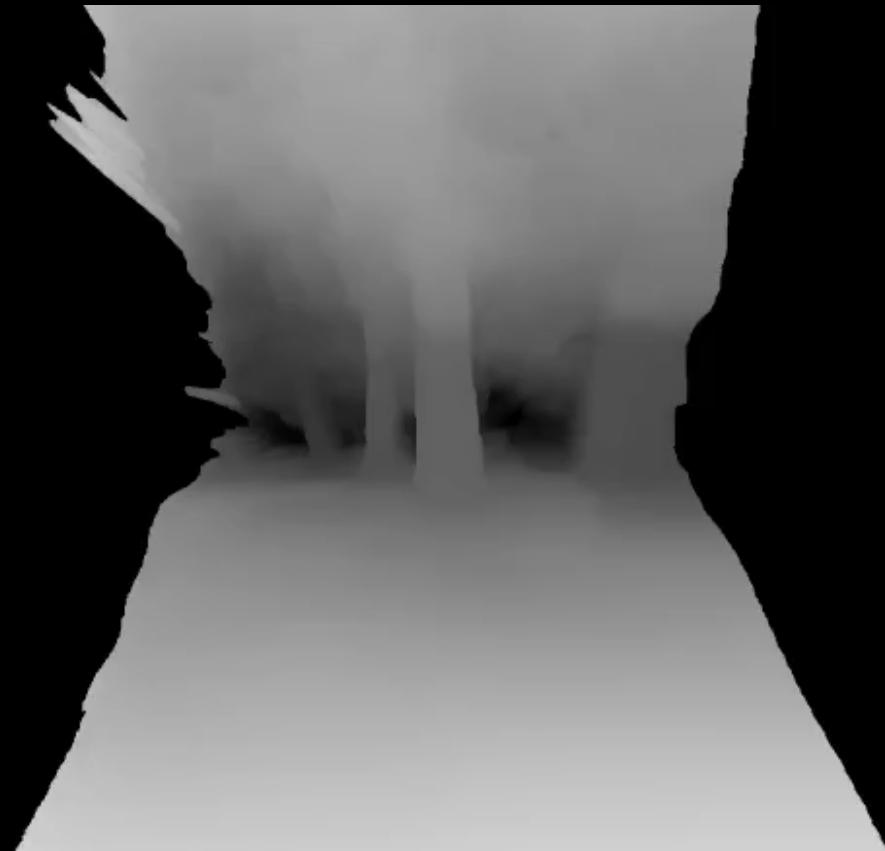


True depth



Inferred depth





Input

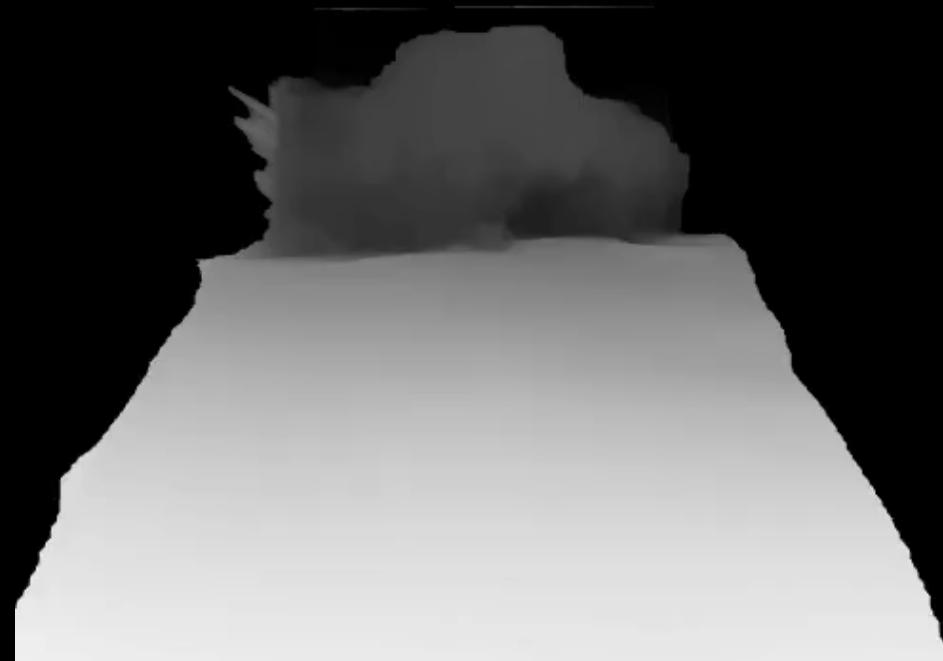


True depth



Inferred depth





$$\sum_{i \in \text{pixels}} \left[\sum_{C \in \text{candidates}} w_i (|D_i - C_i|_1 + \boxed{\gamma |\nabla D_i - \nabla C_i|_1}) \right] \\ + \alpha s_i |\nabla D_i|_1 + \beta |D_i - \text{prior}_i|_1$$

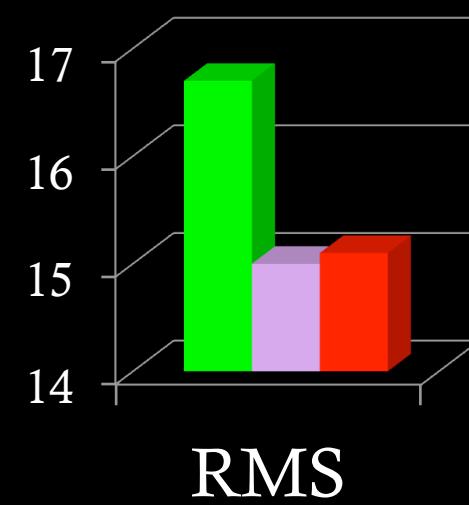
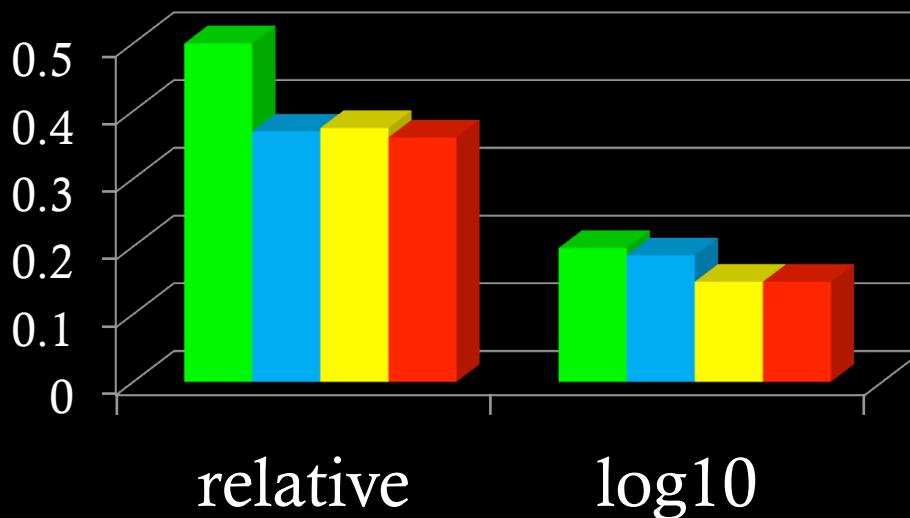
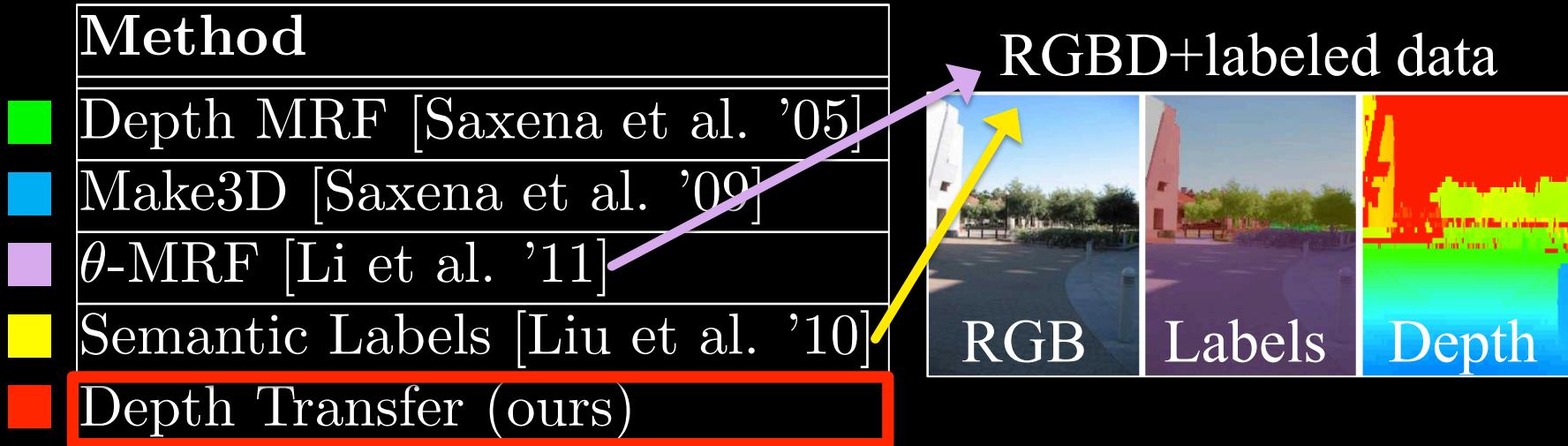
Result *without* relative
depth term ($\gamma = 0$)



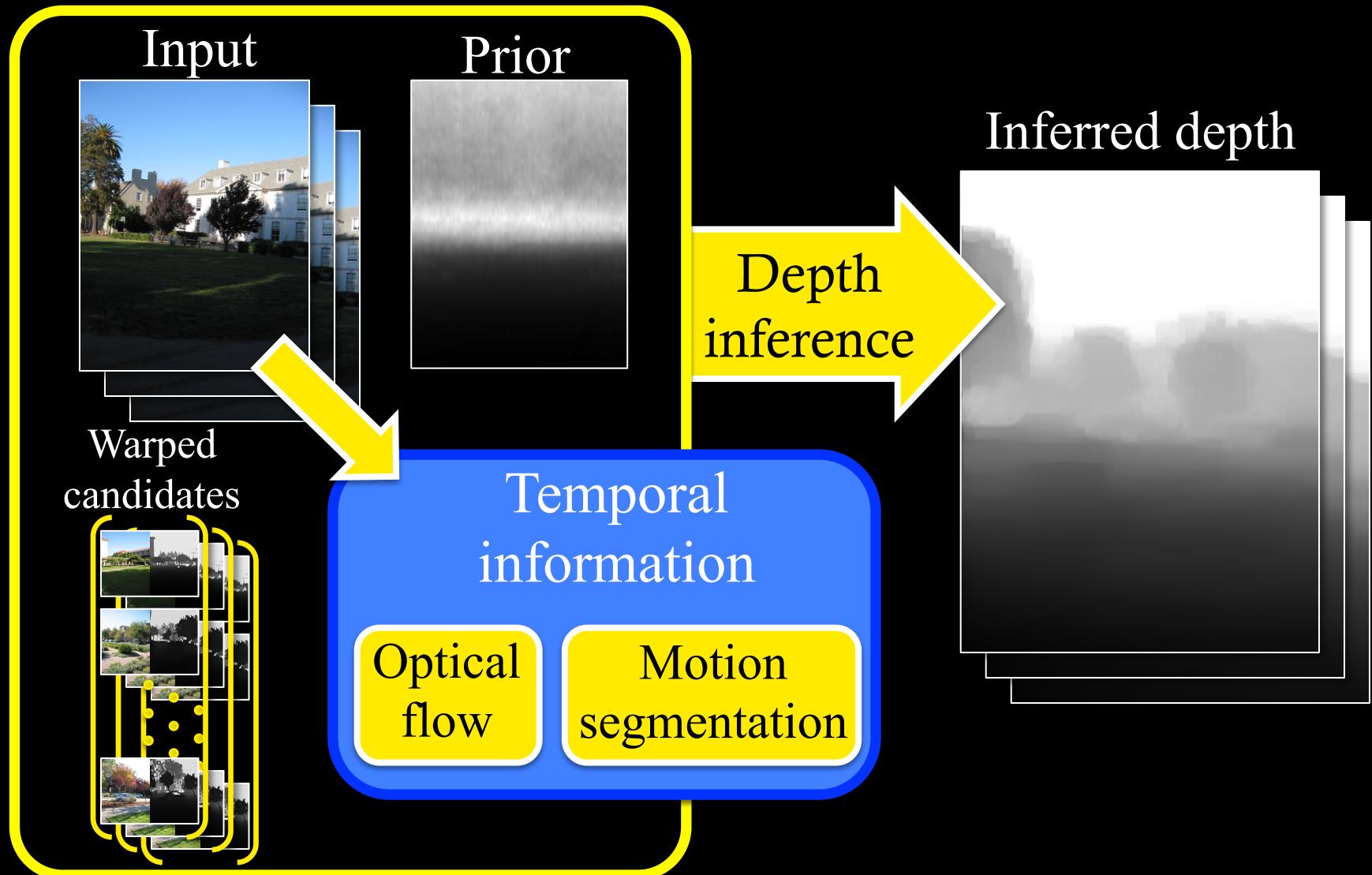
Result *with* relative
depth term ($\gamma > 0$)



Evaluation: Make3D Dataset



Video Extension



Video Inference

$$\operatorname{argmin}_D E_{\text{video}}(D) =$$

$$E(D) + \sum_{i \in \text{pixels}} \zeta t_i |\nabla_{flow} D_i|_1 + \eta m_i |D_i - \mathcal{M}_i|_1$$

Single
image
objective

m : binary motion mask
 \mathcal{M} : hypothesized depth
of motion mask
 ζ, η : constant weights

- Depth changes are gradual frame-to-frame
- Moving objects are usually on the ground

Video Inference

$$\underset{D}{\operatorname{argmin}} E_{\text{video}}(D) =$$

$$\underbrace{E(D)}_{\text{Single image objective}} + \sum_{i \in \text{pixels}} \underbrace{\zeta t_i |\nabla_{flow} D_i|_1}_{\text{Smooth along direction of optical flow}} + \eta m_i |D_i - \mathcal{M}_i|_1$$

m : binary motion mask
 \mathcal{M} : hypothesized depth of motion mask
 ζ, η : constant weights

- Depth changes are gradual frame-to-frame
- Moving objects are usually on the ground

Video Inference

$$\operatorname{argmin}_D E_{\text{video}}(D) =$$

$$E(D) + \sum_{i \in \text{pixels}} \underbrace{\zeta t_i |\nabla_{flow} D_i|_1}_{\text{Smooth along direction of optical flow}} + \underbrace{\eta m_i |D_i - \mathcal{M}_i|_1}_{\text{Coerce moving objects to be “grounded”}}$$

- Depth changes are gradual frame-to-frame
- Moving objects are usually on the ground
 - Motion mask = threshold flow-weighted, relative pixel differences
 - Ce Liu's optical flow <http://people.csail.mit.edu/celiu/OpticalFlow>

m : binary motion mask
 \mathcal{M} : hypothesized depth of motion mask
 ζ, η : constant weights

Input



Inferred depth

without
temporal info

with
temporal info



Results







MSR-V3D evaluation

Input



Kinect*



Ours



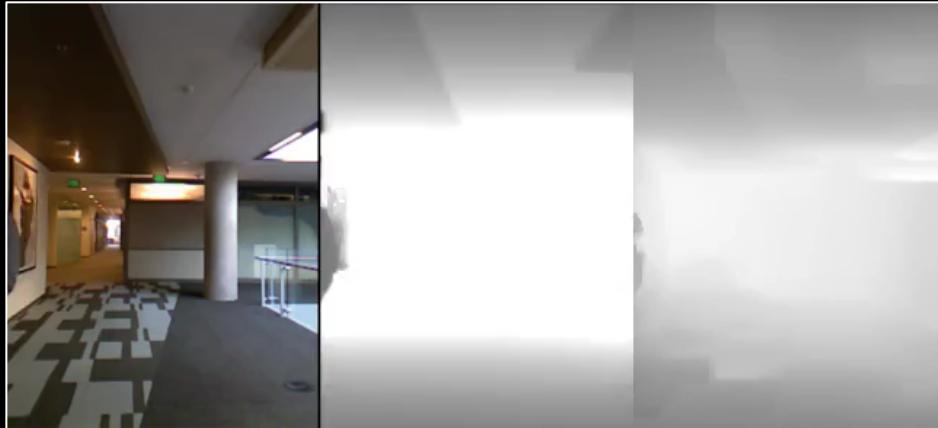
Input



Kinect*

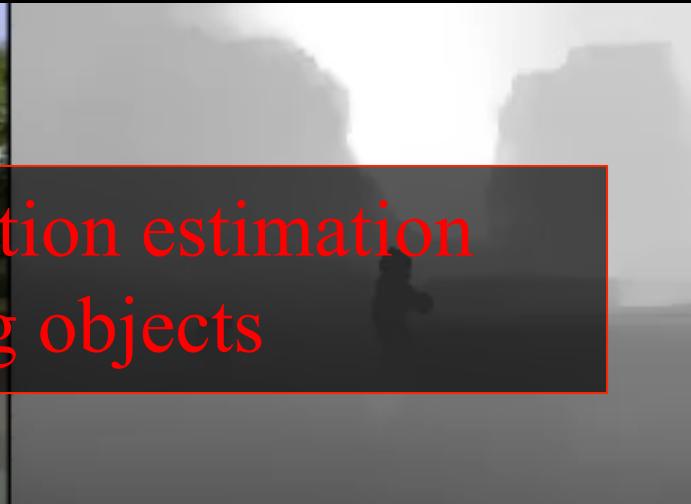


Ours



*Naïve hole filling applied to Kinect data (for visualization only)

Limitations

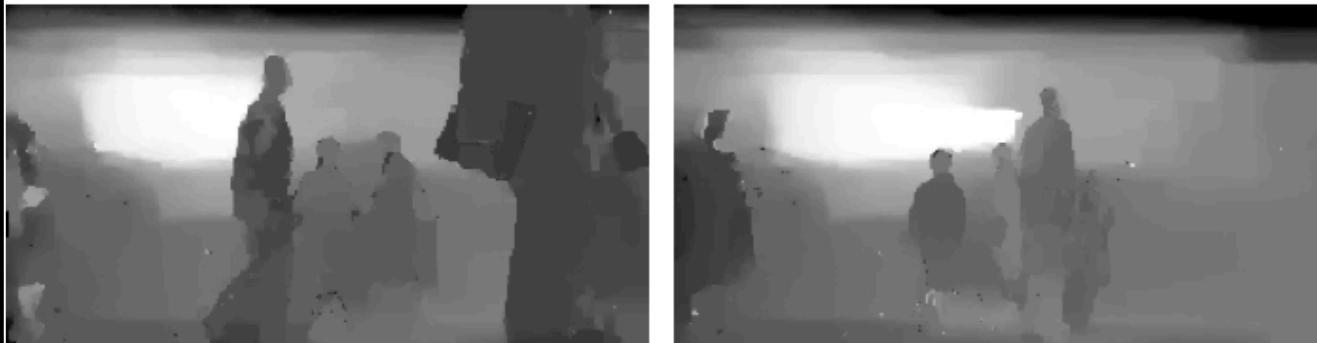


Application: 2D-to-3D

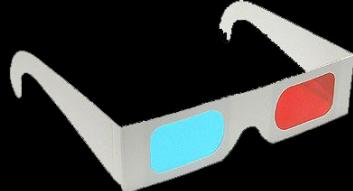
Input



Depth



Anaglyph
“3D”



Thanks!

More results, code and dataset available at:

<http://kevinkarsch.com/depthtransfer>

Our 2D-to-3D



Youtube 2D-to-3D

