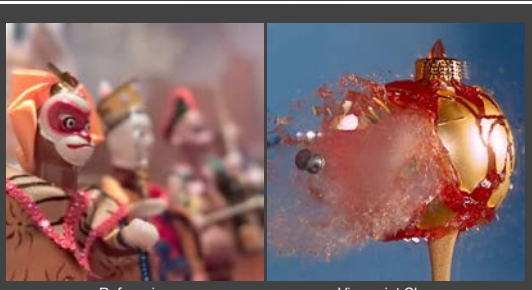
Light Fields: From Shape Recovery to Sparse Reconstruction

Ravi Ramamoorthi
University of California, San Diego

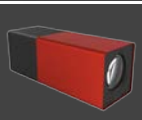
L4CV Keynote, Jul 26, 2017

Light fields



Refocusing Viewpoint Change

Consumer light field cameras



Lytro (first generation)



Pelican



Light



RayTrix



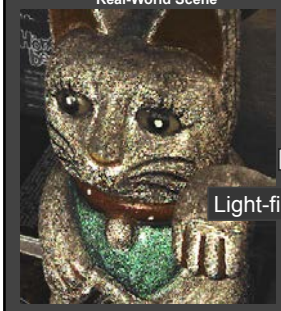
Lytro Illum

Outline

- Motivation
- *Light Fields for Passive 3D Capture*
- Specular Objects and SVBRDF Invariants
- Sparse Light Field Interpolation, Reconstruction
- Insights and Future Work

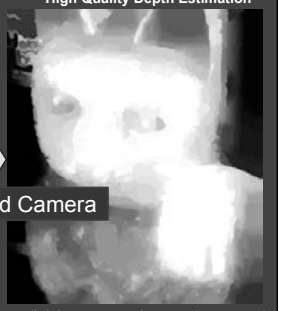
Goal: Passive easy-to-use 3D

Real-World Scene



Light-field Camera

High Quality Depth Estimation

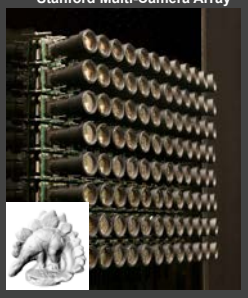


(brighter means closer to the camera)

Tao et al. 13, 14,15

Prior Work: Depth from Stereo

Stanford Multi-Camera Array



Stereo Pair:
Scharstein et al. 2002, Min et al. 2013, …
Multi-view Stereo:
Okutomi and Kanade 1993, Li et al. 2010,…

Pros:
+ Robust in most cases
+ One time setup
+ Baseline modifiable

Cons:
- Multiple cameras needed
- Difficult setup (image rectification)
- Baseline dependent
- Relies on ***correspondence***

Prior Work: Depth from Defocus

DSLR with a focusing mechanism



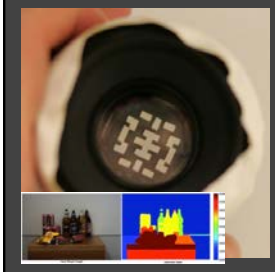
Depth from defocus:
Klarquist 1995, Schechner 2000, …

Pros:
+ Robust in most cases
+ Aperture modifiable
+ One camera solution

Cons:
- Difficult to obtain image (multi-exposures)
- Aperture size dependent
- Relies on ***defocus***

Prior Work: Modifying Cameras

DSLR with a focusing mechanism



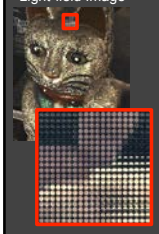
Masks:
Liang 2008, Levin 2010, …

Pros:
+ Robust in most cases
+ Aperture modifiable
+ One camera solution

Cons:
- Some require multiple captures
- Masks?
- How to add masks?

Novelty : The Four Cues

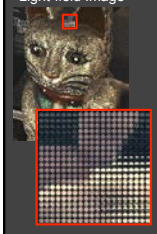
INPUT:
Light-field Image



OUTPUT:
High quality depth map

Novelty : The Four Cues

INPUT:
Light-field Image



Core Depth Estimation

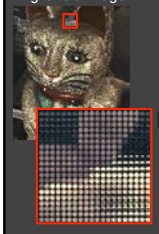
Depth from **Correspondence** and **Defocus** (Tao 13)

OUTPUT:
High quality depth map



Novelty : The Four Cues

INPUT:
Light-field Image

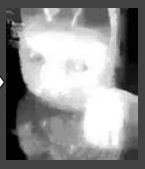


Separate **Secularities** (Tao 14,15)

Improve Input

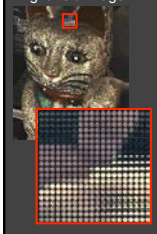
Depth from **Correspondence** and **Defocus** (Tao 13)

OUTPUT:
High quality depth map



Novelty : The Four Cues

INPUT:
Light-field Image



Separate **Secularities** (Tao 14,15)

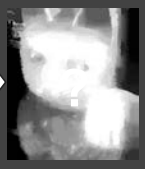
Improve Input

Depth from **Correspondence** and **Defocus** (Tao 13)

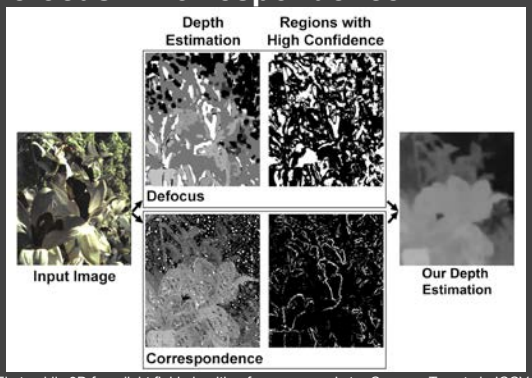
Improve Output

Output constraints using **Shading** information (Tao 15,16)

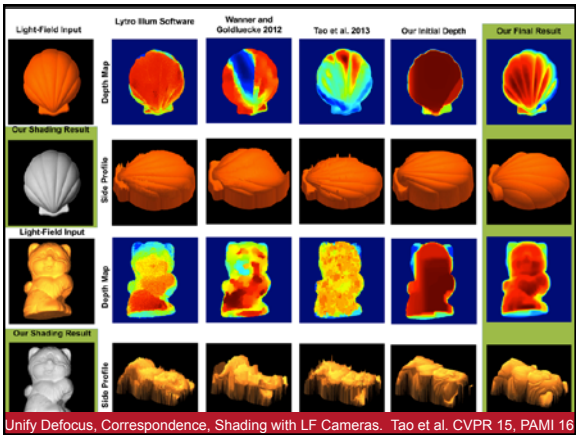
OUTPUT:
High quality depth map



Defocus + Correspondence



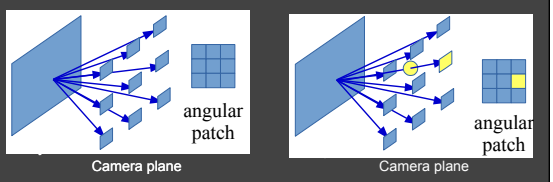
First public 3D from light field algorithm for consumer Lytro Camera: Tao et al., ICCV 13



Unify Defocus, Correspondence, Shading with LF Cameras. Tao et al. CVPR 15, PAMI 16

Occlusion

- What's the problem with occlusions?

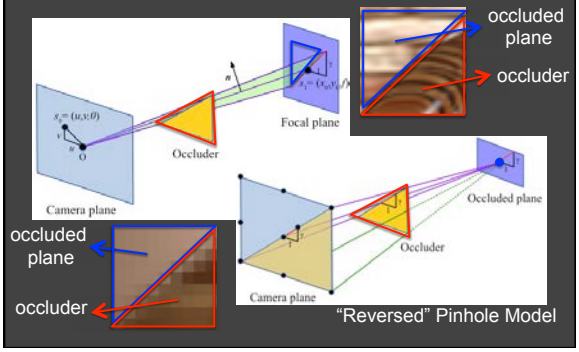


No occlusion

With occlusion

Wang et al. ICCV 15, PAMI 16

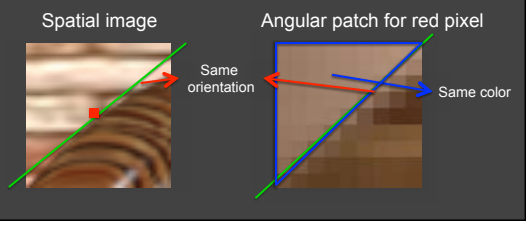
Occlusion model



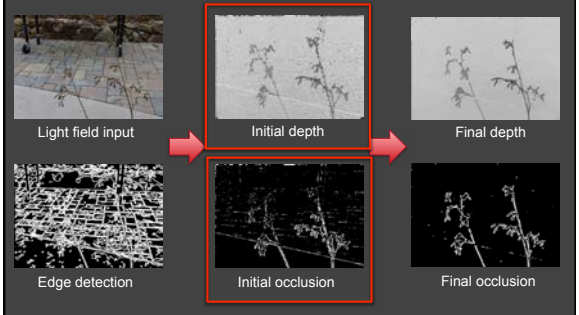
"Reversed" Pinhole Model

Occlusion theory

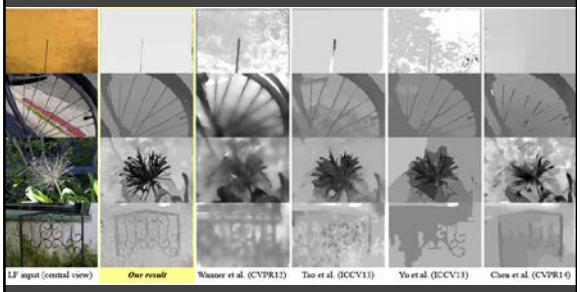
- Insight:
  - The angular and spatial edges have same orientation
  - Half the angular patch still follows photo-consistency



Algorithm overflow



Results with Occlusions

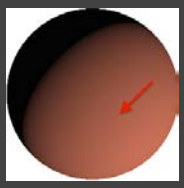


Outline

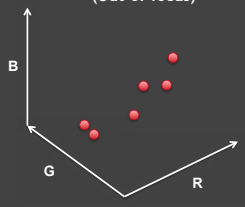
- Motivation
- Light Fields for Passive 3D Capture
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Specularity: Point vs Line Consistency

Lambertian Diffuse Surface

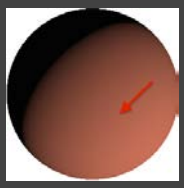


RGB 3D Scatter Plot of Angular (Out-of-focus)

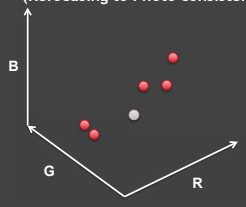


Specularity: Point vs Line Consistency

Lambertian Diffuse Surface

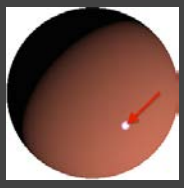


RGB 3D Scatter Plot of Angular (Refocusing to Photo consistency)

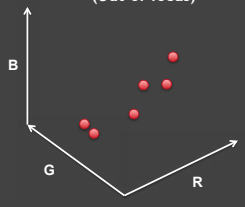


Specularity: Point vs Line Consistency

Lambertian Diffuse+Specular Surface

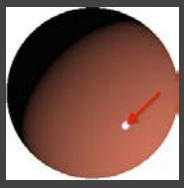


RGB 3D Scatter Plot of Angular (Out-of-focus)

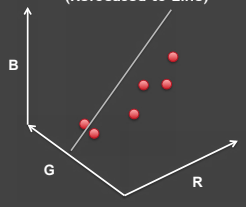


Specularity: Point vs Line Consistency

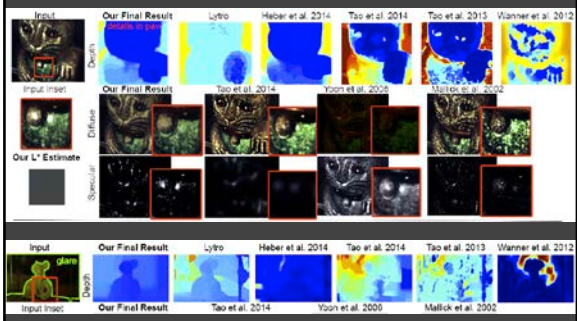
Lambertian Diffuse+Specular Surface



RGB 3D Scatter Plot of Angular (Refocused to Line)



Specularity: Line Consistency



Point and Line Consistency with Light Field Cameras: Tao et al. PAMI 15

SVBRDF-Invariant Equation

- Instead of separating specularity, (SV)BRDF invariance
- Build on differential motion theory [Chandraker 14]
- Use light field cameras instead
  - More views → more robust
  - First framework proven to be *SV*BRDF-Invariant

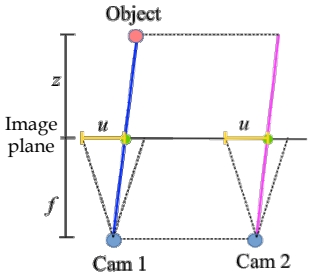




- Extend traditional optical flow to glossy objects

Wang et al. CVPR 16, PAMI 17

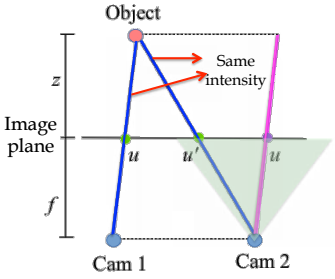
Optical Flow (Lambertian)



$$\Delta I = I_2(u) - I_1(u)$$

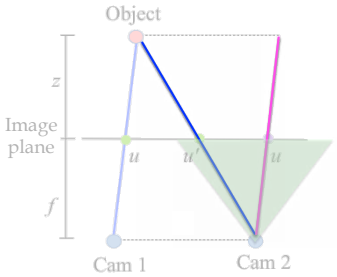
Slides from Wang et al. CVPR 16, PAMI 17

Optical Flow (Lambertian)



$$\Delta I = I_2(u) - I_1(u)$$

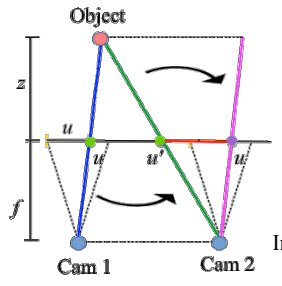
Optical Flow (Lambertian)



$$\Delta I = I_2(u) - I_1(u)$$
$$= p(z)$$

depth is solvable by one motion!

Optical Flow (Glossy)



Spatial change (same)
$p(z)$

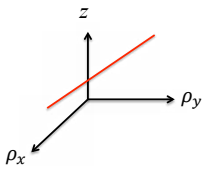
+

Viewpoint change
$q(\rho_x)$

In 3D: 3 unknowns (z, ρ_x, ρ_y)
solvable by 3 motions!

SVBRDF-Invariant Equation

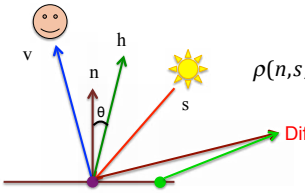
- Directly solve ~~rank deficiency~~ → a line of solutions



Use assumption on BRDF model

BRDF Model

- Diffuse + 1-lobe *unknown* function of half-angle



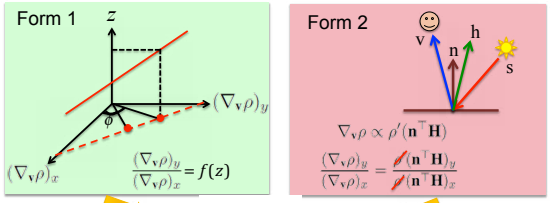
unknown function, unknown diffuse term

$$\rho(n,s,v) = \rho_s(\theta) + \sigma$$

Different BRDFs!

SVBRDF-Invariant Equation

- Represent BRDF ratio $\frac{(\nabla_v \rho)_y}{(\nabla_v \rho)_x}$ in two ways → combine



$f(z)$ = $g(n_x, n_y)$

Invariant to SVBRDF!

Quadratic Regularization

- SVBRDF-invariant equation → function of **a**
  - $f(z) = g(n_x, n_y)$
  - Directly solving requires initial conditions
- Assume shape is locally polynomial

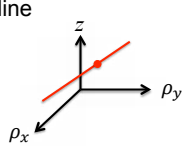


z, n_x, n_y → functions of **a**

Quadratic shape $z = a_1x^2 + a_2y^2 + a_3xy + a_4x + a_5y + a_6$

Reflectance Estimation

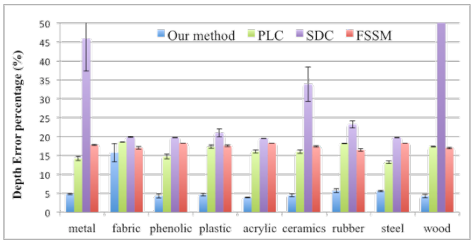
- Recall the solution lies on a line



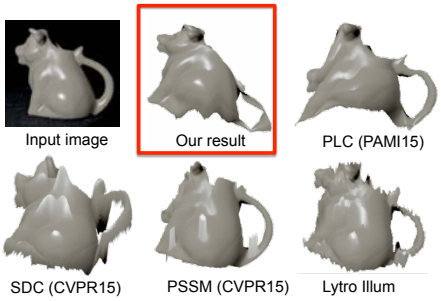
- z is known → ρ_x and ρ_y are known
- Finally, the BRDF ρ can be recovered

Synthetic Results

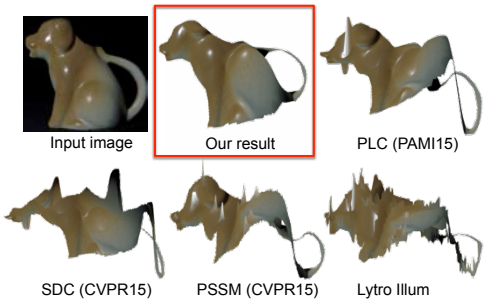
- 100 materials → 9 categories



Real Results



Real Results



Can also be inserted in a robust geometric optimization framework.
See Li et al. CVPR 2017

Outline

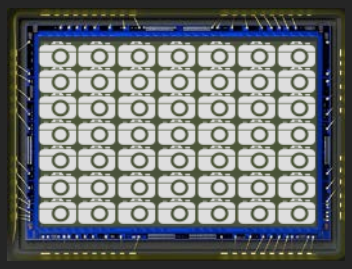
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Resolution trade-off

Limited resolution

High angular

Low spatial



UC San Diego Kalantari et al.

Solution: angular super-resolution



UC San Diego Kalantari et al.

Straightforward solution

- Model the process with a single CNN



UC San Diego

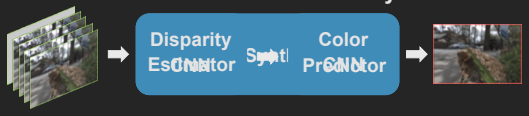
Single CNN's result



UC San Diego

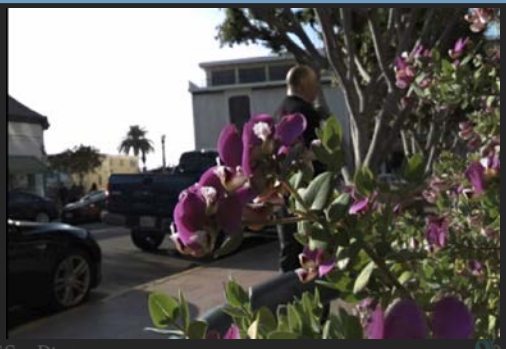
High-level idea

- Follow the pipeline of existing techniques and break the process into two components
  Goesele et al. [2010]; Chaurasia et al. [2013]
  - Disparity estimator
  - Color predictor
- Model the components using learning
- Train both models simultaneously



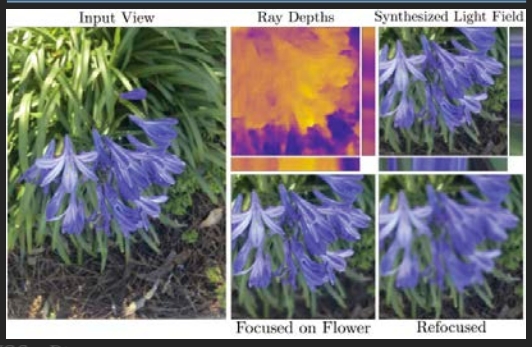
UC San Diego

Our result



UC San Diego Kalantari et al.

4D RGBD Light Fields from 2D Image



UC San Diego Srinivasan et al. ICCV 17

Light field video

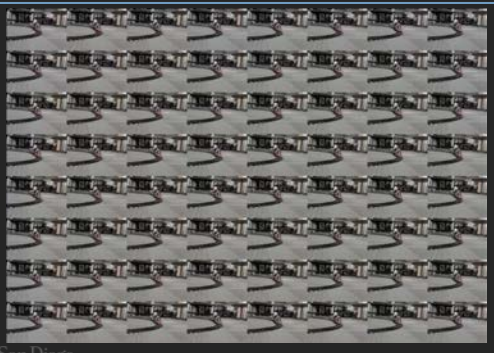
- Consumer light field cameras limited bandwidth
- Capture low frame rate videos



Lytro Illum (3 fps video)

UC San Diego Wang et al. SIGGRAPH 17

Lytro video



UC San Diego

Hybrid Light Field Video System



Our result



Outline

- Motivation
- Light Fields for Passive 3D Capture
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Shape, Reflectance, Resolution

- Significant progress in recovering overall shape
- Can we recover fine-scale shape, reflectance
  - Hair, microstructure, detailed BRDFs
- Light field camera as a reflectance device
  - Two-shot near-field acquisition: Xu et al. SIGGRAPH Asia 16
- Theoretical limits of shape/reflectance ambiguity
- Resolution limits (Liang and Ramamoorthi TOG 15)
- Easy, sparse light field capture for VR
- Super-resolution limits with learning

Deep learning for analysis



Classification
Krizhevsky et al. 2012

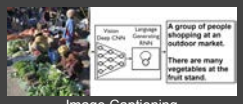
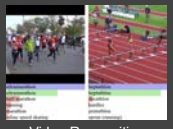


Image Captioning
Vinyals et al. 2014



Object Detection
Girshick et al. 2014



Video Recognition
Karpathy et al. 2014

Deep learning for synthesis

- Generally received much less attention
  - Strong physical foundation
  - Designed for reducing an image to a label
  - Insufficient data in some applications
- This talk: Learning system architecture inspired by physically-based solutions
- Leverage physics, use learning bypass hard problems (occlusion). Best of both worlds

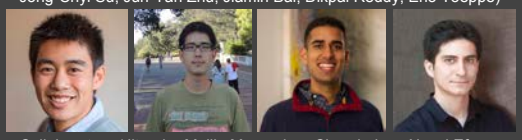
New Applications in Computer Vision

- Light Fields for Scene Flow (Tao et al. ICCV 15)
- Light Field Material Recognition (Wang et al. ECCV 16)
- Light Field Motion Deblurring (Srinivasan et al. CVPR 16)
- Light Field Descattering (Tian et al. ICCV 17)
- **Computer vision with multiple views/images**



Acknowledgements

- Students and Postdocs (**Michael Tao, Ting-Chun Wang, Pratul Srinivasan**, **Nima Kalantari,** Zak Murez, Zhengqin Li, Zexiang Xu, Jong-Chyi Su, Jun-Yan Zhu, Jiamin Bai, Dikpal Reddy, Eno Toeppe)



- Collaborators (Jitendra Malik, Manmohan Chandraker, Alexei Efros, Szymon Rusinkiewicz,, Ren Ng, Chia-Kai Liang, Ebi Hiroaki, Jiandong Tian, Sunil Hadap)
- Funding: NSF, ONR (x2), UC San Diego Center for Visual Computing (Google, Sony, Adobe, Nokia, Samsung, Draper)