Light Fields: From Shape Recovery to Sparse Reconstruction

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Light fields

Viewpoint Change

Refocusing

Outline

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

Consumer light field cameras

- Lytro (first generation)
- Pelican
- Light
- RayTrix
- Lytro Illum

Goal: Passive easy-to-use 3D

Real-World Scene

High Quality Depth Estimation

(brighter means closer to the camera)

Light-field Camera

Prior Work: Depth from Stereo

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

Tan et al. 13, 14, 15
Prior Work: Depth from Defocus

DSLR with a focusing mechanism

Depth from defocus: Klarquist 1990, Sahelhar 2000, etc.

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, etc.

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

Depth from Correspondence and Defocus (Tao 13)

Separate Secularities (Tao 14,15)

Improve Input

Improve Output

Output constraints using Shading information (Tao 15,16)
Defocus + Correspondence

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

Results

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

Occlusion

What's the problem with occlusions?

Camera plane

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

Light field input

Initial depth

Final depth

Initial occlusion

Final occlusion
Results with Occlusions

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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 SVBRDF-Invariant

Extend traditional optical flow to glossy objects

Optical Flow (Lambertian)

\[ \Delta I = I_2(u) - I_1(u) \]

depth is solvable by one motion!

Optical Flow (Lambertian)

\[ \Delta I = I_2(u) - I_1(u) \]

Optical Flow (Lambertian)

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

Optical Flow (Glossy)

Spatial change (same)

\[ p(z) \]

Viewpoint change

\[ q(\rho_z) \]

In 3D: 3 unknowns \((z, \rho_x, \rho_y)\) 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

- Different BRDFs!

**SVBRDF-Invariant Equation**

- Represent BRDF ratio $\frac{\frac{\nabla v}{\nabla \rho}}{\frac{\nabla v}{\nabla \rho}}$ in two ways $\rightarrow$ combine

- Form 1

- Form 2

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

- Invariant to SVBRDF!

**Quadratic Regularization**

- SVBRDF-invariant equation $\rightarrow$ function of $a$

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

- Directly solving requires initial conditions

- Assume shape is locally polynomial

- Quadratic shape $z = a_1 x^2 + a_2 y^2 + a_3 x y + a_4 x + a_5 y + a_6$

**Reflectance Estimation**

- Recall the solution lies on a line

- $z$ is known $\rightarrow$ $\rho_x$ and $\rho_y$ are known

- Finally, the BRDF $\rho$ can be recovered

**Synthetic Results**

- 100 materials $\rightarrow$ 9 categories

- Our method vs. SDC, SDC, and FSSM
Real Results

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Resolution trade-off

Solution: angular super-resolution

Straightforward solution

- Model the process with a single CNN
Single CNN’s result

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

Disparity Estimator → Color Predictor →

Our result

4D RGBD Light Fields from 2D Image

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

Lytro video

Kalantari et al., Srinivasan et al. ICCV 17

Kalantari et al., Wang et al. SIGGRAPH 17
Hybrid Light Field Video System

Our result

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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

Deep learning for synthesis

Deep learning for analysis

Krizhevsky et al. 2012
Object Detection
Girshick et al. 2014

Image Captioning
Vinyals et al. 2014

Video Recognition
Kapathy 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

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