### Learning 3D Vision

Computer Vision Fall 2018 Columbia University

### Project FAQ

- "What happens if my proposal is different from my final project?"
  - We want to see that you have a clear idea and plausible path to the solution
  - My first attempt almost never works.
  - Just do a cool project!

### Project FAQ

- "I don't have 500 GPUs"
  - In my last paper, I only used 1 GPU, no parameter tuning
  - Isolate your idea and focus on it

### **Binocular Stereo**







Key Idea: use feature motion to understand shape

### **Photometric Stereo**







Key Idea: use pixel brightness to understand shape

### Learning-based 3D







Key Idea: learn it from data



epipolar lines

### Matching is hard



?



### Structure depends on priors



#### The world is not ideal diffuse



### We want to recognize objects in 3D











 $V_1$ 



 $V_2$ 

John Flynn et al. DeepStereo



С

#### Given v1 and v2, reconstruct the new view C





 $V_1$ 



 $V_2$ 

С

#### **Stereo with three cameras?**



### **Multi-view Stereo**



Point Grey's Bumblebee XB3



Point Grey's ProFusion 25



CMU's 3D Room

### **Multi-view Stereo**

### Input: calibrated images from several viewpoints Output: 3D object model



Figures by Carlos Hernandez







Google







### Multi-view stereo: Basic idea









# Why multi-view stereo?

1. Some cameras have a closer view



#### Cameras 2 and 3 can more clearly see point p.



#### Cameras 1 and 2 can more clearly see point q.

# Why multi-view stereo?

- 1. Some cameras have a closer view
- 2. Cameras can't see everything



Camera 5 can't see point r.



Camera 1 can't see point s.

# Why multi-view stereo?

- 1. Some cameras have a closer view
- 2. Cameras can't see everything
- 3. Multiple cameras can reduce measurement error





<image>









Estimated points contain some error.


Estimated points contain some error.





# Multiview Stereo (version 0)

-Pick one reference view

-For each point and for each candidate depth

• keep depths with low SSD error in all other views



Problem: not all points are visible in all other views: (declusion and visibility major nuisance!)

# Plane-sweep Stereo

Sweep over voxel plane-by-plane, starting closest-to-front

Quickly validate voxels in a plane by computing their appearance in a virtual view using all N cameras



Store photoconsistent color in a 3D voxel grid (don't need a reference image) Reconstuct shape *and* appearance

Red:

Green:

Blue:



 $d_m$  = 520 meter

Red:

Green:

Blue:



 $d_m$  = 583 meter

Red:

Green:

Blue:



 $d_m$  = 706 meter

Red:

Green:

Blue:



 $d_m$  = 790 meter

Red:

Green:

Blue:



 $d_m$  = 1026 meter

Red:

Green:

Blue:



*d<sub>m</sub>* = 2168 meter

#### Plane sweep stereo example

• ZNCC scores for different depths and *k* 





#### **Plane sweep and ambiguities**

• Multiple views can resolve ambiguities in difficult areas!





### What about other camera steups?





### Panoramic depth ordering

Seitz & Dyer



Layers radiate inwardly/outwardly







 $V_1$ 





 $V_2$ 

С

### Synthesizing C from V1 and V2

John Flynn et al. DeepStereo



Train deep network select pixel from 1 of K depth planes (At each pixel, output 1 of K classes)





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# Light rays interacting with a surface



$$L_r = \rho(\theta_i, \theta_r) L_i \cos \theta_i$$

- Special case 1: Perfect mirror
  - $\rho(\theta_i, \theta_r) = 0$  unless  $\theta_i = \theta_r$
- Special case 2: Matte surface
  - $\rho(\theta_i, \theta_r) = \rho_0$  (constant)



Image



Reflectance Shape Shading

[Neural Face Editing with Intrinsic Image Disentangling]

# Applications

Object insertion



[Rendering Synthetic Objects into Legacy Photographs]

# Applications

• Material editing



[Learning Non-Lambertian Object Intrinsics...]

# Applications

Shadow/shading removal



[Removing shadows from images using retinex]

## Intrinsic Images In the Wild

- Thousands of real world images
- Relative annotation (which is darker)
- Sparsely annotated















[Intrinsic Images in the Wild]

### Intrinsic Images In the Wild











[Intrinsic Images in the Wild]

## Intrinsic Images In the Wild



Automatic intrinsic image decomposition

[Intrinsic Images in the Wild]

### MPI Sintel Dataset



Image

Ground-truth Albedo

Ground-truth Shading

[A naturalistic open source movie for optical flow evaluation]

## **Direct Intrinsics**

• Pixel-wise regression task



### output albedo image



C N N

output shading image



[Narihira et al. 2015]

# What changes across views?



# What changes across time?



[Deriving intrinsic images from image sequences]

# Intrinsic Image Decomposition



[Single Image Intrinsic Decomposition without...]

## Intrinsic Image Decomposition






#### Estimating depth from a single image

• Why is this even possible?



Slide Credit: Bharath Hariharan

#### Estimating depth from a single image

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#### Estimating depth from a single image

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Slide Credit: Bharath Hariharan

#### First we need lots of data...

# Find a gaming friend



### Collect depth data





for XBOX 360.

#### NYU Depth v2

#### Then create a neural net



### Go back to gaming friend



### Predict depth & normals



## Predict depth & normals



#### David Eigen and Rob Fergus, NYU

# Missing Depth



Raw Depth (D) from Intel R200 camera

Slide from Thomas Funkhouser

### Go back to gaming friend

## Go back to gaming friend

#### Playing for Depth

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Figure 1: Images and Depths extracted from the game Grand Theft Auto V

## **Depth predictions**



Figure 9: Qualitative Results. From left to right: Input Image, Eigen [8], DIW (Full) [10], Our Approach

## Depth predictions



No flowers in Grand Theft Auto V?

> Figure 11: Failure Cases. From left to right: Input Image, Eigen [8], DIW (Full) [10], Our Approach

#### Go make a game





Weifeng Chen, Donglai Xiang, Jia Deng Surface Normal Estimation in the Wild

### Normal predictions



Weifeng Chen, Donglai Xiang, Jia Deng Surface Normal Estimation in the Wild

