THE UNIVERSITY OF BRITISH COLUMBIA

CPSC 425: Computer Vision

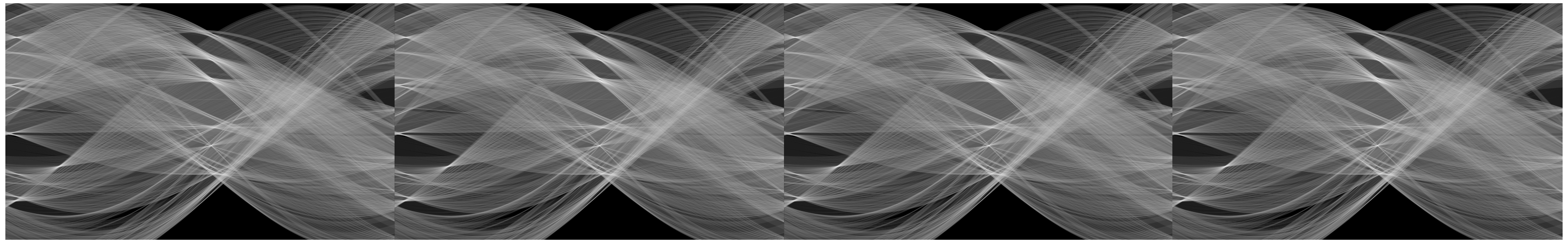


Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 24: Stereo Vision

Menu for Today (**November 2, 2018**)

Topics:

— Stereo Vision (cont)
— Block Matching
— Energy Minimization
— Structured Light

Redings:

— **Today's** Lecture: None
— **Next** Lecture: Forsyth & Ponce (2nd ed.) 10.6, 6.2.2, 9.3.1, 9.3.3, 9.4.2

Reminders:

— **Assignment 4**: Local Invariant Features and RANSAC due **November 14th**

RANSAC vs. **Hough** Transform

Hough is better with **large number of outliers**, well over > 50%

Setting bin size to account for certain level of **noise** is more difficult in Hough

RANSAC better for **high dimensional parameter spaces**

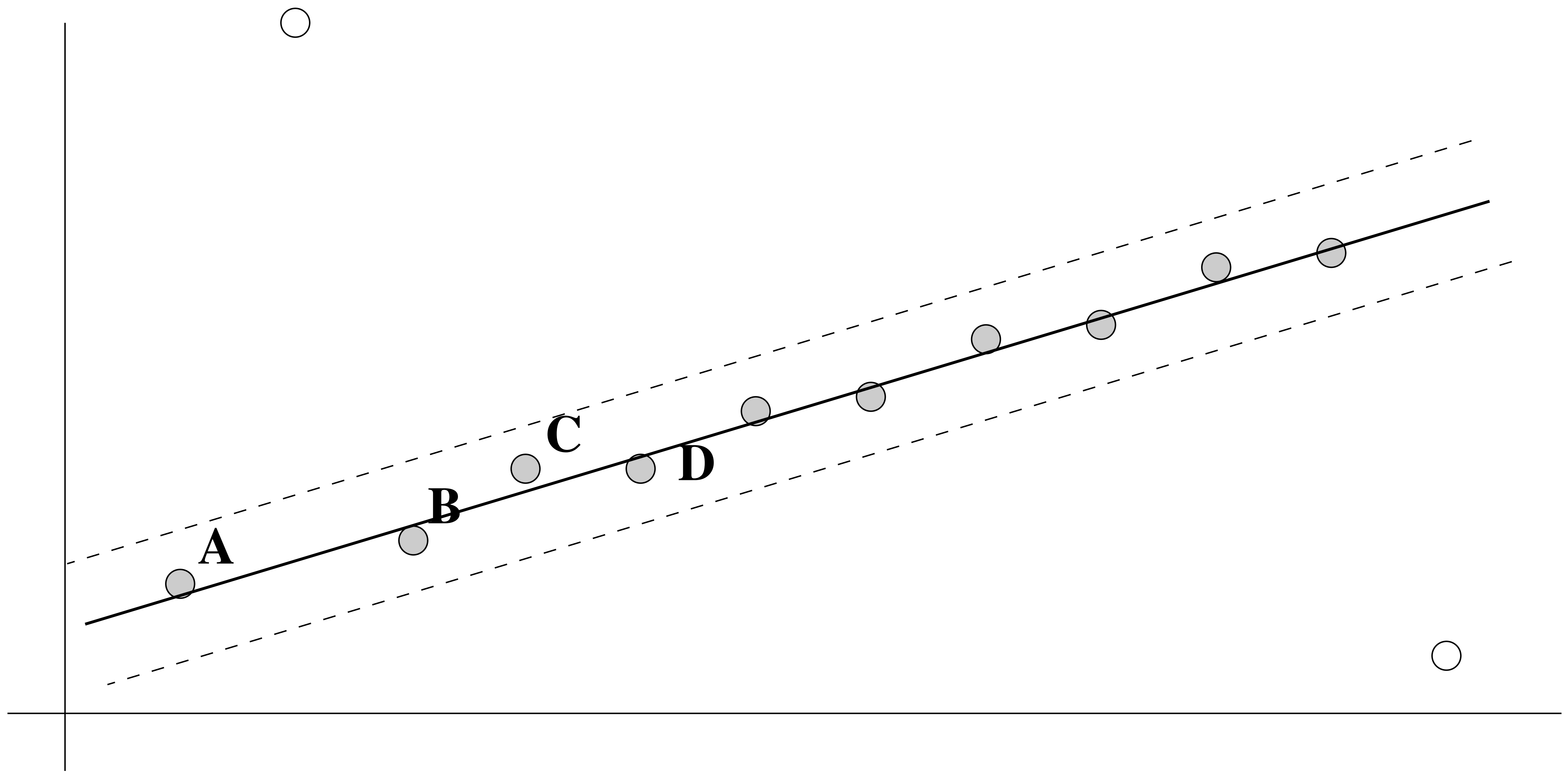


Figure Credit: Hartley & Zisserman

RANSAC vs. Hough Transform

Good scenario for Hough

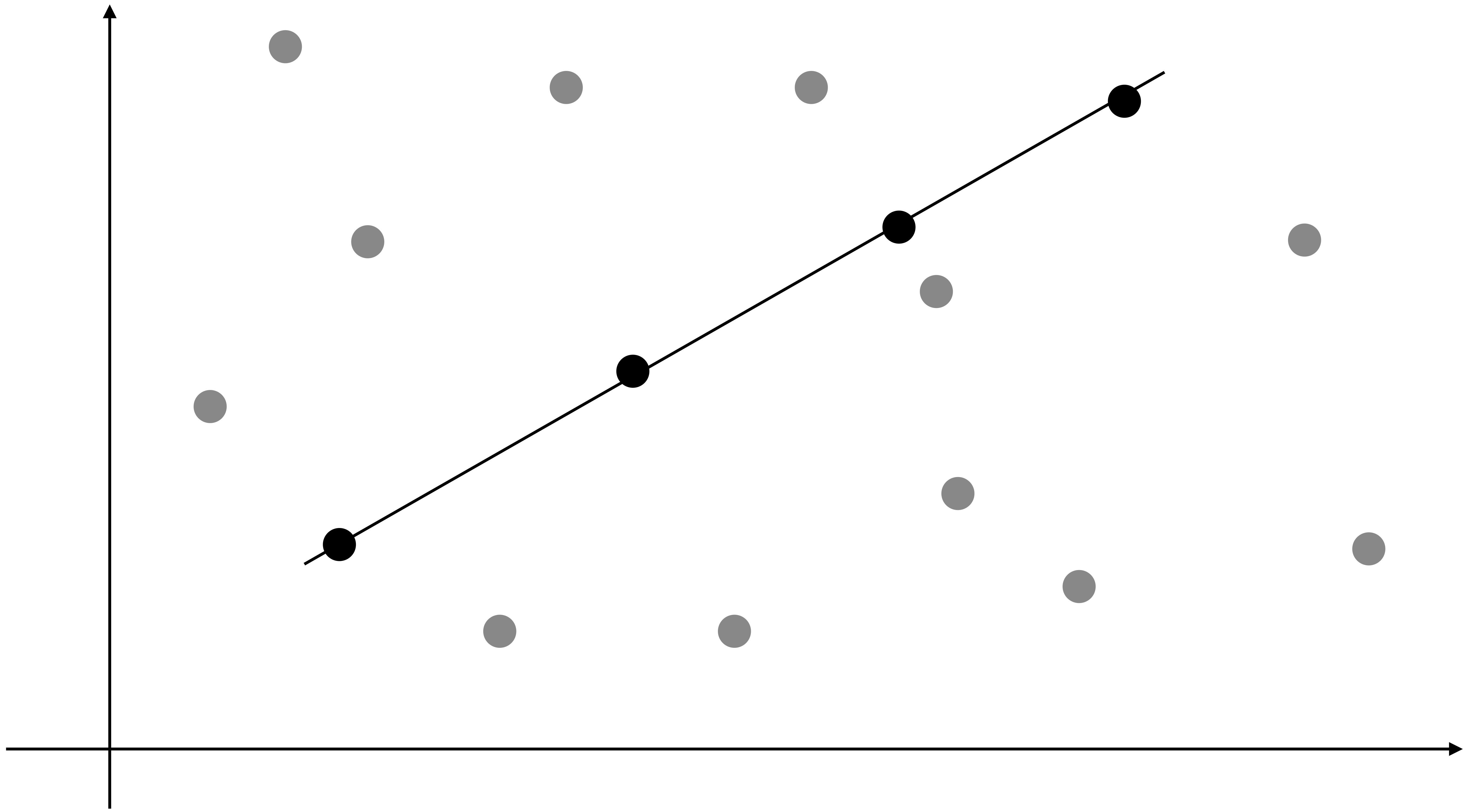


Figure Credit: Hartley & Zisserman

RANSAC vs. **Hough** Transform

Not so Good scenario for Hough

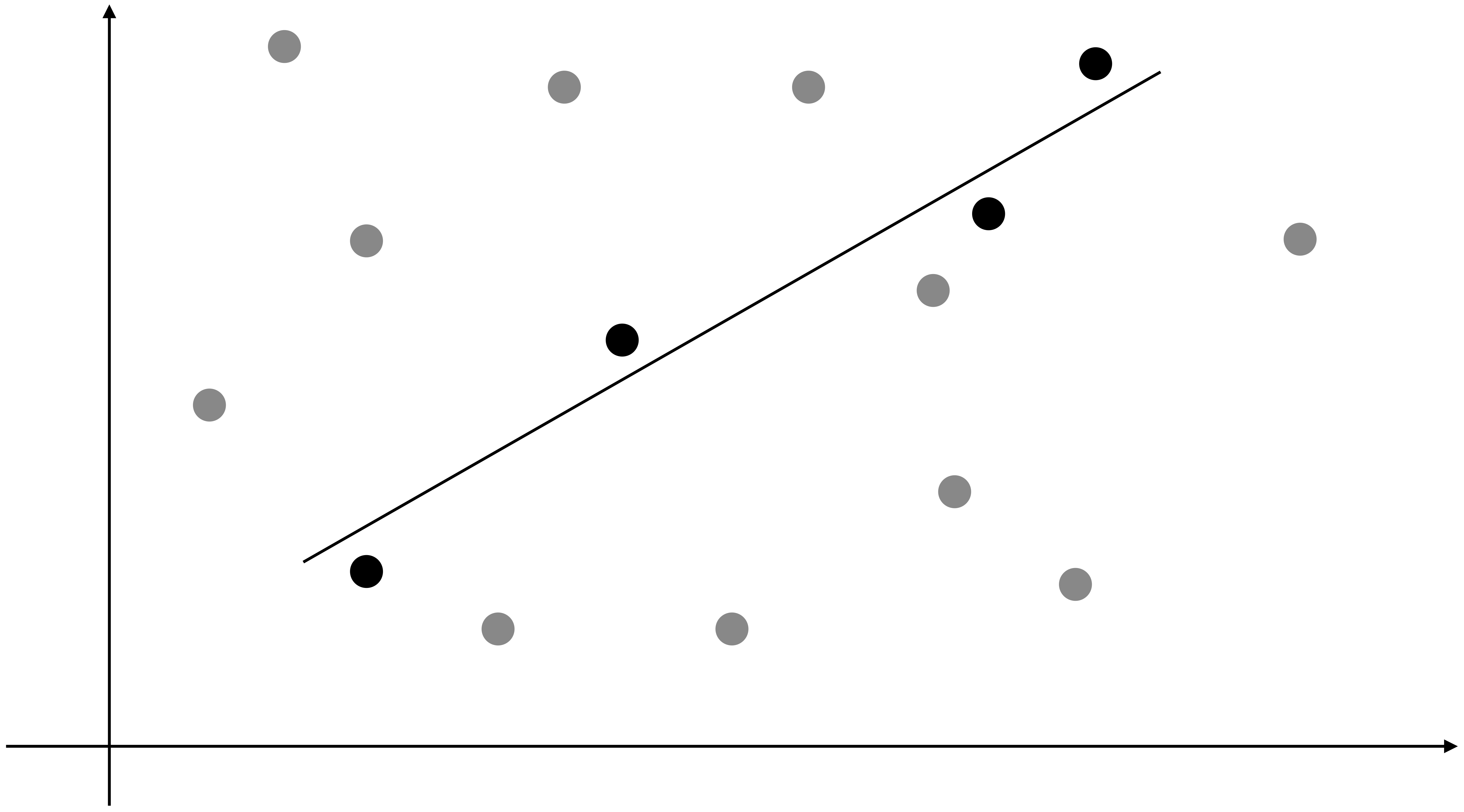
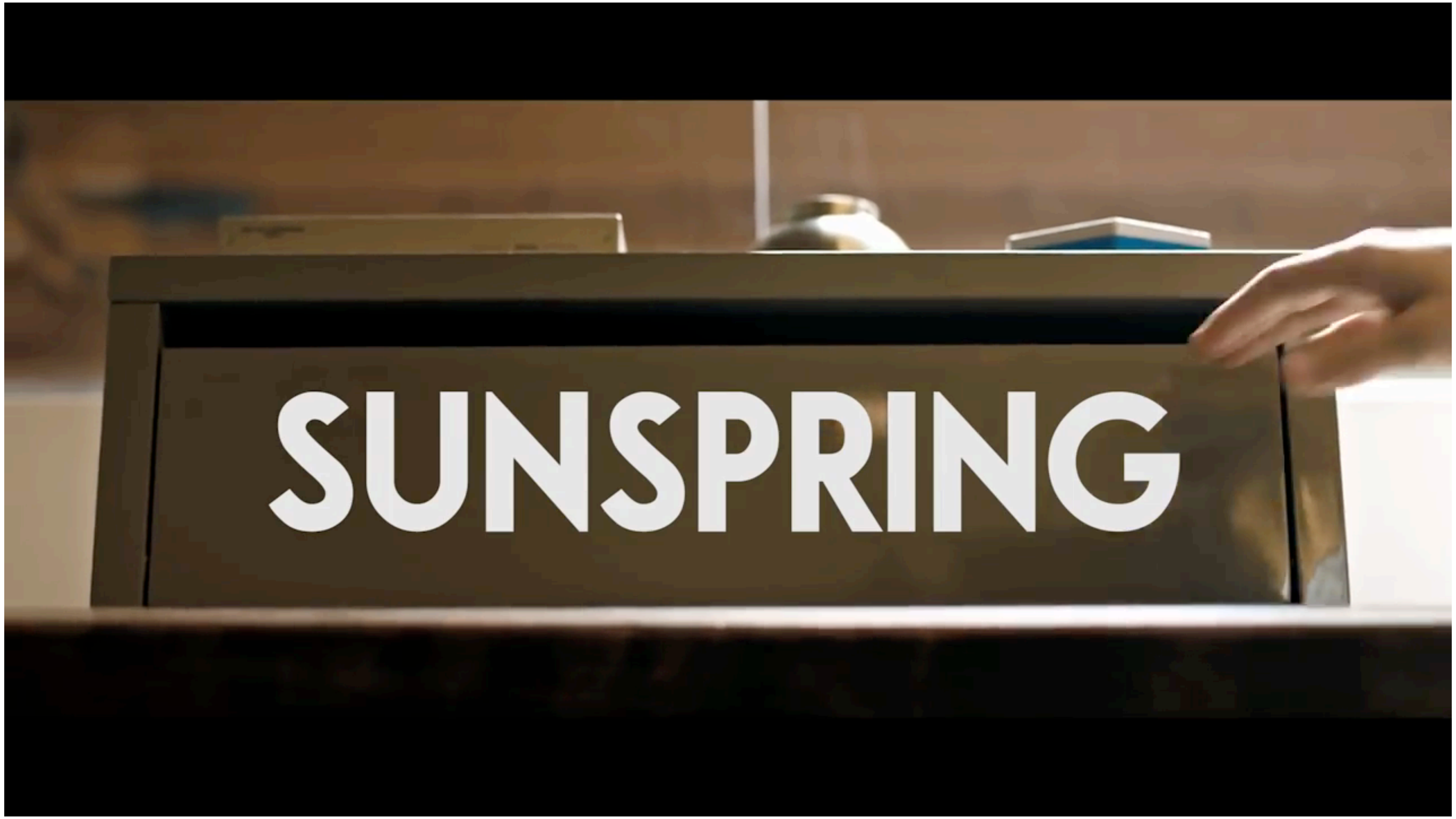


Figure Credit: Hartley & Zisserman

Today's "**fun**" Example: Sunspring



Lecture 23: Re-cap

Task: Compute depth from two images acquired from (slightly) different viewpoints

Approach: "Match" locations in one image to those in another

Sub-tasks:

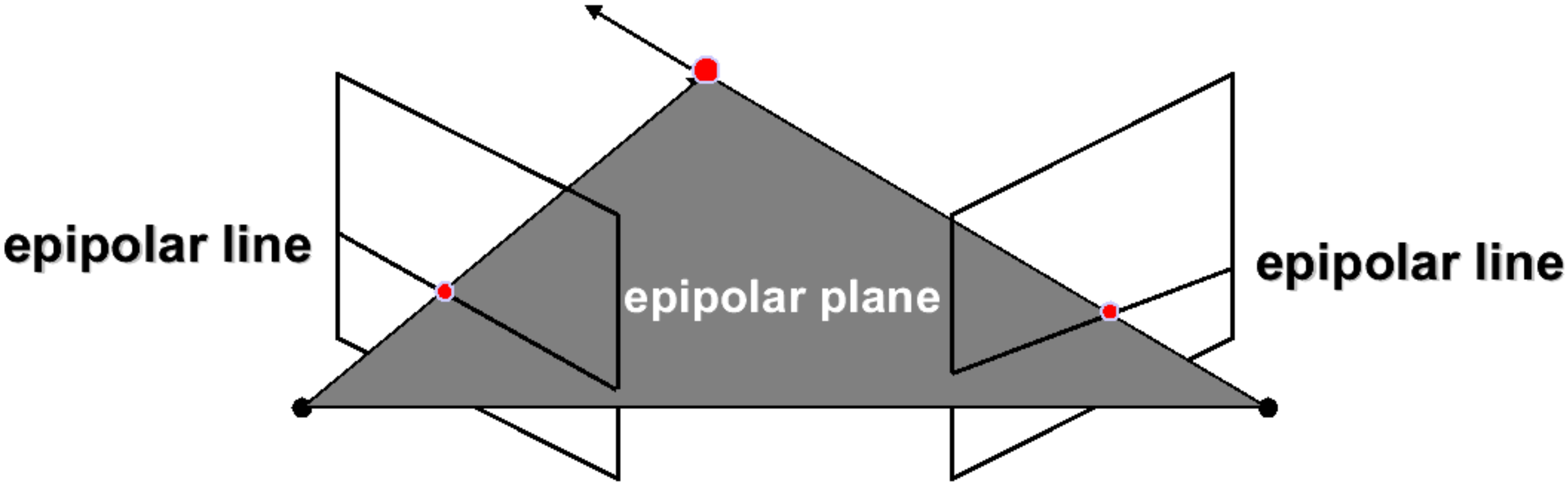
— Calibrate cameras and camera positions

  — Image rectification

— Find all corresponding points (the hardest part)

— Compute depth and surfaces

Lecture 23: Re-cap



Matching points lie along corresponding epipolar lines

Reduces correspondence problem to 1D search along conjugate epipolar lines

Greatly reduces cost and ambiguity of matching

Slide credit: Steve Seitz

Lecture 23: Re-cap (simple) Rectified Case

Image planes of cameras are **parallel**

Focal **points** are at same height

Focal **lengths** same

Then, **epipolar lines** fall along the **horizontal scan lines** of the images

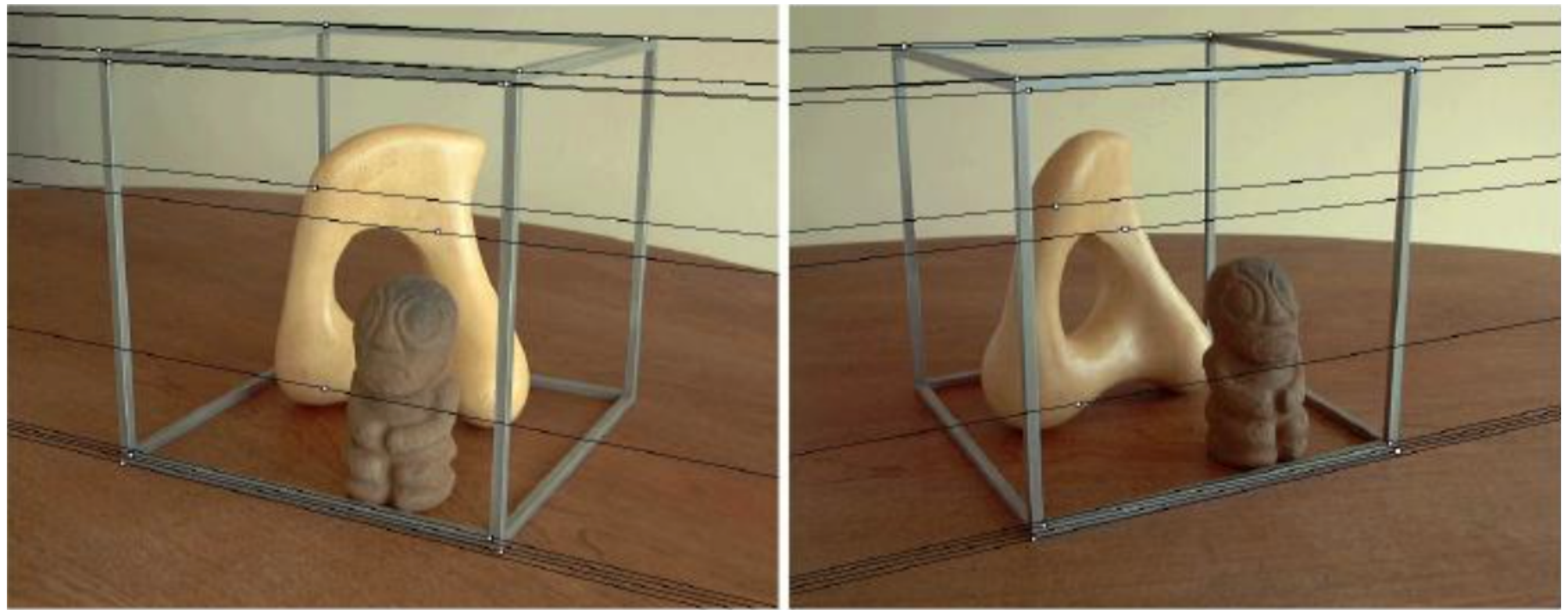
We assume images have been **rectified** so that epipolar lines correspond to scan lines

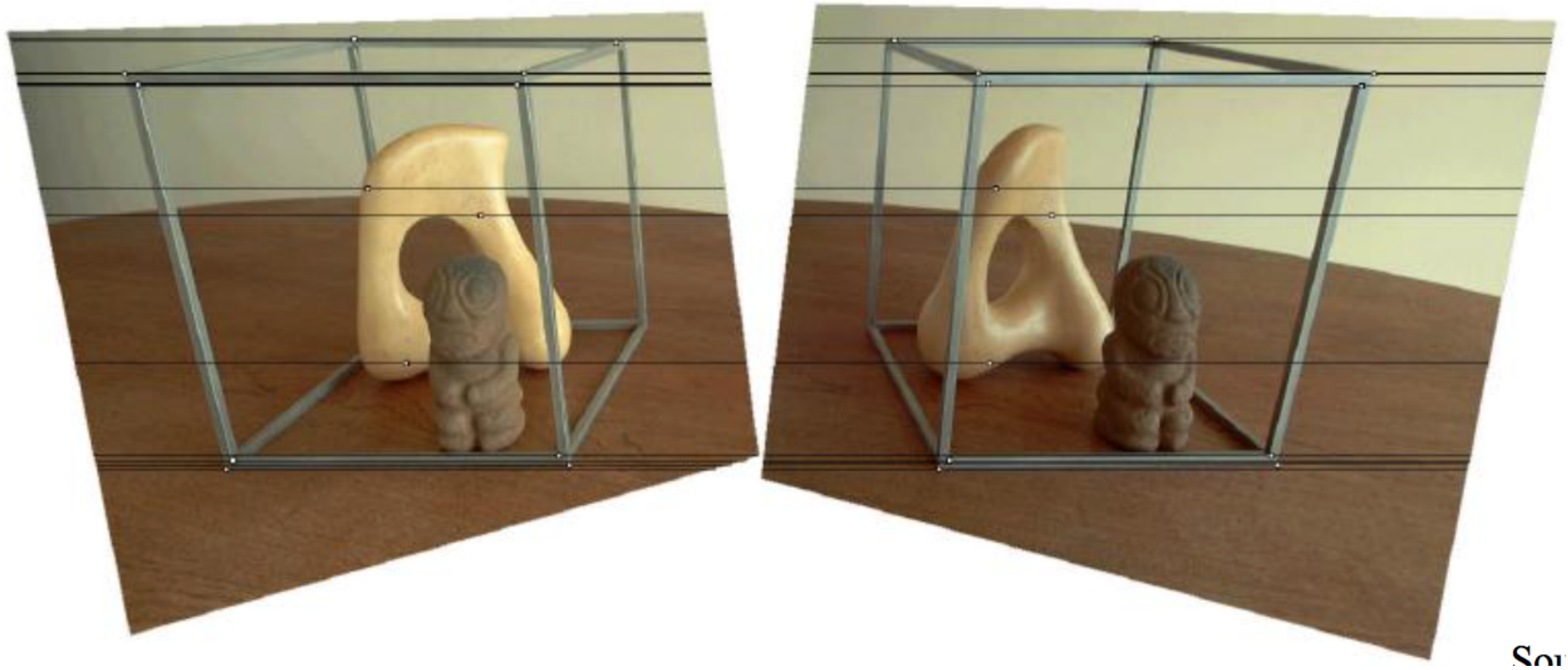
— Simplifies algorithms

— Improves efficiency

Rectified Stereo Pair: Example

Before Rectification

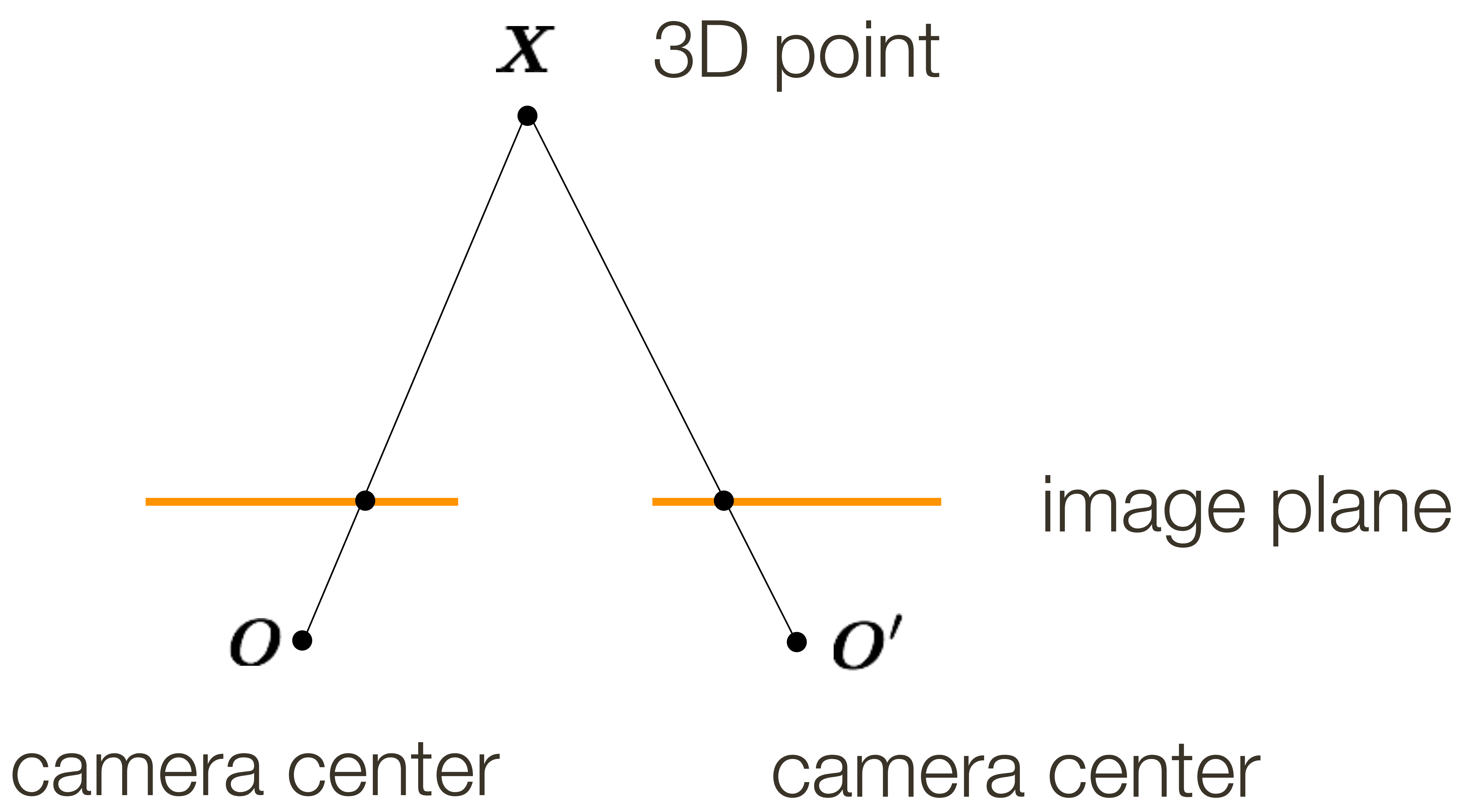




After Rectification

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate

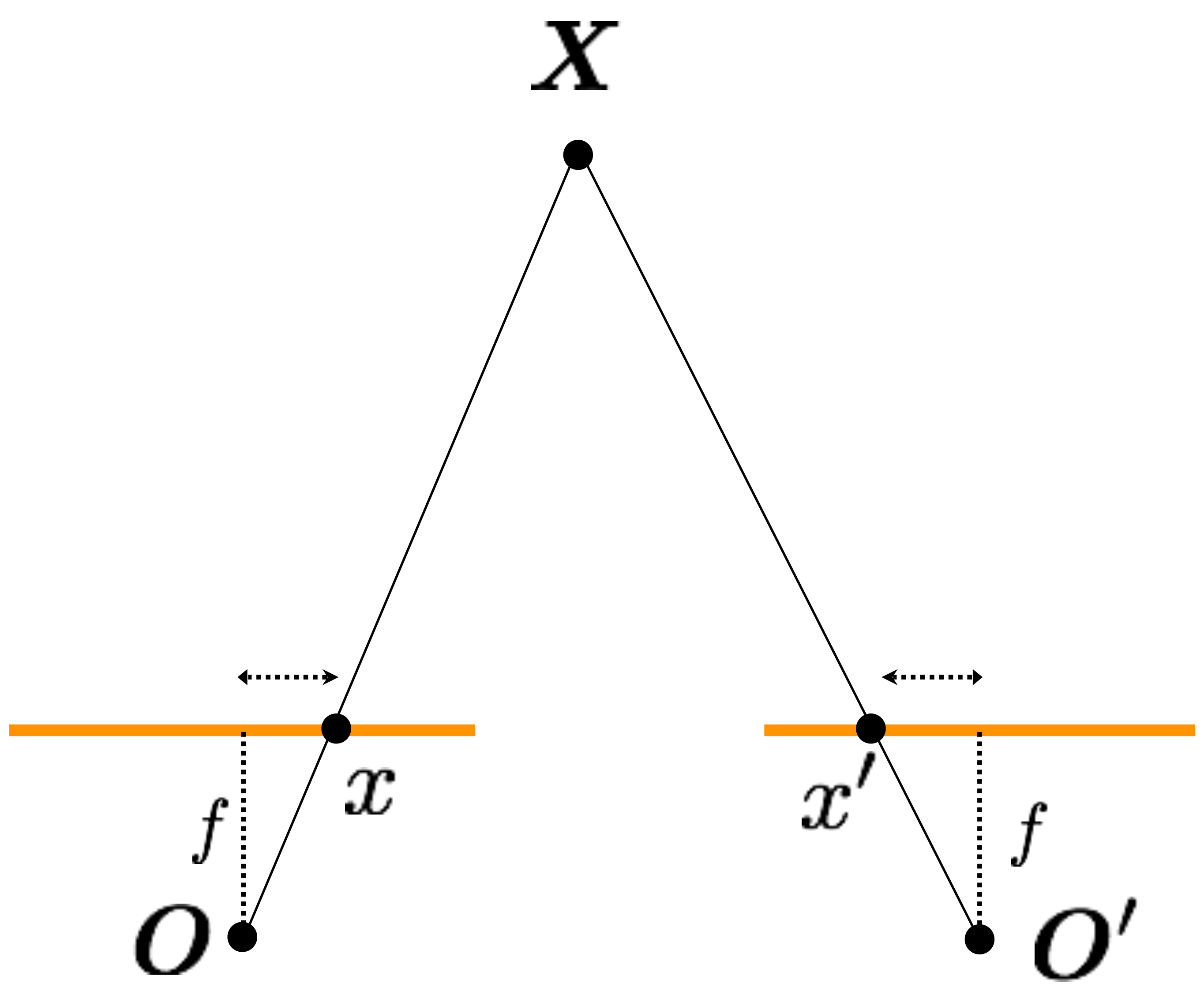
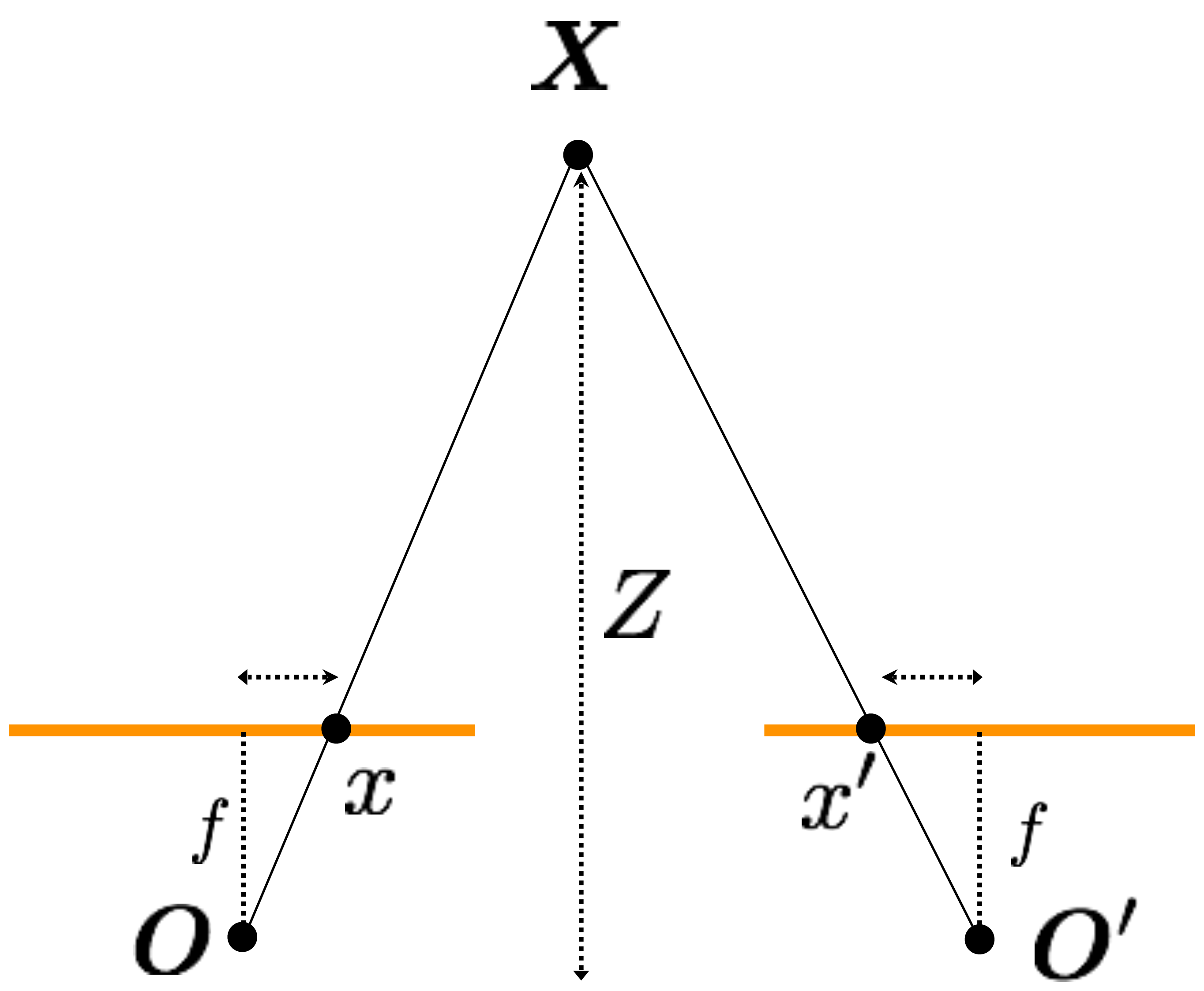


image plane

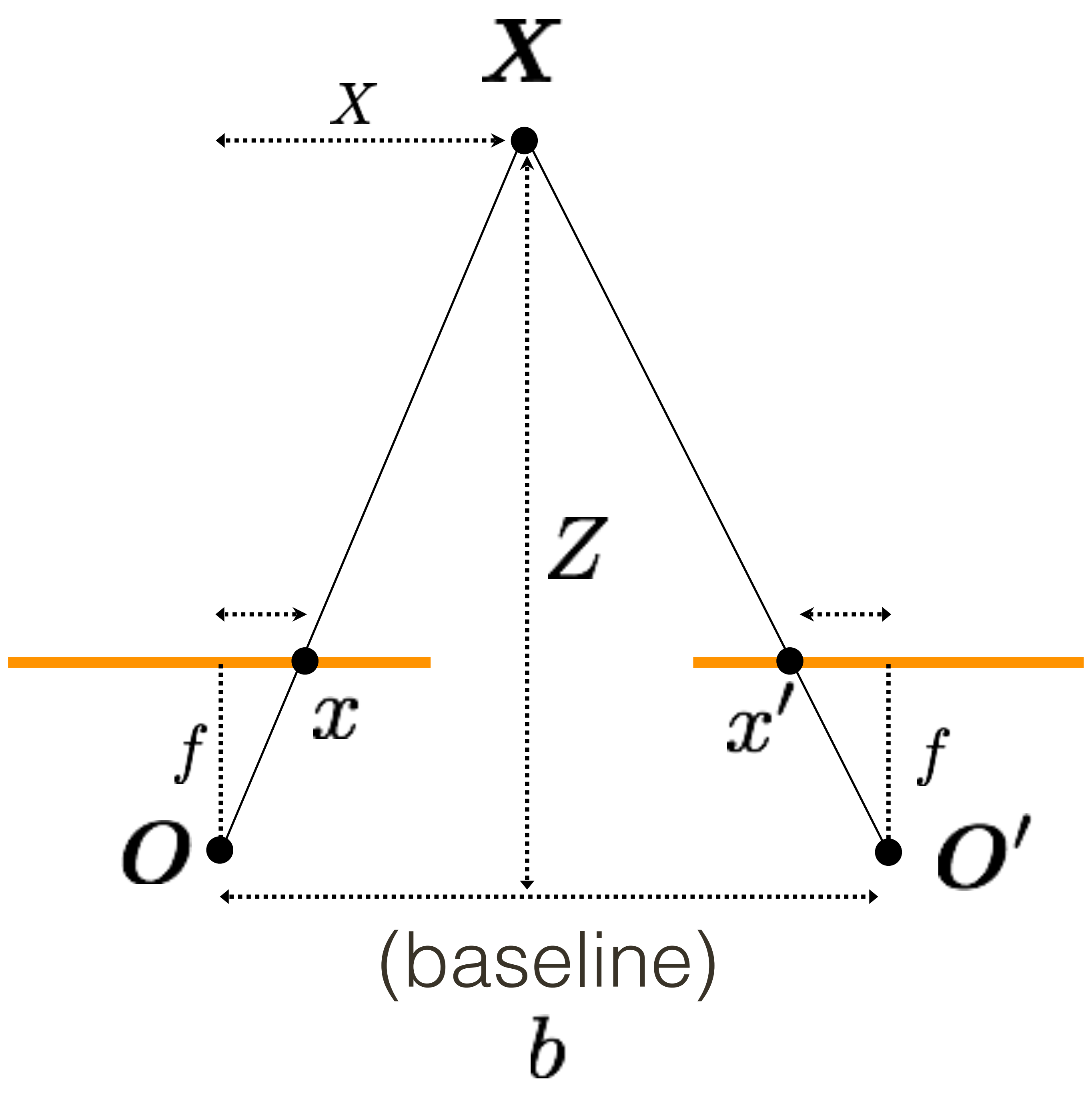
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

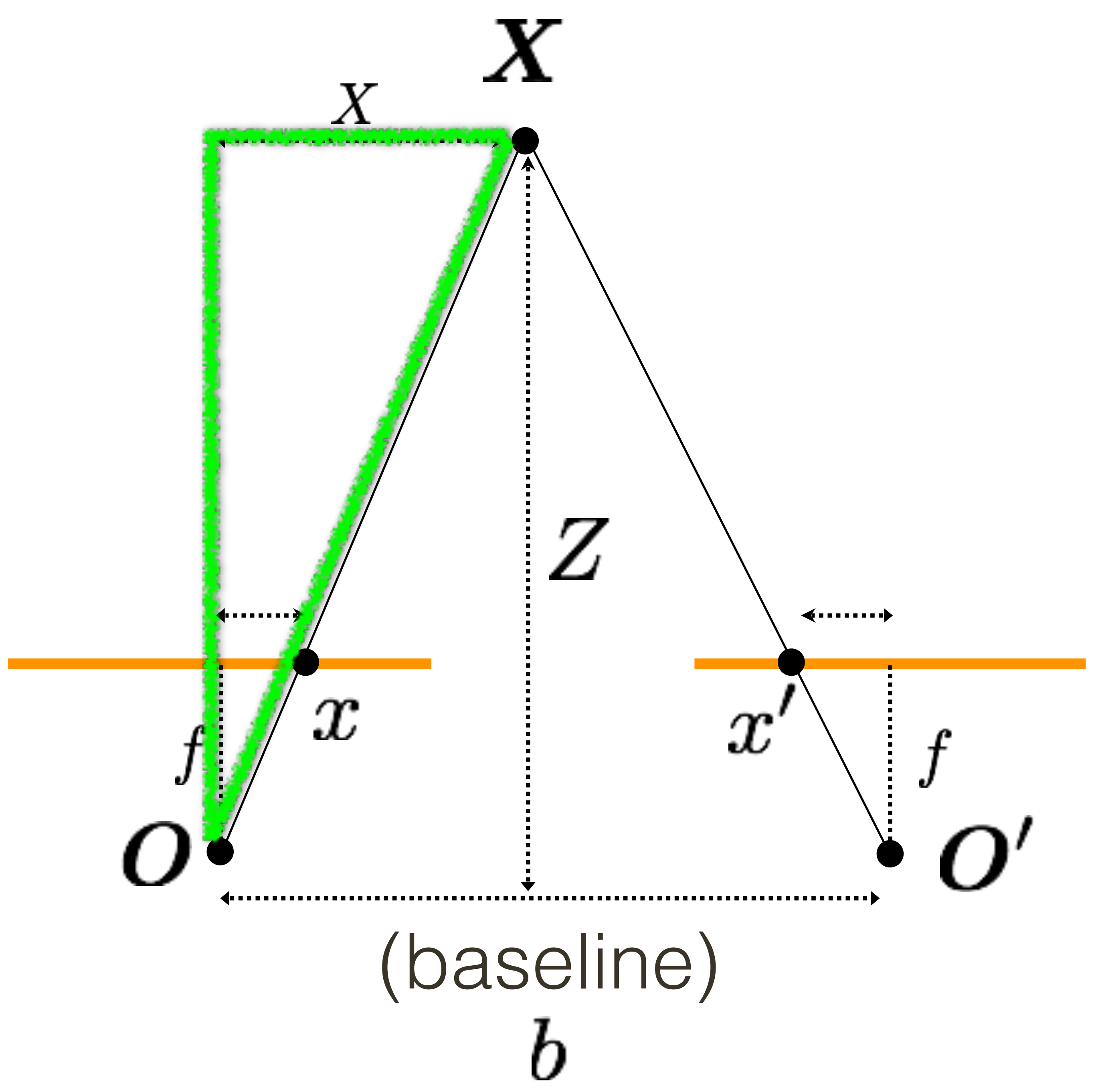
Rectified Stereo Pair: Depth Estimate



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate

$$\frac{X}{Z} = \frac{x}{f}$$



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate

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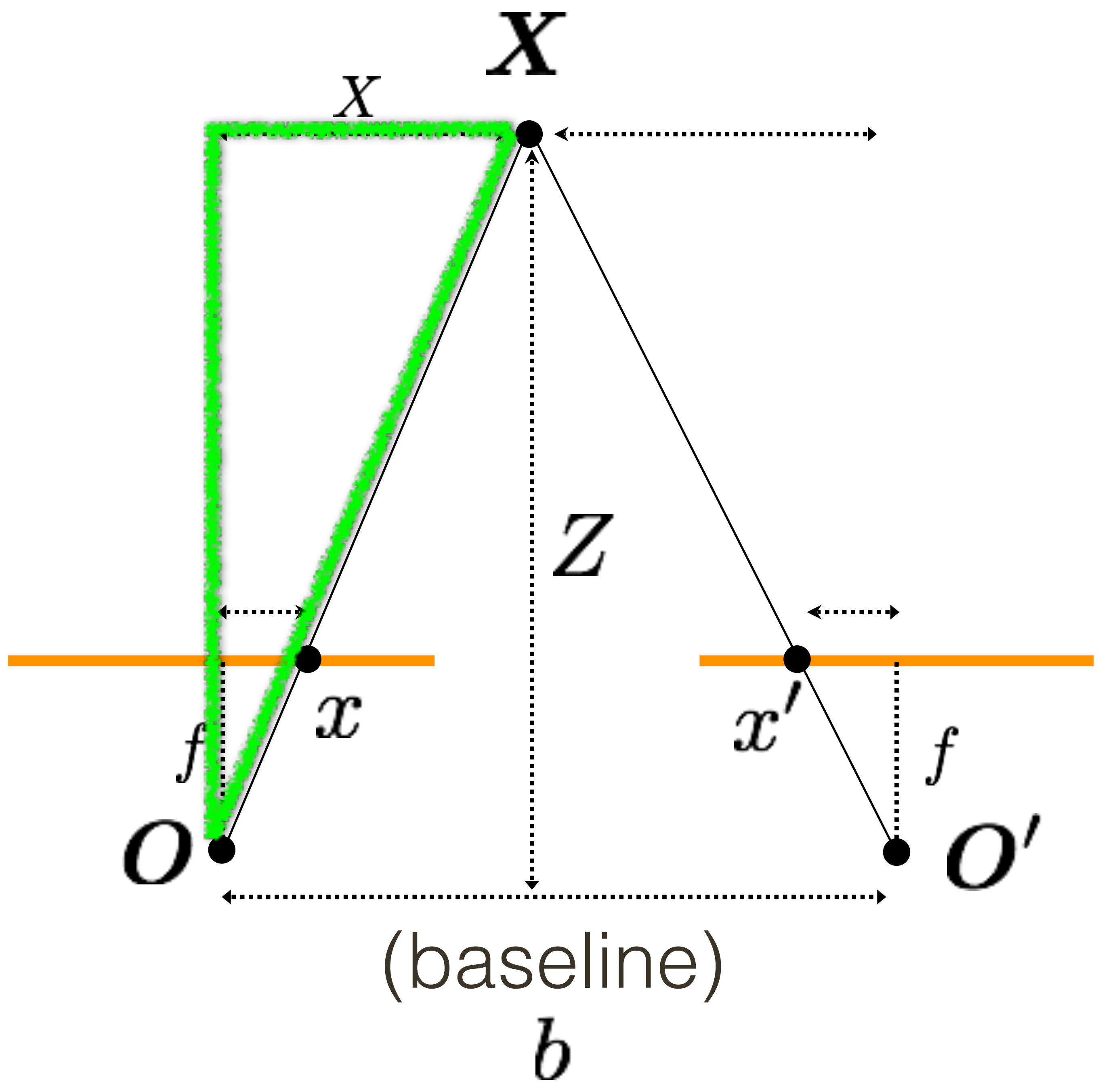

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Rectified Stereo Pair: Depth Estimate

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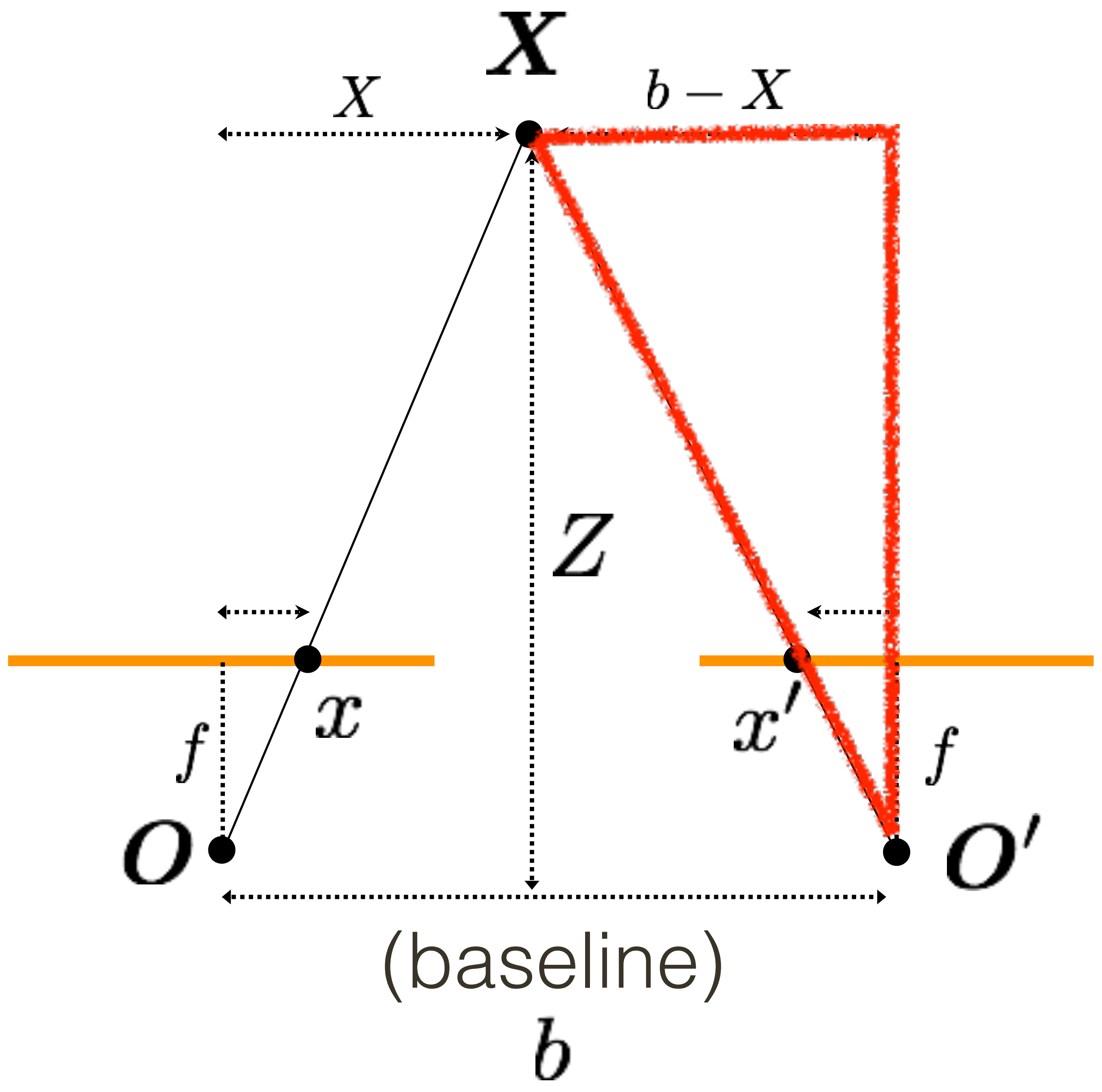
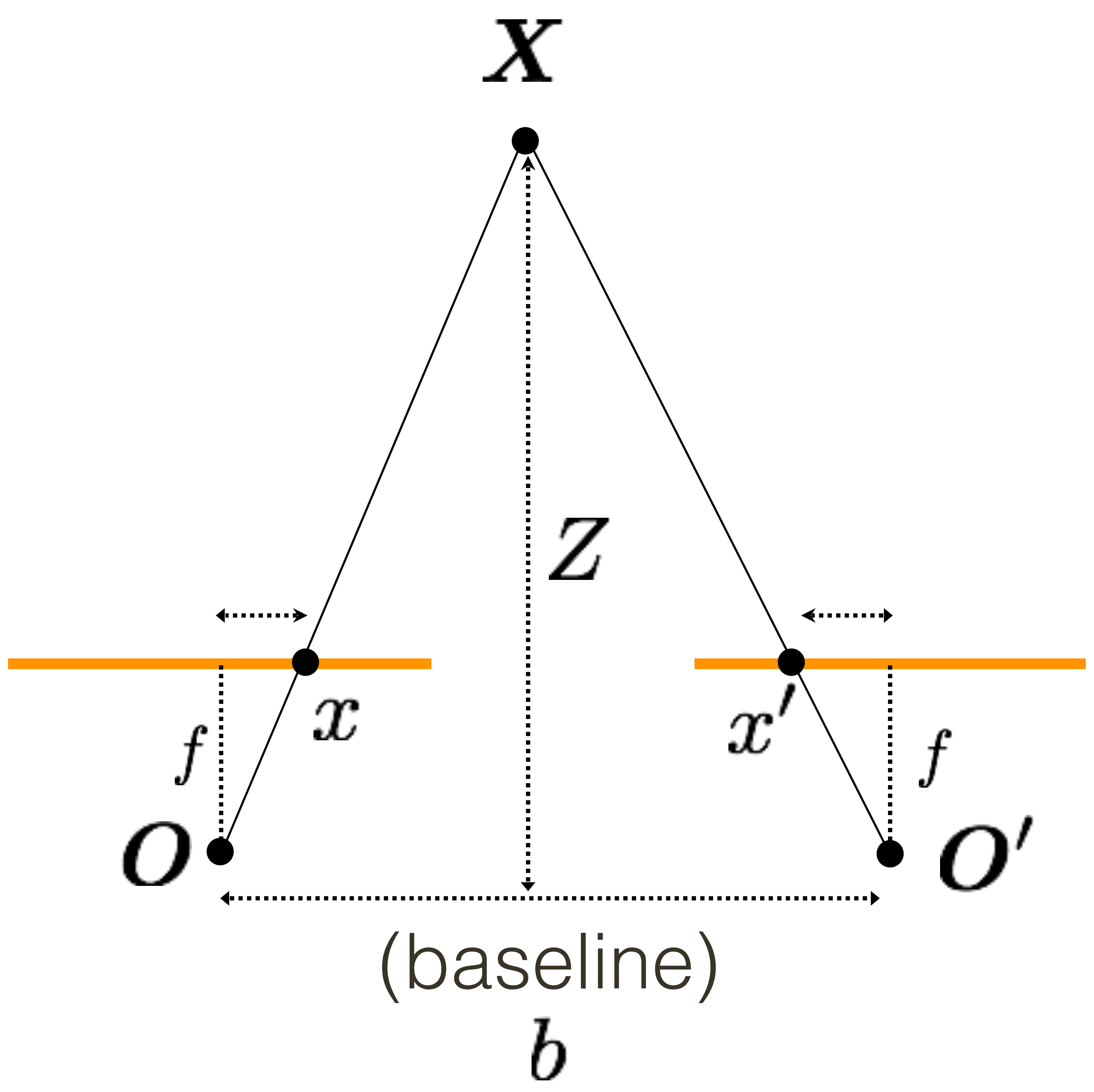


$$\frac{b - X}{Z} = \frac{x'}{f}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate

$$\frac{X}{Z} = \frac{x}{f}$$



$$\frac{b - X}{Z} = \frac{x'}{f}$$

Disparity

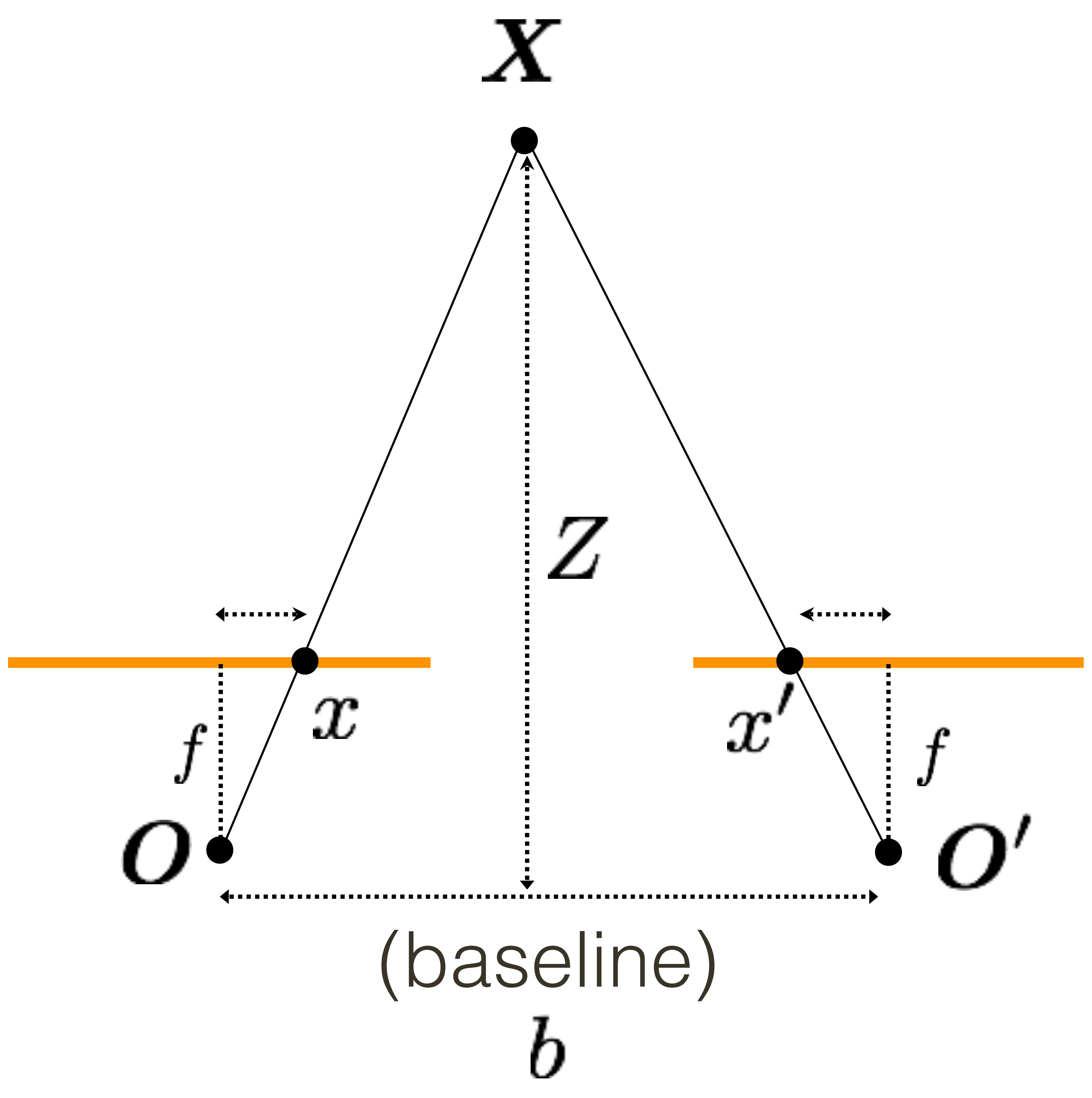
$$d = x - x'$$ (wrt to camera origin of image plane)

$$= \frac{bf}{Z}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Rectified Stereo Pair: Depth Estimate

$$\frac{X}{Z} = \frac{x}{f}$$



$$\frac{b - X}{Z} = \frac{x'}{f}$$

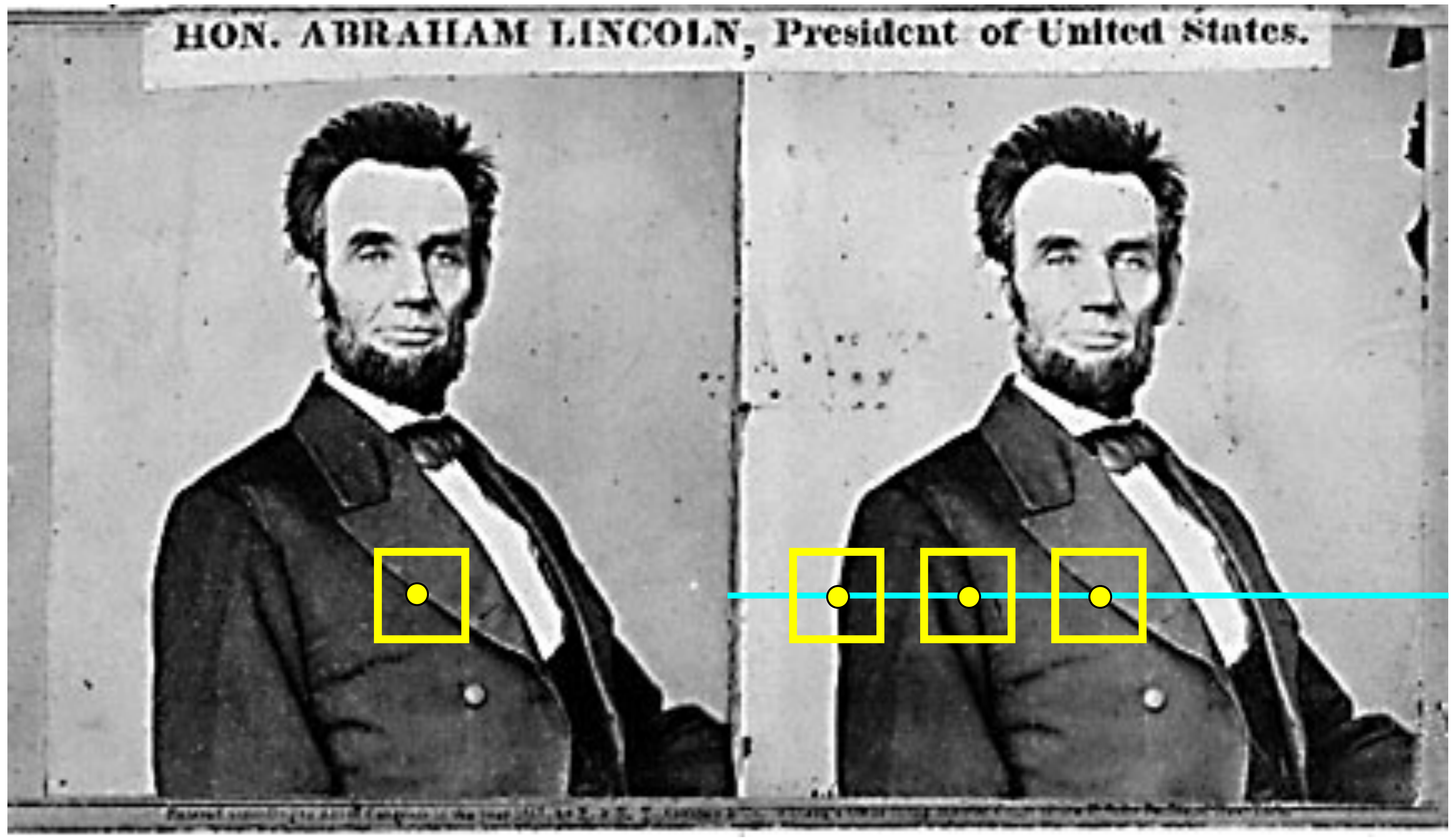
Disparity

$$d = x - x'$$
$$= \frac{bf}{Z}$$

inversely proportional to depth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(simple) **Stereo** Algorithm

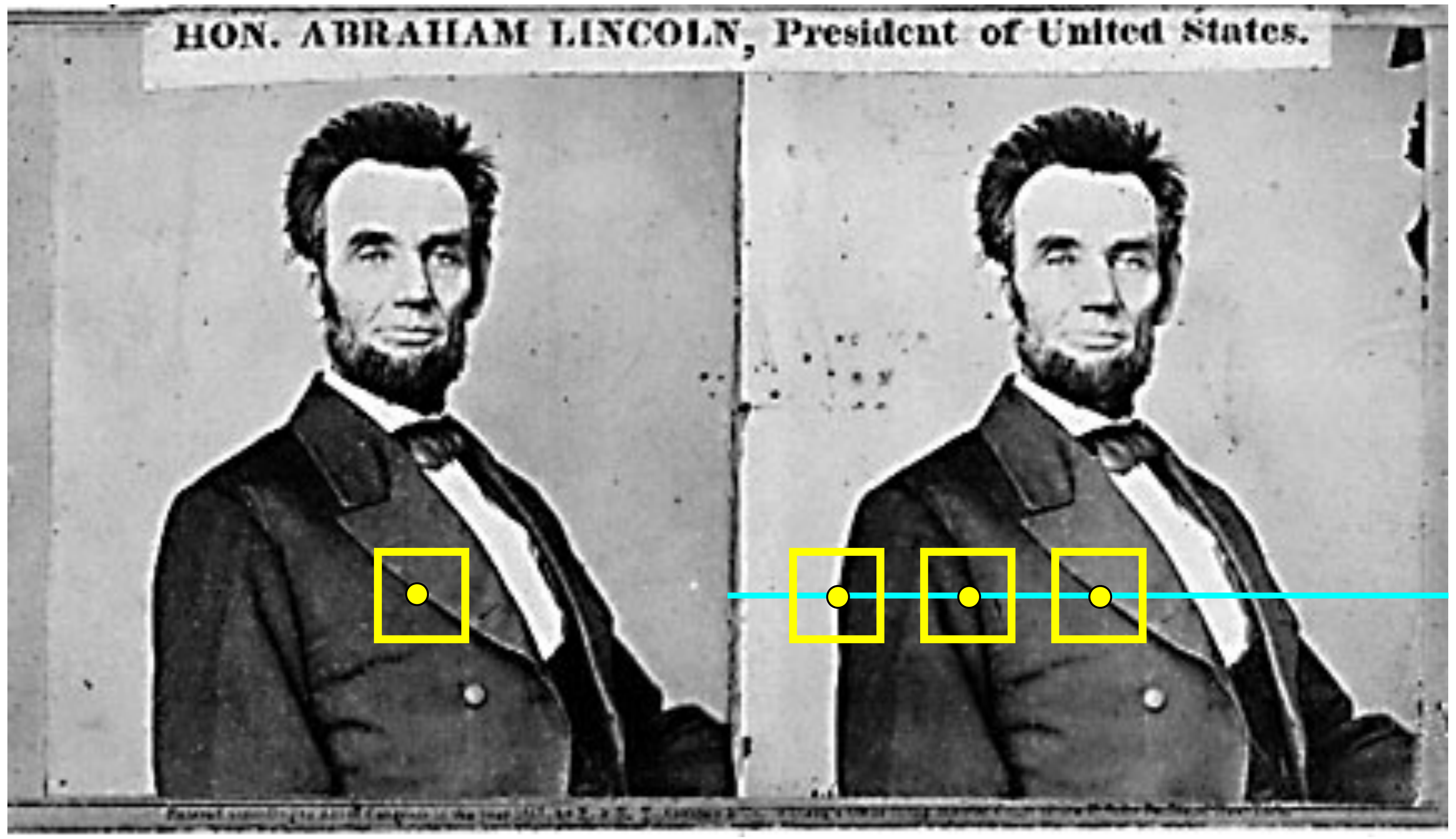



```
1.Rectify images
  (make epipolar lines horizontal)
2.For each pixel
  a.Find epipolar line
  b.Scan line for best match
  c.Compute depth from disparity
```

$$Z = \frac{bf}{d}$$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

(simple) **Stereo** Algorithm



1. Rectify images
   (make epipolar lines horizontal)
2. For each pixel
   a. Find epipolar line
   b. Scan line for best match
   c. Compute depth from disparity $Z = \frac{bf}{d}$

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Correspondence: What should we match?

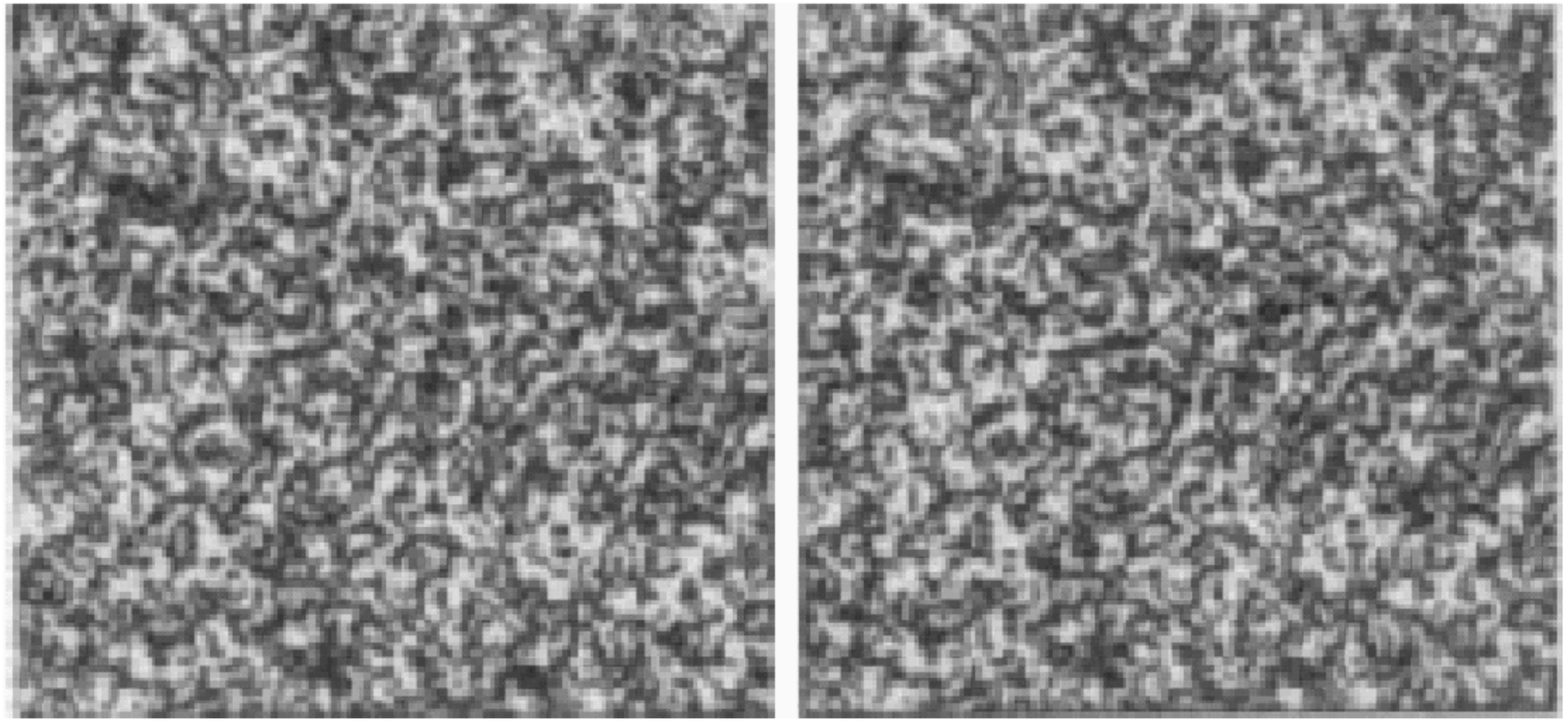
Objects?

Edges?

Pixels?

Collections of pixels?

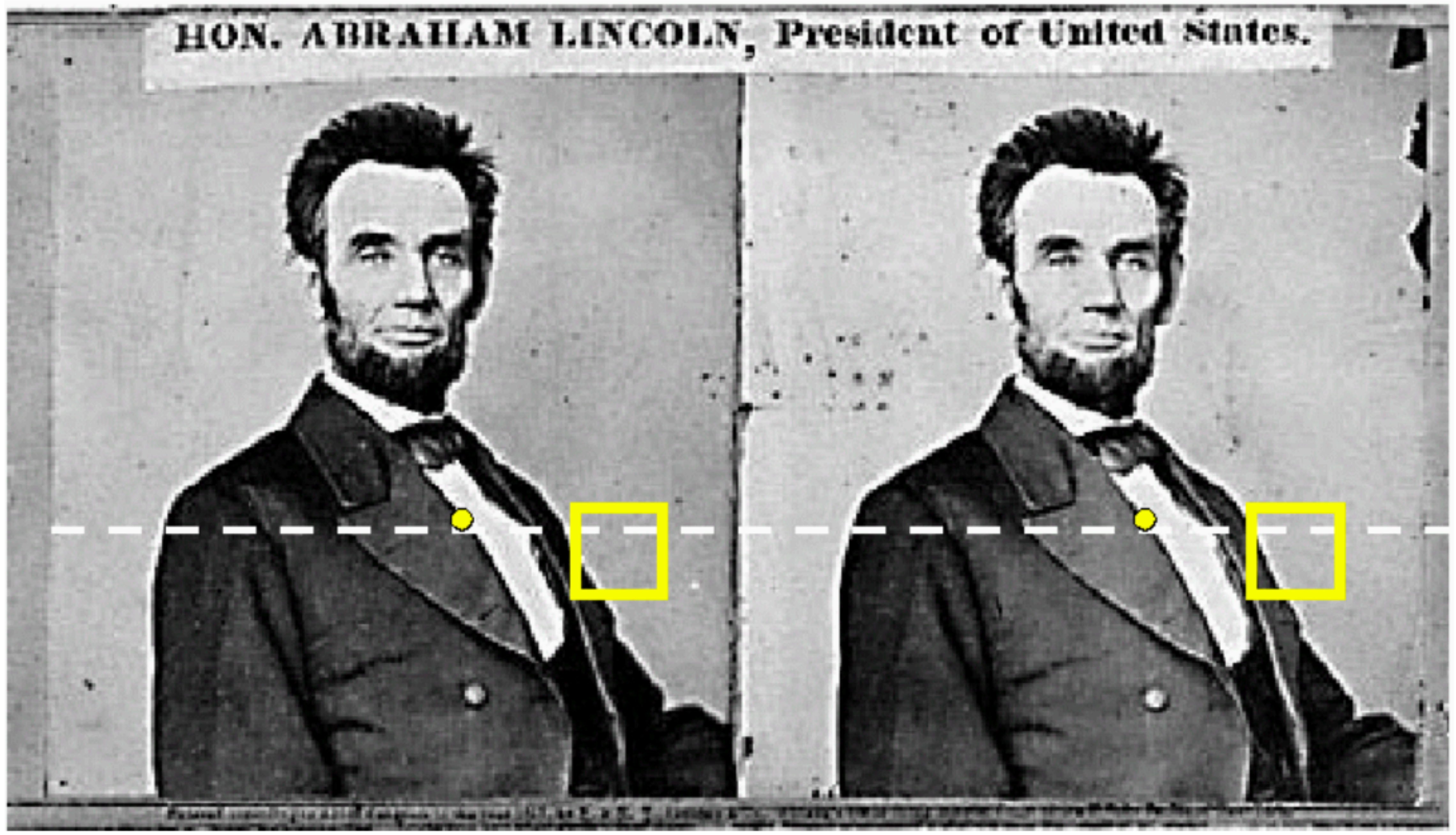
Random Dot Stereograms



Julesz (1960) showed that **recognition is not needed** for stereo

"When viewed monocularly, the images appear completely random. But when viewed stereoscopically, the image pair gives the impression of a square markedly in front of (or behind) the surround."

Method: Pixel Matching



For each **epipolar line**

For each **pixel** in the left image

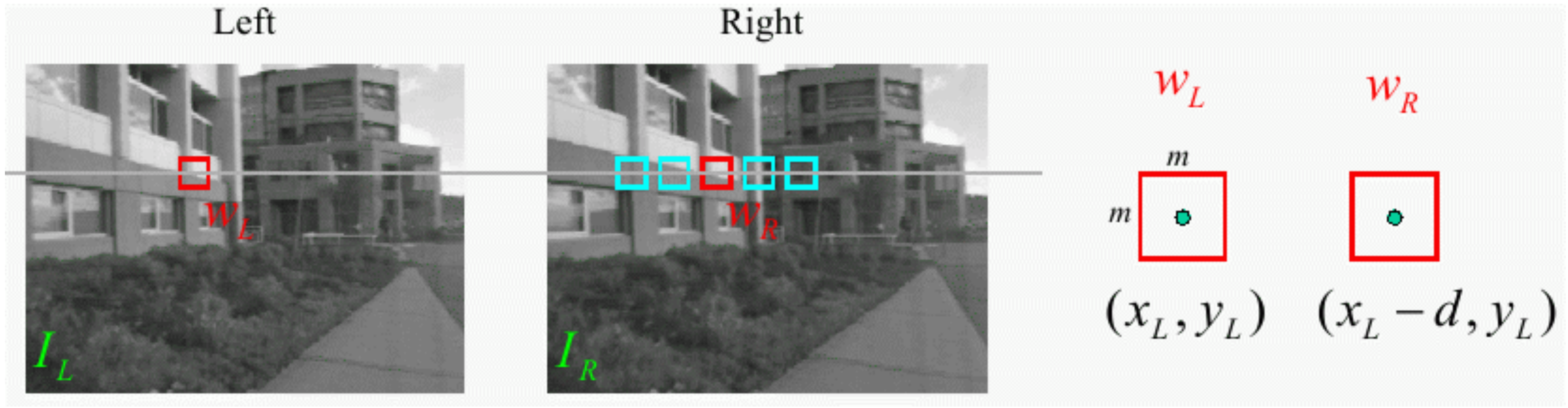
— compare with every pixel on same epipolar line in right image

— pick pixel with minimum match cost

This leaves too much ambiguity!

Slide credit: Steve Seitz

Sum of Squared (Pixel) Differences



$\mathbf{w}_L$ and $\mathbf{w}_R$ are corresponding $m \times m$ windows of pixels

Define the window function, $\mathbf{W}_m(x,y)$, by

$$\mathbf{W}_m(x,y) = \left\{(u,v) \mid x - \frac{m}{2} \leq u \leq x + \frac{m}{2}, y - \frac{m}{2} \leq v \leq y + \frac{m}{2}\right\}$$

SSD measures intensity difference as a function of disparity:

$$C_R(x,y,d) = \sum_{(u,v)\in\mathbf{W}_m(x,y)} [I_L(u,v) - I_R(u-d,v)]^2$$

Image Normalization

$$\bar{I} = \frac{1}{|\mathbf{W}_m(x,y)|} \sum_{(u,v)\in\mathbf{W}_m(x,y)} I(u,v)$$

Average Pixel

$$||I||_{\mathbf{W}_m(x,y)} = \sqrt{\sum_{(u,v)\in\mathbf{W}_m(x,y)} [I(u,v)]^2}$$

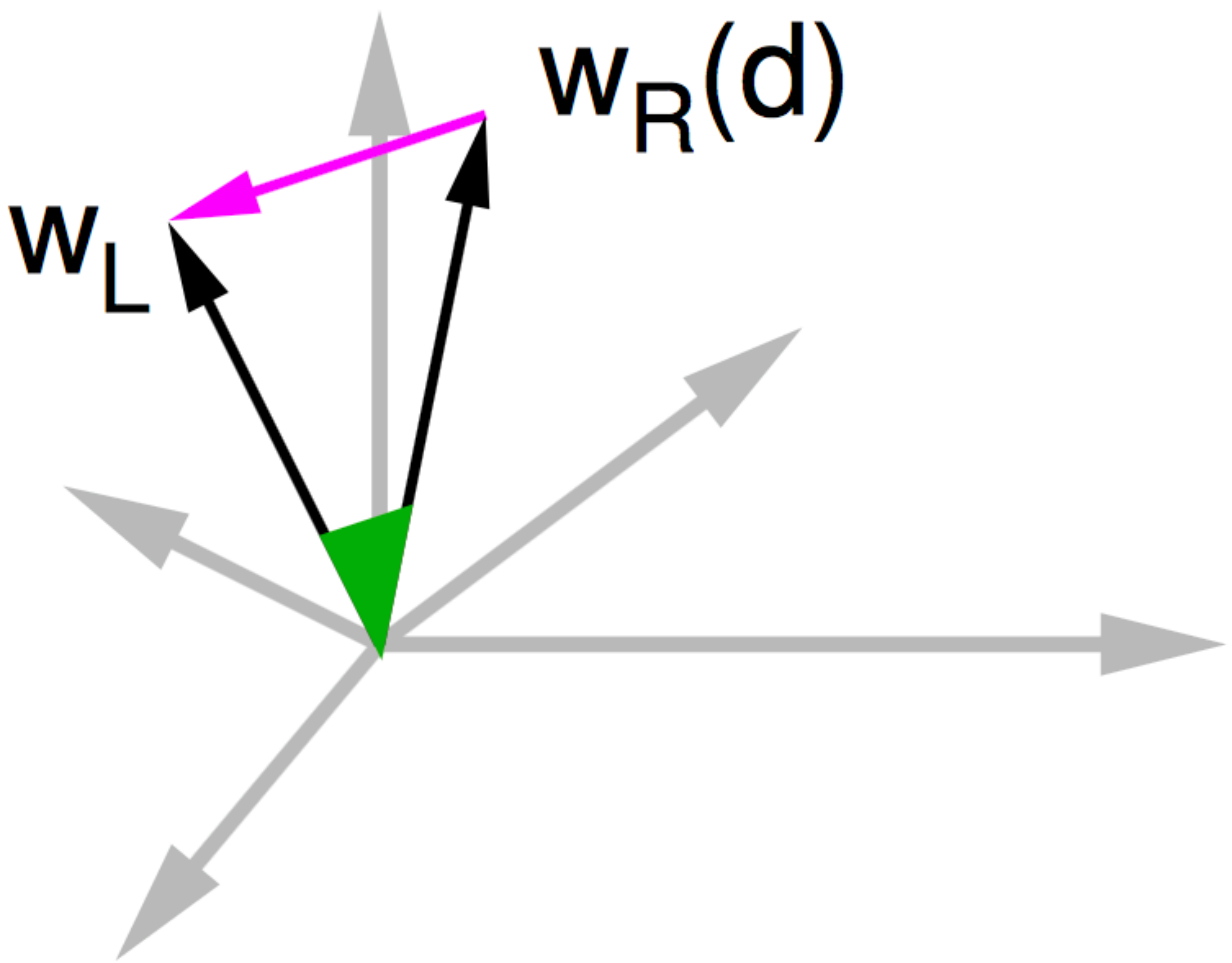
Window Magnitude

$$\hat{I}(x,y) = \frac{I(x,y) - \bar{I}}{||I - \bar{I}||_{\mathbf{W}_m(x,y)}}$$

Normalized Pixel: subtract the mean, normalize to unit length

Image **Metrics**

(Normalized) Sum of Squared Differences



(Normalized) Correlation

Image **Metrics**

Assume $\mathbf{w}_L$ and $\mathbf{w}_R(d)$ are normalized to unit length (Normalized)

Sum of Squared Differences:

$$C_{SSD}(d) = \sum_{(u,v)\in\mathbf{W}_m(x,y)} \left[\hat{I}_L(u,v) - \hat{I}_R(u-d,v)\right]^2$$

$$= ||\mathbf{w}_L - \mathbf{w}_R(d)||^2$$

(Normalized) **Correlation**:

$$C_{NC}(d) = \sum_{(u,v)\in\mathbf{W}_m(x,y)} \hat{I}_L(u,v)\hat{I}_R(u-d,v)$$

$$= \mathbf{w}_L \cdot \mathbf{w}_R(d) = \cos\theta$$

Image **Metrics**

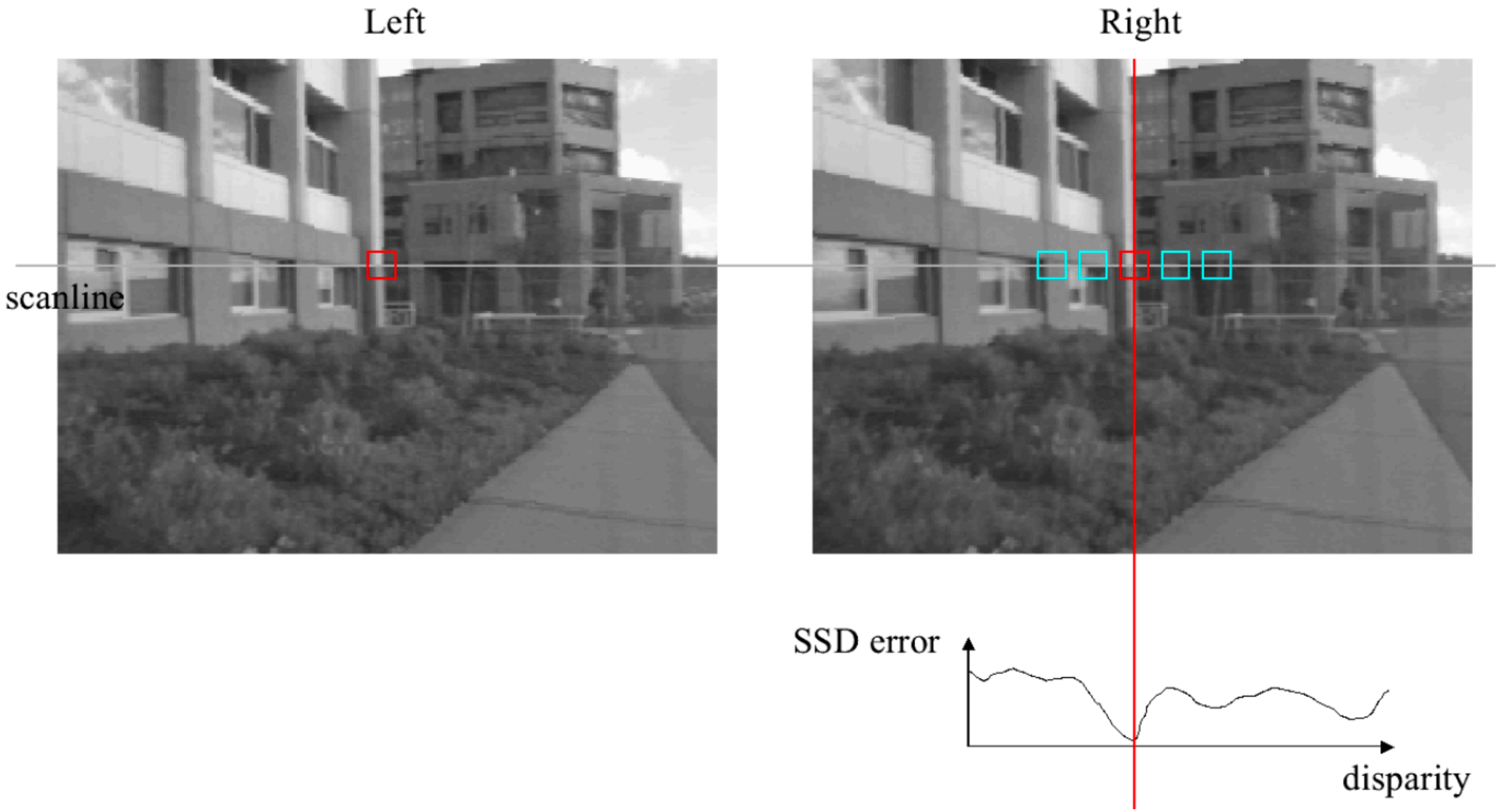
Let d^* be the value of d that minimizes C_{SSD}

Then d^* also is the value of d that minimizes C_{NC}

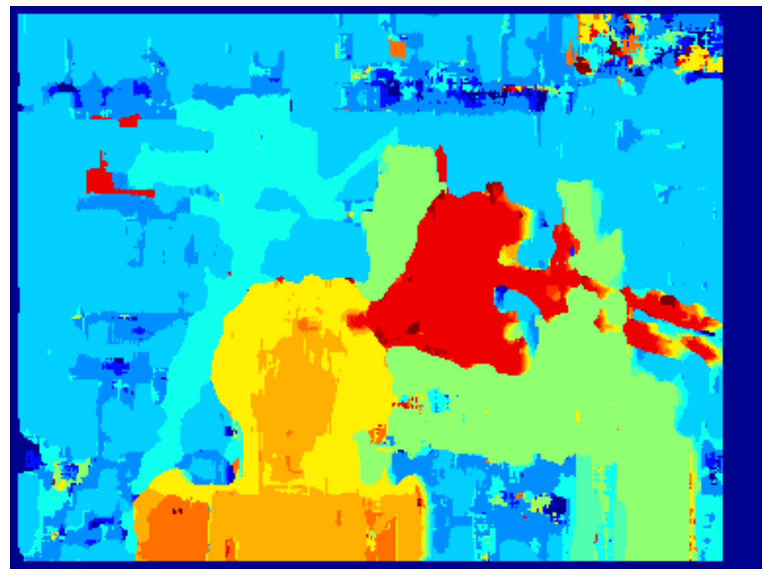
That is,

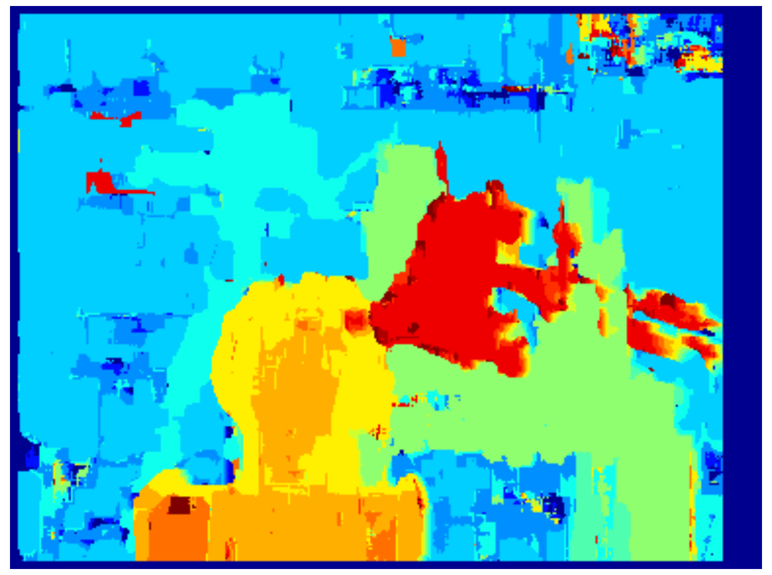
$$d^* = \arg\min_d ||\mathbf{w}_L - \mathbf{w}_R(d)||^2 = \arg\min_d \mathbf{w}_L \cdot \mathbf{w}_R(d)$$

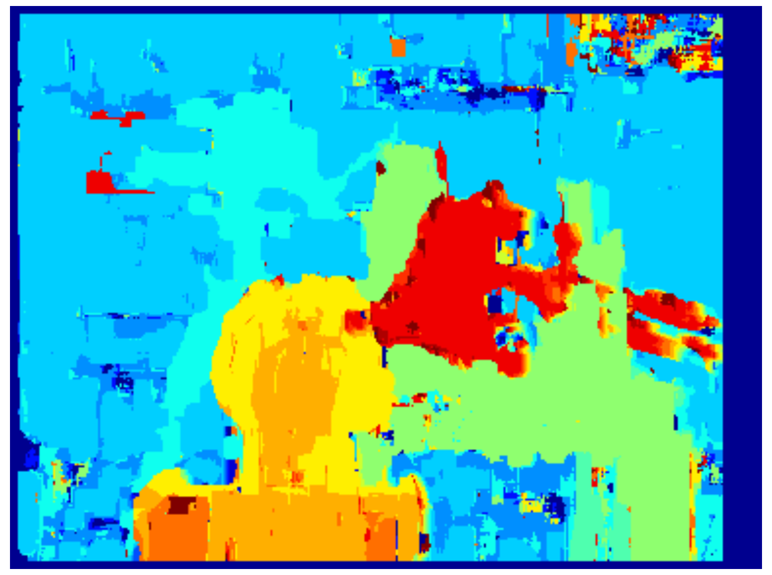
Method: Correlation



Similarity Measure	Formula
Sum of Absolute Differences (SAD)	$\sum_{(i,j)\in W} \lvert I_1(i,j) - I_2(x+i, y+j) \rvert$
Sum of Squared Differences (SSD)	$\sum_{(i,j)\in W} \left(I_1(i,j) - I_2(x+i, y+j)\right)^2$
Zero-mean SAD	$\sum_{(i,j)\in W} \lvert I_1(i,j) - \bar{I}_1(i,j) - I_2(x+i, y+j) + \bar{I}_2(x+i, y+j) \rvert$
Locally scaled SAD	$\sum_{(i,j)\in W} \lvert I_1(i,j) - \frac{\bar{I}_1(i,j)}{\bar{I}_2(x+i, y+j)} I_2(x+i, y+j) \rvert$
Normalized Cross Correlation (NCC)	$\frac{\sum_{(i,j)\in W} I_1(i,j) . I_2(x+i, y+j)}{\sqrt[2]{\sum_{(i,j)\in W} I_1^2(i,j) . \sum_{(i,j)\in W} I_2^2(x+i, y+j)}}$


SAD

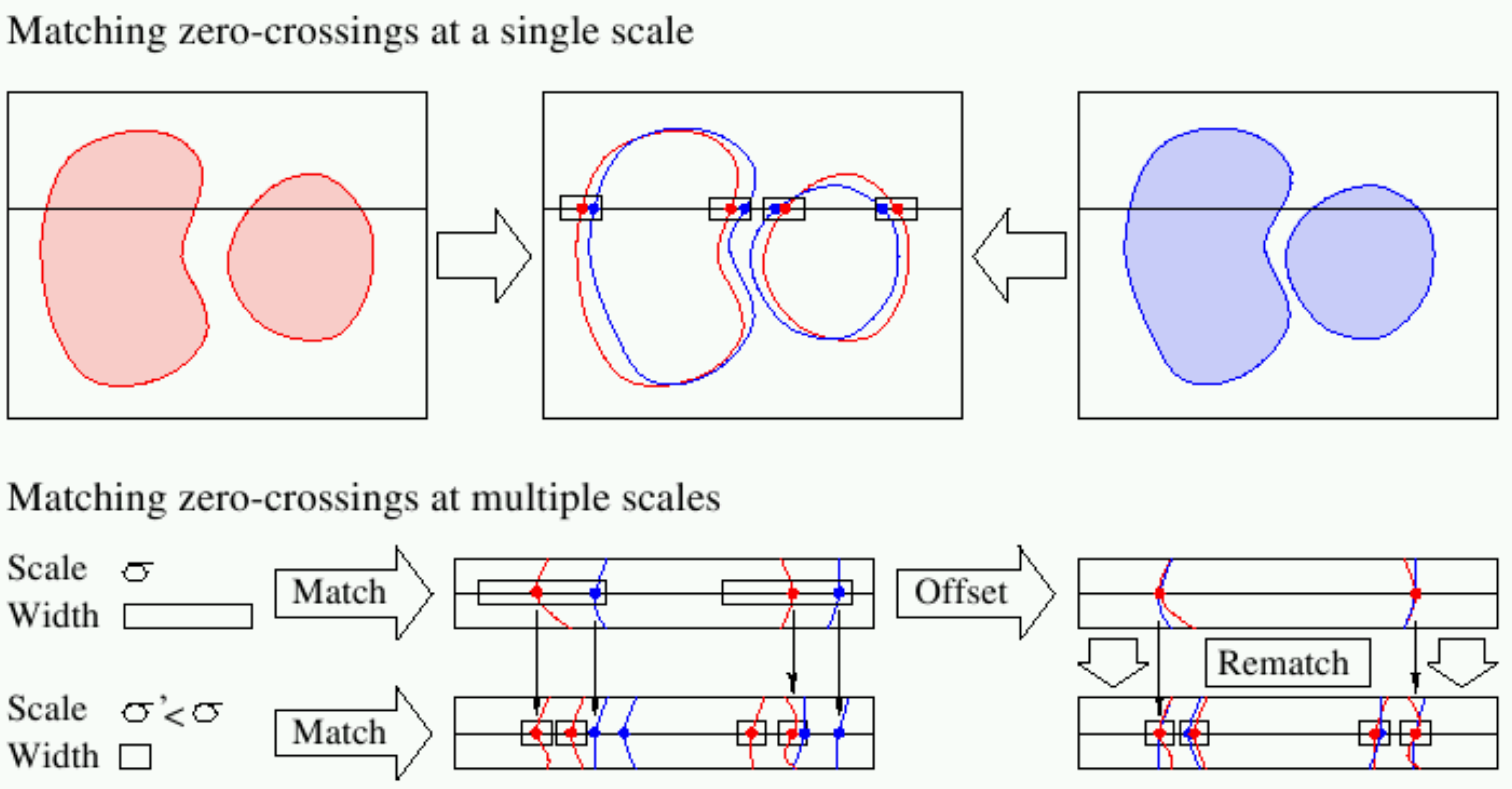

SSD


NCC


Ground truth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Method: Edges



Forsyth & Ponce (2nd ed.) Figure 7.12 (Top & Middle)

Method: Edges (aside)

The **Marr/Poggio** (1979) multiscale stereo algorithm:

1. Convolve the two (rectified) images with $\nabla^2 G_\sigma$ filters of increasing
$\sigma_1 < \sigma_2 < \sigma_3 < \sigma_4$

2. Find zero crossings along horizontal scanlines of the filtered images

3. For each filter scale σ, match zero crossings with the same parity and roughly equal orientations in a $[-\mathbf{w}_\sigma, +\mathbf{w}_\sigma]$ disparity range, with $\mathbf{w}_\sigma = 2\sqrt{2}\sigma$

4. Use the disparities found at larger scales to control eye vergence and cause unmatched regions at smaller scales to come into correspondence

Which Method is **Better**: Correlation or Edges?

Edges are more “meaningful” [Marr]. . . . . . . but hard to find!

Edges tend to fail in dense texture (outdoors)

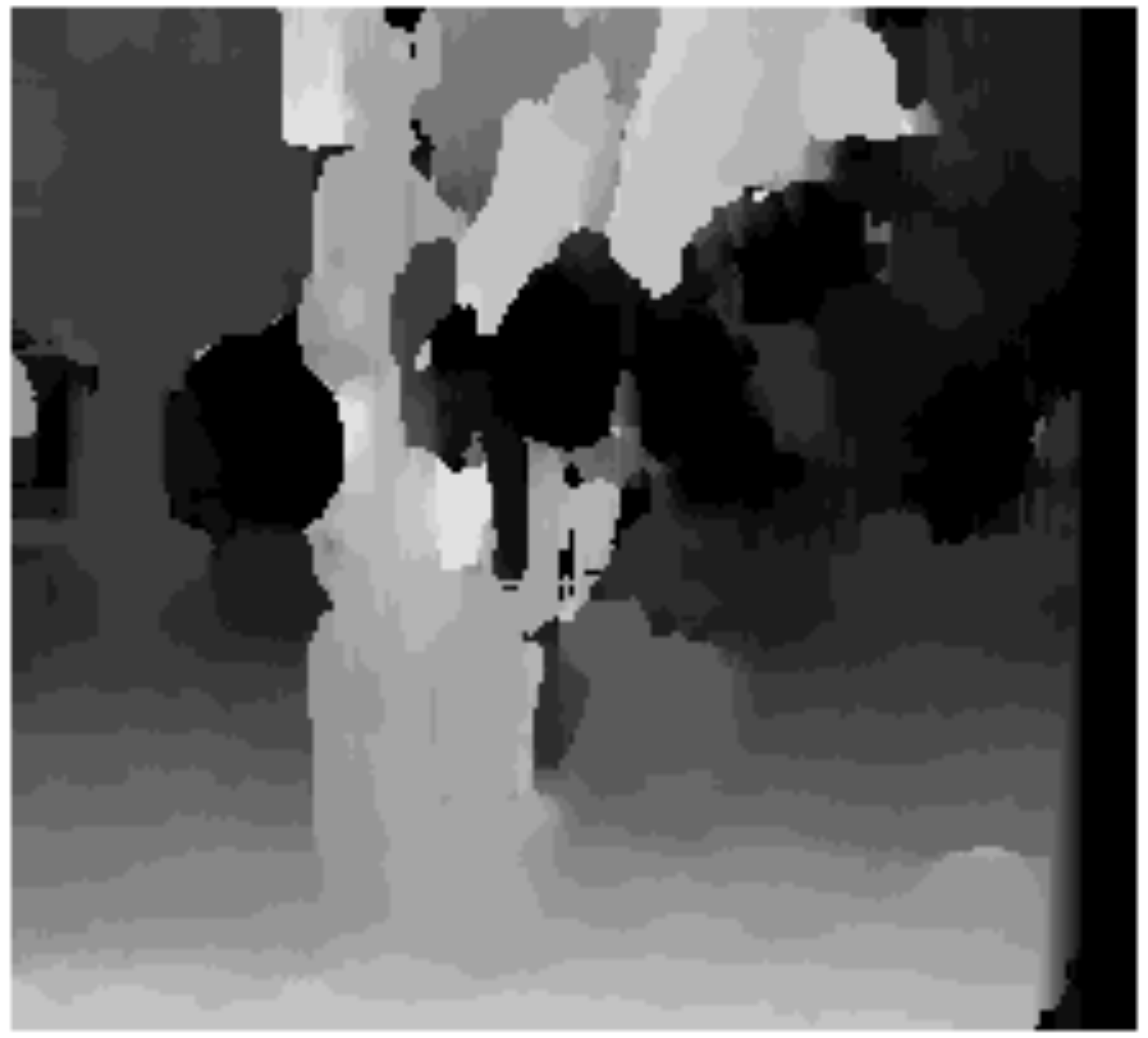
Correlation tends to fail in smooth, featureless regions

Note: Correlation-based methods are “dense.” Edge-based methods are “relatively sparse”

Effect of **Window Size**

W = 3

Smaller window
+ More detail
- More noise



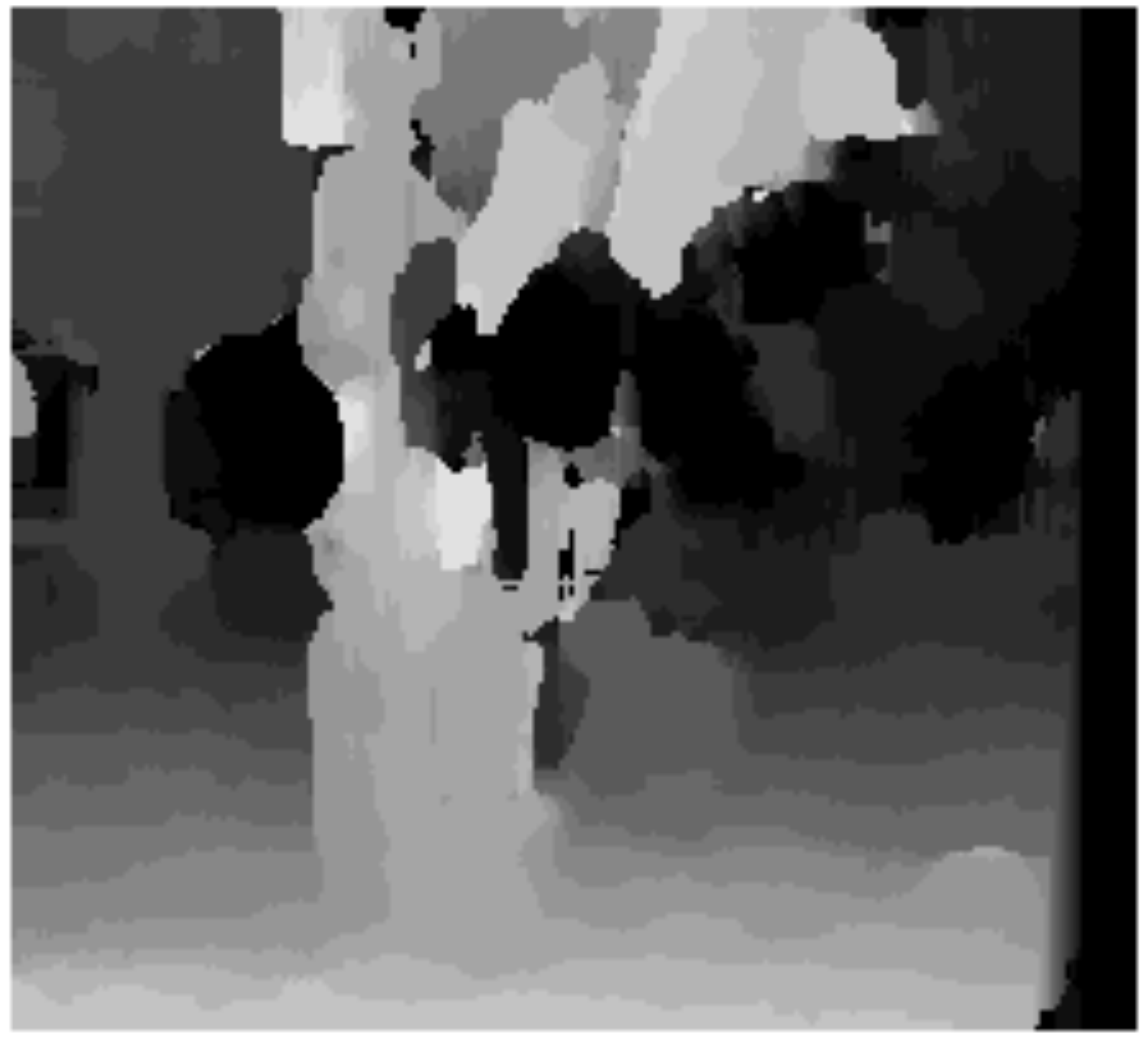
W = 20

Larger window
+ Smoother disparity maps
- Less detail
- Fails near boundaries

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Effect of **Window Size**

W = 3

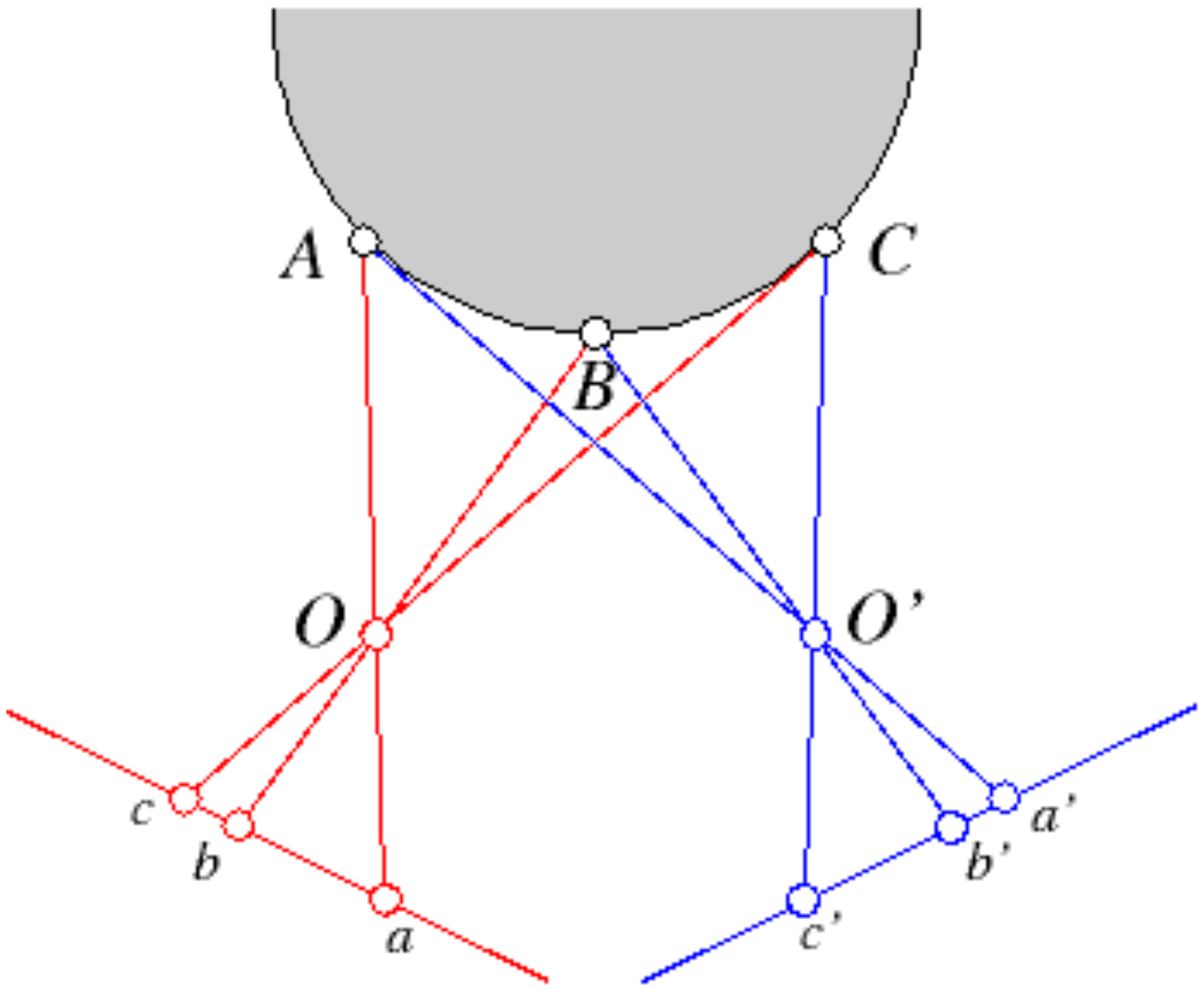


W = 20

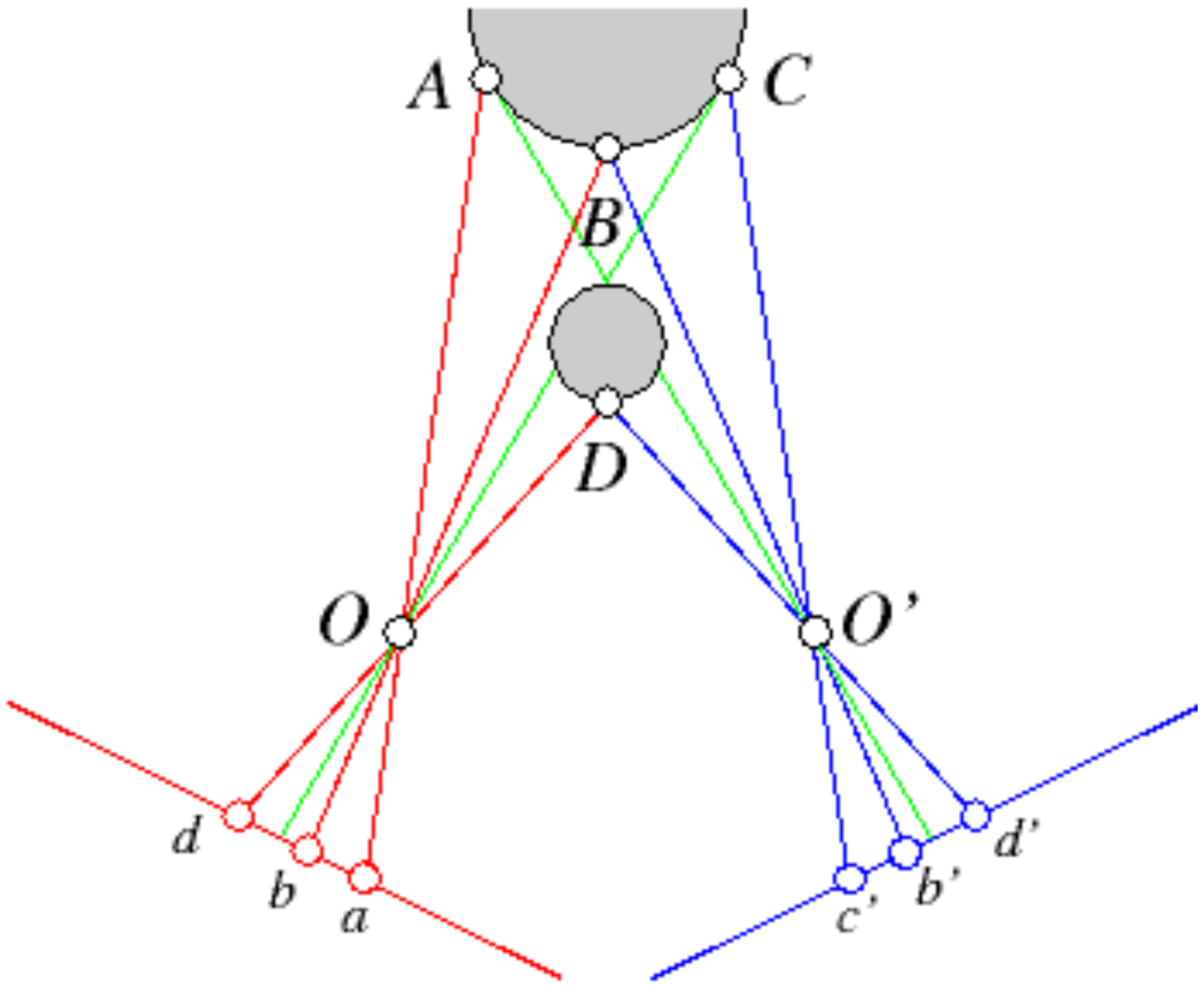
Note: Some approaches use an adaptive window size — try multiple sizes and select best match

Ordering Constraints

Ordering constraint …

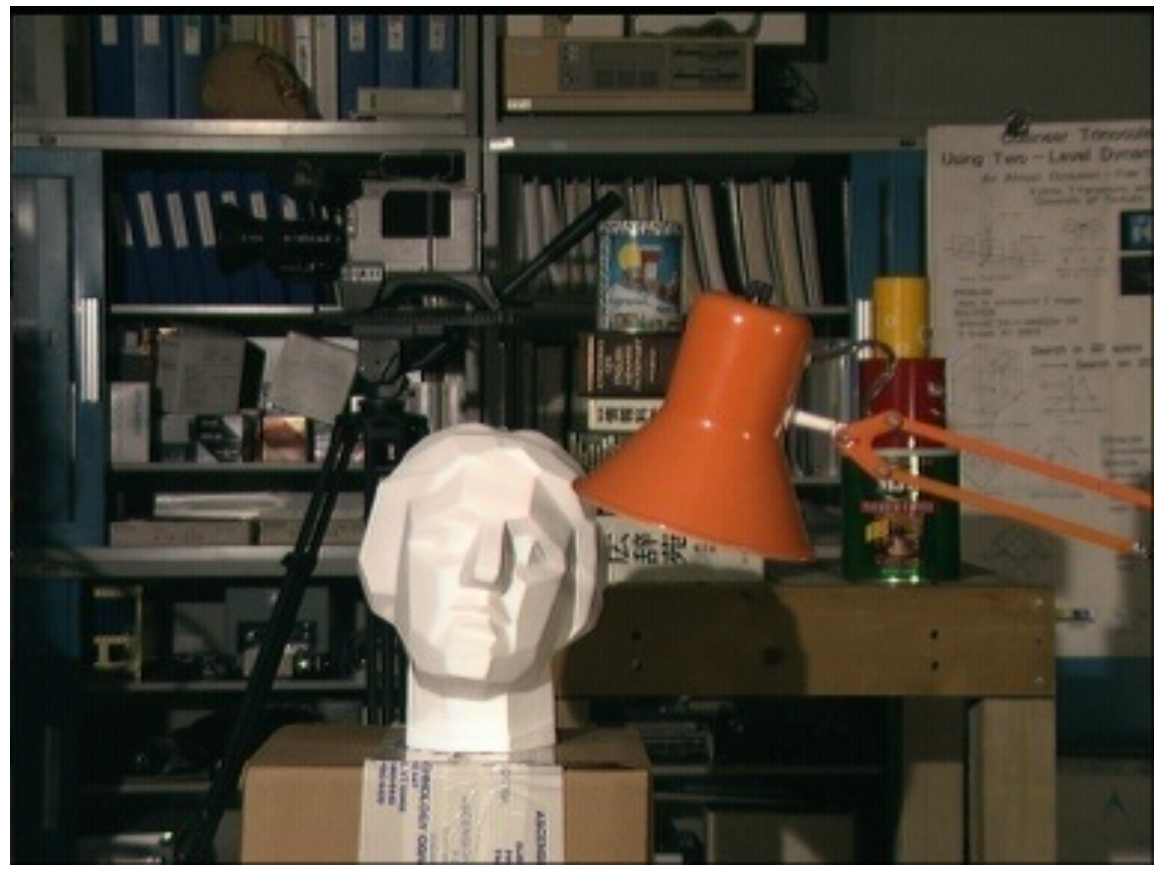


…. and a **failure** case

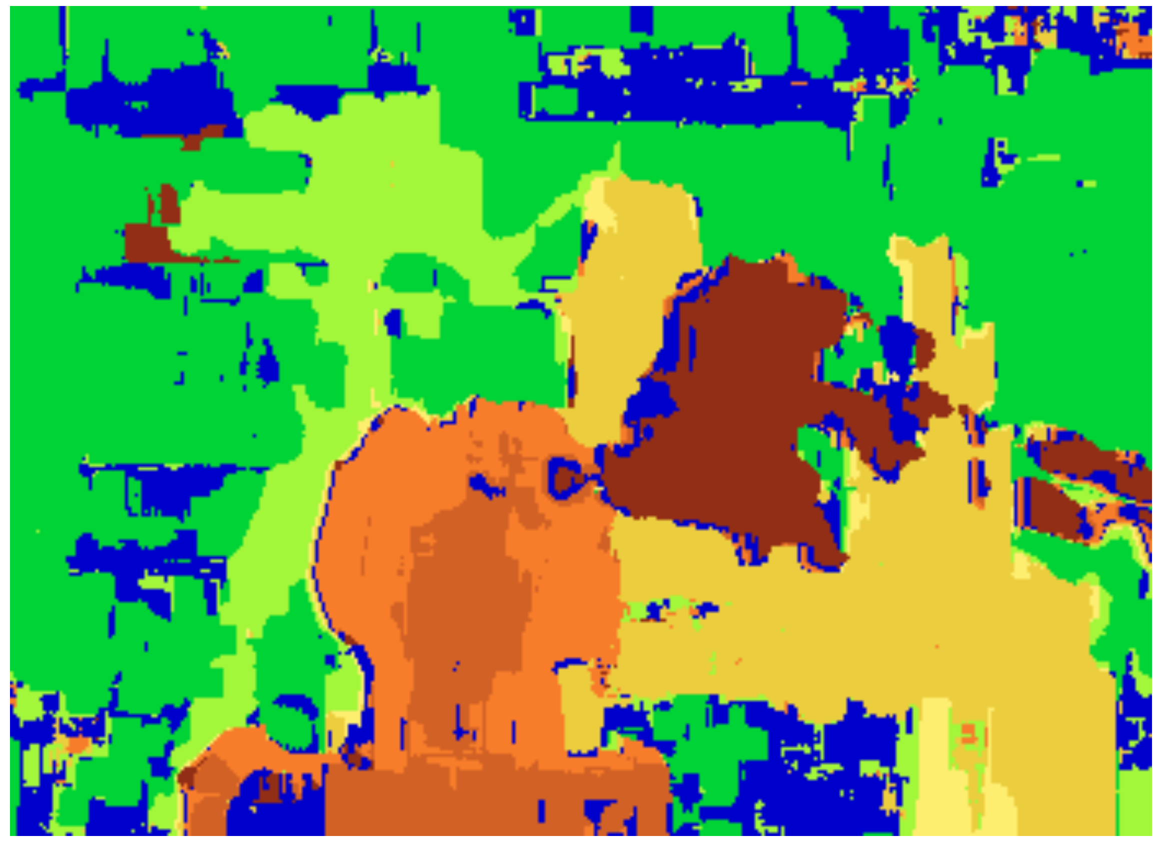


Forsyth & Ponce (2nd ed.) Figure 7.13

Block Matching Techniques: Result



Block matching



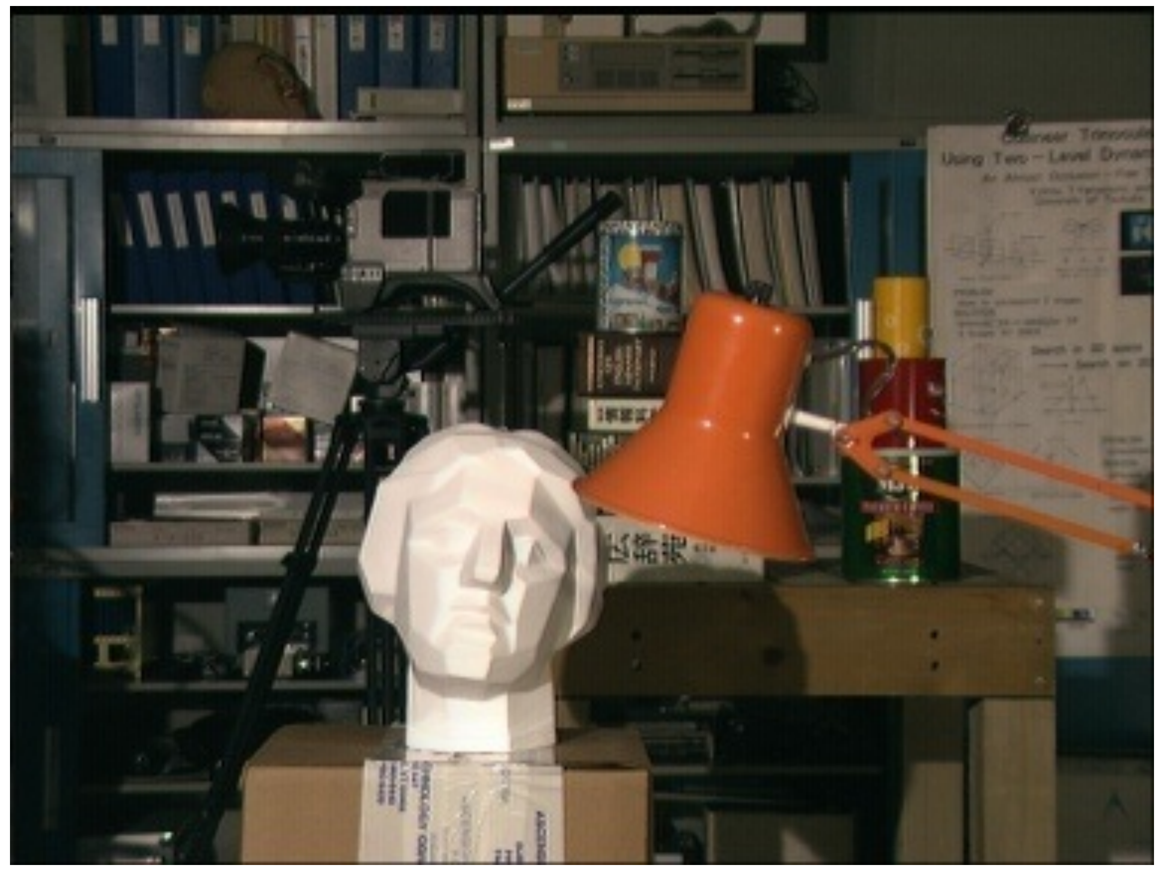
Ground truth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

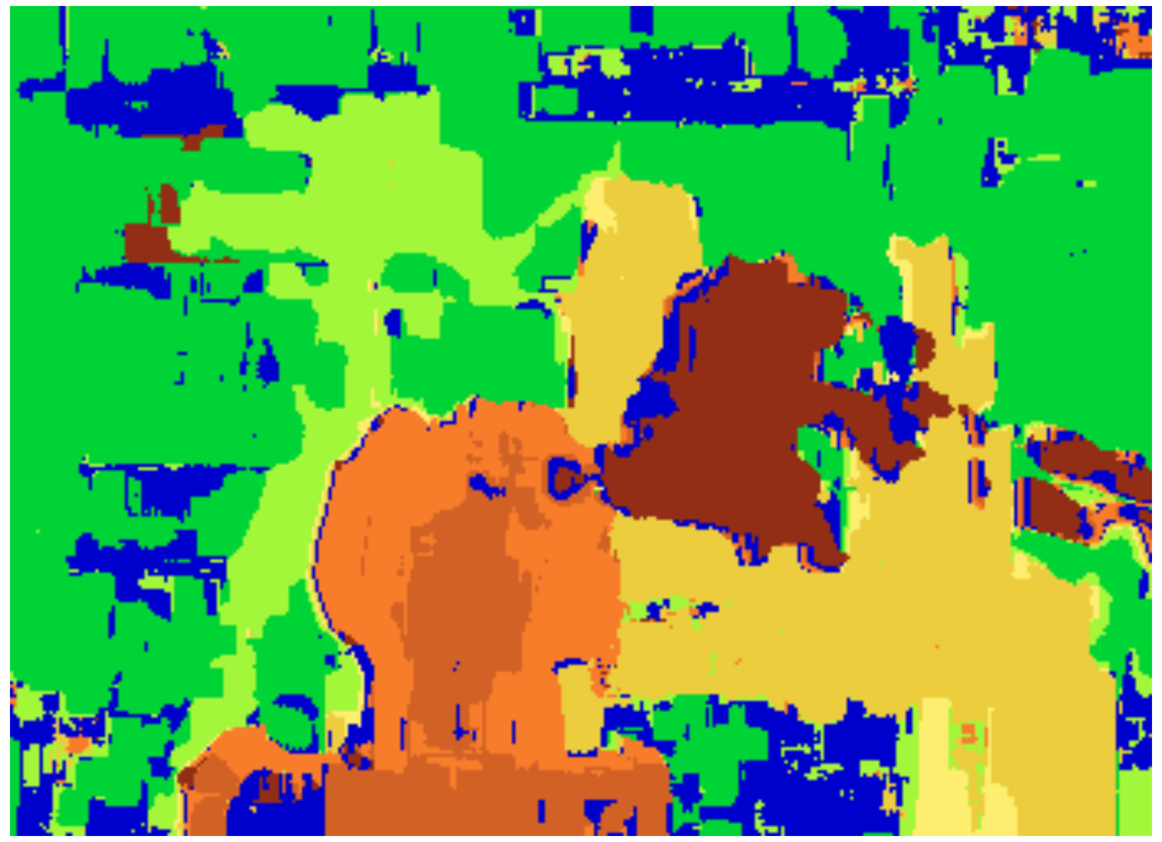
Block Matching Techniques: Result

Too many **discontinuities**.
We expect disparity values to change slowly.

Let's make an assumption:
depth should change smoothly



Block matching



Ground truth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Stereo Matching as **Energy Minimization**

energy function
(for one pixel)

$$E(d) = \underbrace{E_d(d)}_{\text{data term}} + \lambda \underbrace{E_s(d)}_{\text{smoothness term}}$$

Want each pixel to find a good match in the other image

(block matching result)

Adjacent pixels should (usually) move about the same amount

(smoothness function)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

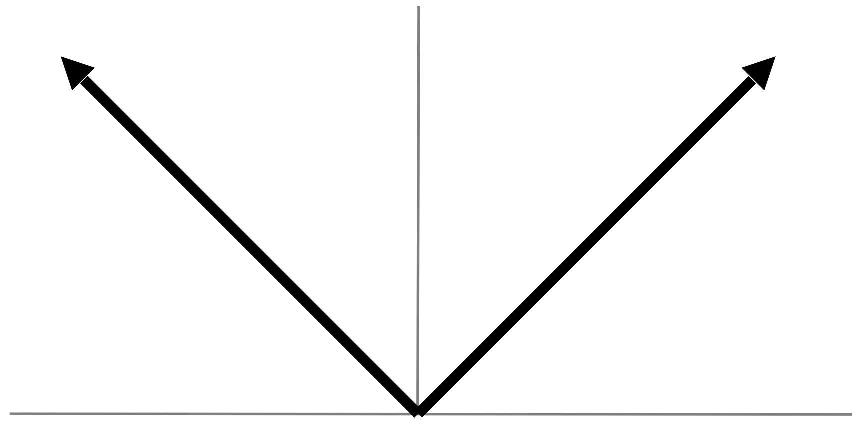
Stereo Matching as **Energy Minimization**

$$E_s(d) = \sum_{(p,q)\in\mathcal{E}} V(d_p, d_q)$$

smoothness term

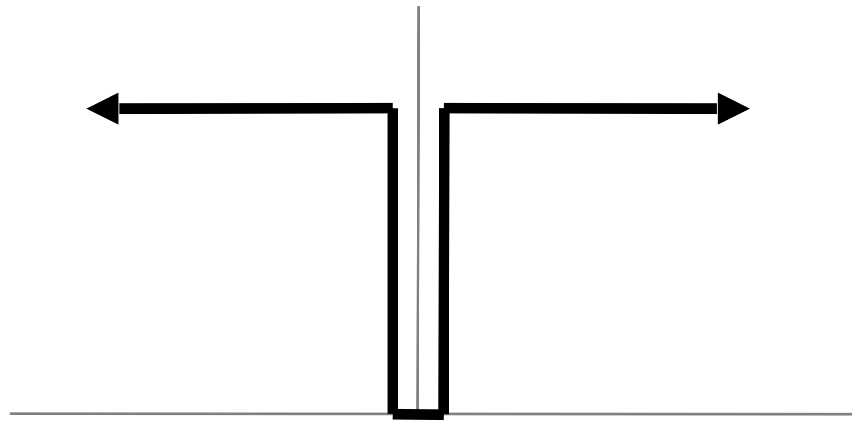
$$V(d_p, d_q) = |d_p - d_q|$$

L_1 distance



$$V(d_p, d_q) = \begin{cases} 0 & \text{if } d_p = d_q \\ 1 & \text{if } d_p \neq d_q \end{cases}$$

"Potts model"



Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

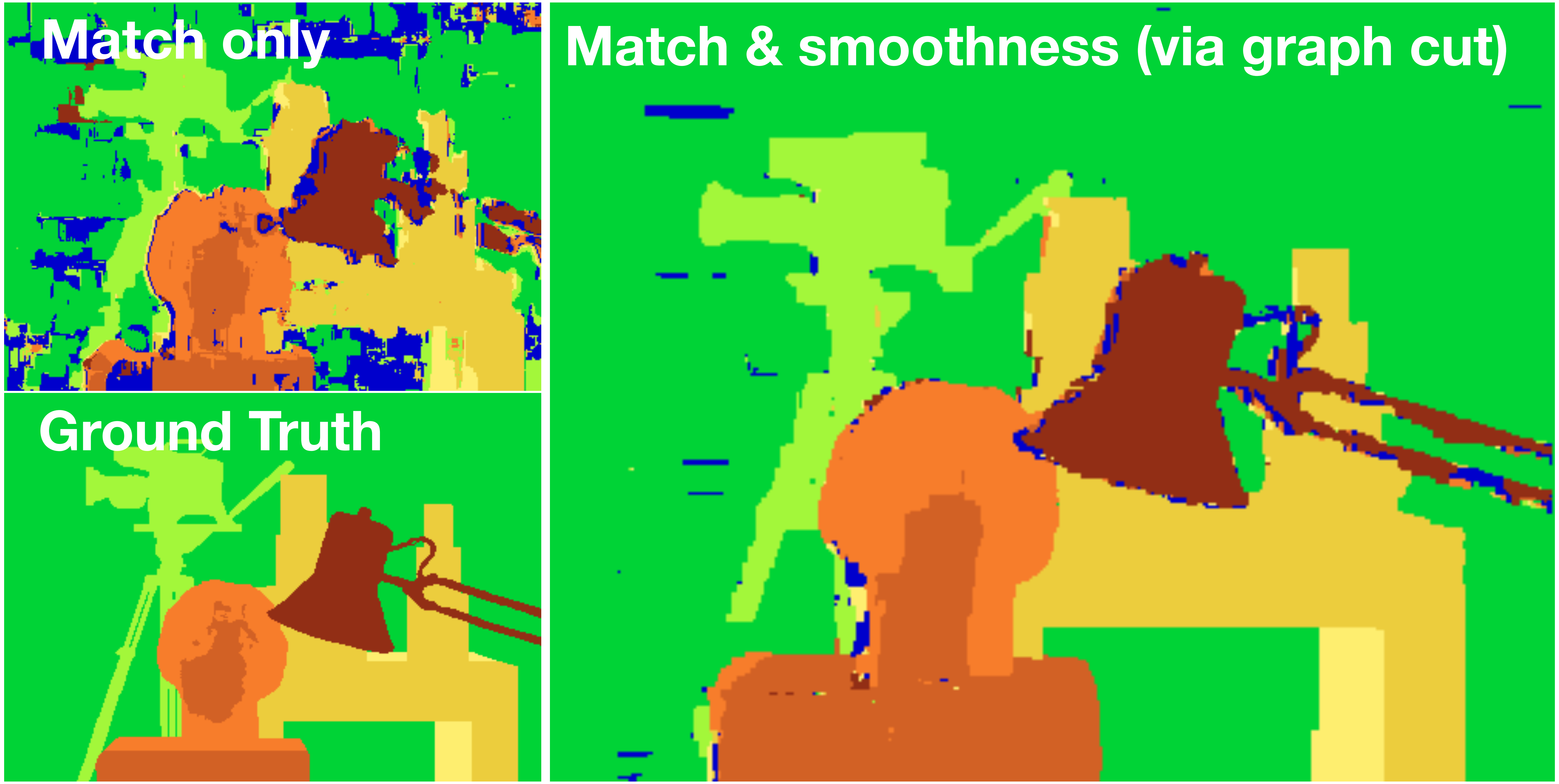
Stereo Matching as **Energy Minimization**: Solution

$$E(d) = E_d(d) + \lambda E_s(d)$$

Can minimize this independently per scanline
using **dynamic programming** (DP)

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Stereo Matching as **Energy Minimization**

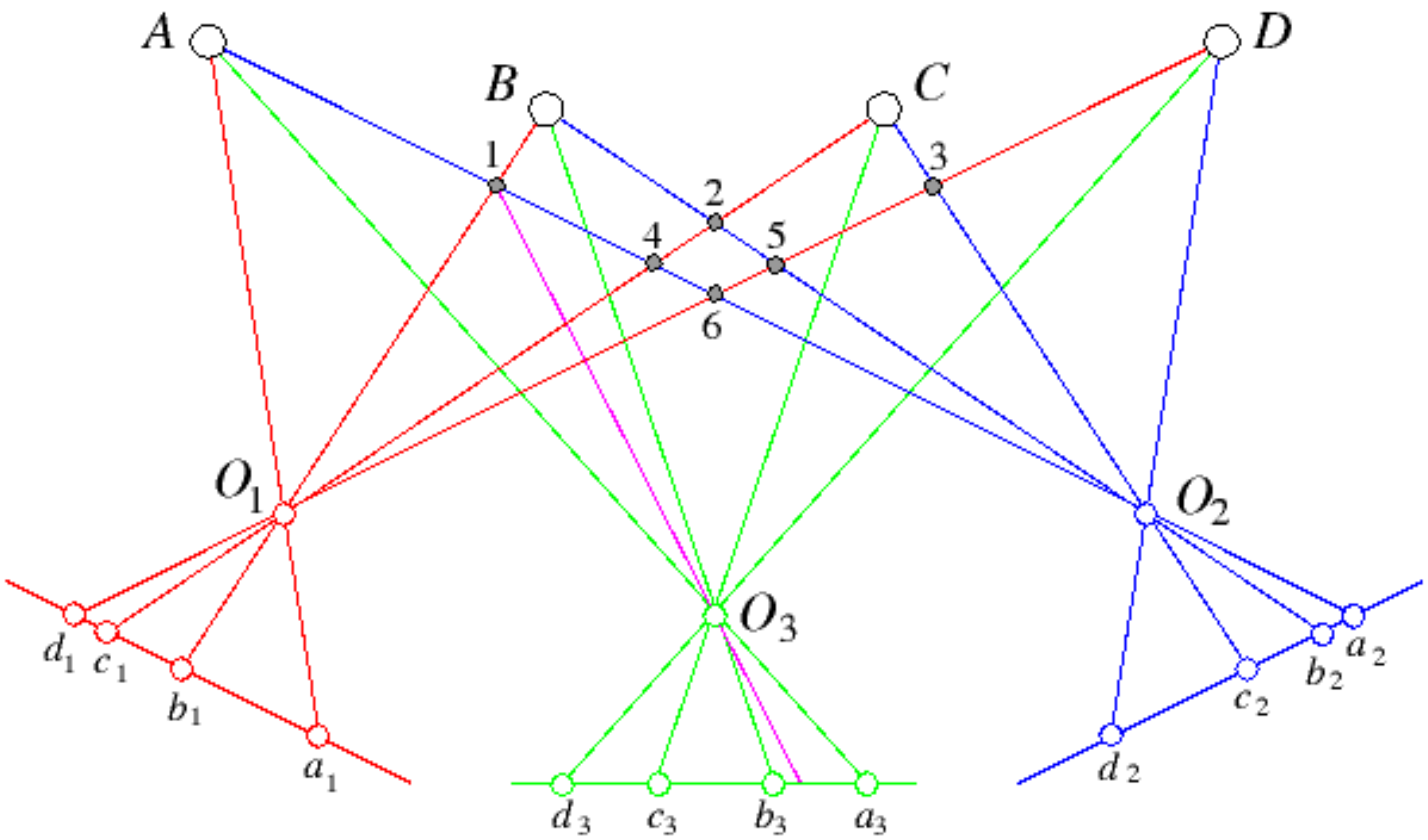


Y. Boykov, O. Veksler, and R. Zabih, Fast Approximate Energy Minimization via Graph Cuts, PAMI 2001

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Idea: Use More Cameras

Adding a third camera reduces ambiguity in stereo matching



Forsyth & Ponce (2nd ed.) Figure 7.17

Point Grey Research **Digiclops**

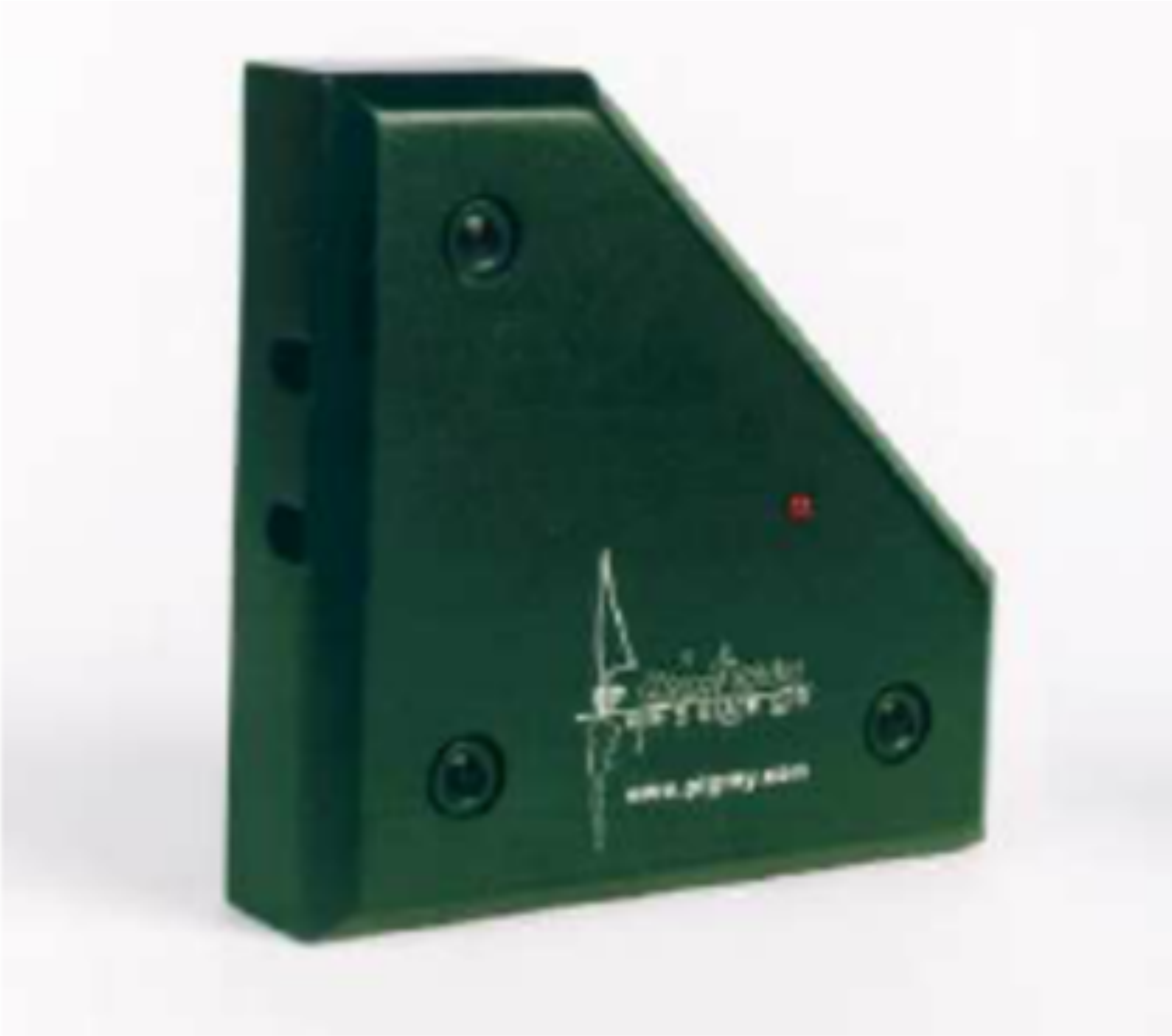
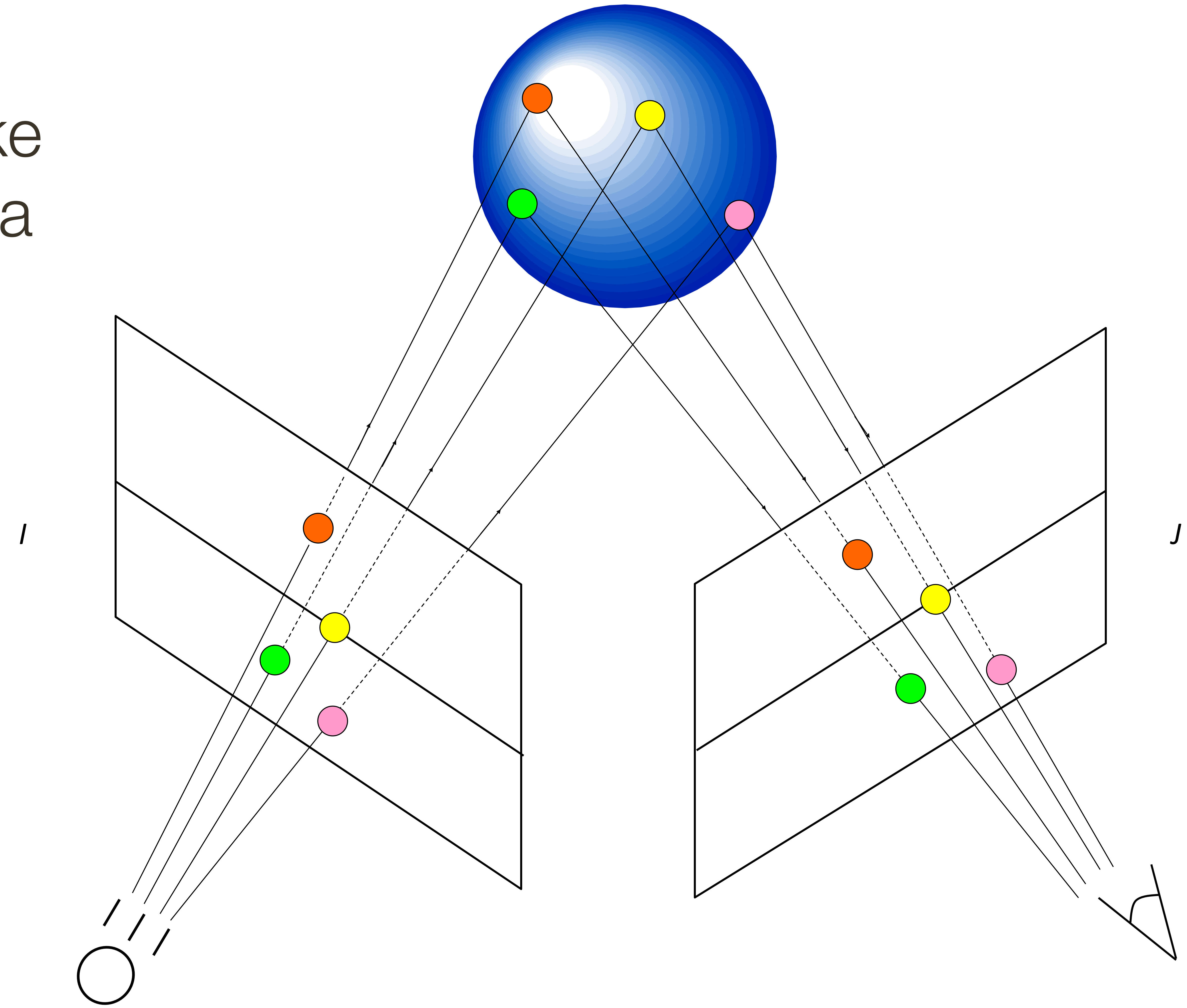


Image credit: Point Grey Research

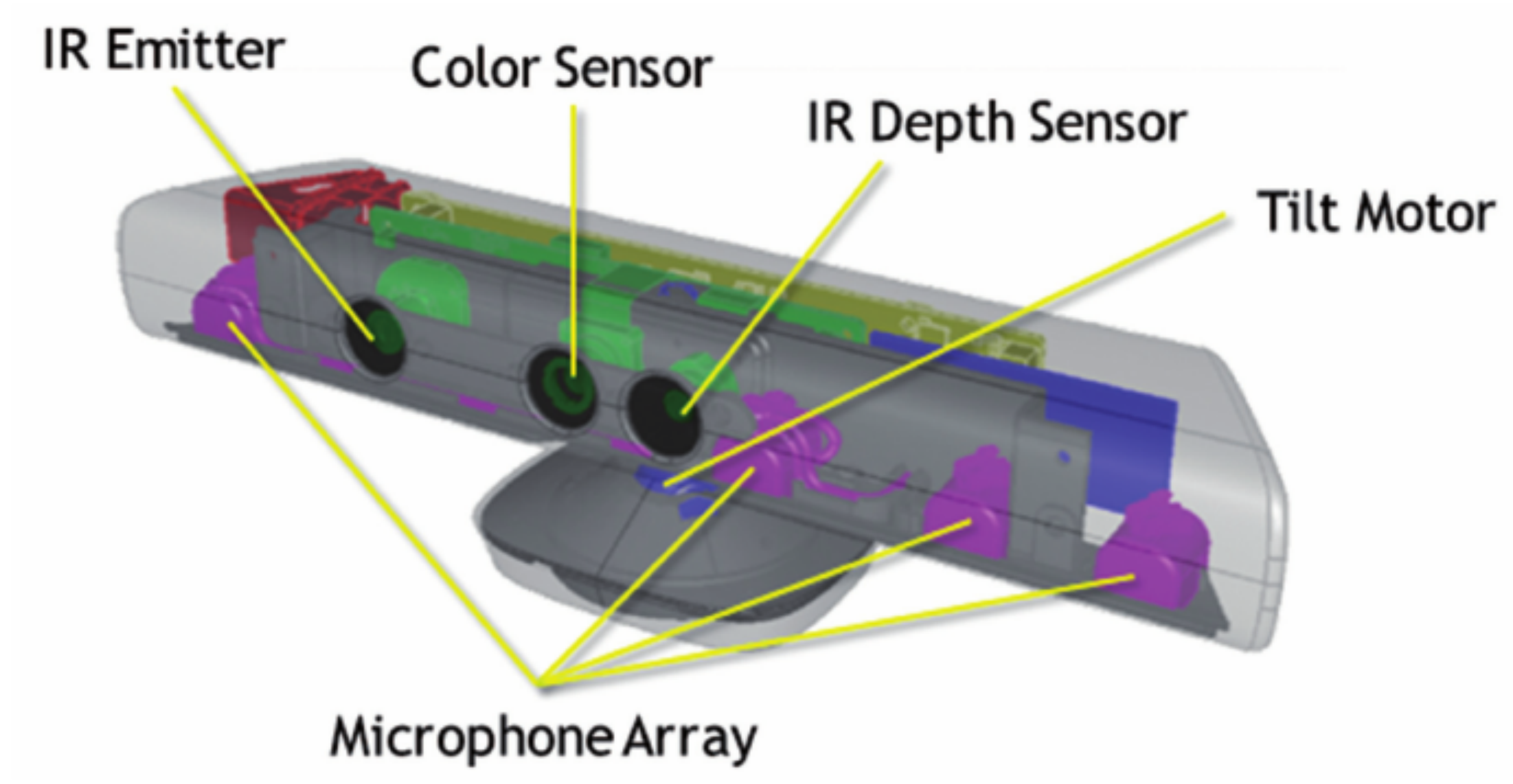
Structured Light Imaging: Structured Light and One Camera

Projector acts like
“reverse” camera

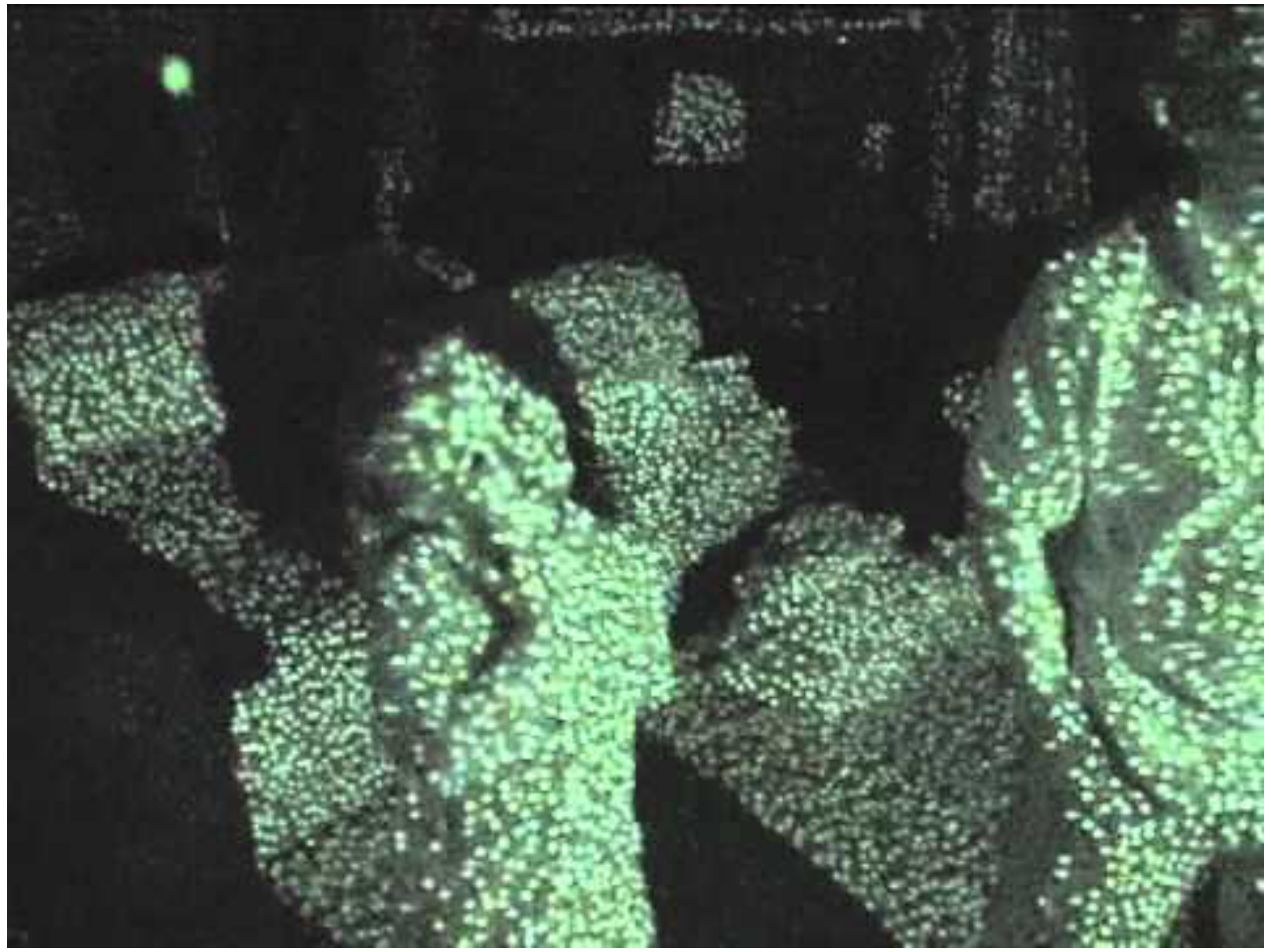


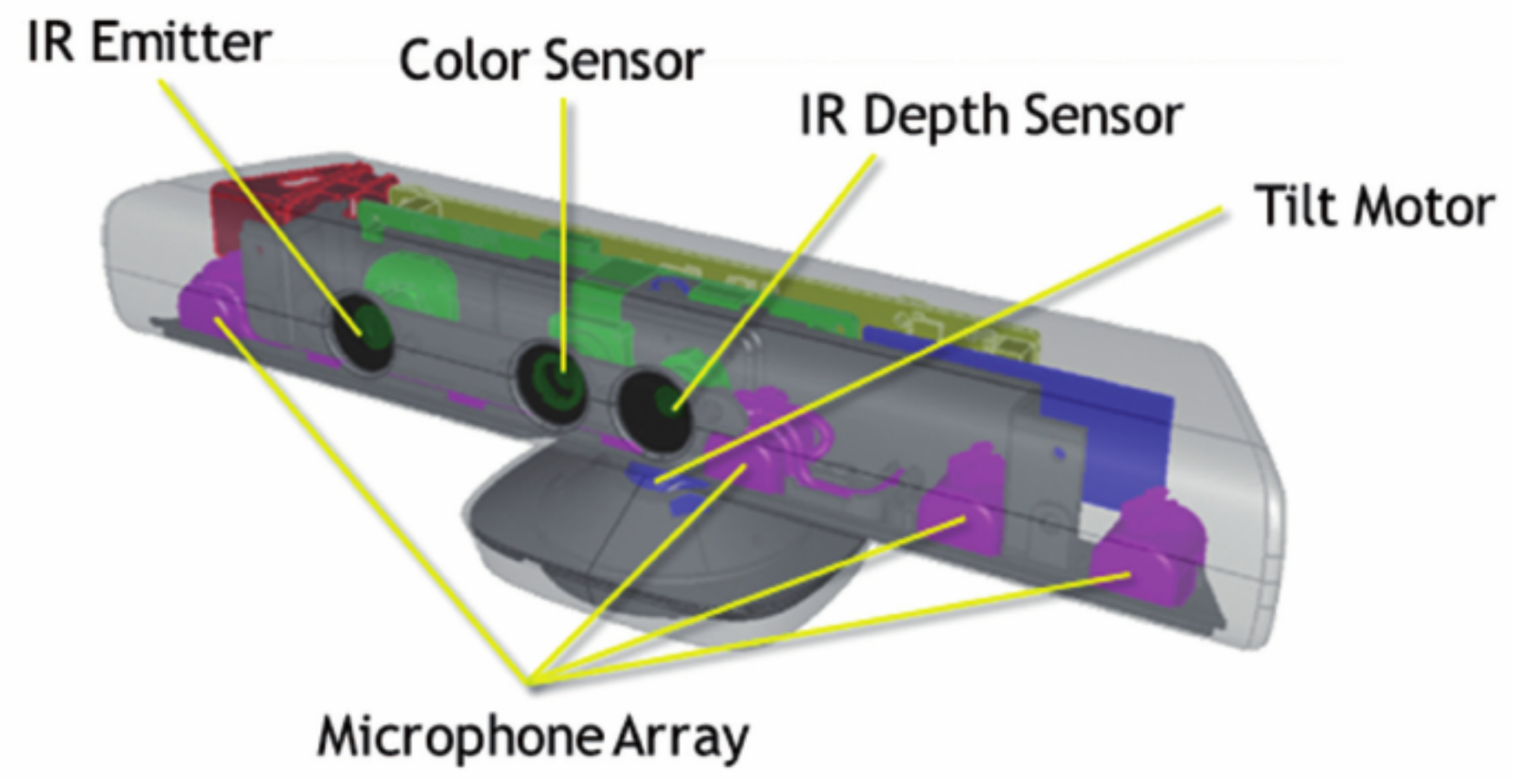
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Microsoft **Kinect**



Microsoft **Kinect**





Summary

Stereo is formulated as a **correspondence** problem

— determine match between location of a scene point in one image and its location in another

If we assume calibrated cameras and image **rectification**, **epipolar lines** are horizontal scan lines

What do we match?

— Individual pixels?

— Patches?

— Edges?