Menu for Today (**March 14, 2019**)

Topics:

— Stereo Vision (cont)

— More Than 2 Cameras

— Structured Light

— Optical Flow

Redings:

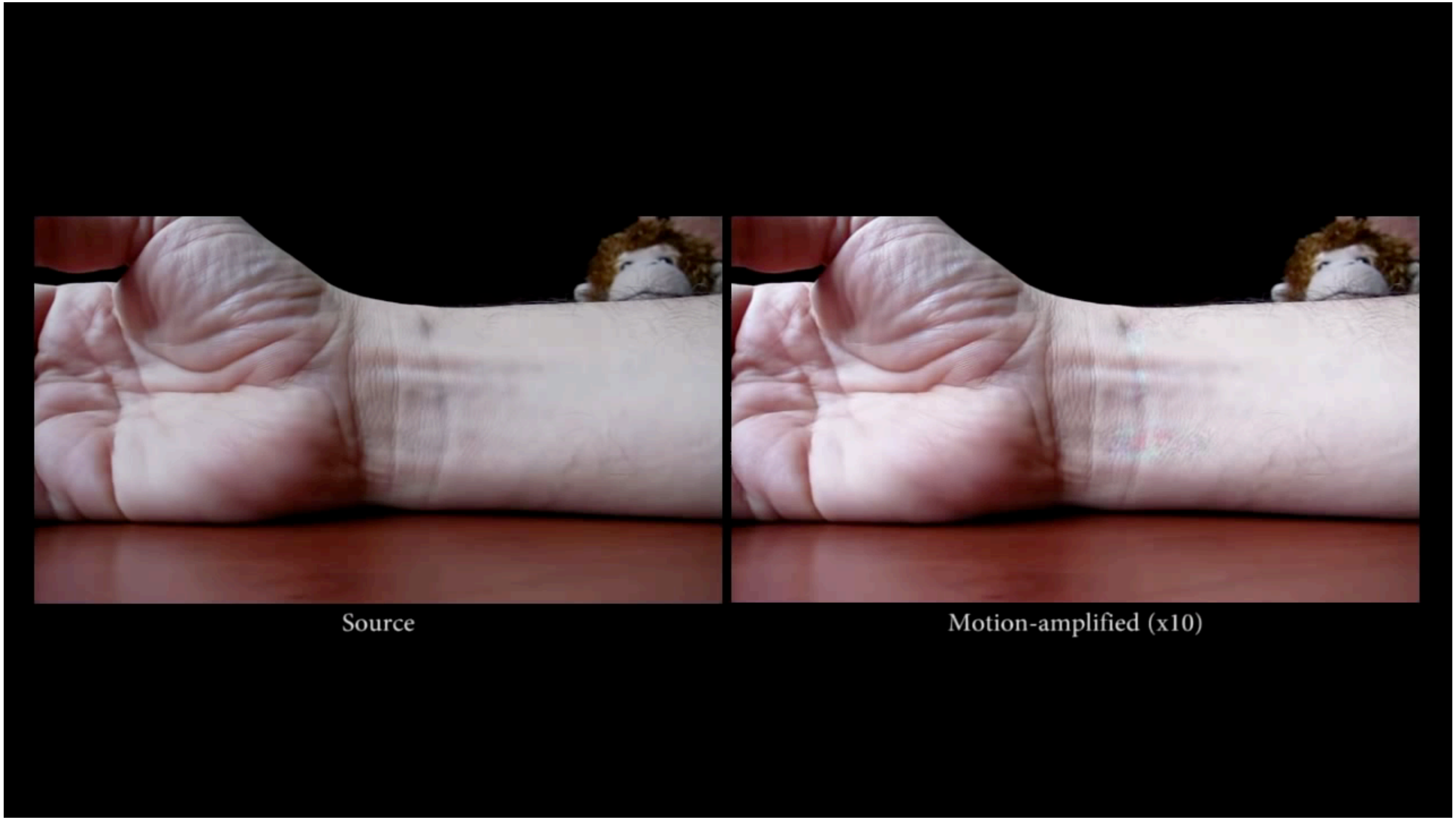
— **Today's** Lecture: Forsyth & Ponce (2nd ed.) 10.6, 6.2.2, 9.3.1, 9.3.3, 9.4.2

— **Next** Lecture: None

Reminders:

— **Assignment 4**: Local Invariant Features and RANSAC due **March 19th**

Today's "**fun**" Example: Eulerian Video Magnification



Video From: Wu at al., Siggraph 2012

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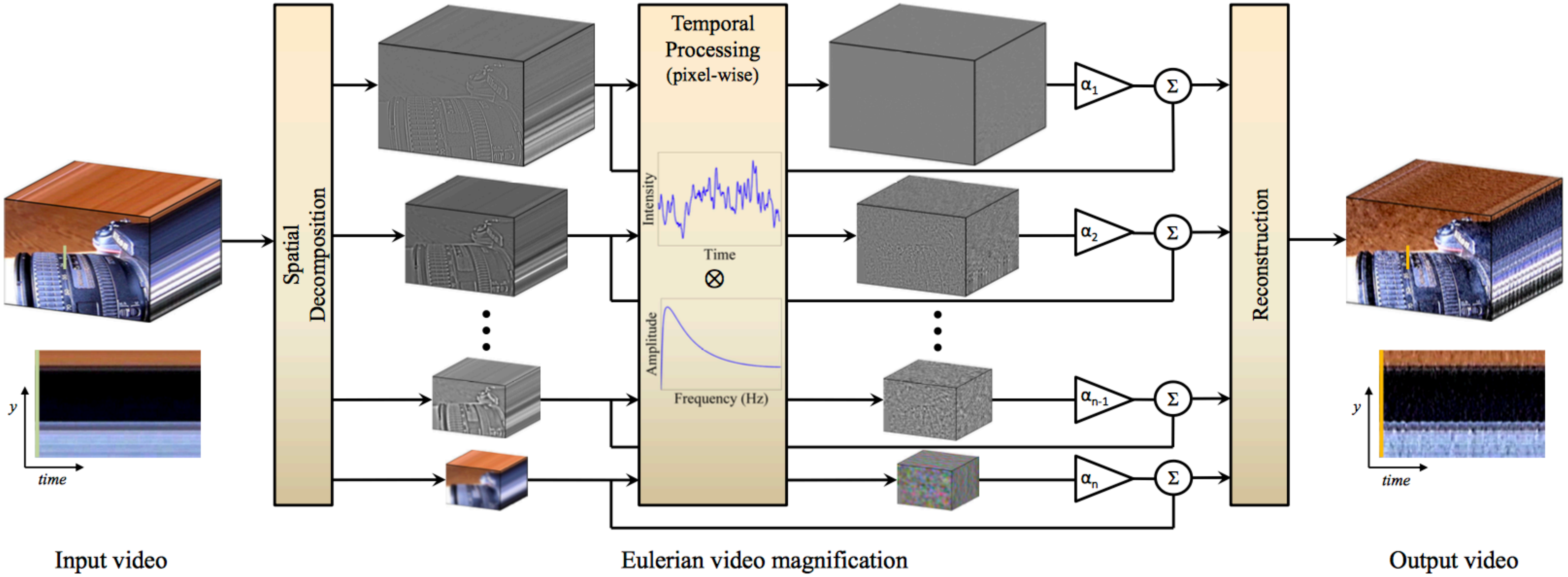
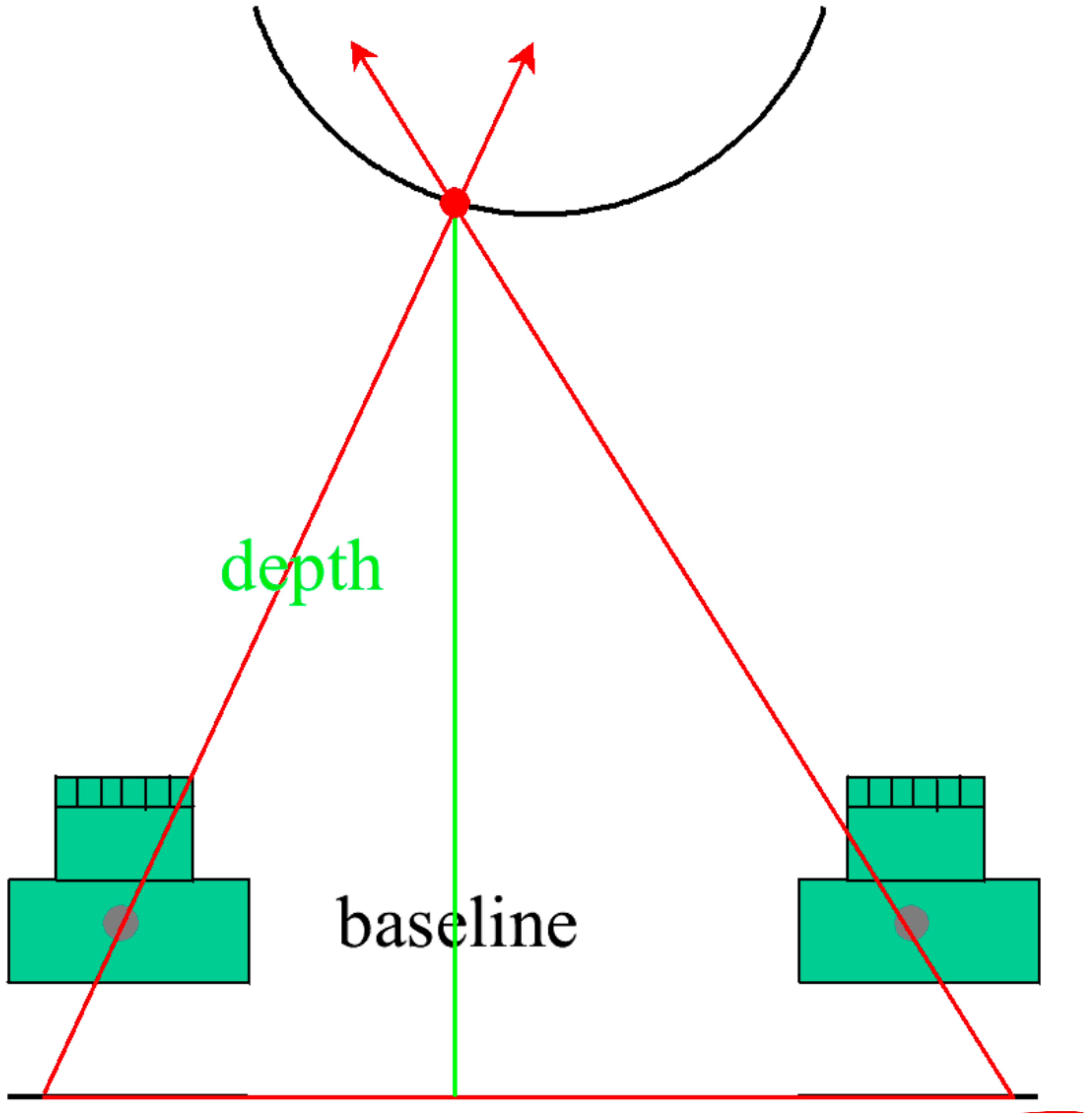


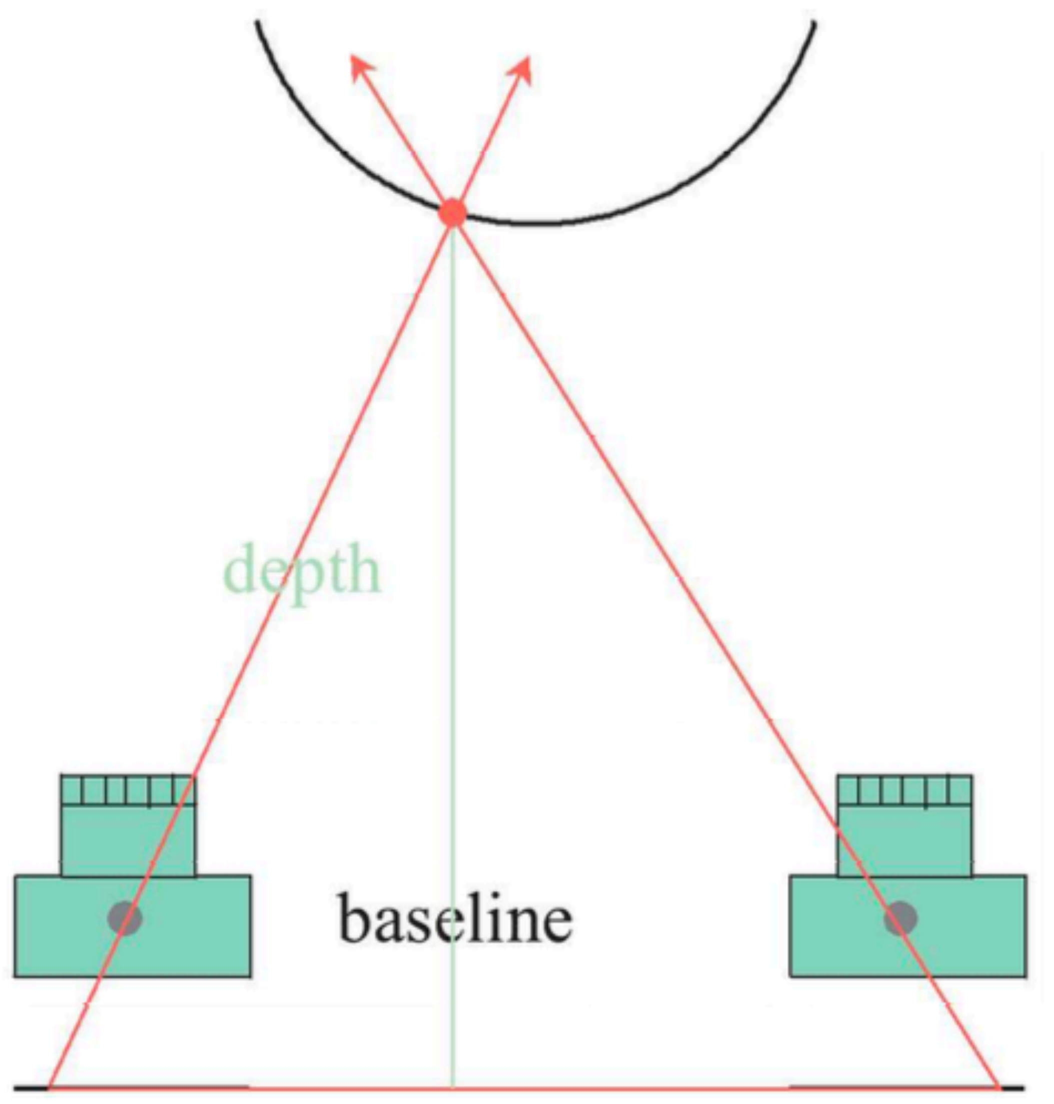
Figure From: Wu at al., Siggraph 2012

Lecture 18: Re-cap

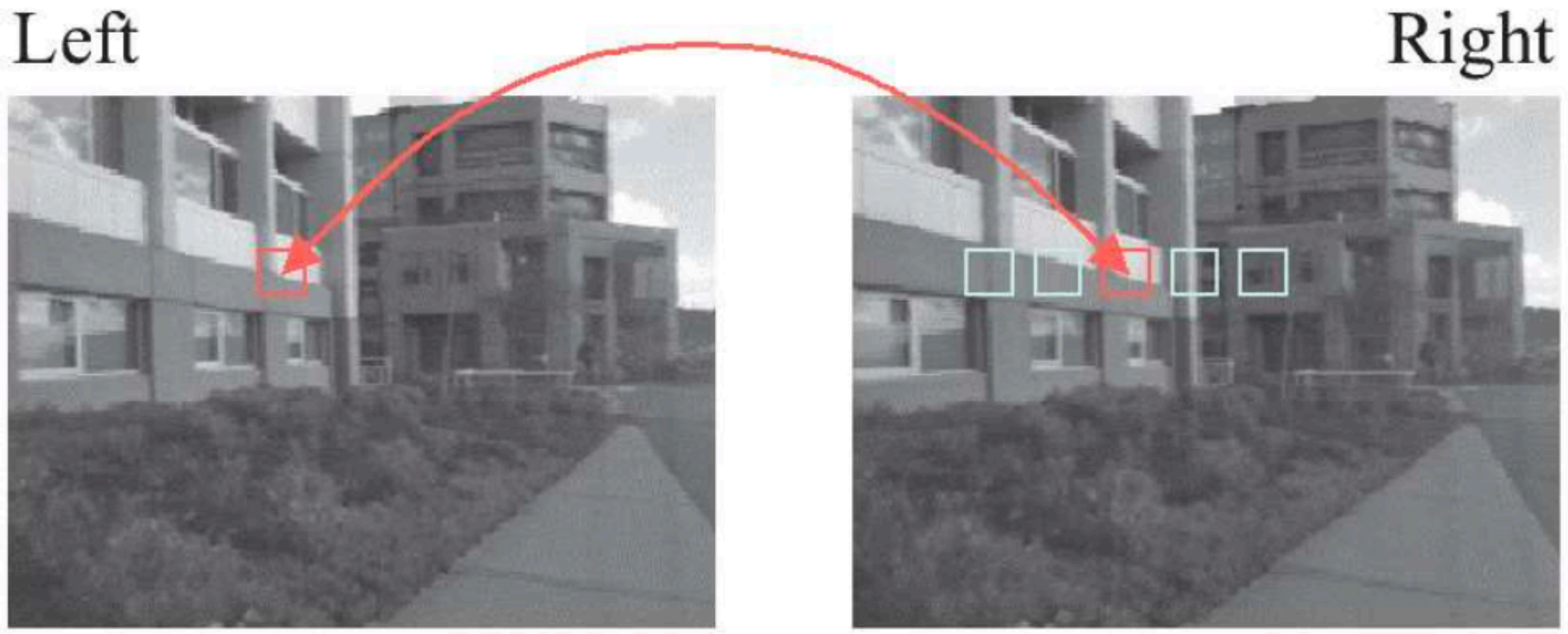


Slide credit: Trevor Darrell

Lecture 18: Re-cap



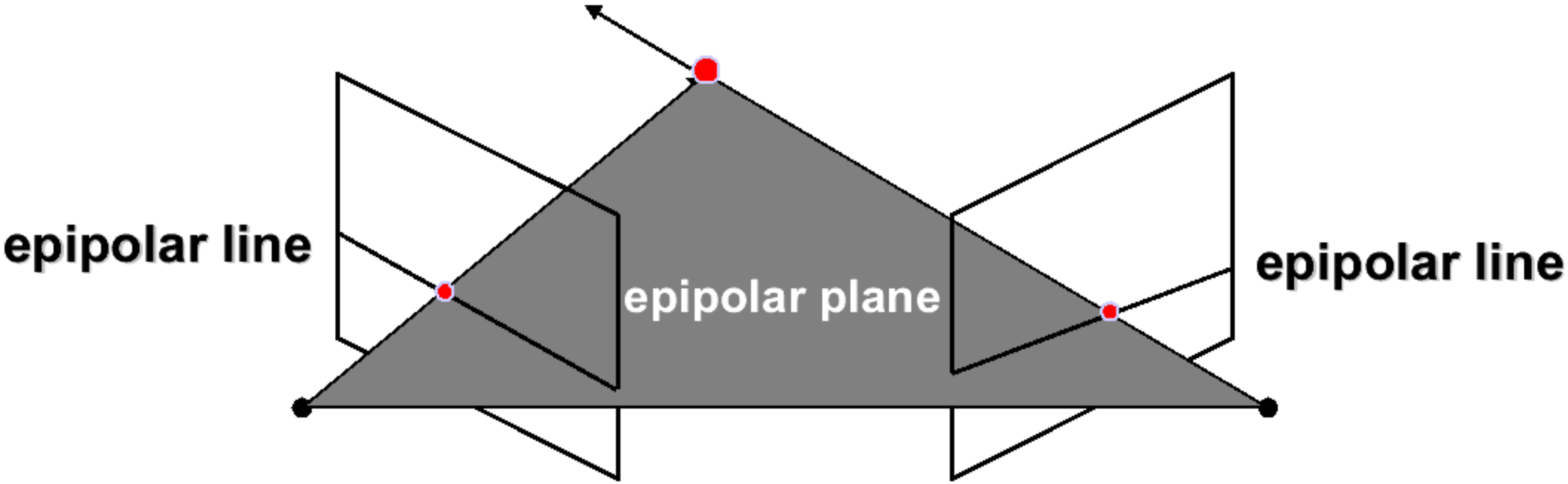
Triangulate on two images of the same point



Match correlation windows across scan lines

Image credit: Point Grey Research
Slide credit: Trevor Darrell

Lecture 18: Re-cap



Matching points lie along corresponding epipolar lines

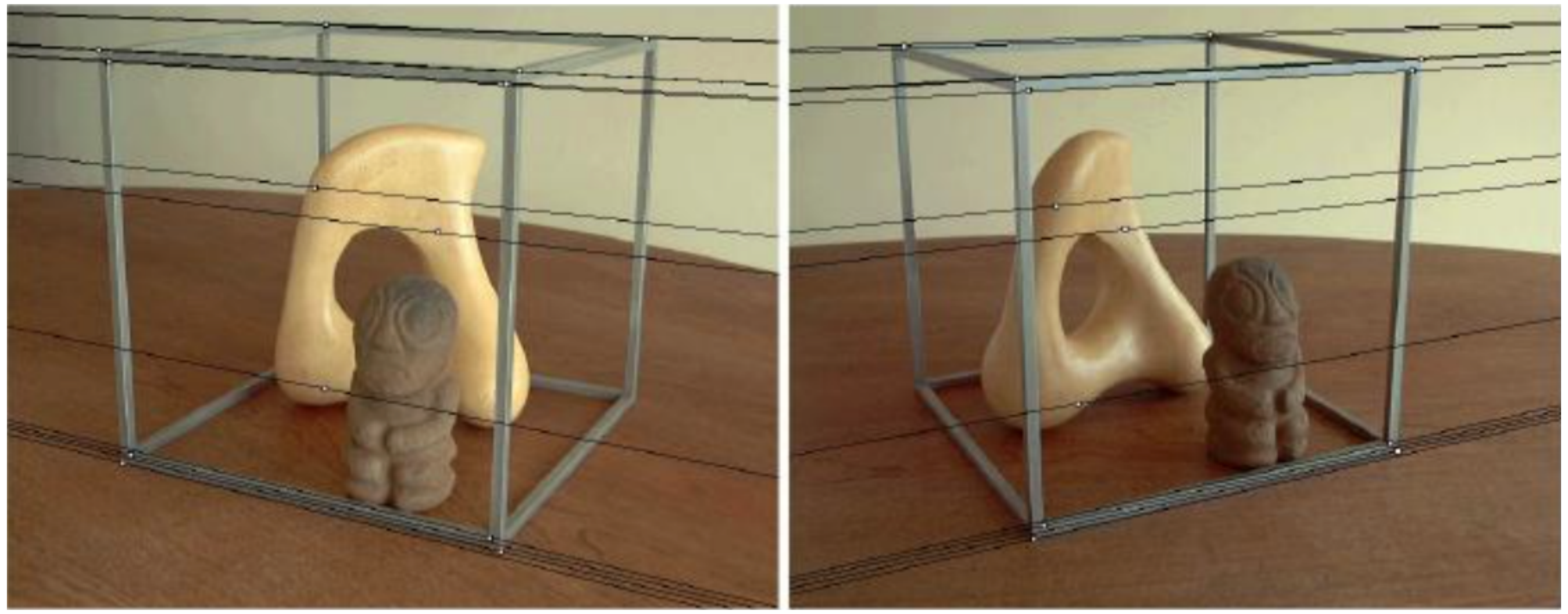
Reduces correspondence problem to 1D search along conjugate epipolar lines

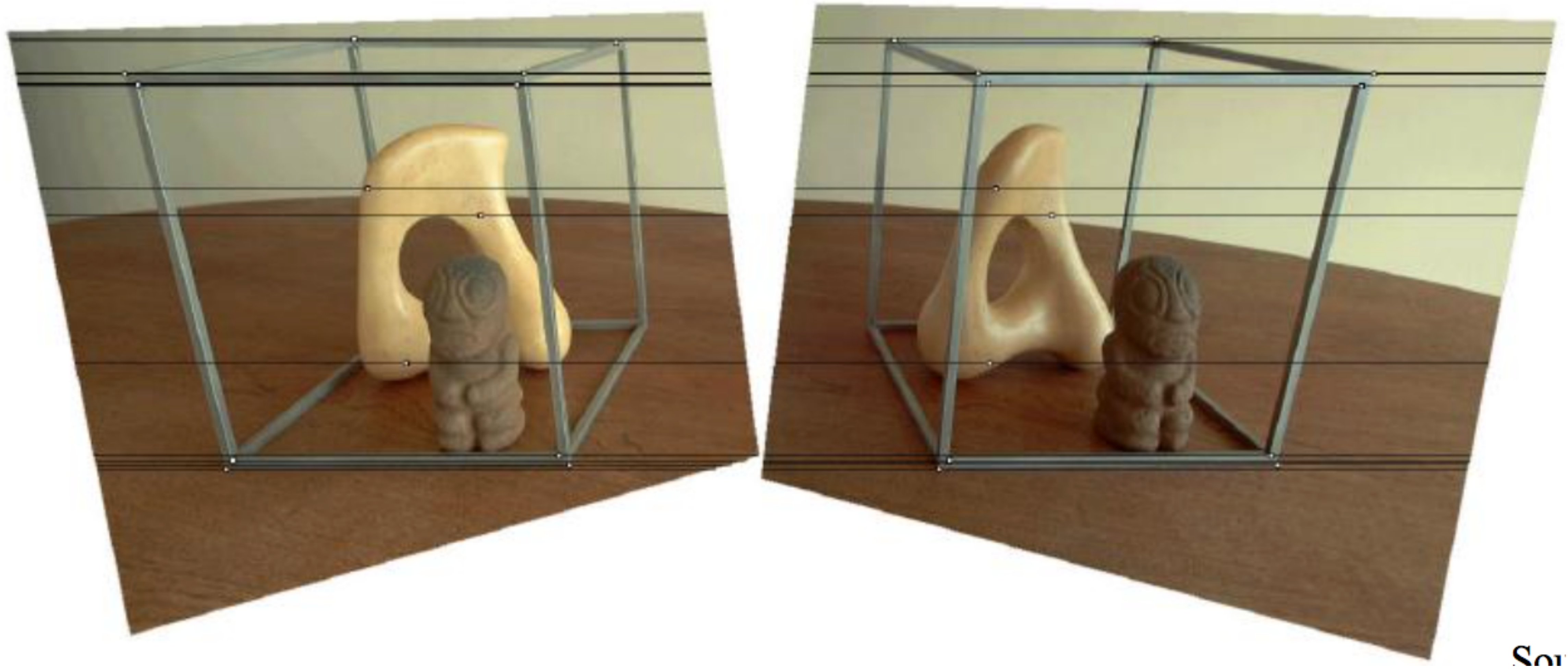
Greatly reduces cost and ambiguity of matching

Slide credit: Steve Seitz

Lecture 18: Re-cap

Before Rectification



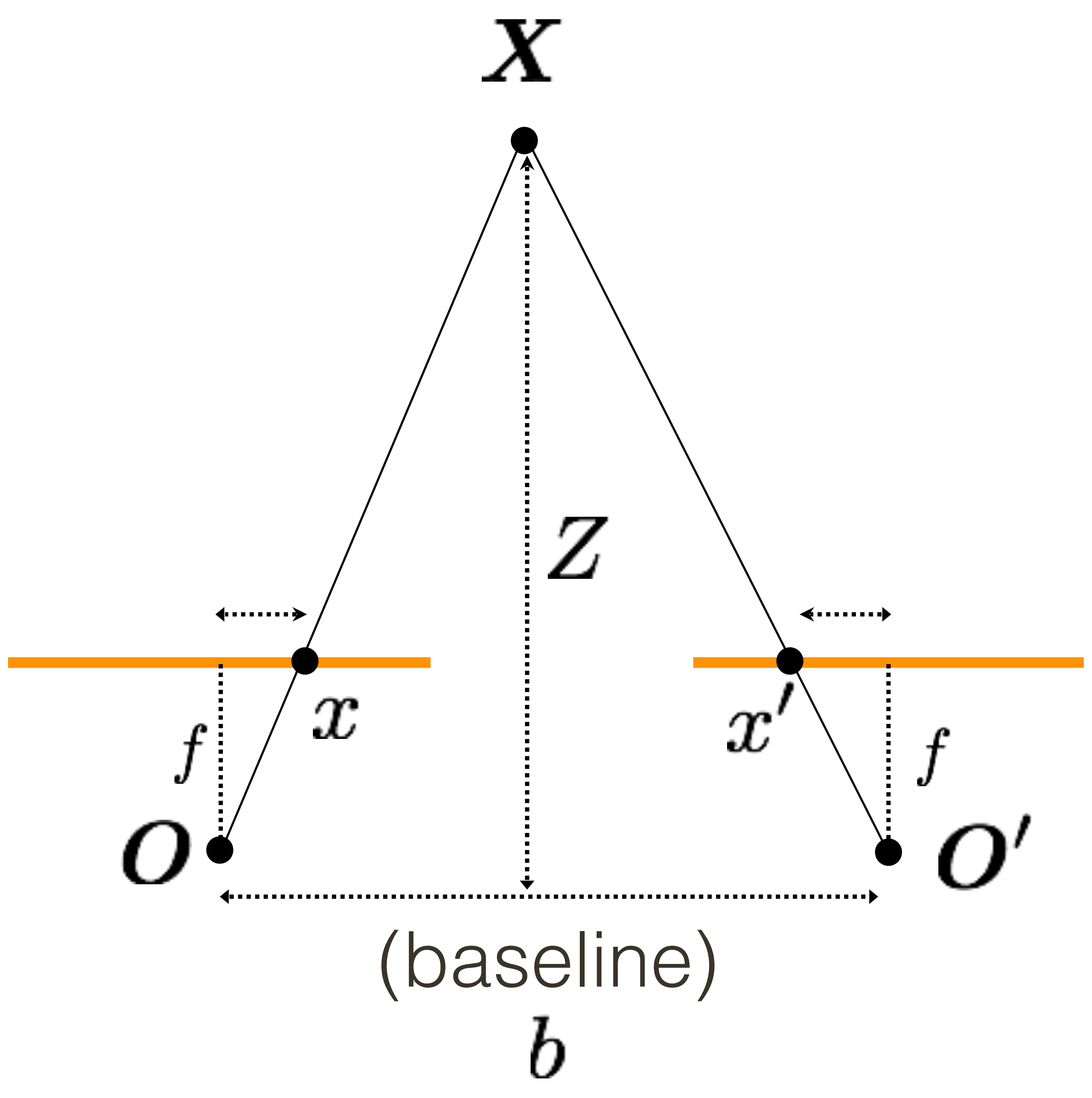


After Rectification

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Lecture 18: Re-cap

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



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

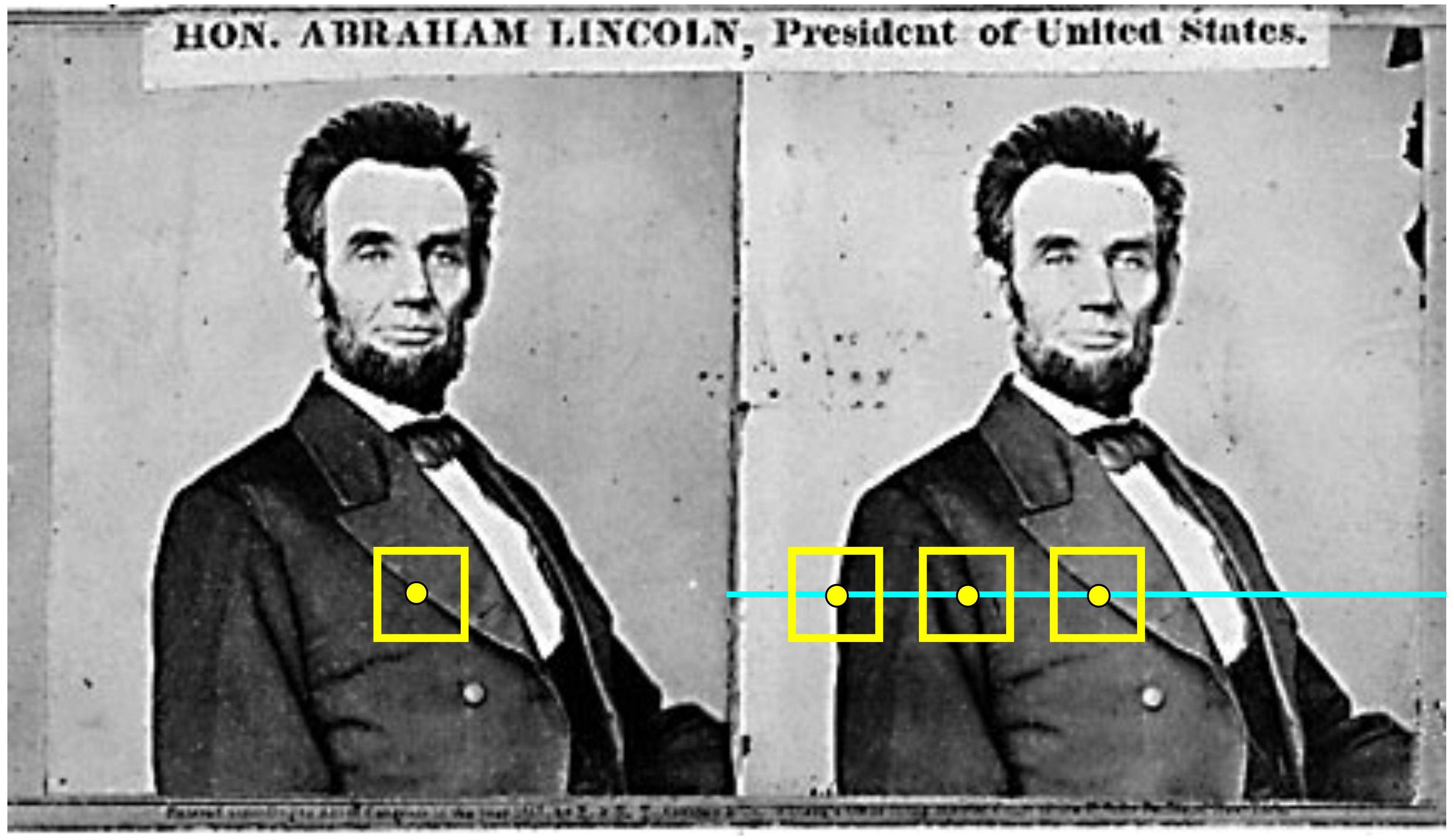
Disparity

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

inversely proportional to depth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

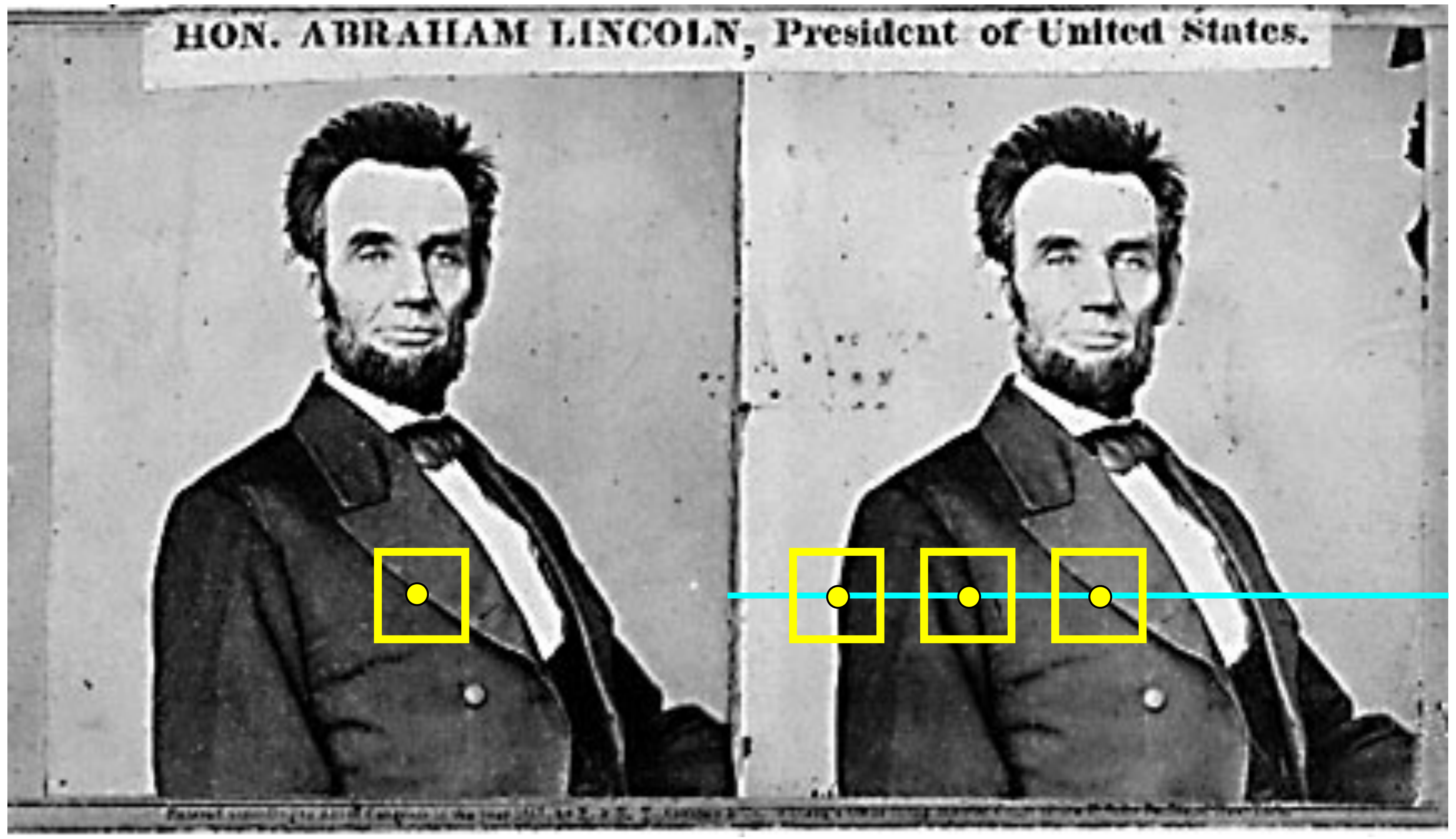
(simple) **Stereo** Algorithm



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



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2. For each pixel
   a. Find epipolar line
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Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Correspondence: What should we match?

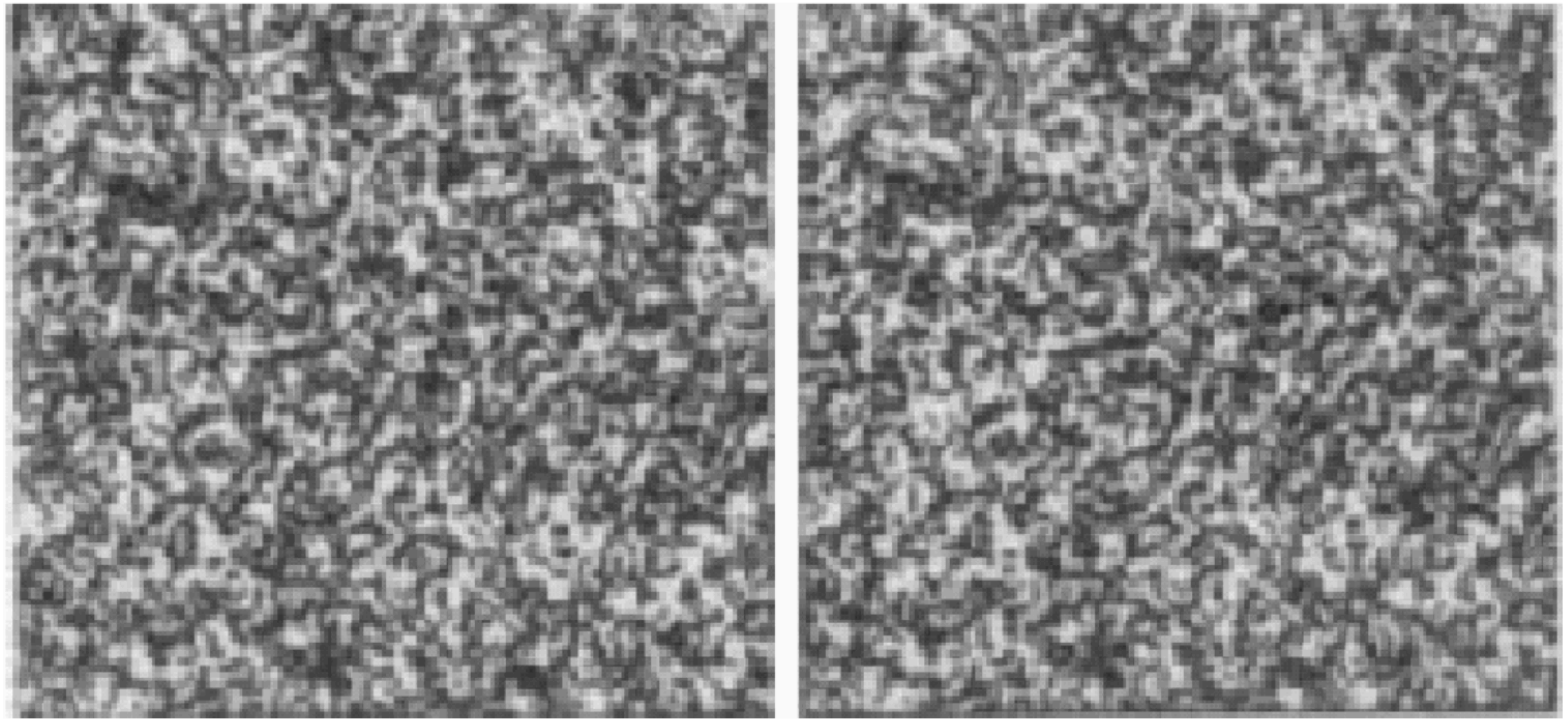
Objects?

Edges?

Pixels?

Collections of pixels?

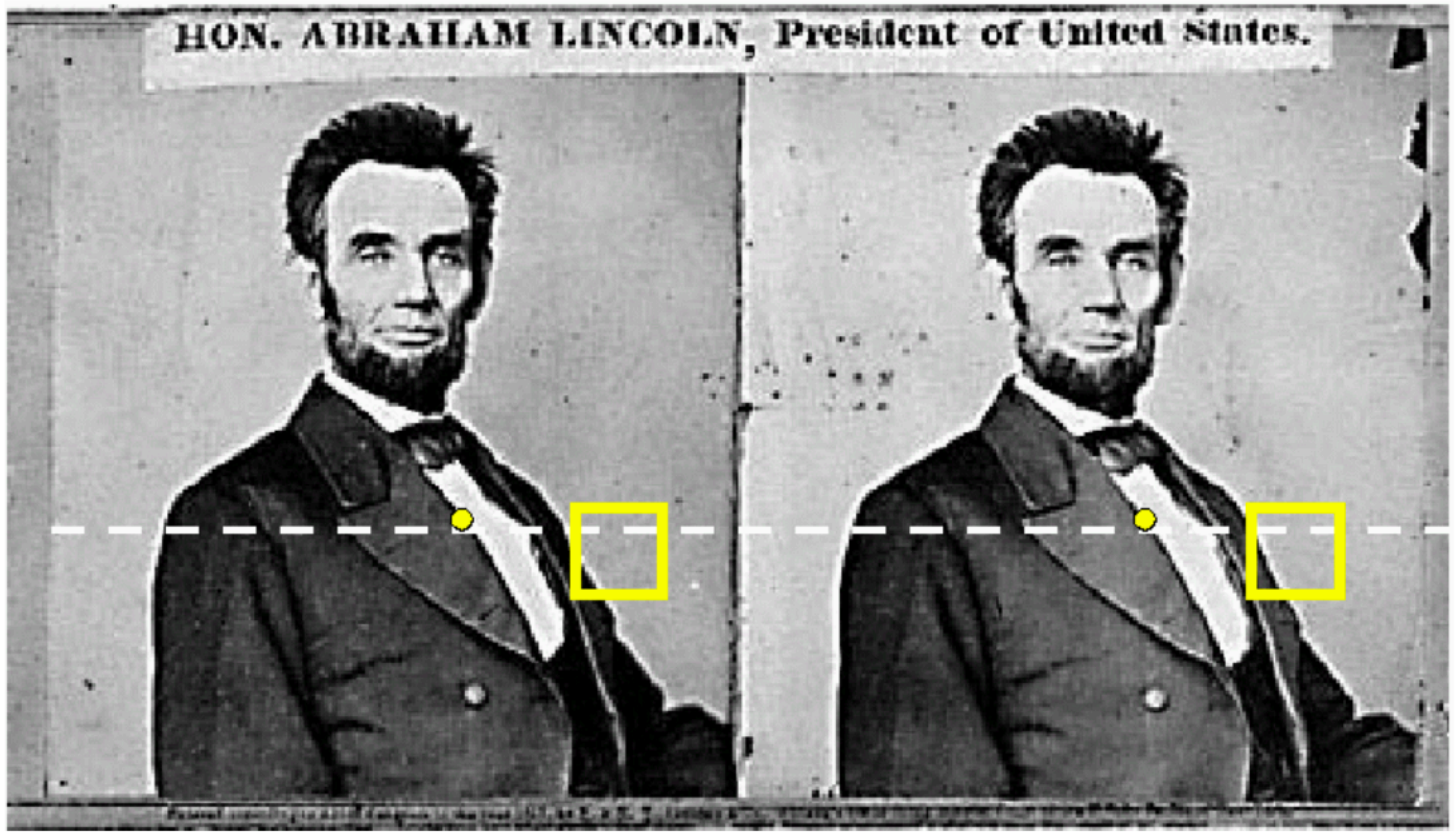
Random Dot Stereograms



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**

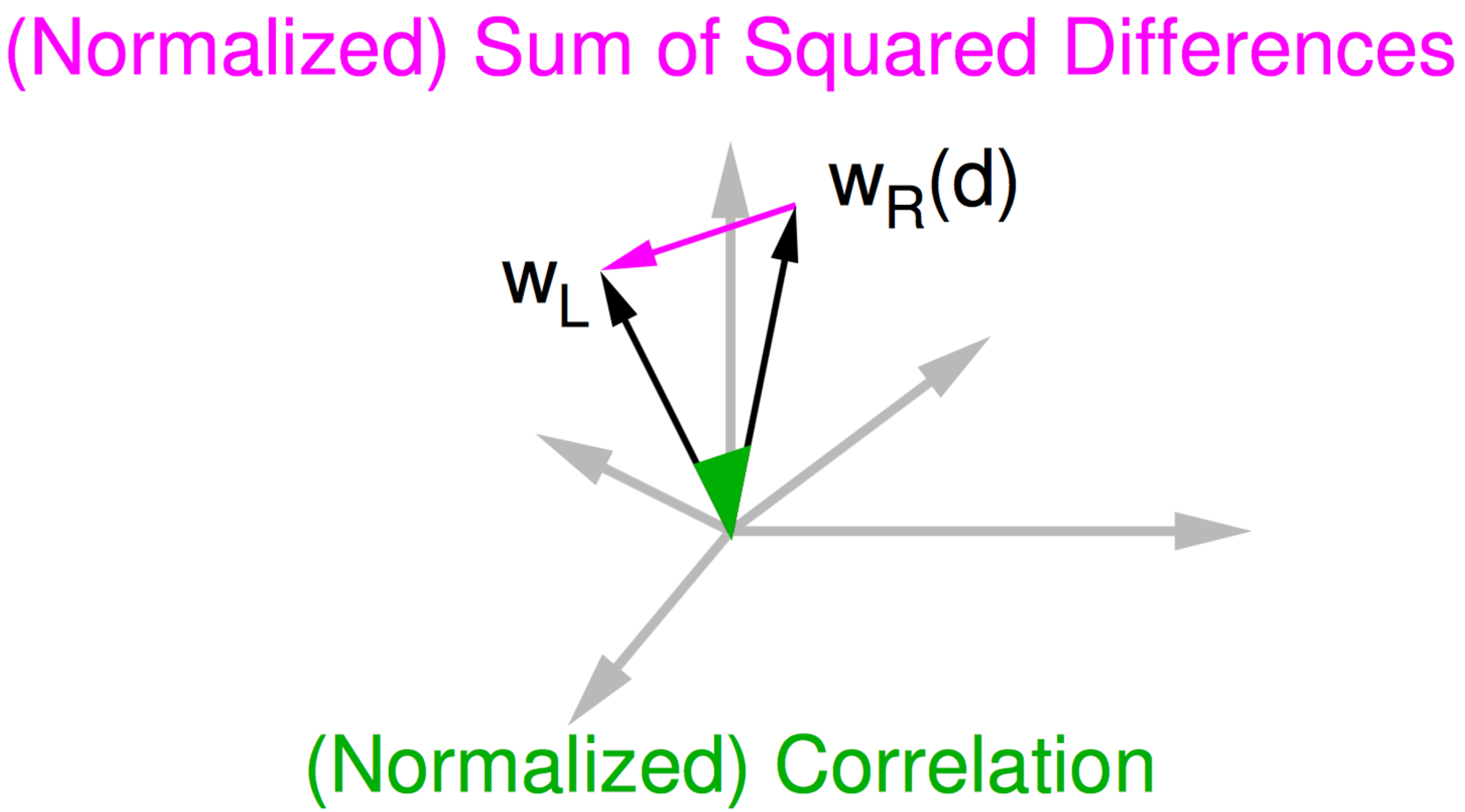


Image **Metrics**

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**

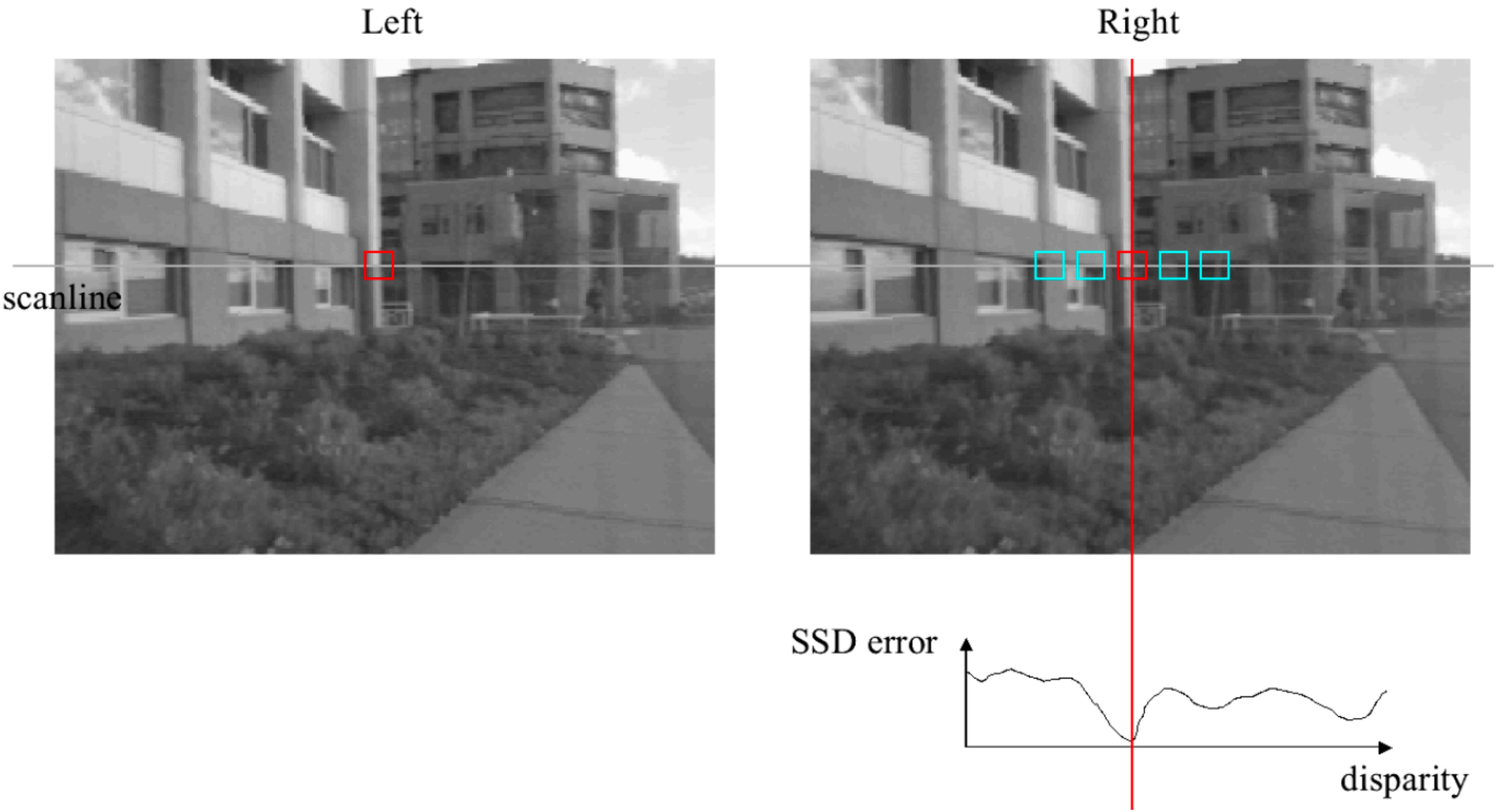
Let d^* be the value of d that minimizes C_{SSD}

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

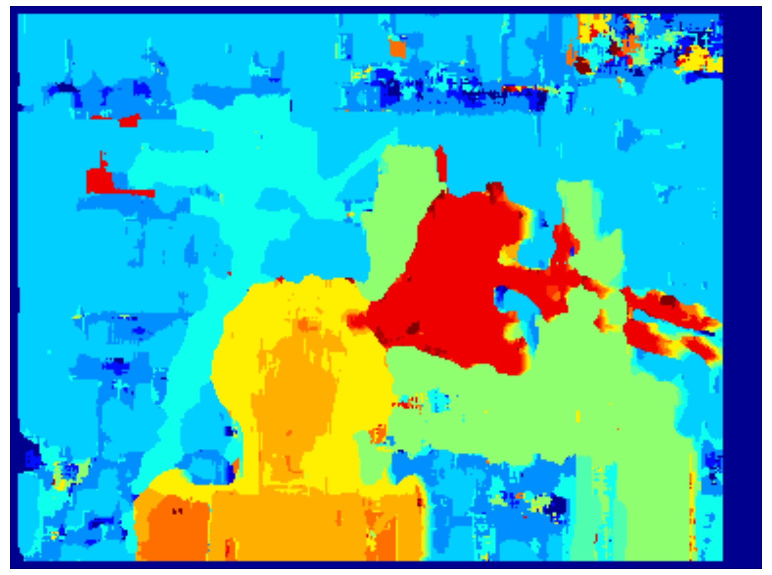
That is,

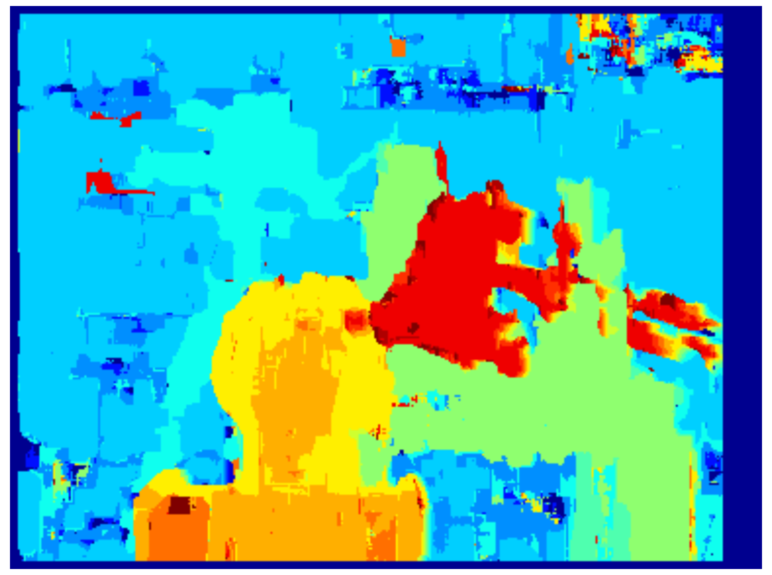
$$d^* = \arg\min_d ||\mathbf{w}_L - \mathbf{w}_R(d)||^2 = \arg\min_d \mathbf{w}_L \cdot \mathbf{w}_R(d)$$

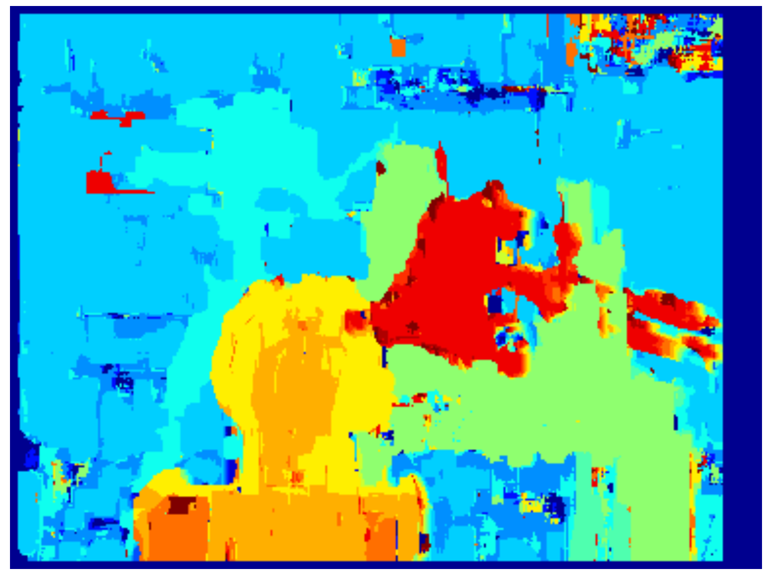
Method: Correlation



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

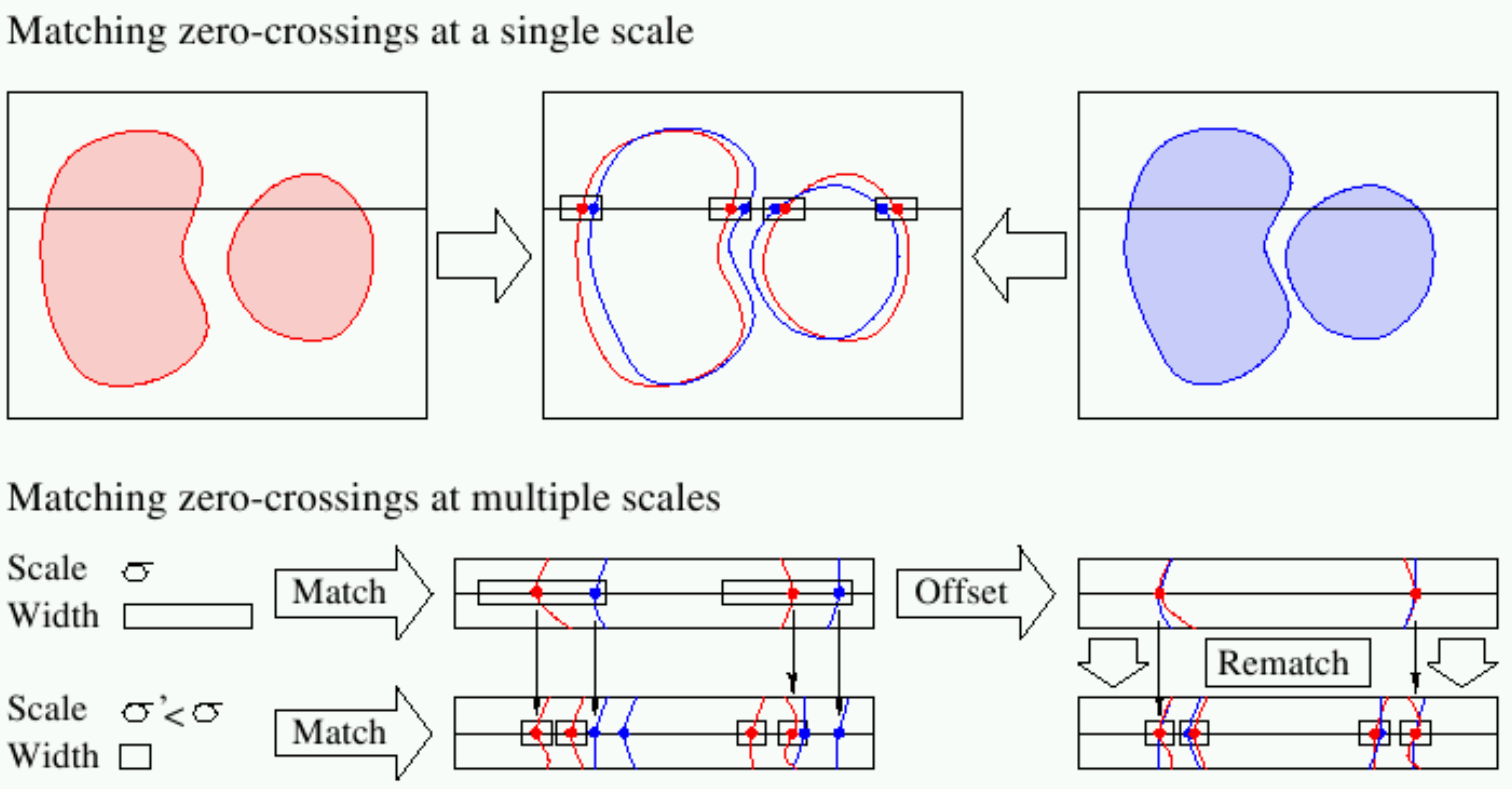

SSD


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)

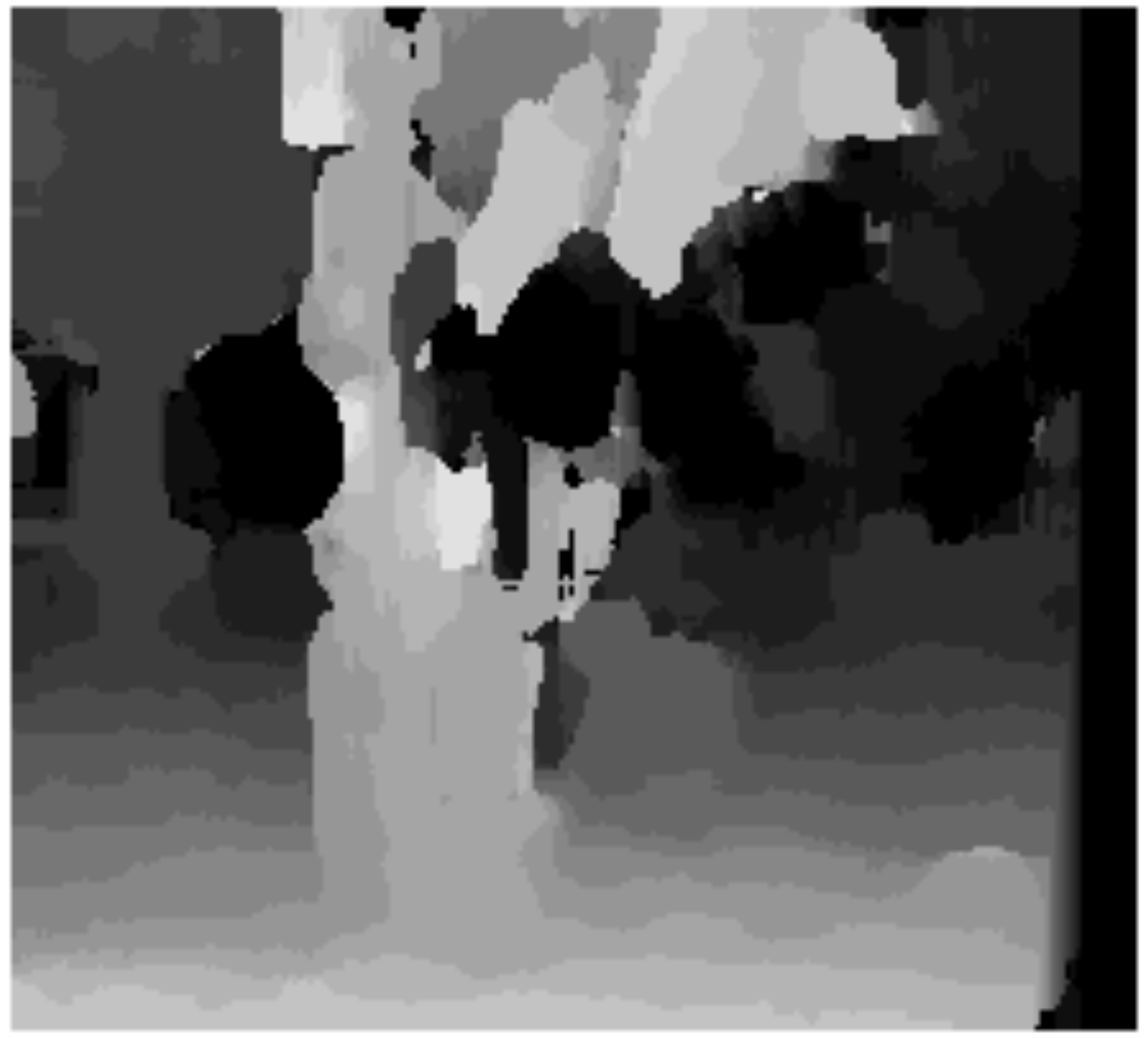
Correlation tends to fail in smooth, featureless regions

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

Effect of **Window Size**

W = 3

Smaller window
+ More detail
- More noise



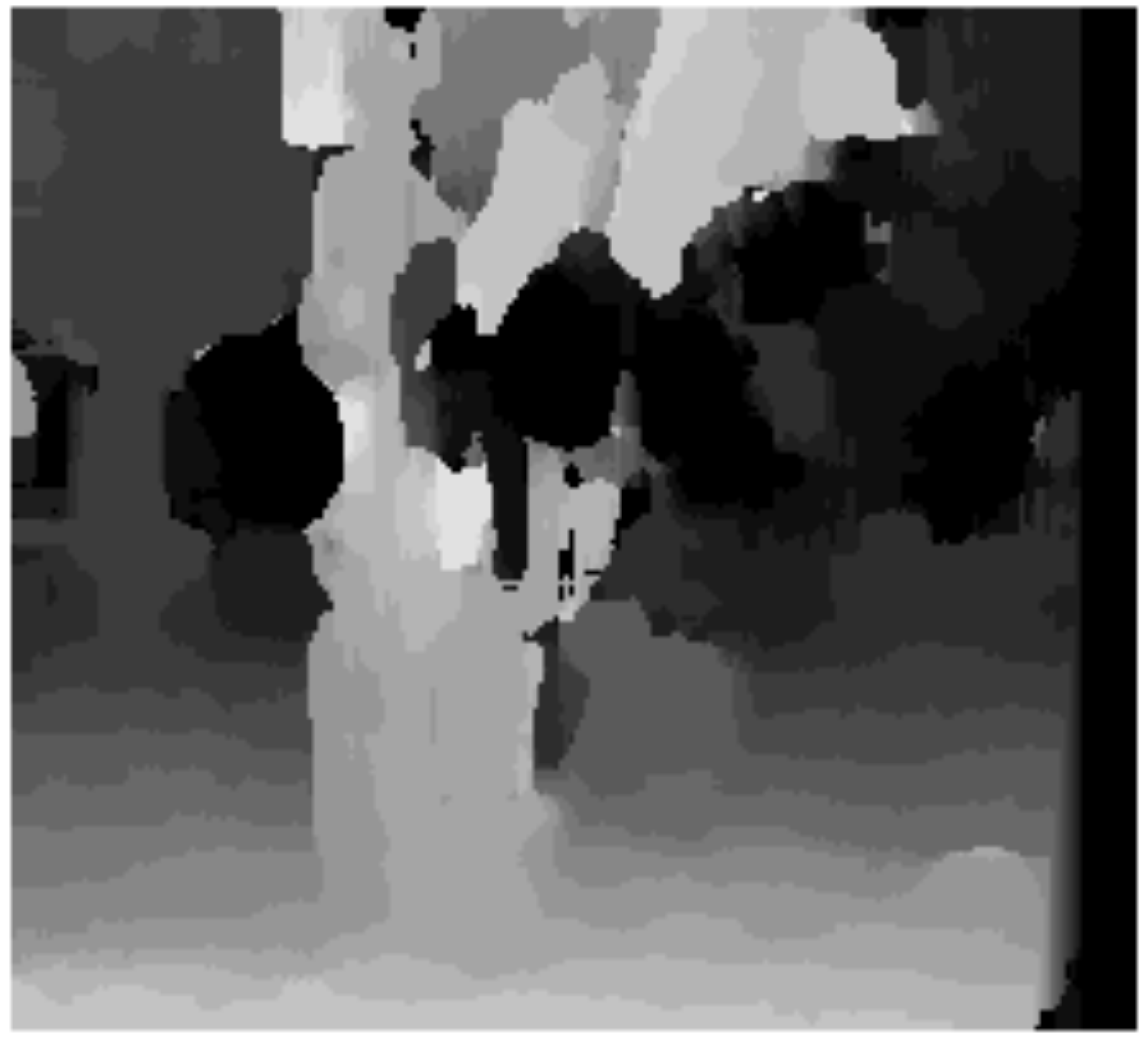
W = 20

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

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Effect of **Window Size**

W = 3

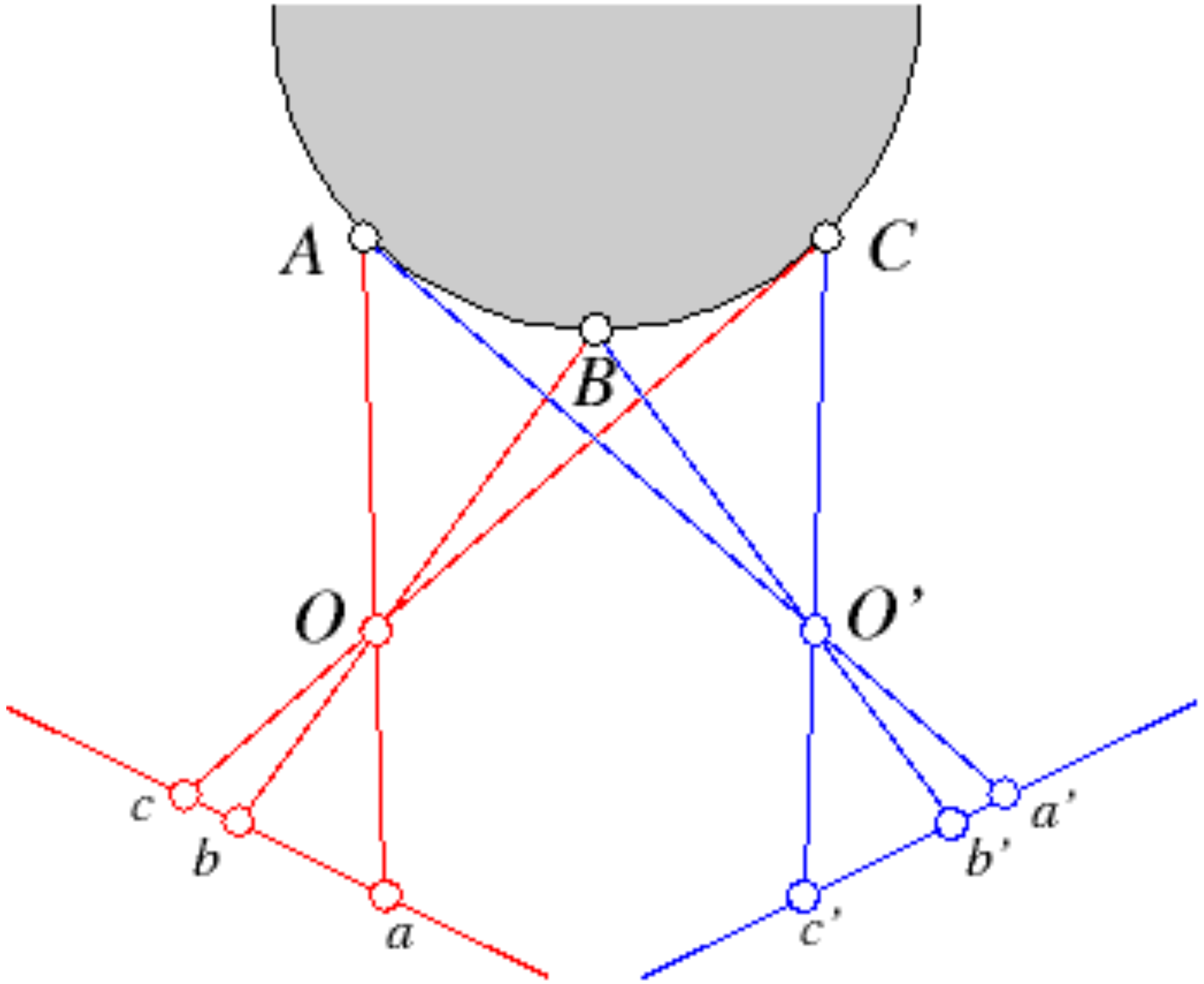


W = 20

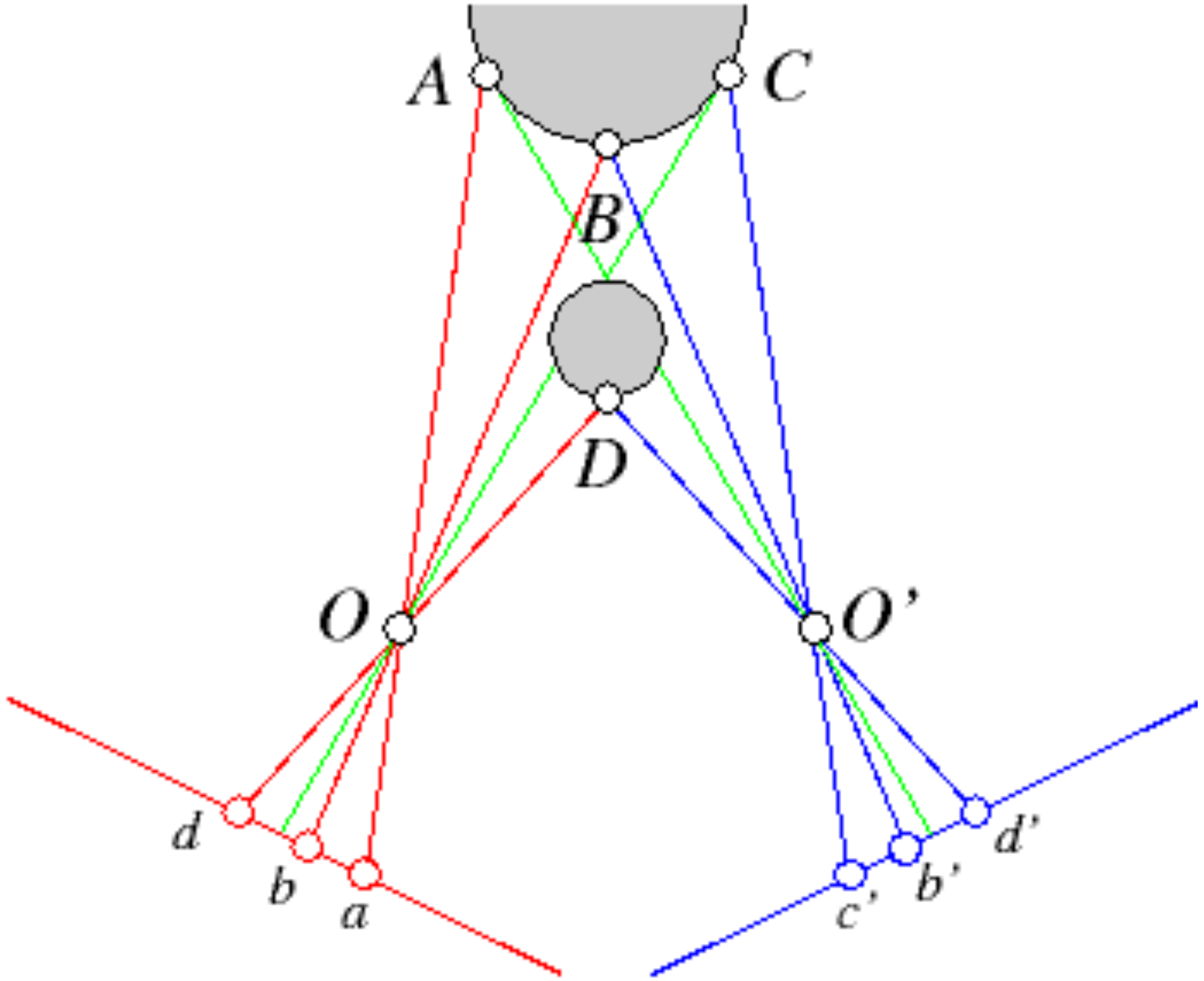
Note: Some approaches use an adaptive window size — try multiple sizes and select best match

Ordering Constraints

Ordering constraint …

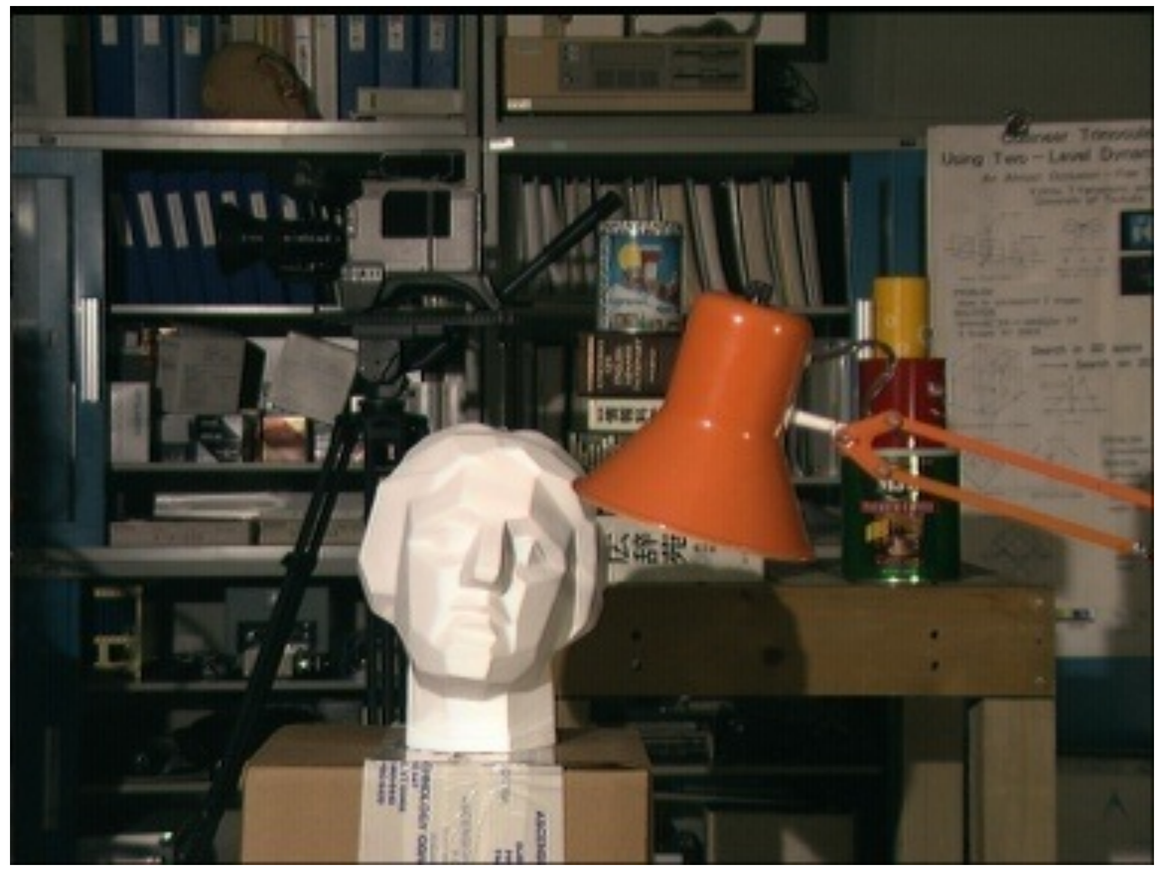


…. and a **failure** case

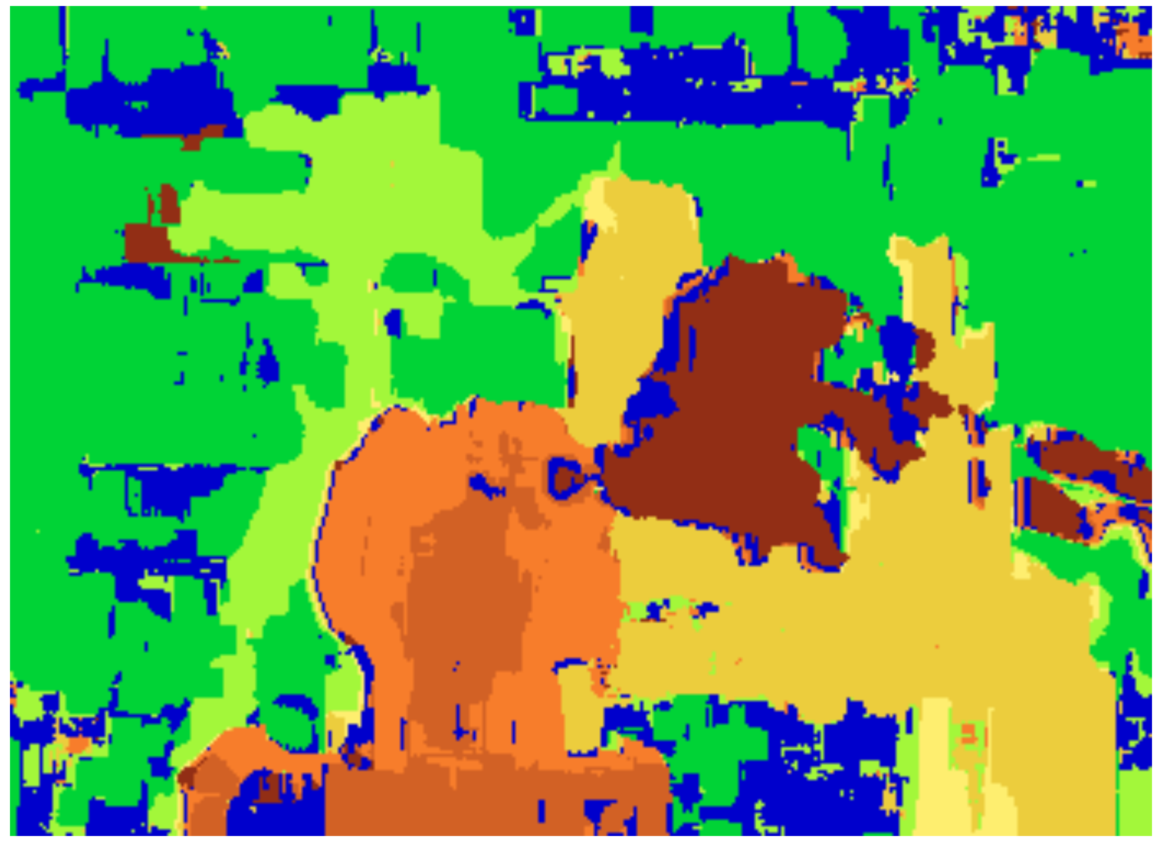


Forsyth & Ponce (2nd ed.) Figure 7.13

Block Matching Techniques: Result



Block matching



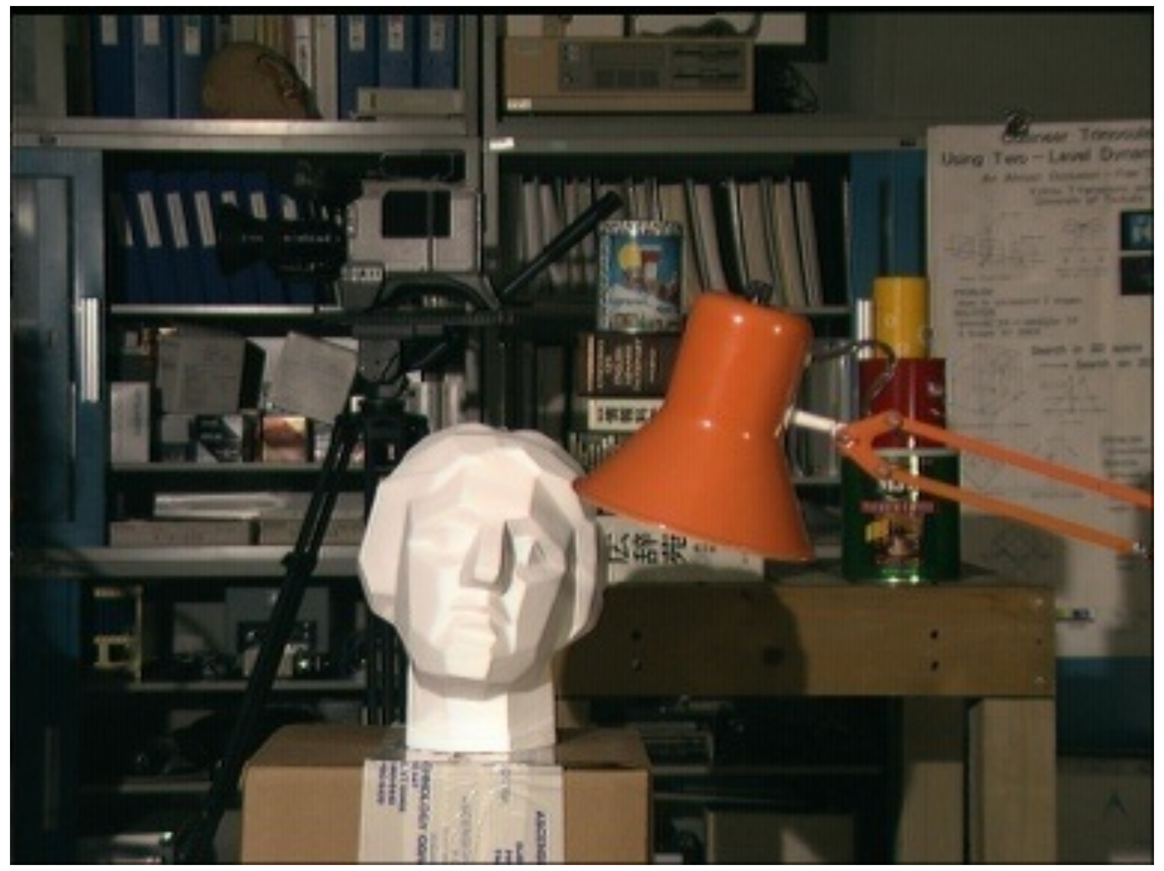
Ground truth

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

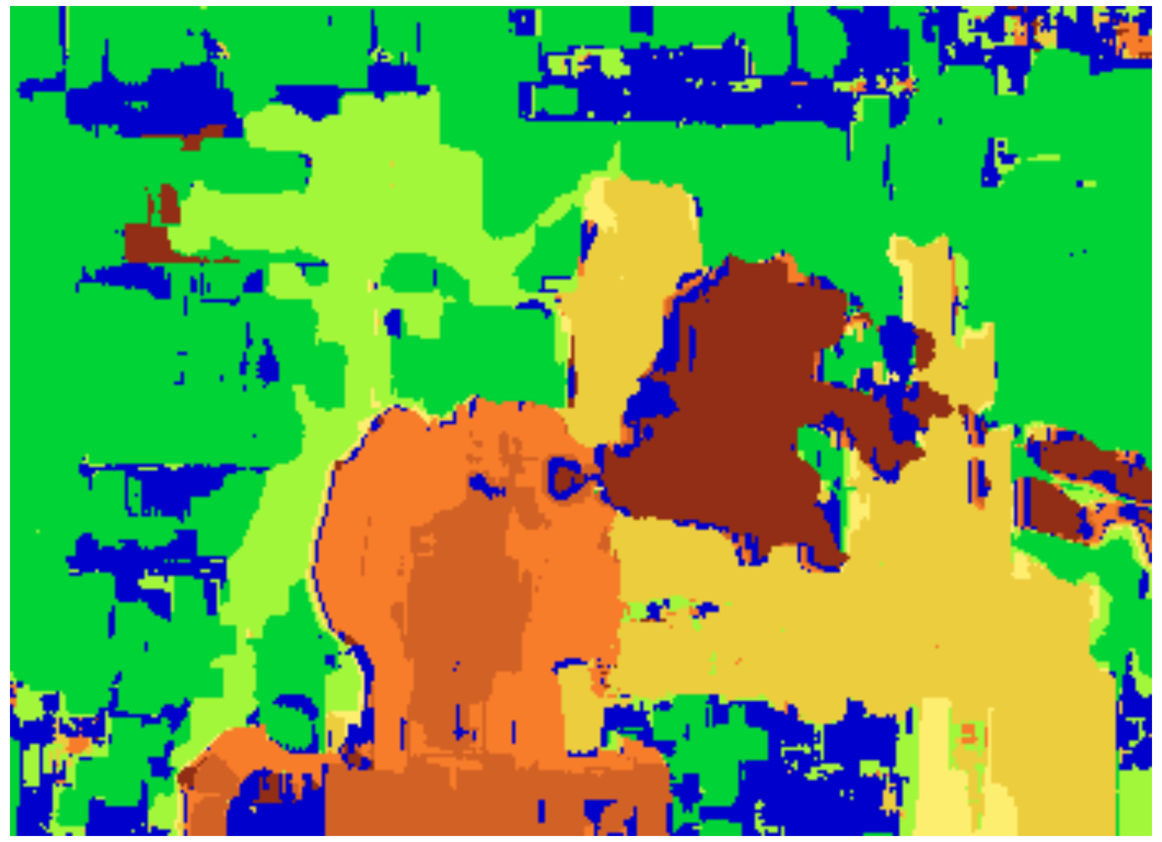
Block Matching Techniques: Result

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)

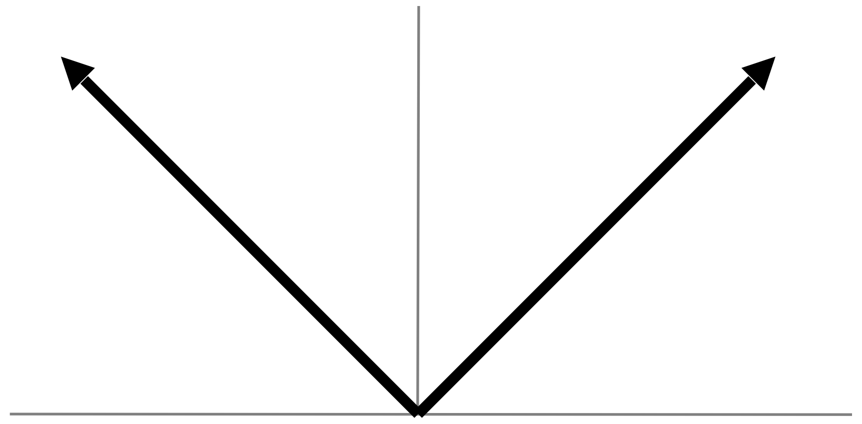
Stereo Matching as **Energy Minimization**

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

smoothness term

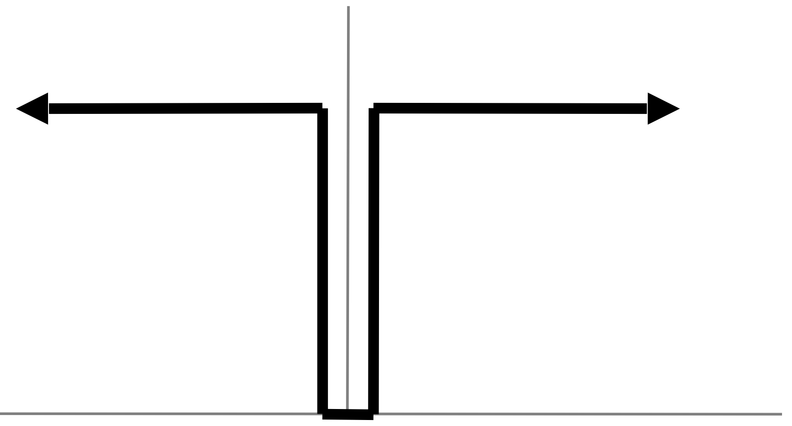
$$V(d_p, d_q) = |d_p - d_q|$$

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)

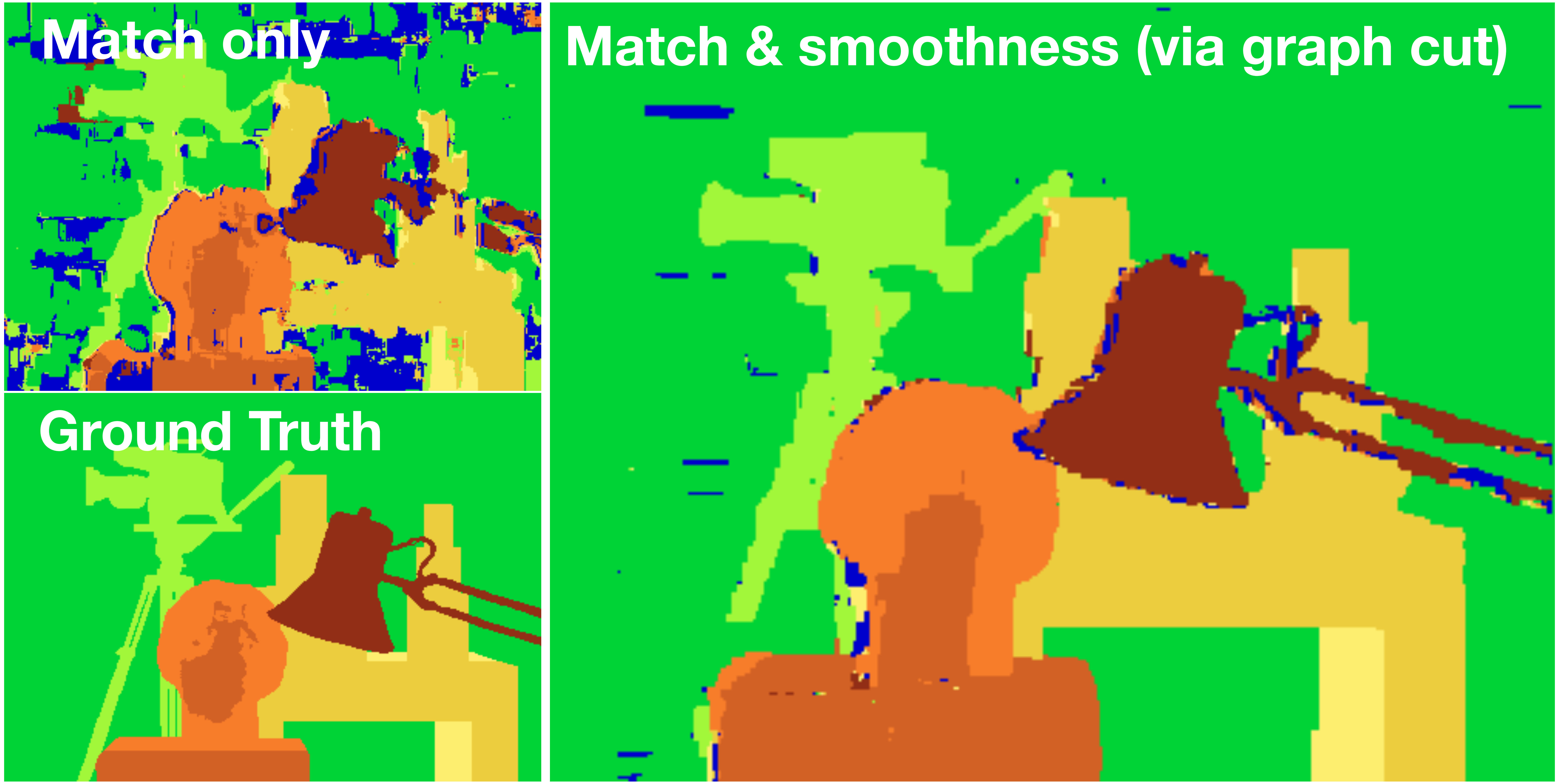
Stereo Matching as **Energy Minimization**: Solution

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

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

Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

Stereo Matching as **Energy Minimization**

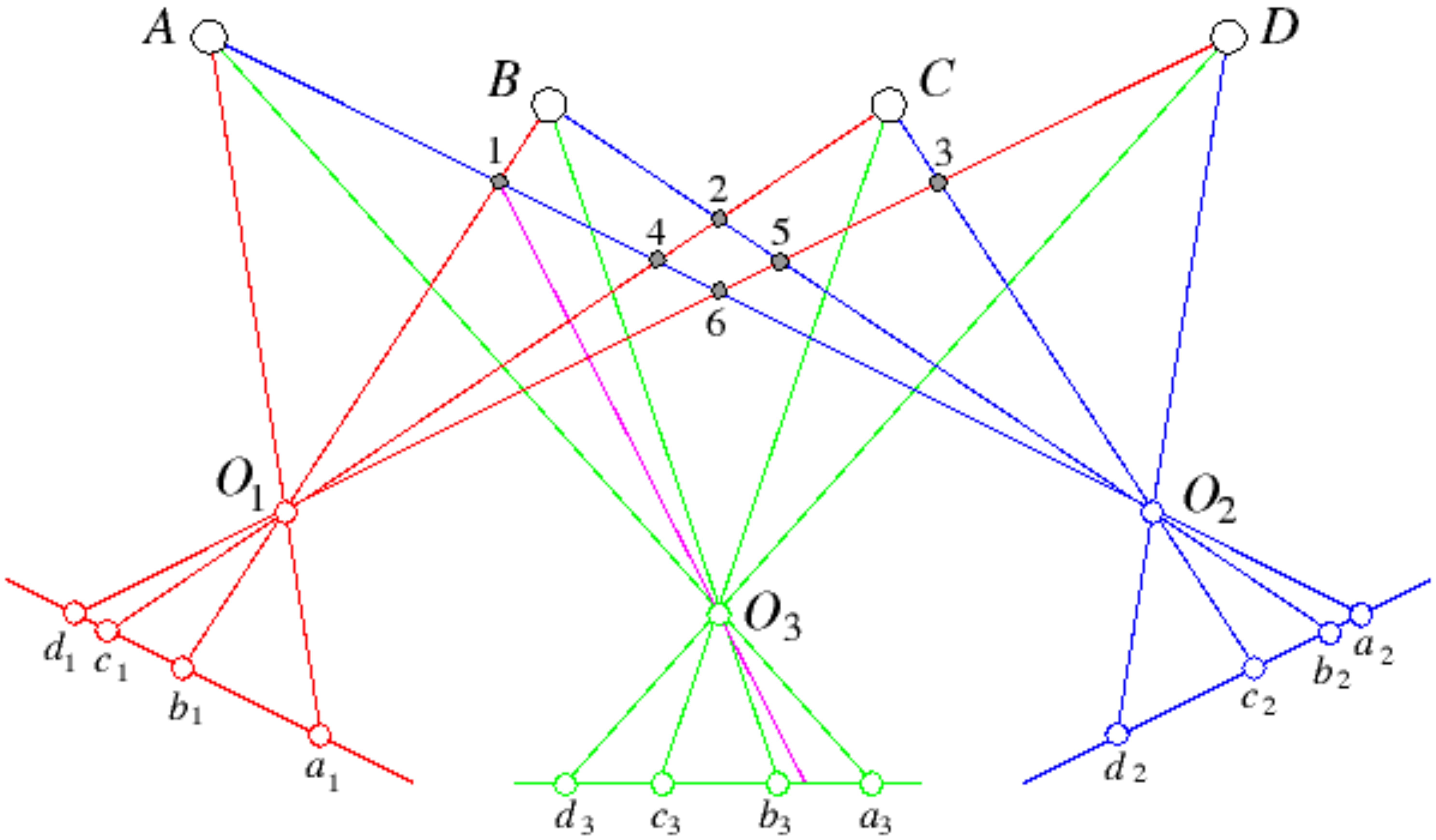


Y. Boykov, O. Veksler, and R. Zabih, Fast Approximate Energy Minimization via Graph Cuts, PAMI 2001

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**

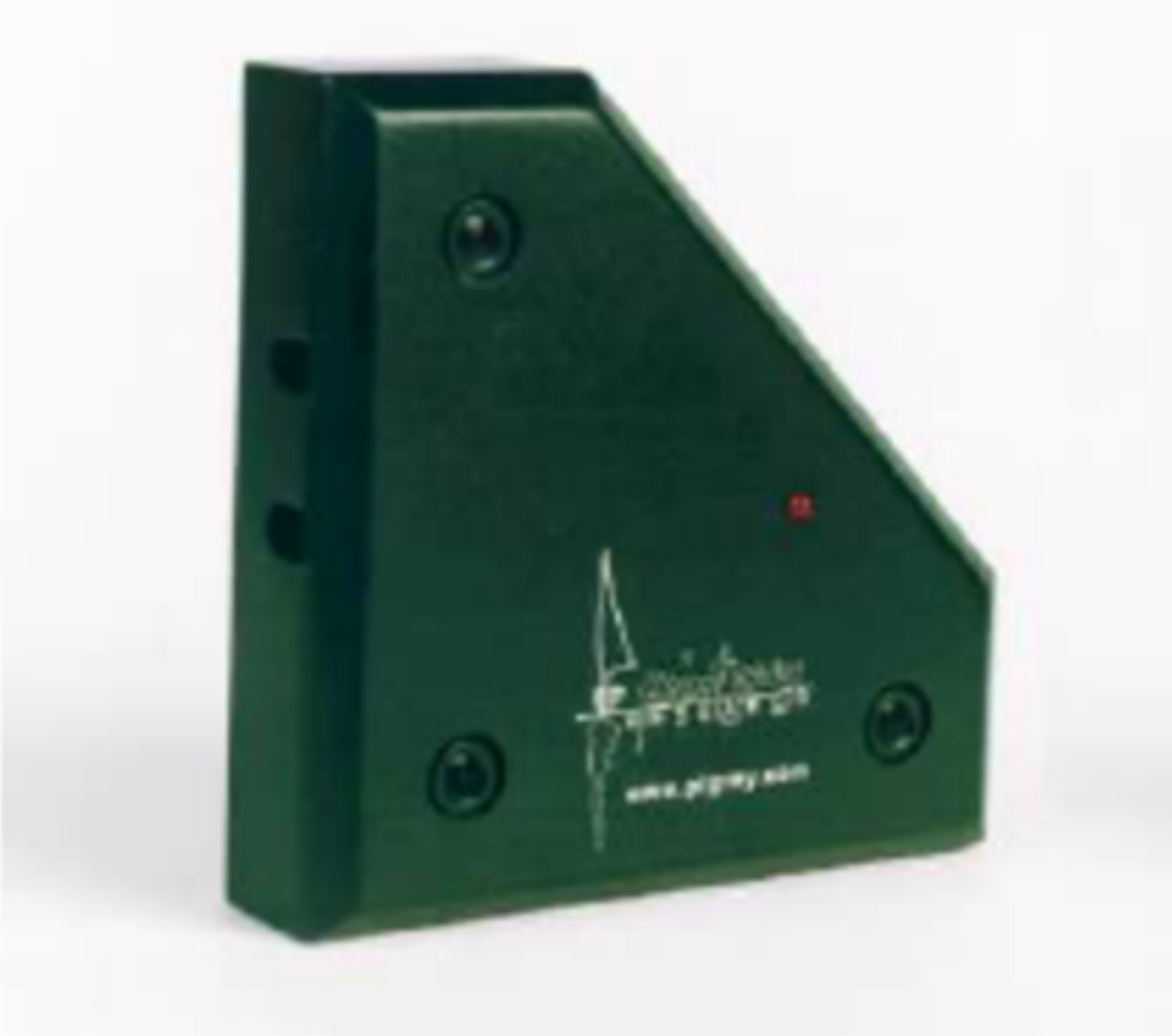
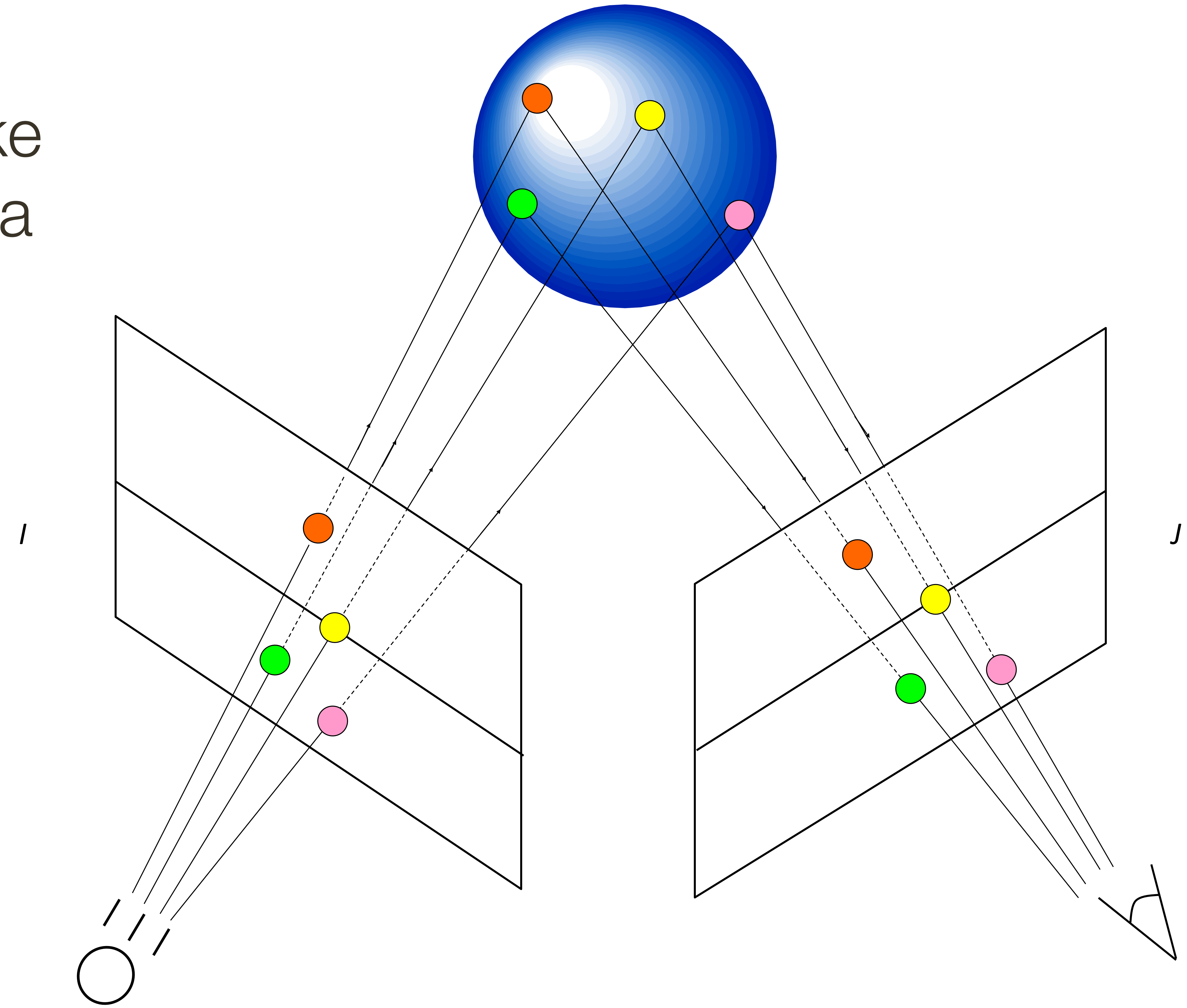


Image credit: Point Grey Research

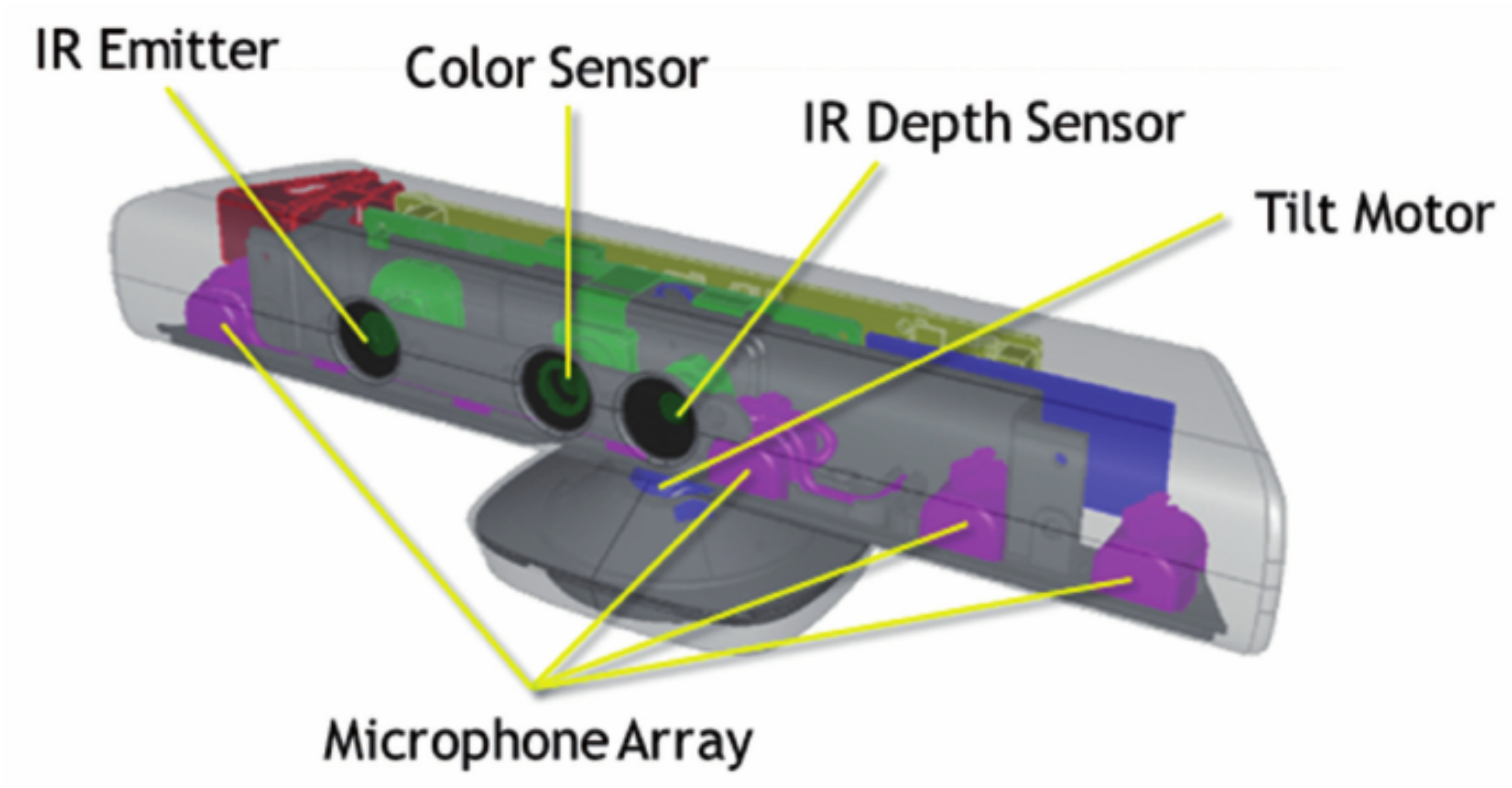
Structured Light Imaging: Structured Light and One Camera

Projector acts like
“reverse” camera

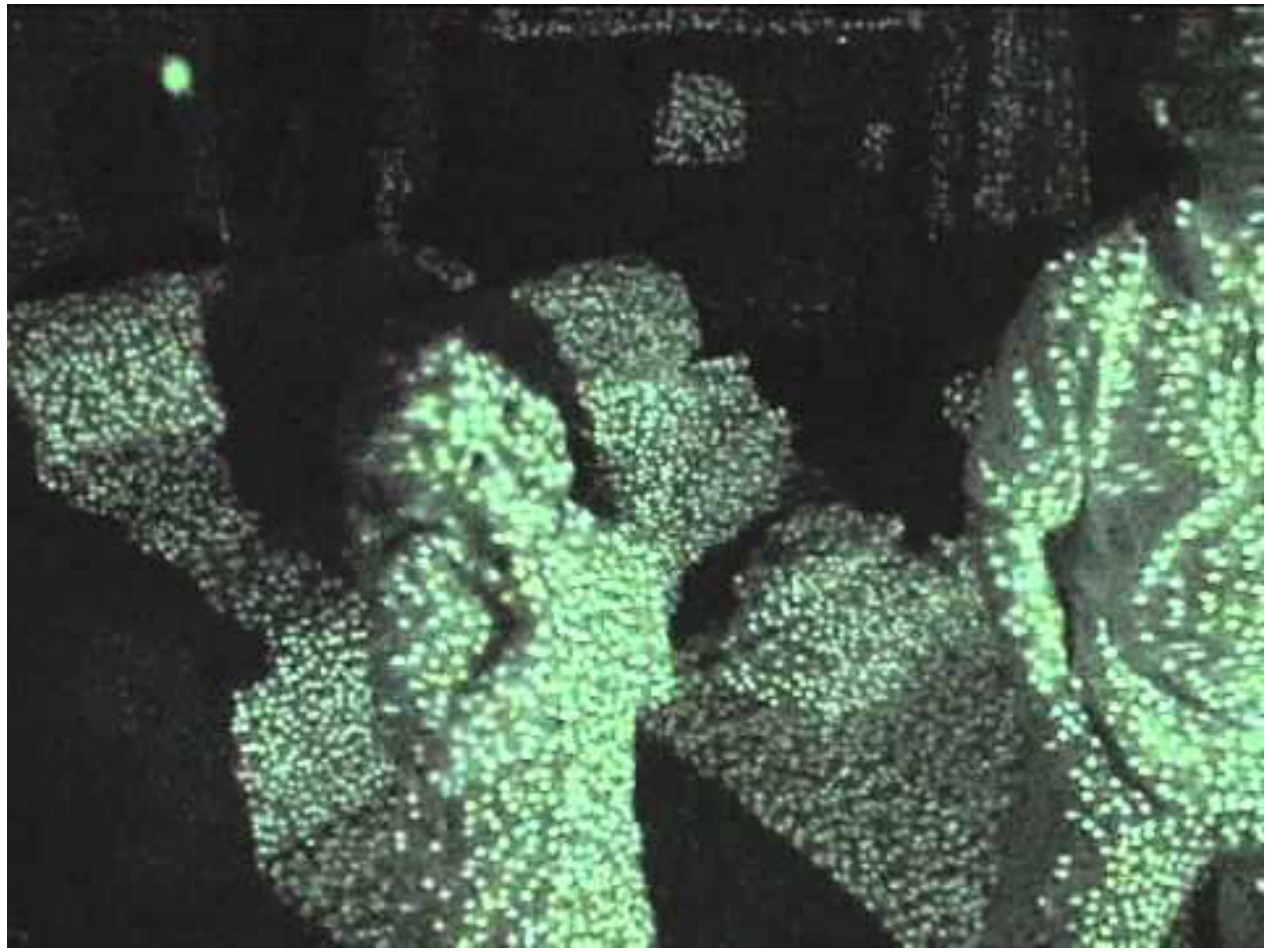


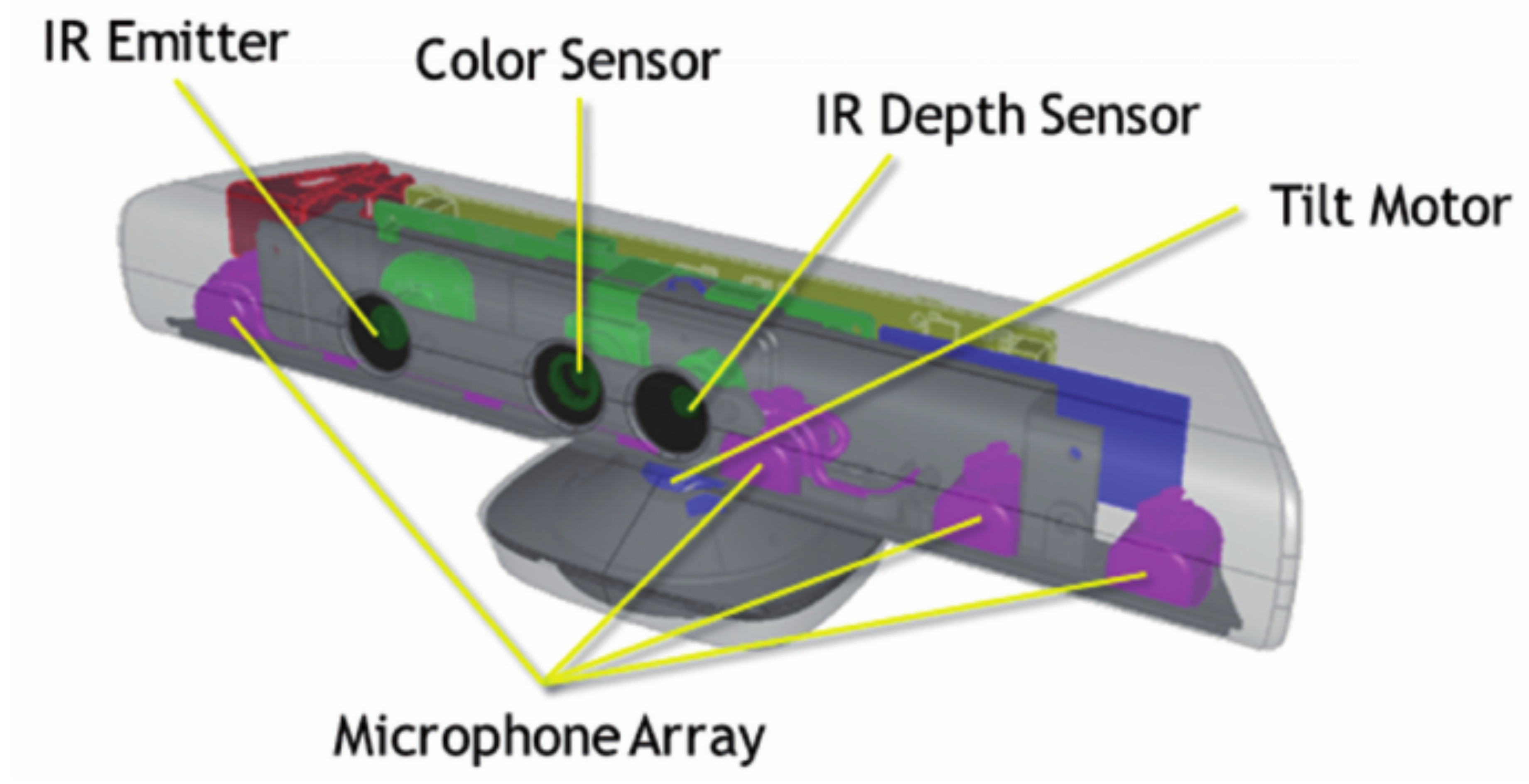
Slide Credit: Ioannis (Yannis) Gkioulekas (CMU)

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

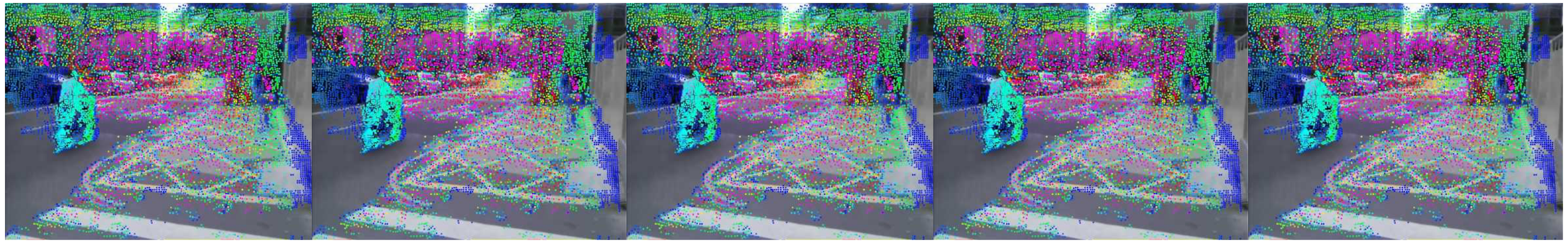
What do we match?

— Individual pixels?

— Patches?

— Edges?

CPSC 425: Computer Vision



Lecture 19: Optical Flow

Optical Flow

Problem:

Determine how objects (and/or the camera itself) move in the 3D world

Key Idea(s):

Images acquired as a (continuous) function of time provide additional constraint. Formulate motion analysis as finding (dense) point correspondences over time.

Optical Flow and 2D Motion

Optical flow is the apparent motion of brightness patterns in the image

Applications

— image and video stabilization in digital cameras, camcorders

— motion-compensated video compression schemes such as MPEG

— image registration for medical imaging, remote sensing

— action recognition

— motion segmentation

Optical Flow and 2D Motion

Motion is geometric

Optical flow is radiometric

Usually we assume that optical flow and 2-D motion coincide ... but this is not always the case!

Optical Flow and 2D Motion

Optical flow but **no motion** . . .

Optical Flow and 2D Motion

Optical flow but **no motion** . . .

. . . moving light source(s), lights going on/off, inter-reflection, shadows

Optical Flow and 2D Motion

Optical flow but **no motion** . . .

. . . moving light source(s), lights going on/off, inter-reflection, shadows

Motion but **no optical flow** . . .

Optical Flow and 2D Motion

Optical flow but **no motion** . . .

. . . moving light source(s), lights going on/off, inter-reflection, shadows

Motion but **no optical flow** . . .

. . . spinning sphere.

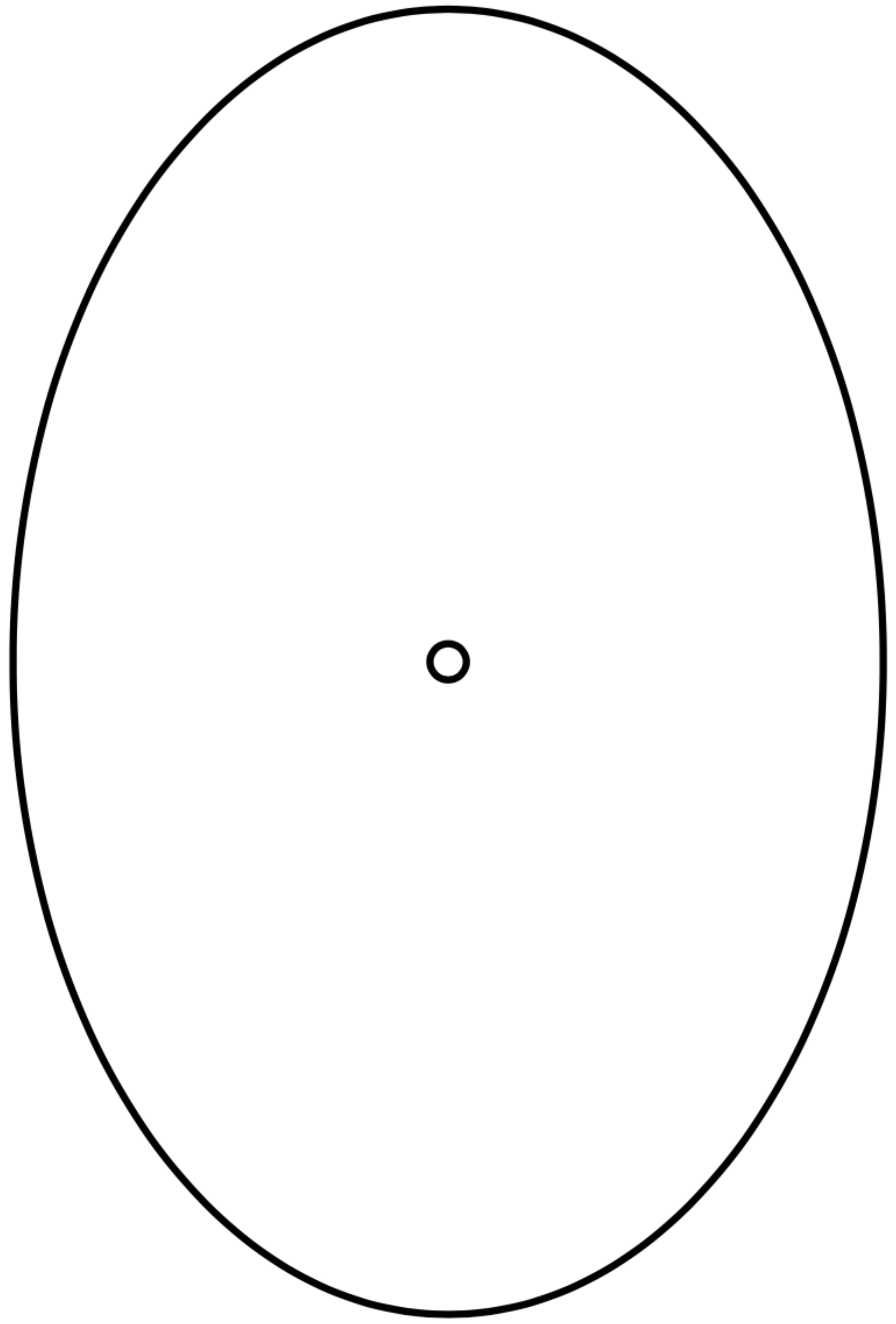
Optical Flow and 2D Motion

Here's a video example of a very skilled Japanese contact juggler working with a clear acrylic ball

Source: http://youtu.be/CtztrcGkCBw?t=1m20s

A key element to the illusion is motion without corresponding optical flow

Example 1: Rotating Ellipse



Example 1: Three "Percepts"

1. **Veridical**:

— a 2-D rigid, flat, rotating ellipse

2. **Amoeboid**:

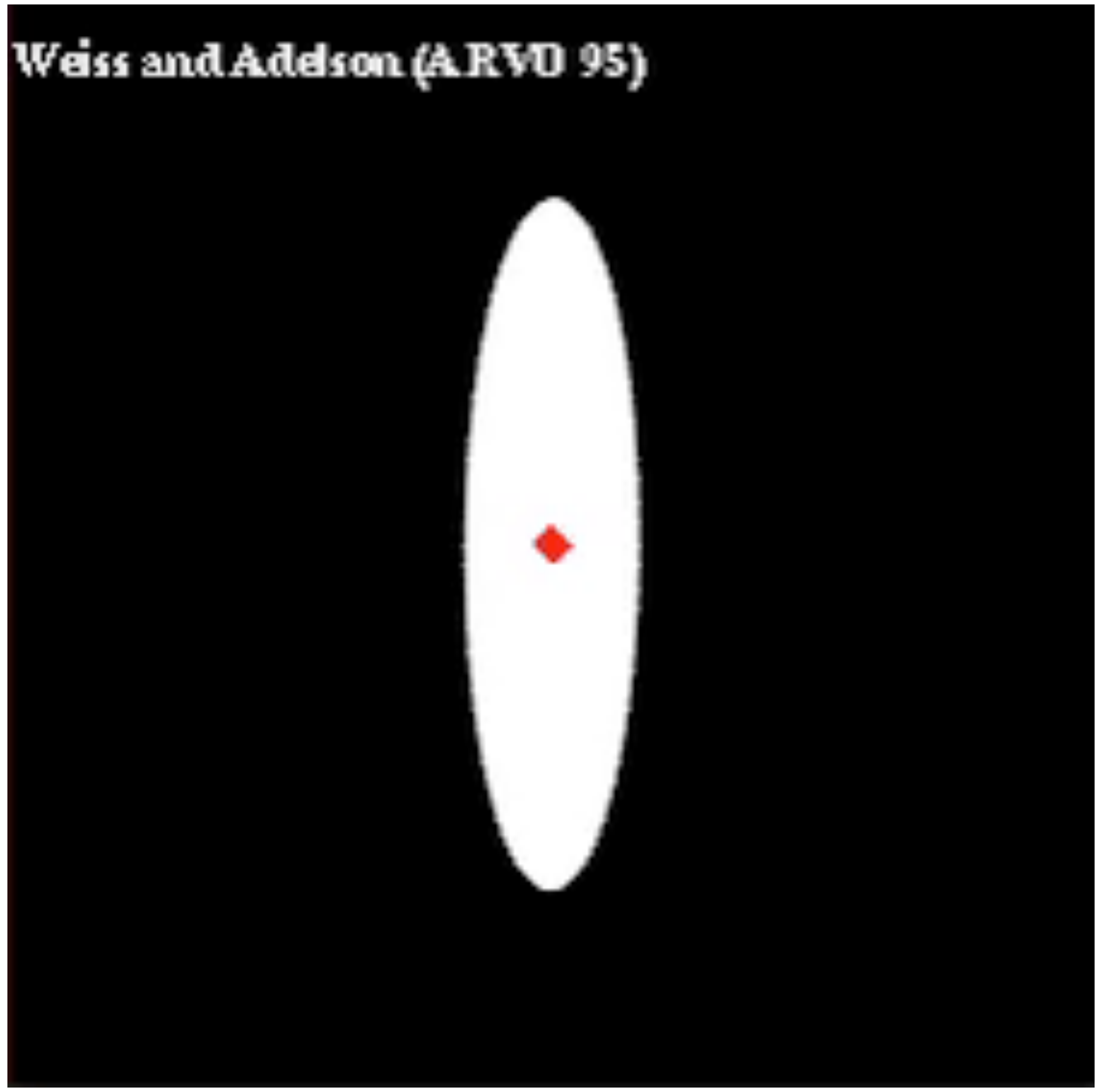
— a 2-D, non-rigid "gelatinous" smoothly deforming shape

3. **Stereokinetic**:

— a circular, rigid disk rolling in 3-D

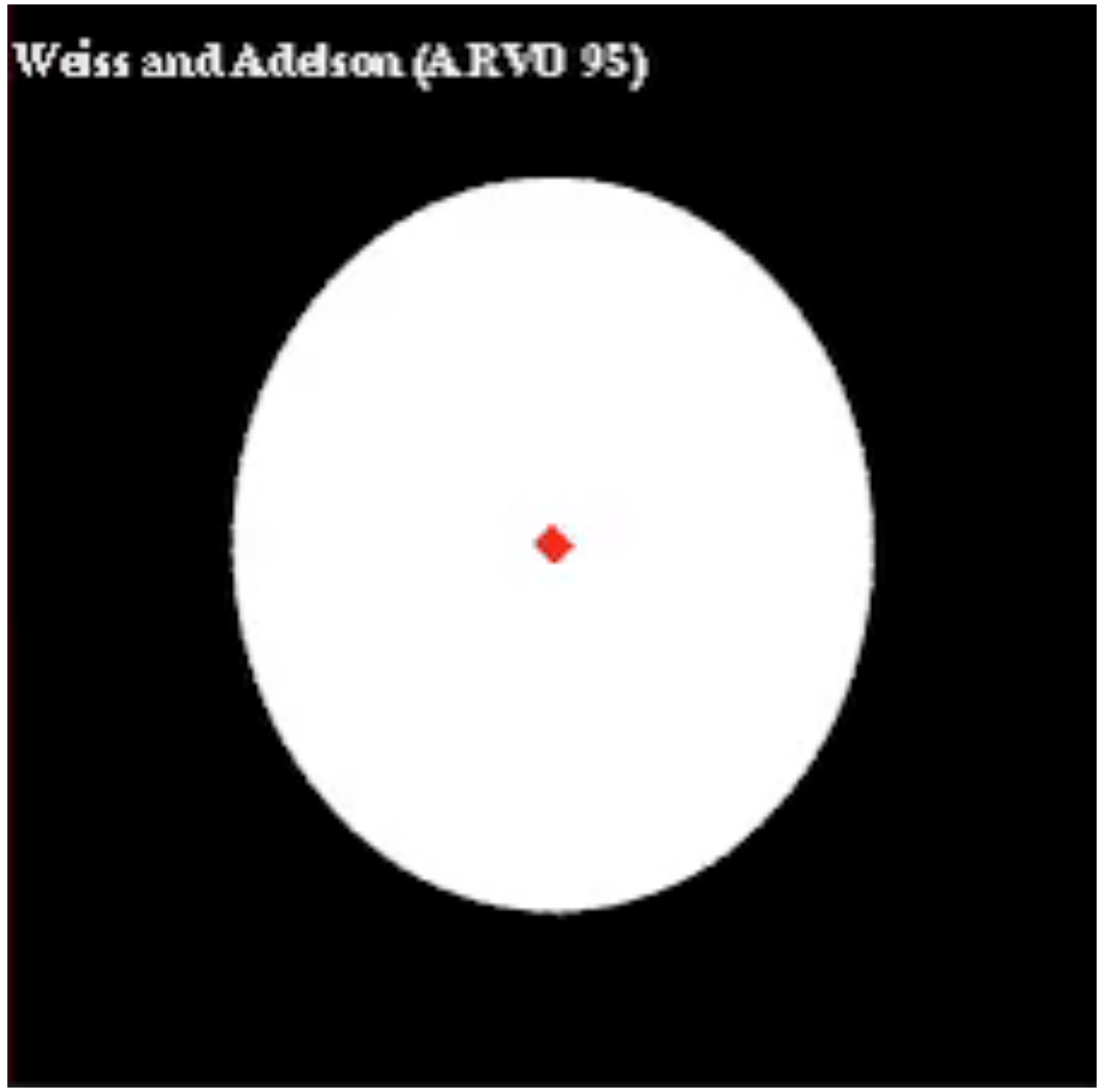
Example 1: Rotating Ellipse

A narrow ellipse oscillating rigidly about its center appears **rigid**



Example 1: Rotating Ellipse

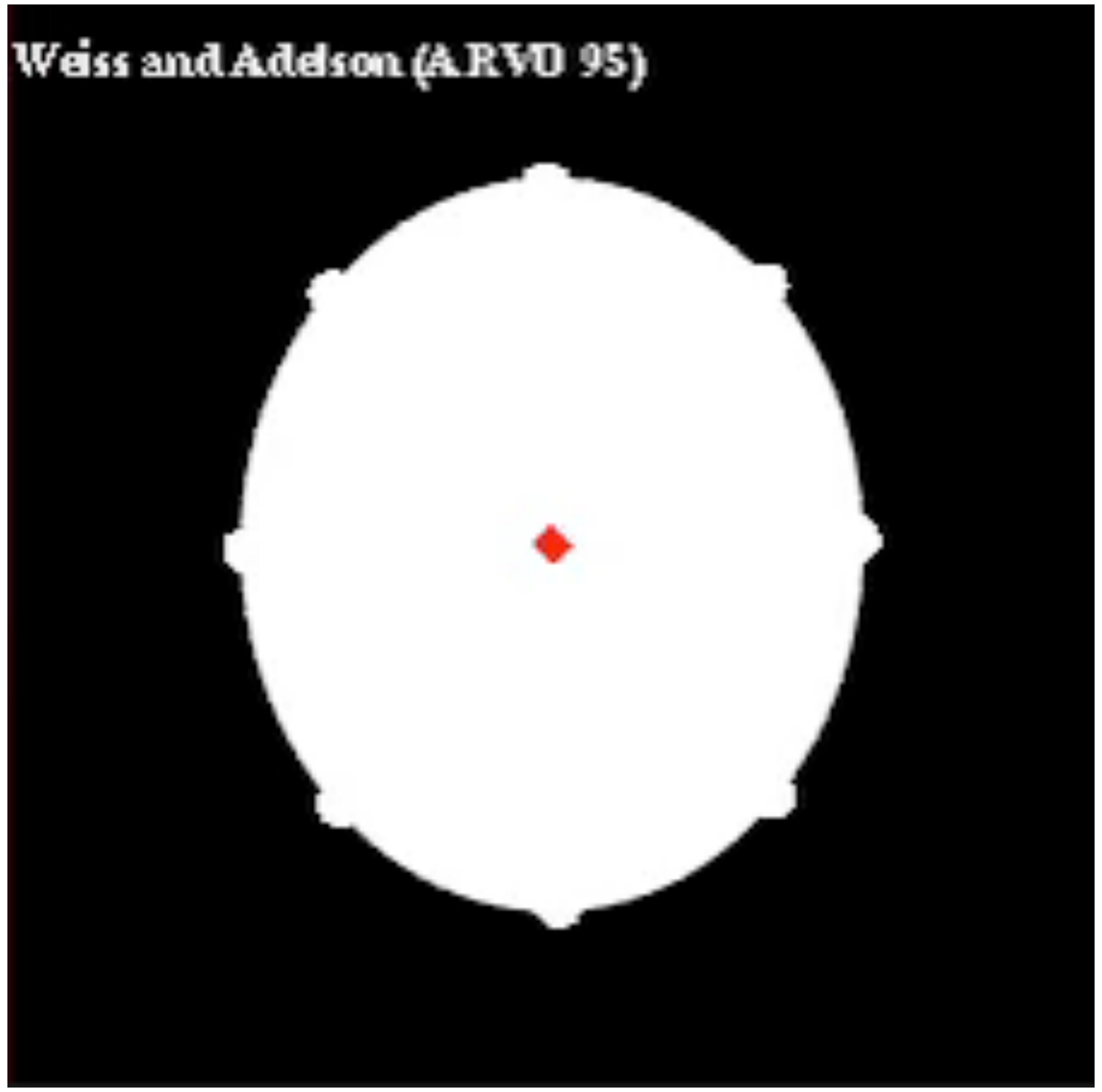
However, a fat ellipse undergoing the same motion appears **nonrigid**



Video credits: Yair Weiss

Example 1: Rotating Ellipse

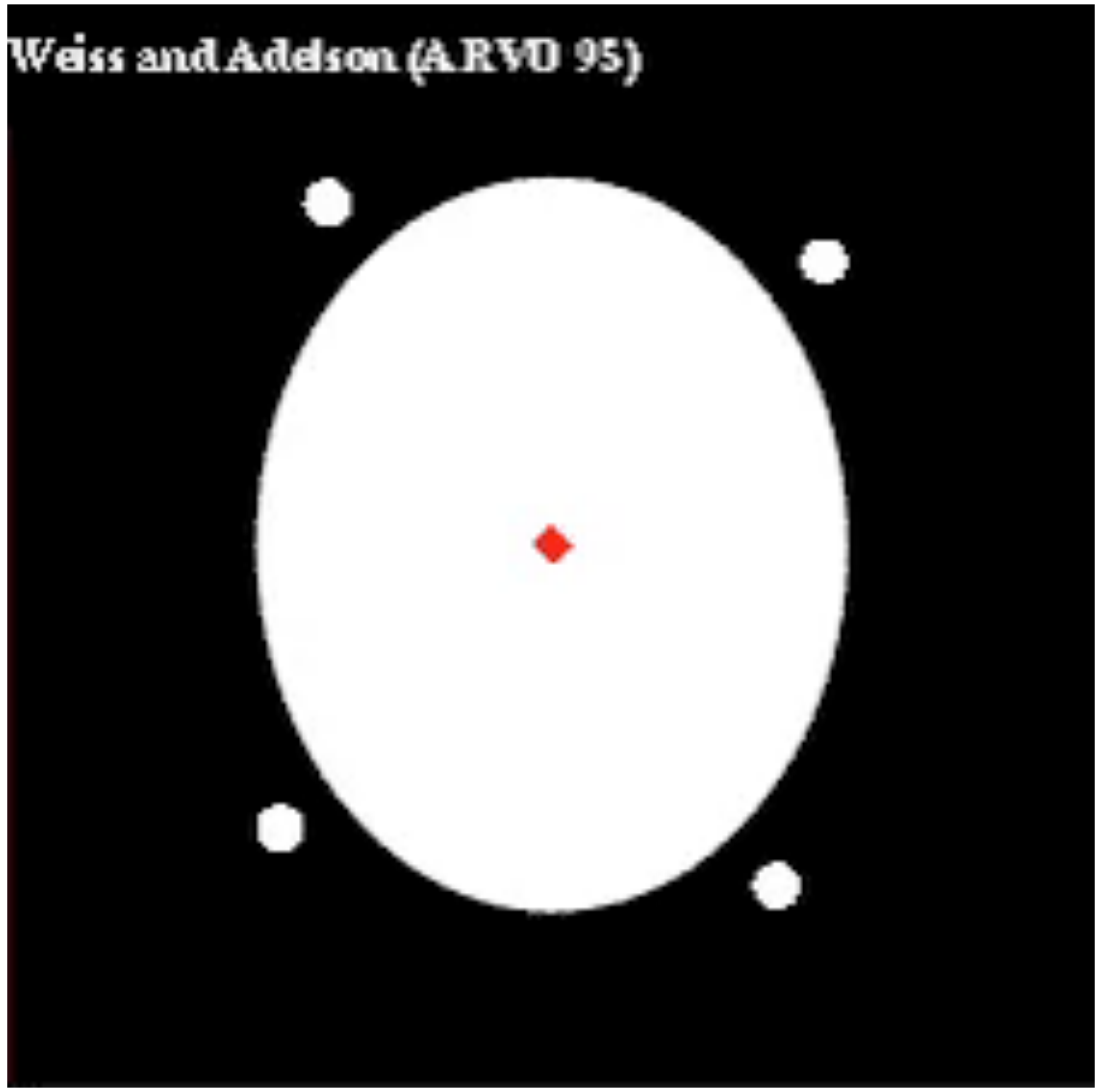
The apparent nonrigidity of a fat ellipse is not really a "visual illusion". A rotating ellipse or a nonrigid pulsating ellipse can cause the exact same stimulation on our retinas. In this sequence the ellipse contour is always doing the same thing, only the markers' motion changes.



Video credits: Yair Weiss

Example 1: Rotating Ellipse

The ellipse's motion can be influenced by features not physically connected to the ellipse. In this sequence the ellipse is always doing the same thing, only the dots' motion changes.



Video credits: Yair Weiss

Example: Flying Insects and Birds

Bees have very limited stereo perception. How do they fly safely through narrow passages?

Example: Flying Insects and Birds

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A simple strategy would be to balance the speeds of motion of the images of the two walls. If wall A is moving faster than wall B, what should you (as a bee) do?

Example: Flying Insects and Birds

Bee strategy: Balance the optical flow experienced by the two eyes

Figure credit: M. Srinivasan

Example: Flying Insects and Birds

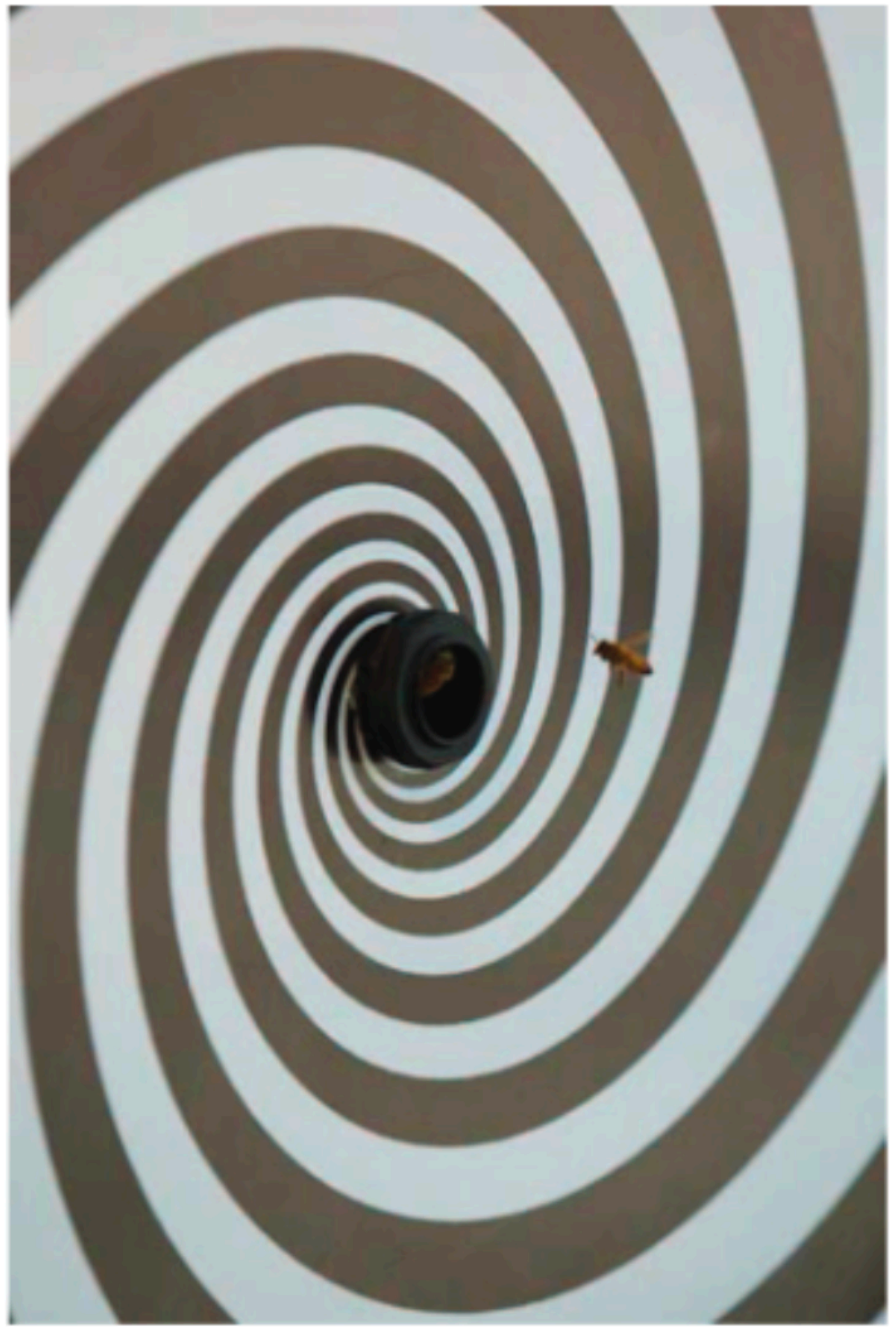
How do bees land safely on surfaces?

During their approach, bees continually adjust their speed to hold constant the optical flow in the vicinity of the target

— approach speed decreases as the target is approached and reduces to zero at the point of touchdown

— no need to estimate the distance to the target at any time

Example: Flying Insects and Birds



Bees approach the surface more slowly if the spiral is rotated to augment the rate of expansion, and more quickly if the spiral is rotated in the opposite direction

Figure credit: M. Srinivasan

Example: Flying Insects and Birds

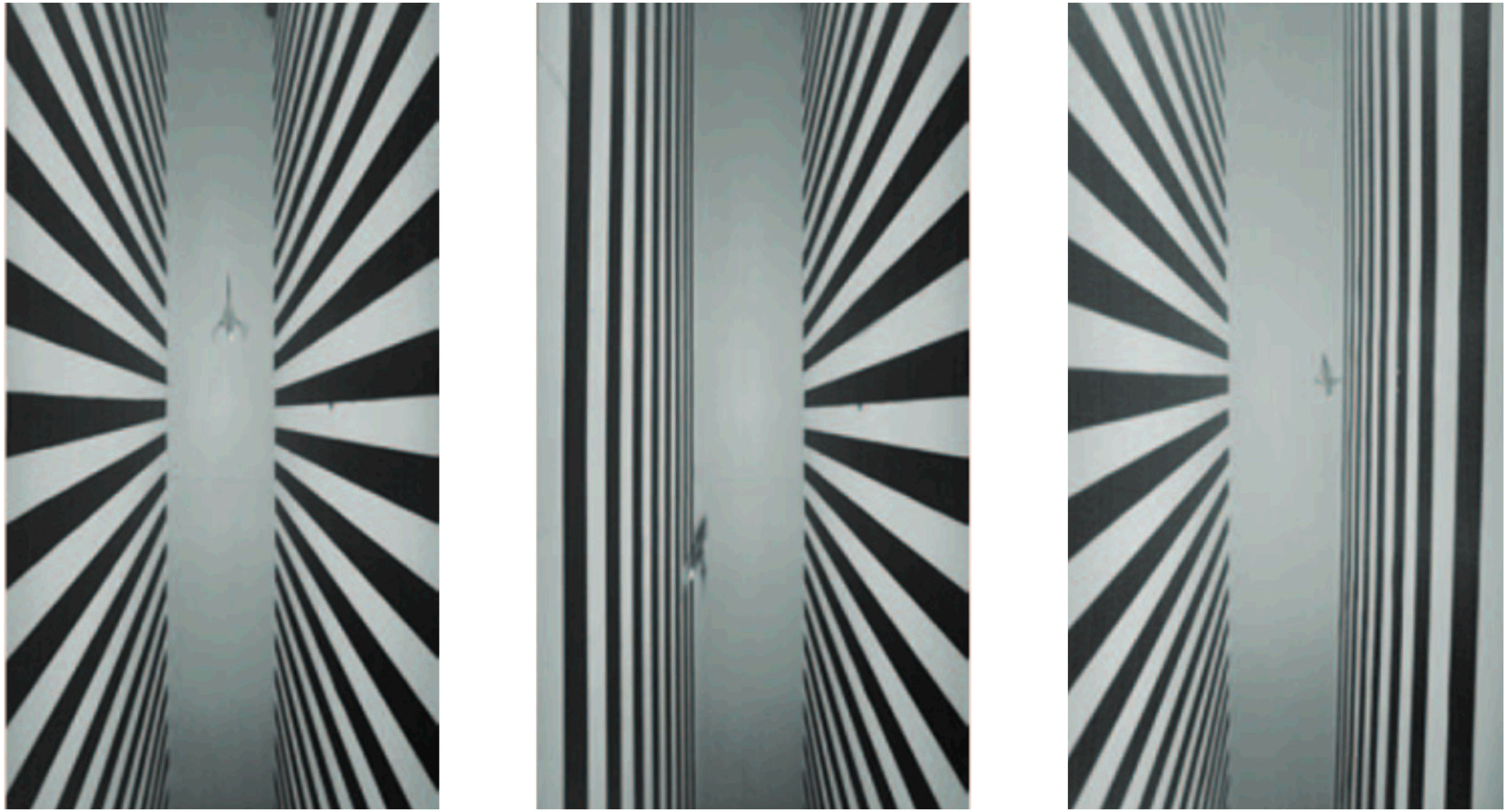
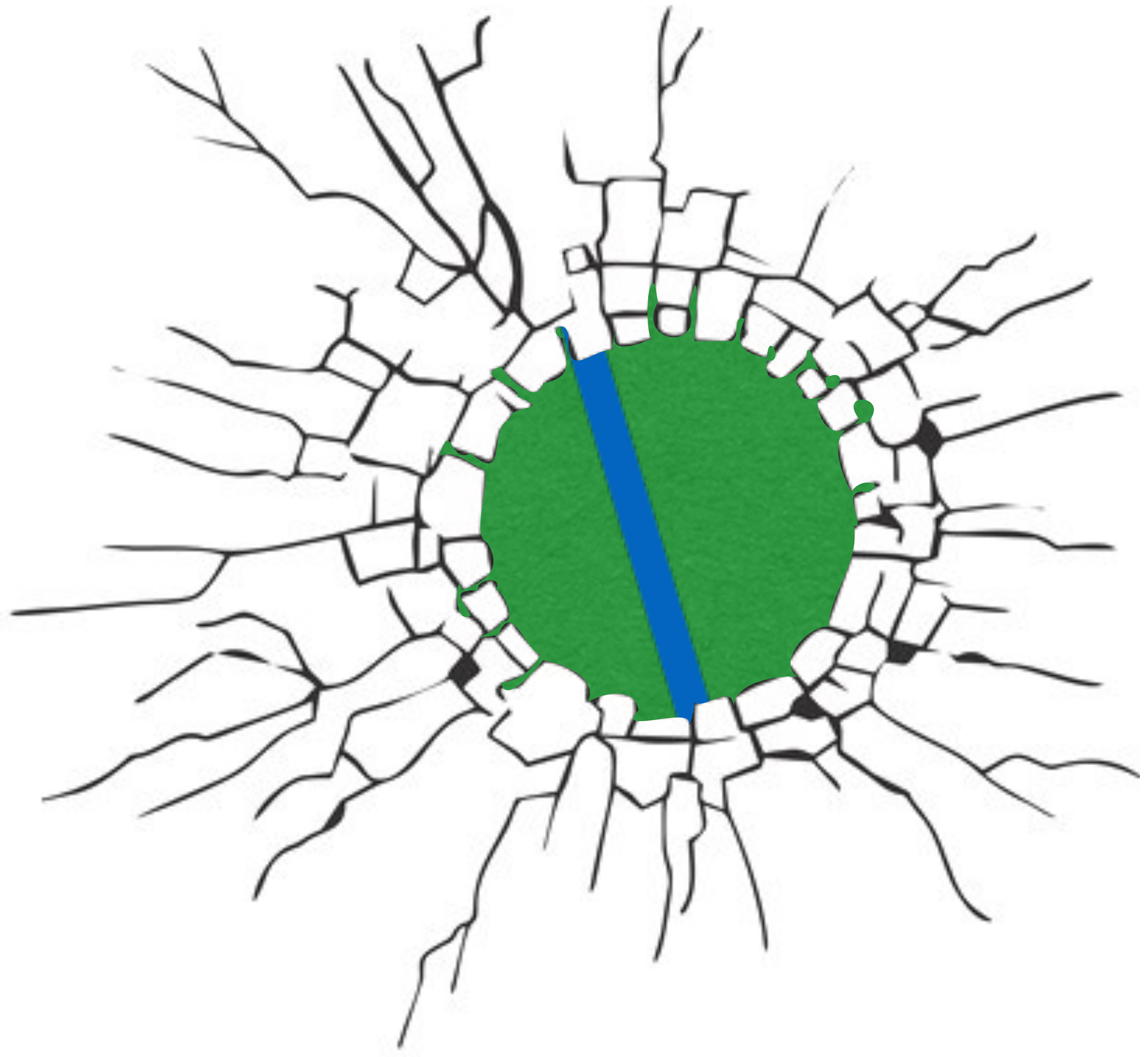


Figure credit: M. Srinivasan

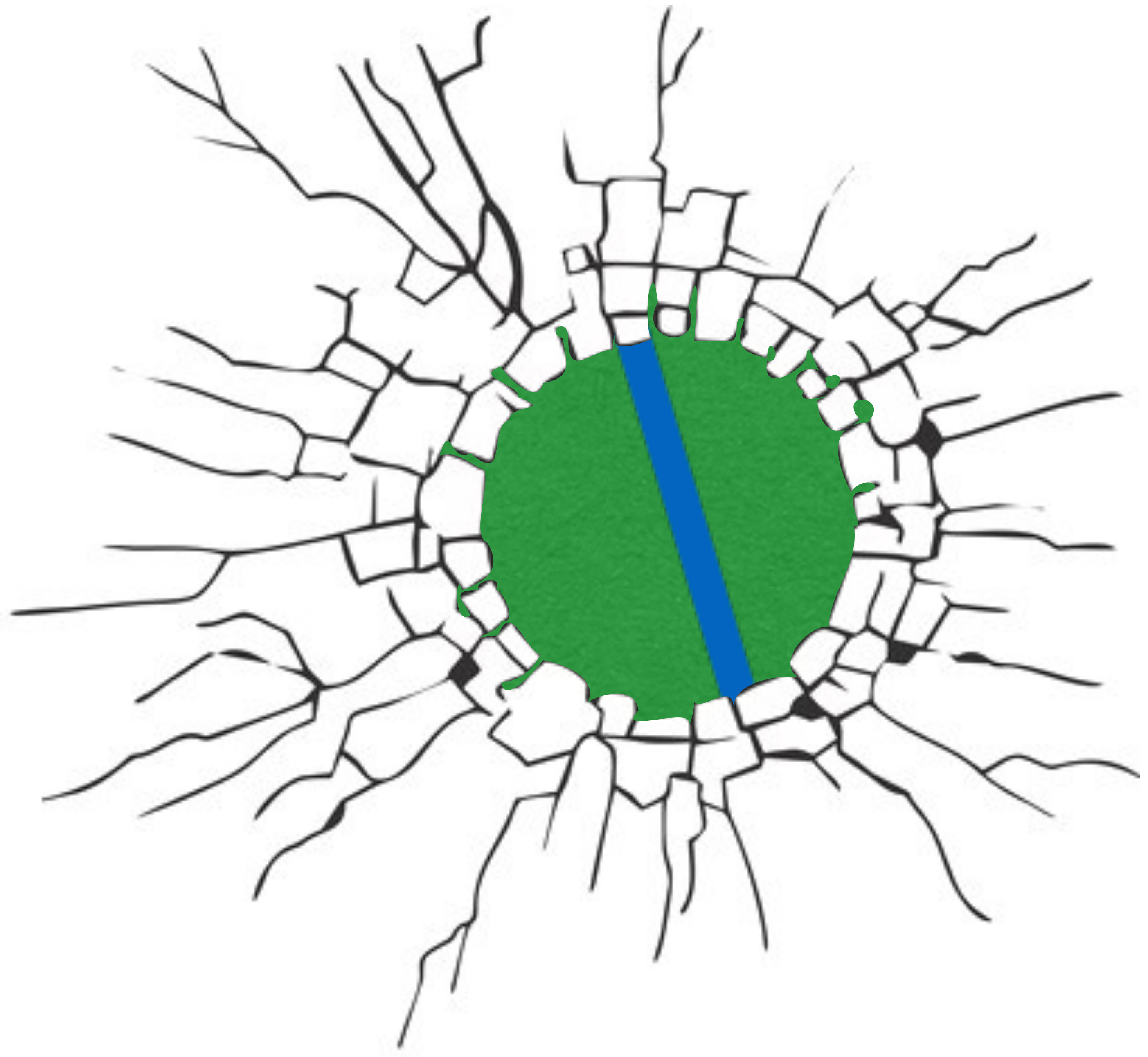
Aperture Problem



In which direction is the line moving?

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)

Aperture Problem



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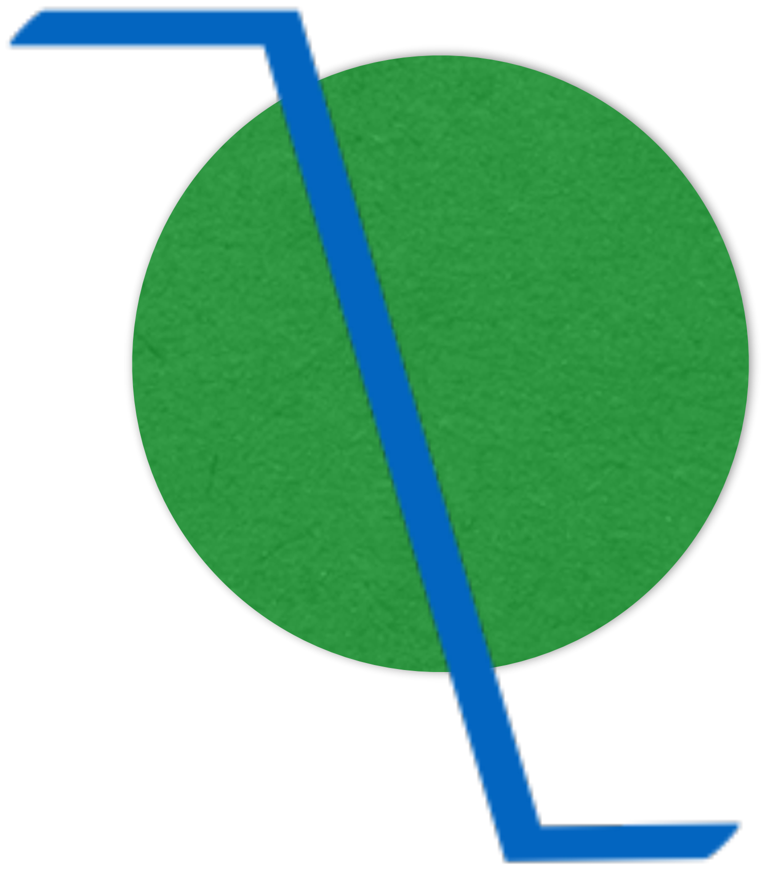

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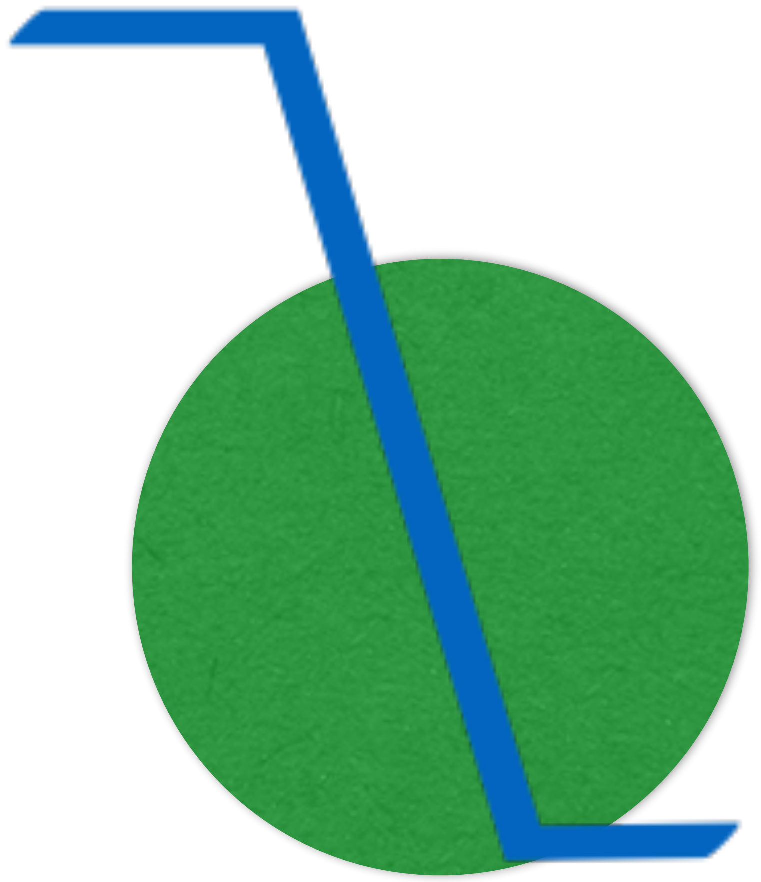

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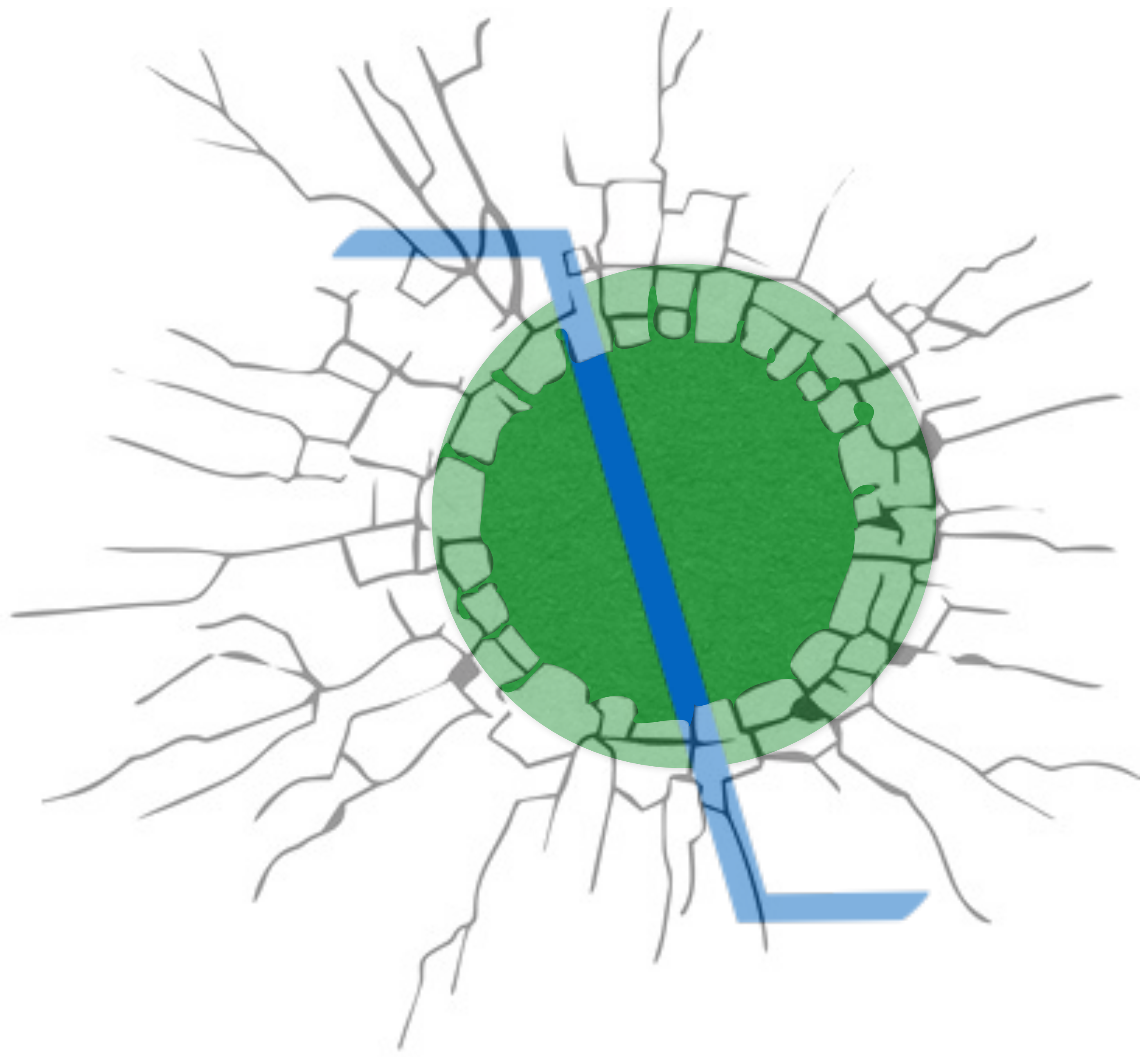

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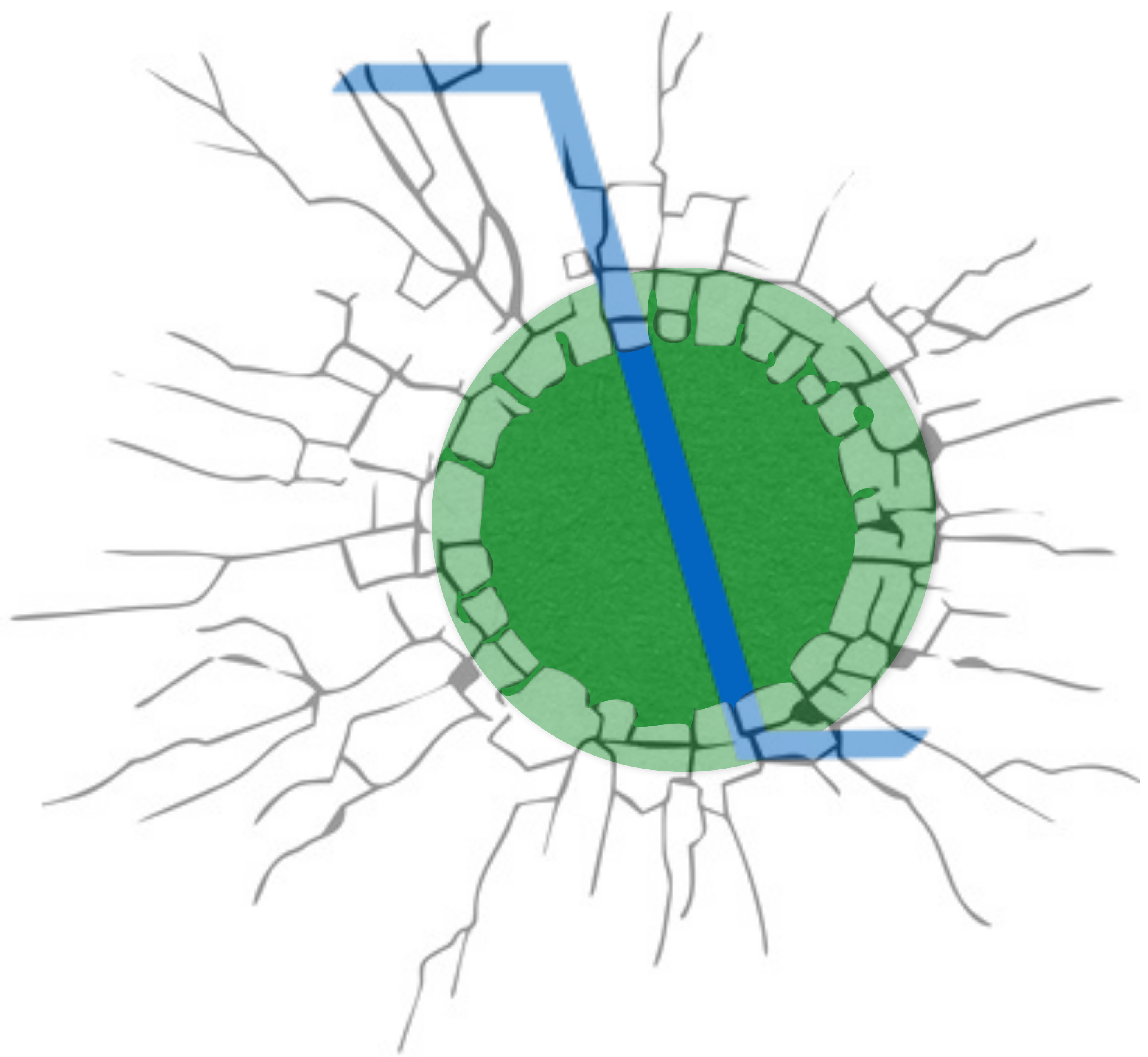

Image Credit: Ioannis (Yannis) Gkioulekas (CMU)