

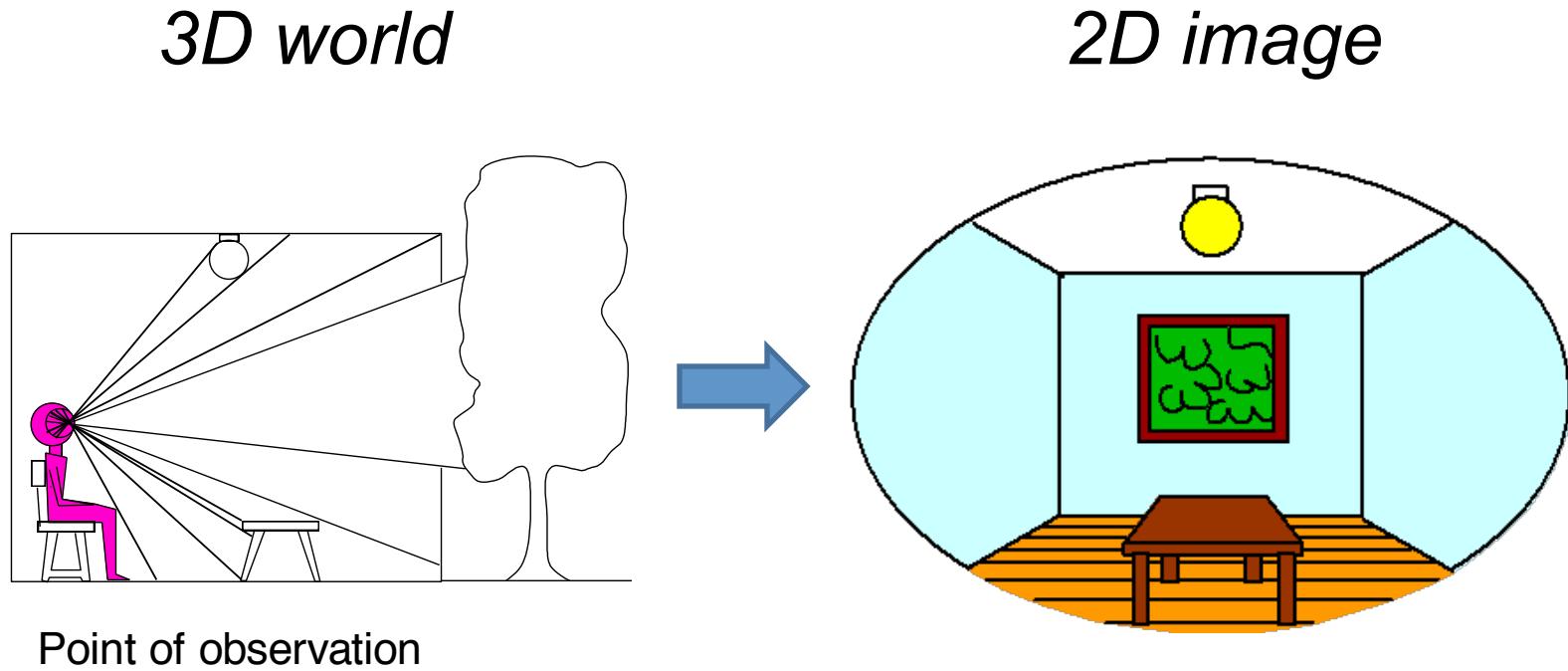


Lecture 9 & 10: Stereo Vision

Dr. Juan Carlos Niebles
Stanford AI Lab

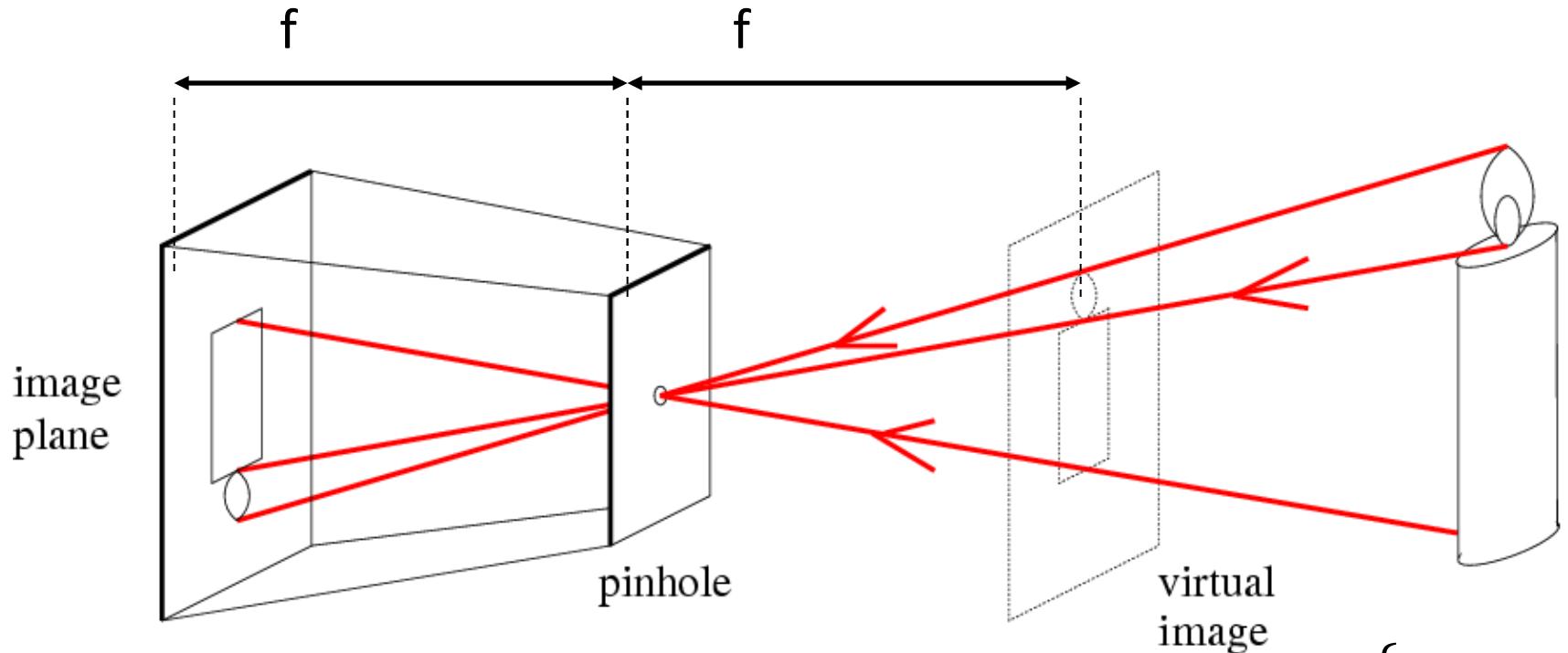
Professor Fei-Fei Li
Stanford Vision Lab

Dimensionality Reduction Machine (3D to 2D)



Figures © Stephen E. Palmer, 2002

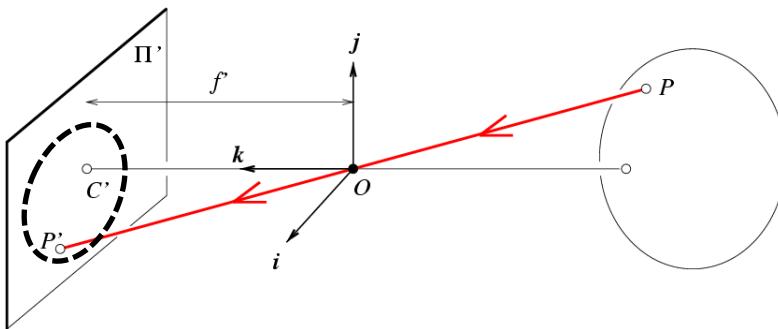
Pinhole camera



- Common to draw image plane *in front* of the focal point
- Moving the image plane merely scales the image.

$$\begin{cases} x' = f \frac{x}{z} \\ y' = f \frac{y}{z} \end{cases}$$

Relating a real-world point to a point on the camera



In homogeneous coordinates:

$$P' = \begin{bmatrix} f & x \\ f & y \\ z \end{bmatrix} = \underbrace{\begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix}}_M \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

ideal world

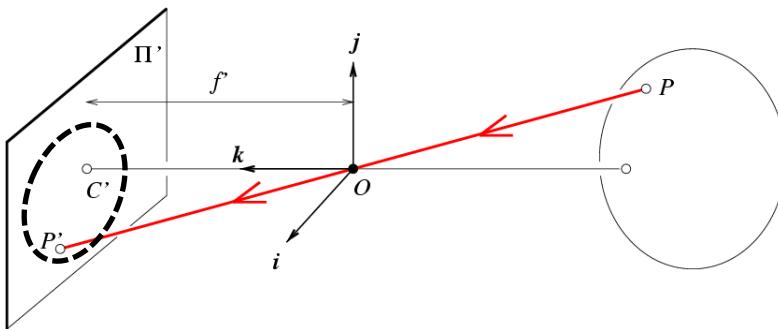
Intrinsic Assumptions

- Unit aspect ratio
- Optical center at $(0,0)$
- No skew

Extrinsic Assumptions

- No rotation
- Camera at $(0,0,0)$

Relating a real-world point to a point on the camera



In homogeneous coordinates:

$$P' = \begin{bmatrix} f & x \\ f & y \\ z \end{bmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} = K \begin{bmatrix} I & 0 \end{bmatrix} P$$

K

Intrinsic Assumptions

- Unit aspect ratio
- Optical center at $(0,0)$
- No skew

Extrinsic Assumptions

- No rotation
- Camera at $(0,0,0)$

Real-world camera

Intrinsic Assumptions

- Optical center at (u_0, v_0)
- Rectangular pixels
- Small skew

Extrinsic Assumptions

- No rotation
- Camera at $(0,0,0)$

$P' = K \begin{bmatrix} I & 0 \end{bmatrix} P \rightarrow w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & s & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$

Intrinsic parameters

Slide inspiration: S. Savarese

Real-world camera + Real-world transformation

Intrinsic Assumptions

- Optical center at (u_0, v_0)
- Rectangular pixels
- Small skew

Extrinsic Assumptions

- Allow rotation
- Camera at (t_x, t_y, t_z)

$$P' = K \begin{bmatrix} R & \bar{t} \end{bmatrix} P \quad \xrightarrow{\text{blue arrow}} \quad w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & s & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

Slide inspiration: S. Savarese

What we will learn today?

- Introduction to stereo vision
- Epipolar geometry: a gentle intro
- Parallel images & image rectification
- Solving the correspondence problem
- Homographic transformation
- Active stereo vision system

Reading:

[HZ] Chapters: 4, 9, 11

[FP] Chapters: 10

What we will learn today?

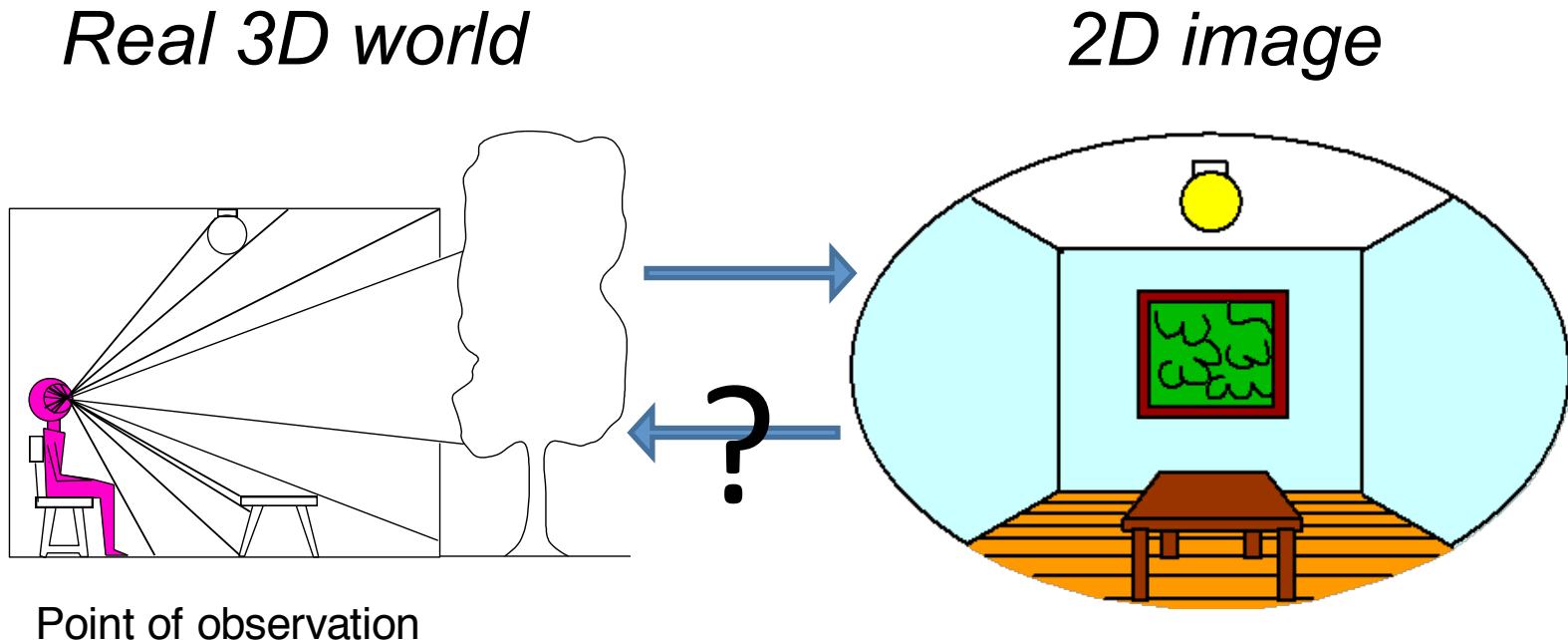
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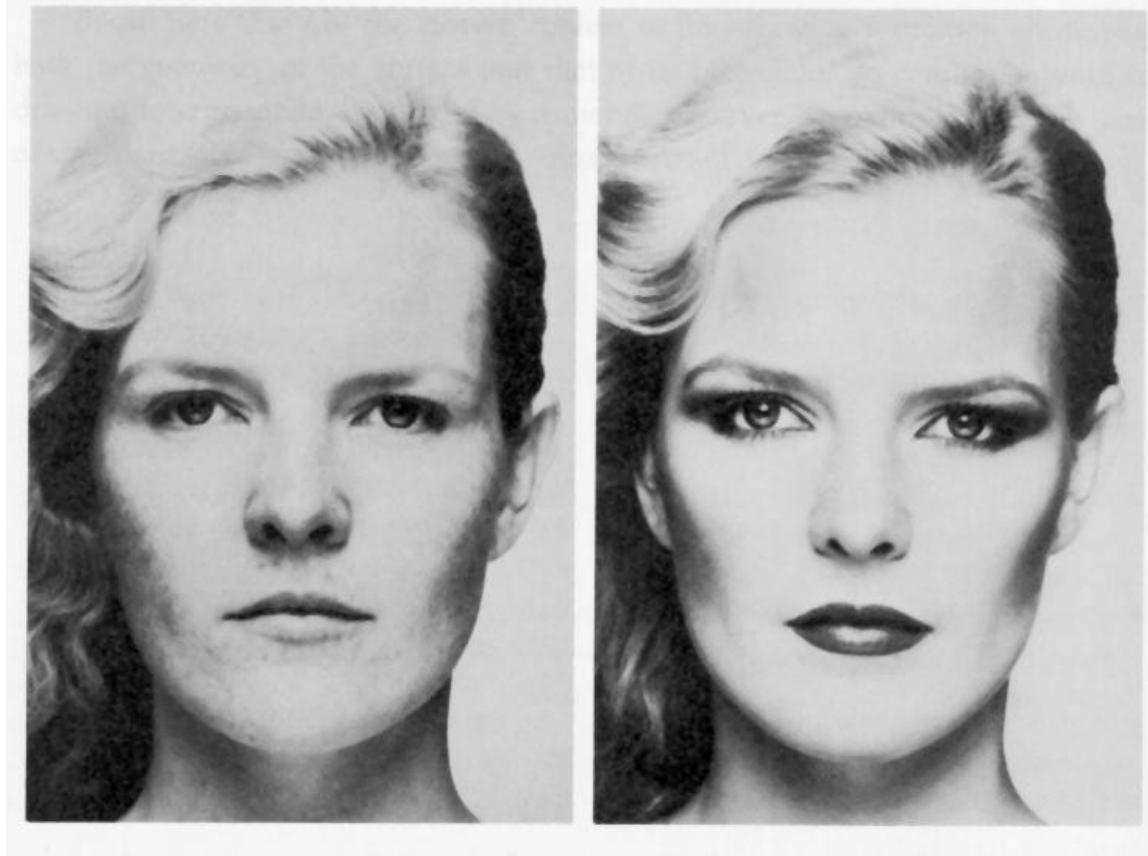
Recovering 3D from Images

- How can we automatically compute 3D geometry from images?
 - What cues in the image provide 3D information?



Visual Cues for 3D

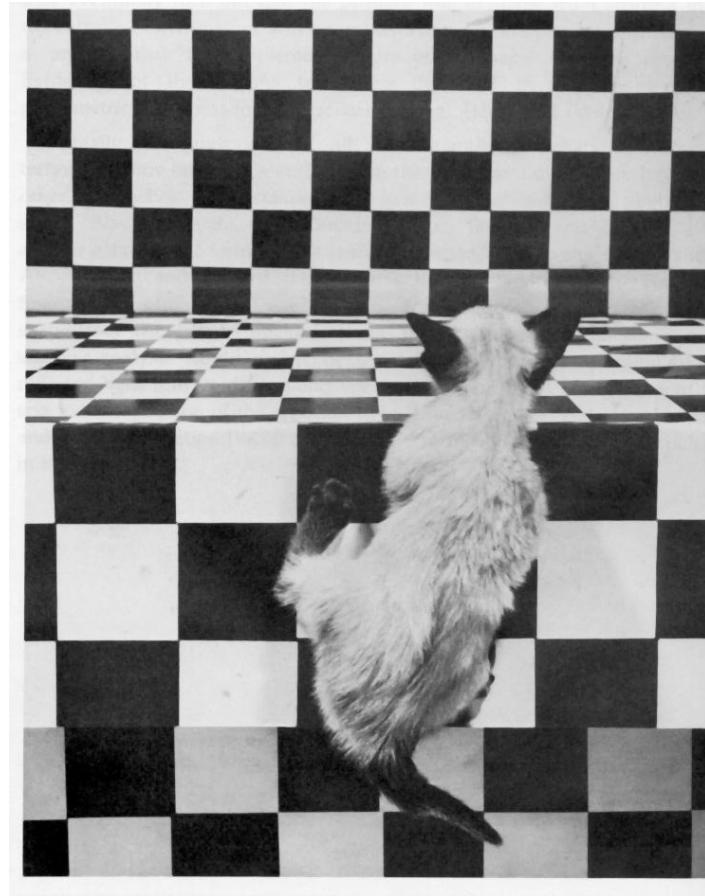
- Shading



Merle Norman Cosmetics, Los Angeles

Visual Cues for 3D

- Shading
- Texture



The Visual Cliff, by William Vandivert, 1960

Visual Cues for 3D

- Shading
- Texture
- Focus



From *The Art of Photography, Canon*

Visual Cues for 3D

- Shading
- Texture
- Focus
- Motion



Visual Cues for 3D

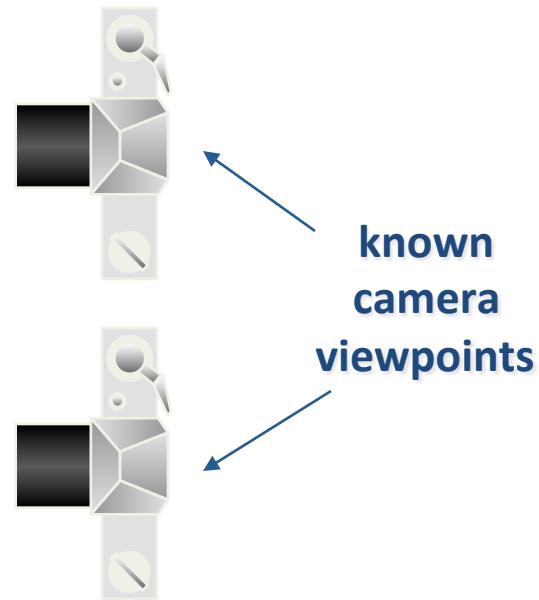
- Shading
 - Texture
 - Focus
 - Motion
- Others:
 - Highlights
 - Shadows
 - Silhouettes
 - Inter-reflections
 - Symmetry
 - Light Polarization
 - ...

Shape From X

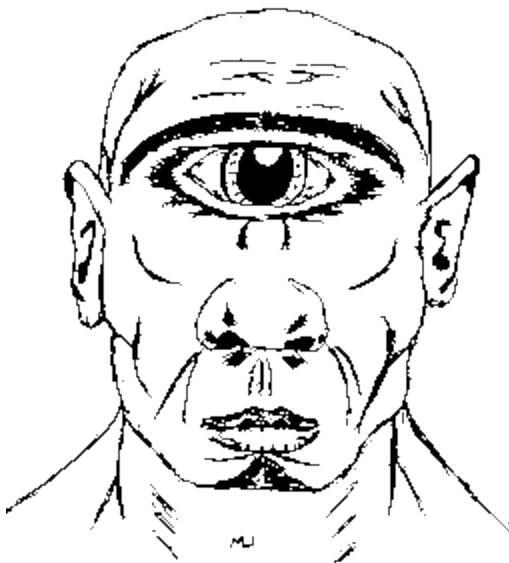
- $X = \text{shading, texture, focus, motion, ...}$
- We'll focus on the motion cue

Stereo Reconstruction

- The Stereo Problem
 - Shape from two (or more) images
 - Biological motivation



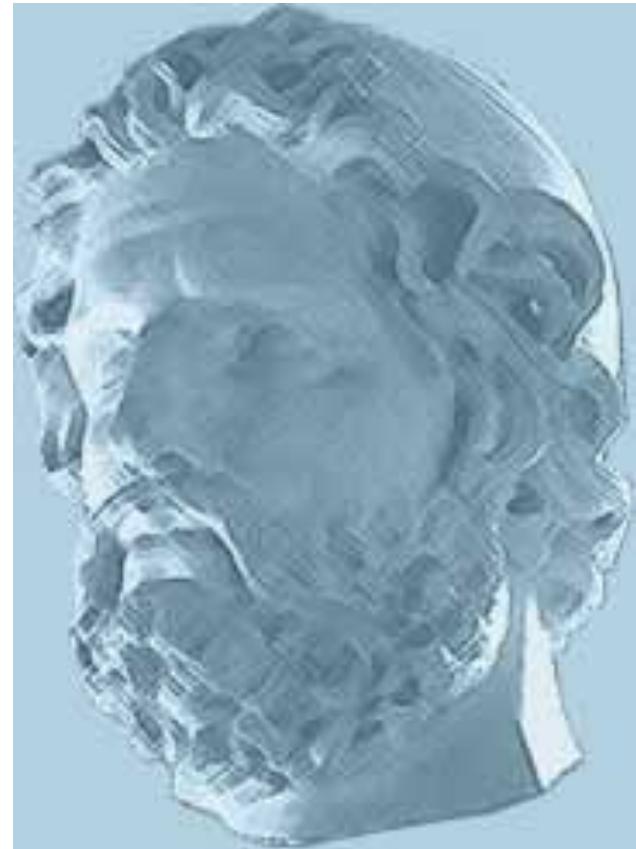
Why do we have two eyes?



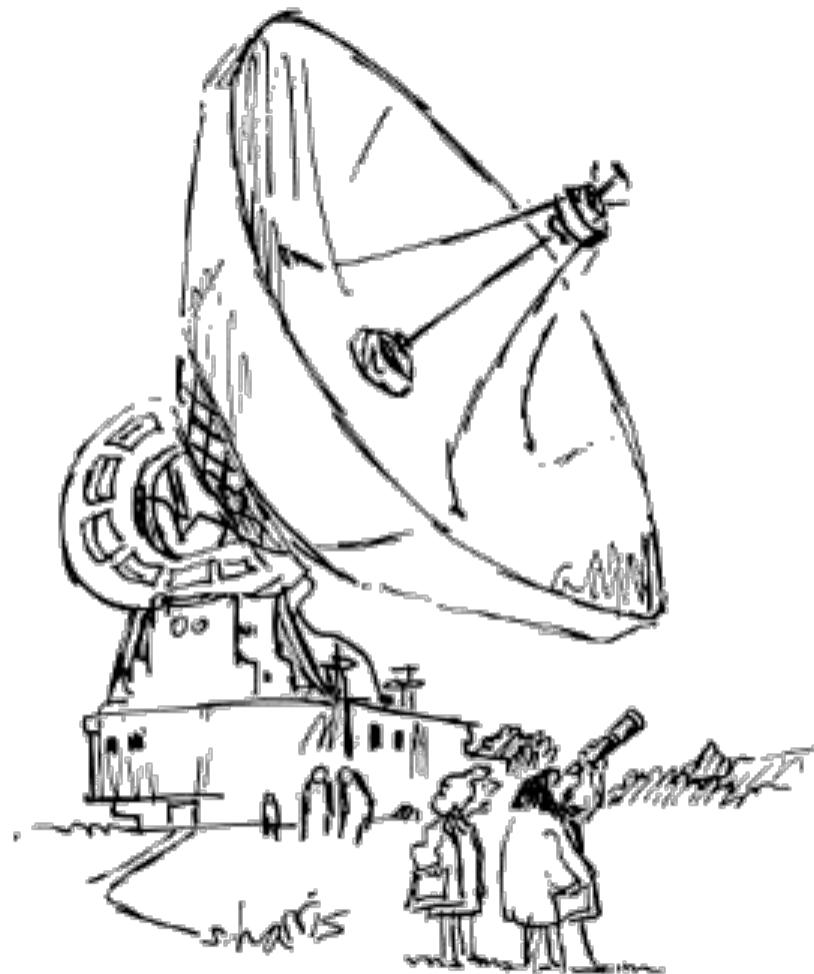
Cyclope

vs.

Odysseus



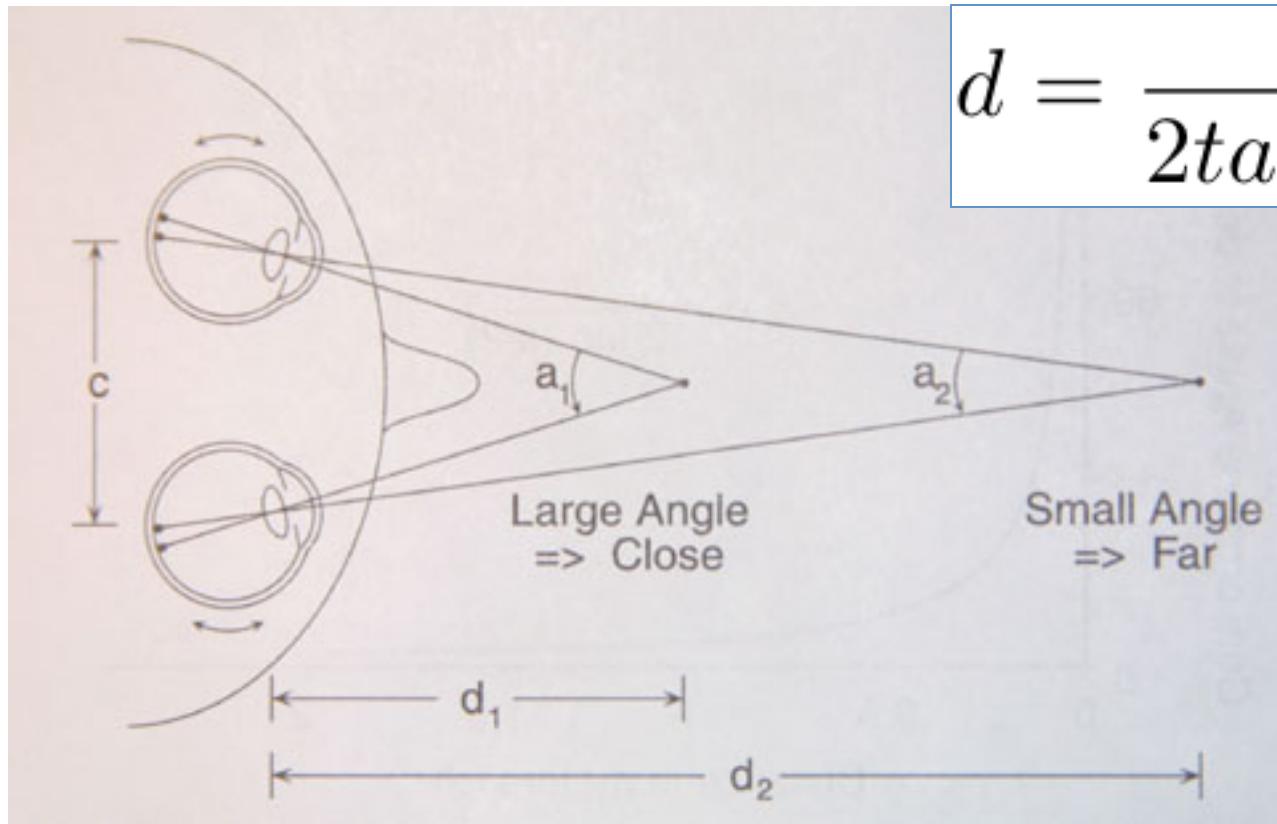
1. Two is better than one



"Just checking."

2. Depth from Convergence

$$d = \frac{c}{2\tan(a/2)}$$



Human performance: up to 6-8 feet

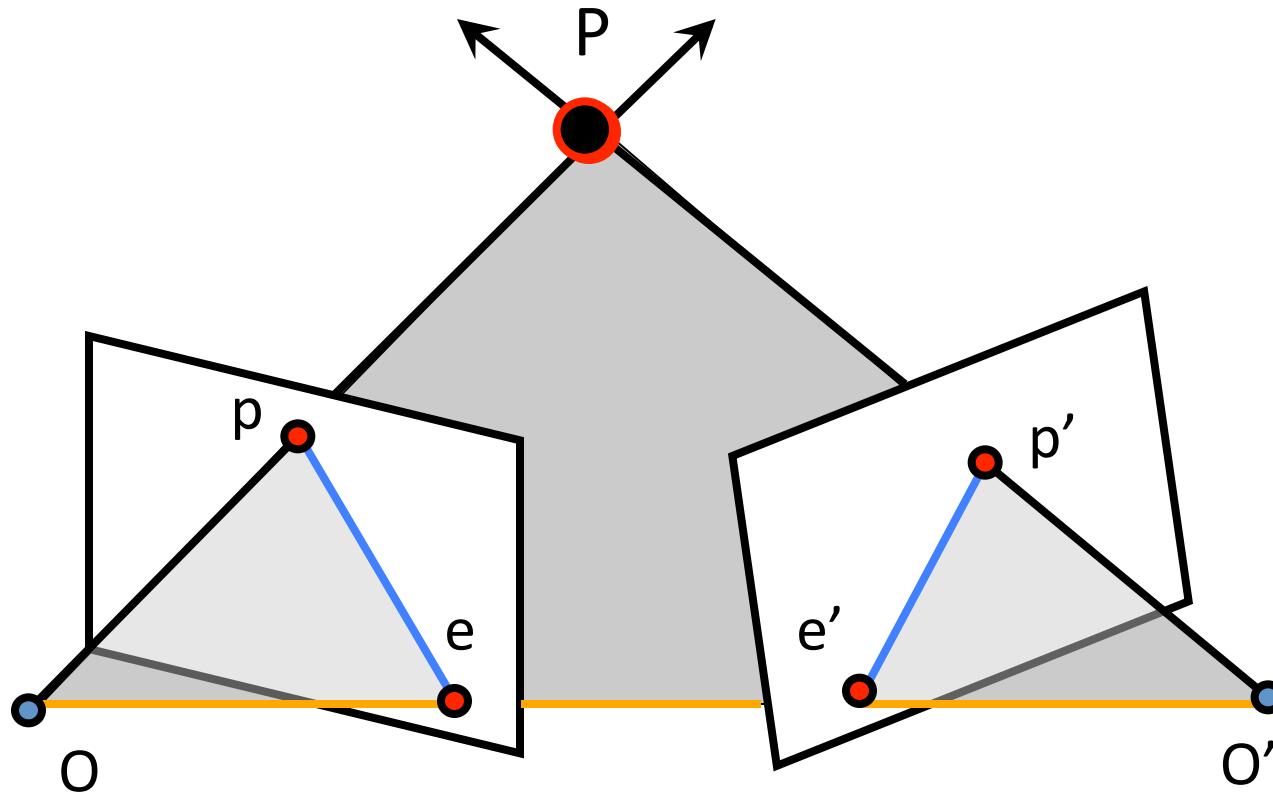
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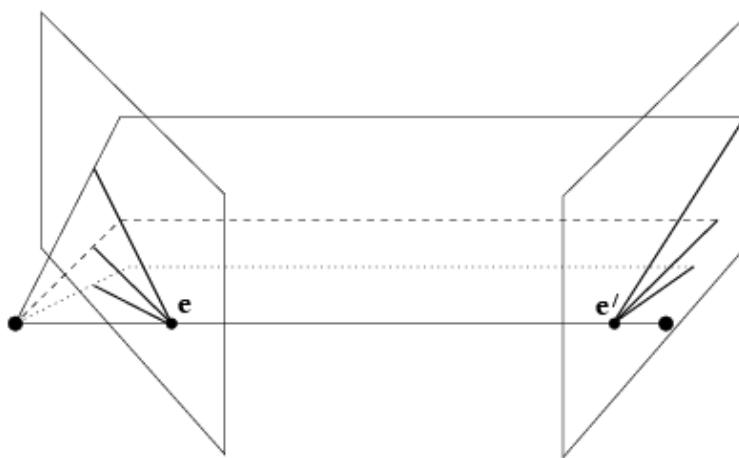
[HZ] Chapters: 4, 9, 11
[FP] Chapters: 10

Epipolar geometry

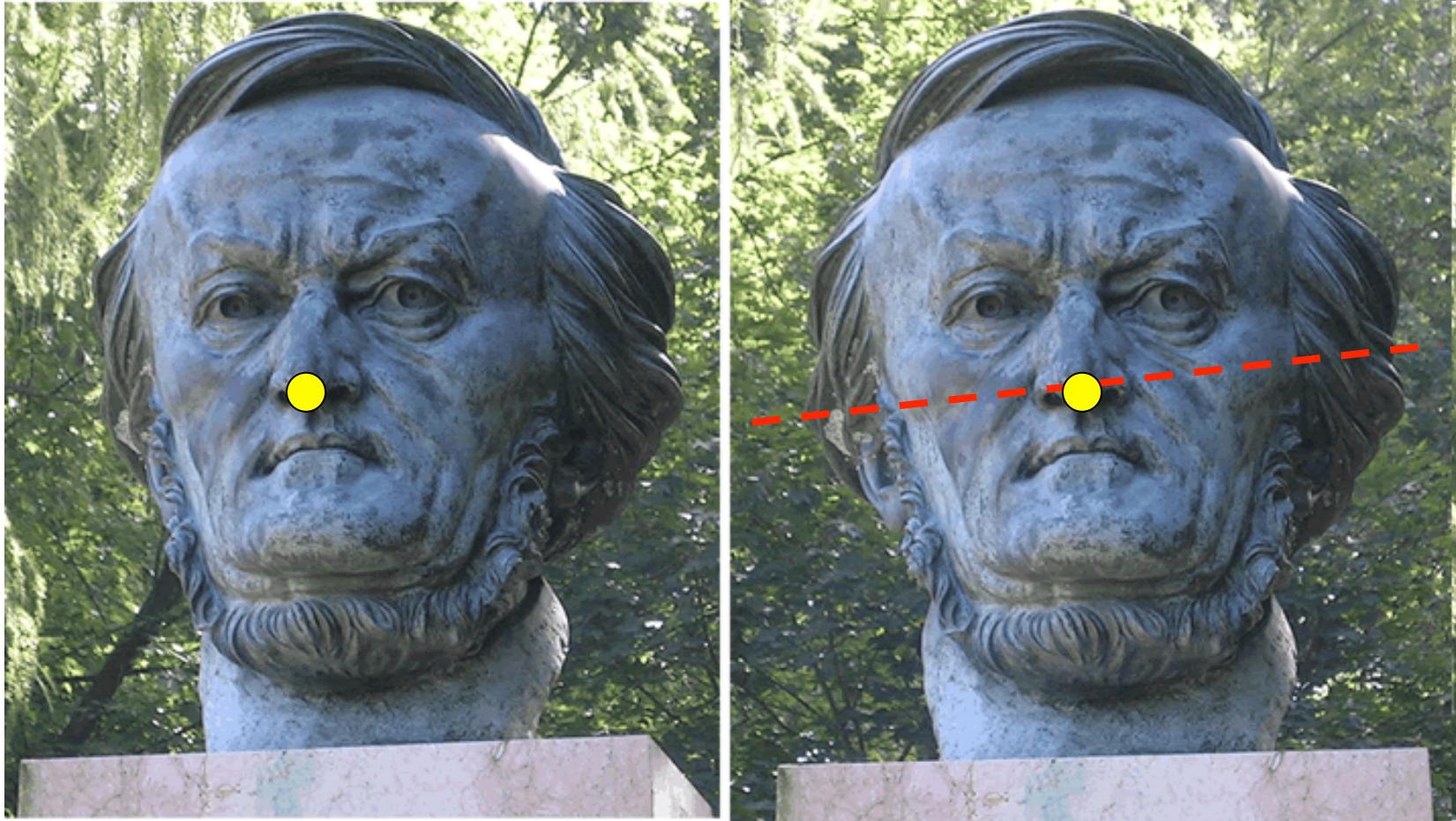


- Epipolar Plane
- Baseline
- Epipolar Lines
- Epipoles e, e'
 - = intersections of baseline with image planes
 - = projections of the other camera center
 - = vanishing points of camera motion direction

Example: Converging image planes

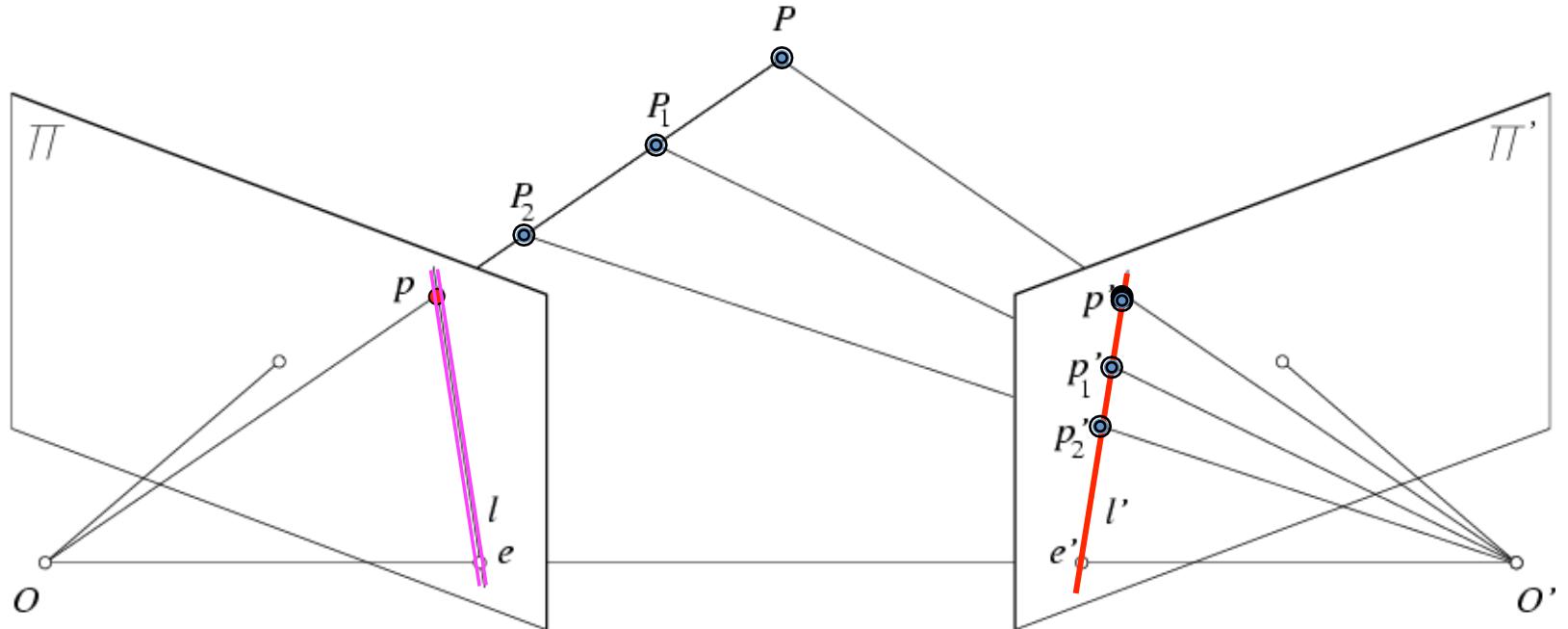


Epipolar Constraint



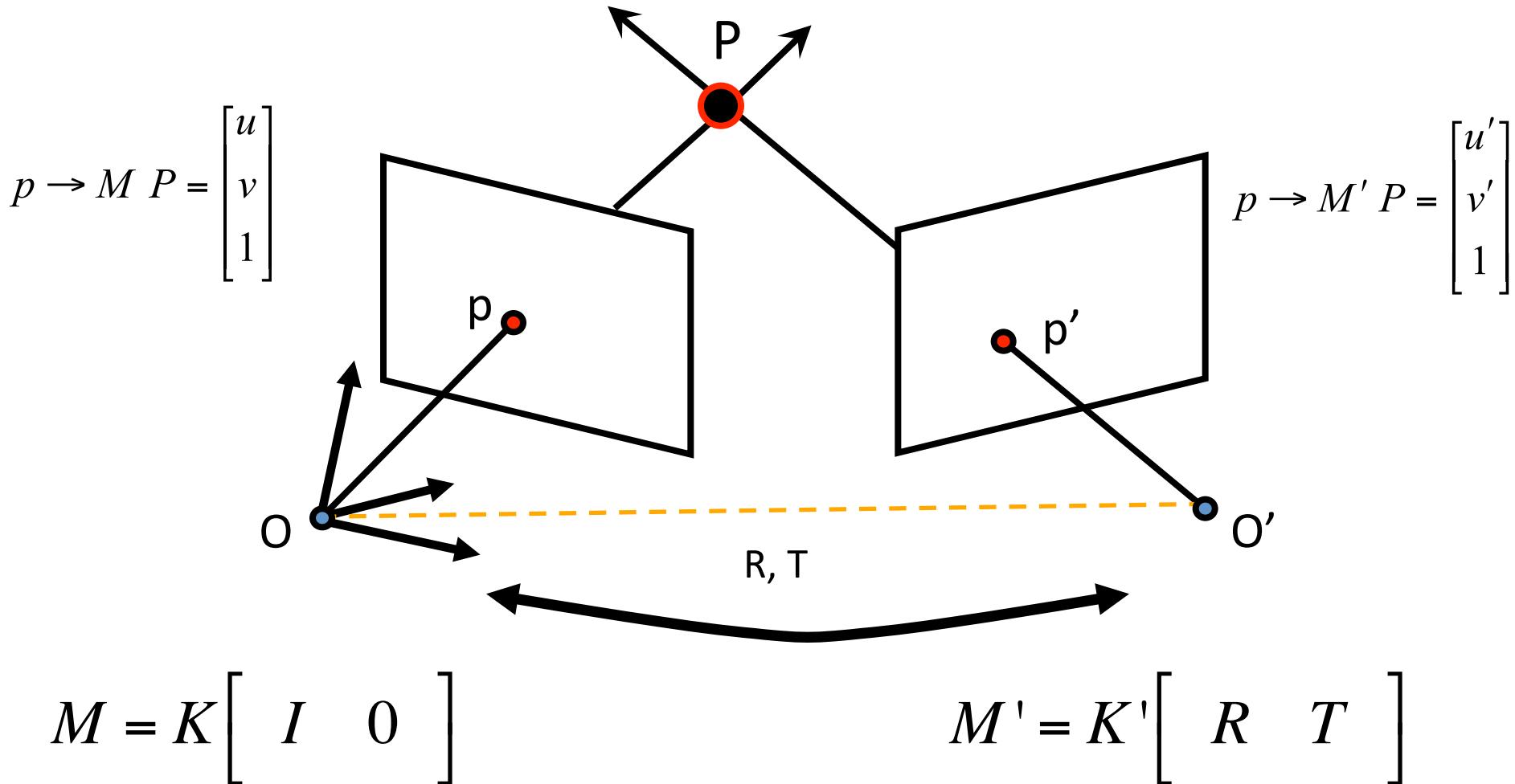
- Two views of the same object
- Suppose I know the camera positions and camera matrices
- Given a point on left image, how can I find the corresponding point on right image?

Epipolar Constraint

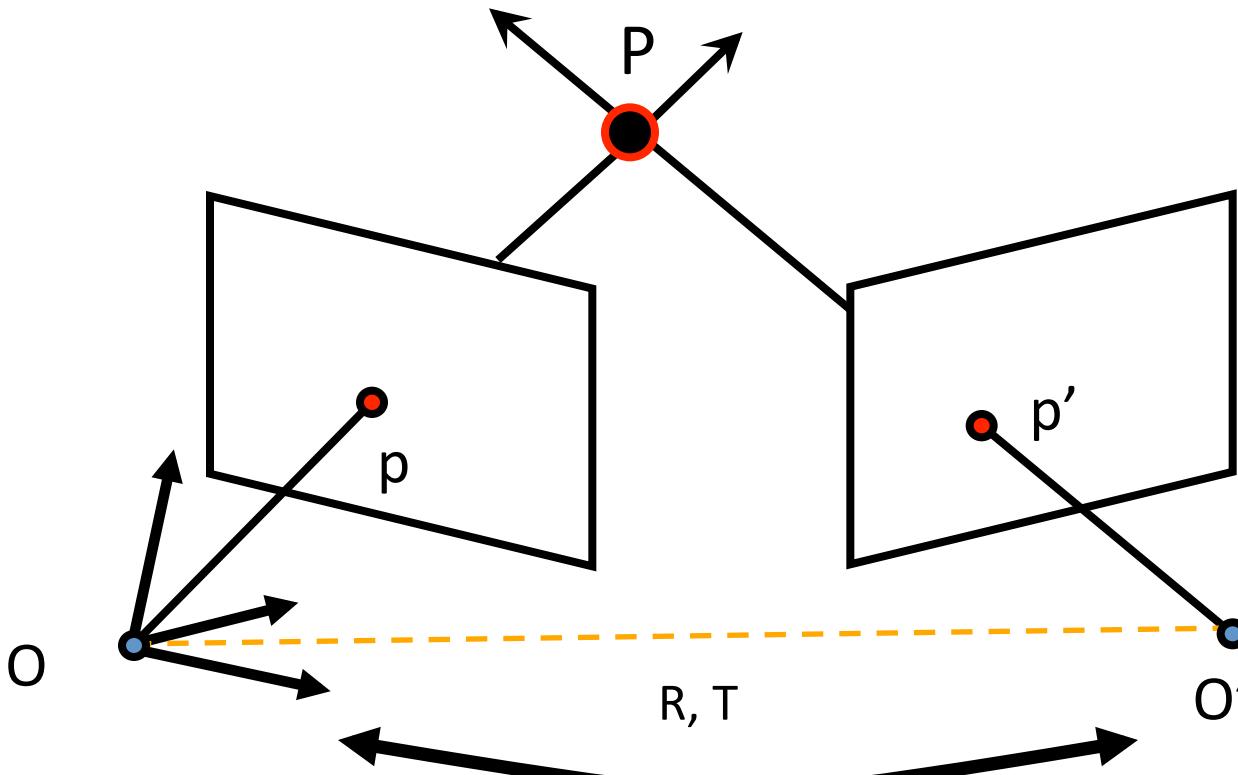


- Potential matches for p have to lie on the corresponding epipolar line l' .
- Potential matches for p' have to lie on the corresponding epipolar line l .

Epipolar Constraint



Epipolar Constraint



$$M = K \begin{bmatrix} I & 0 \end{bmatrix}$$

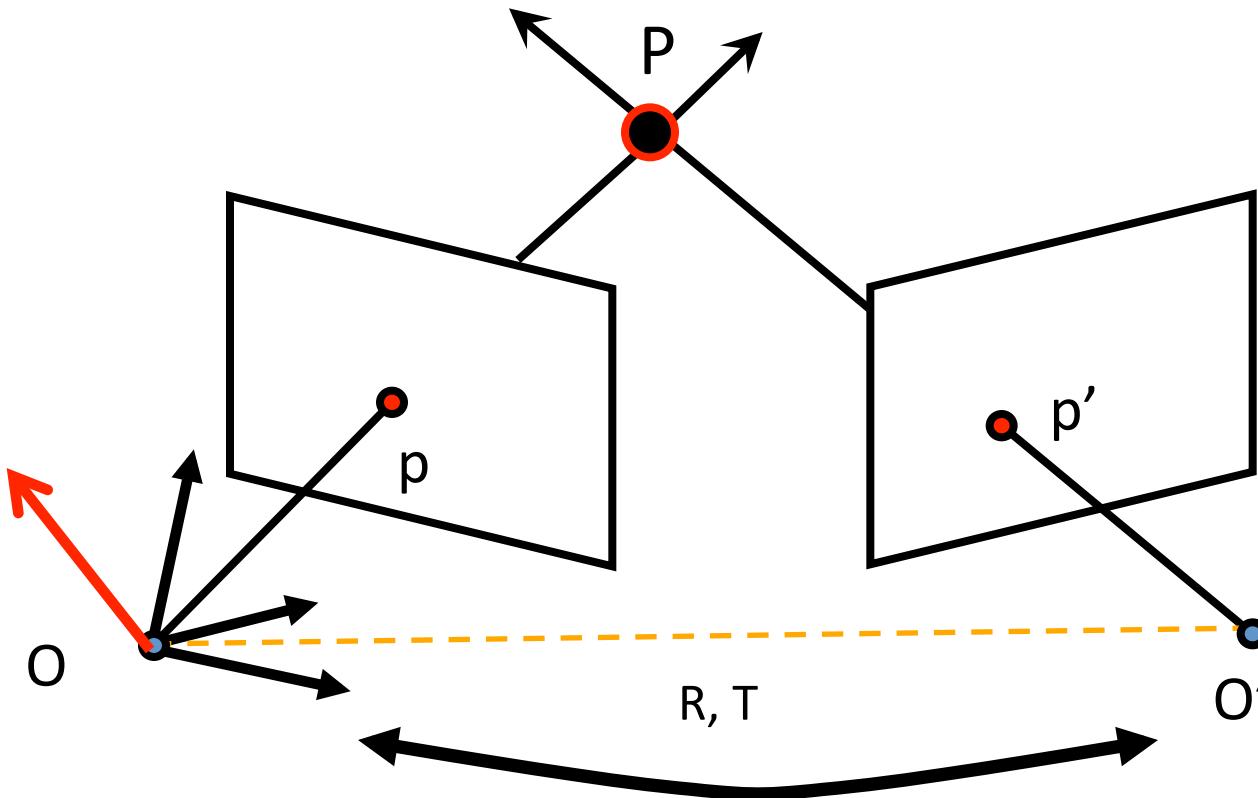
K and K' are known
(calibrated cameras)

$$M = [I \quad 0]$$

$$M' = K' \begin{bmatrix} R & T \end{bmatrix}$$

$$M' = [R \quad T]$$

Epipolar Constraint



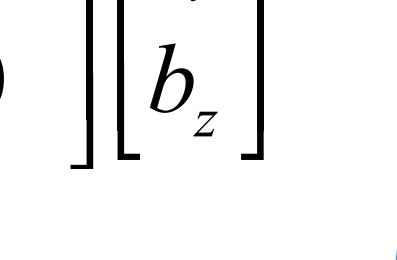
$$T \times (R p')$$

Perpendicular to epipolar plane

$$p^T \cdot [T \times (R p')] = 0$$

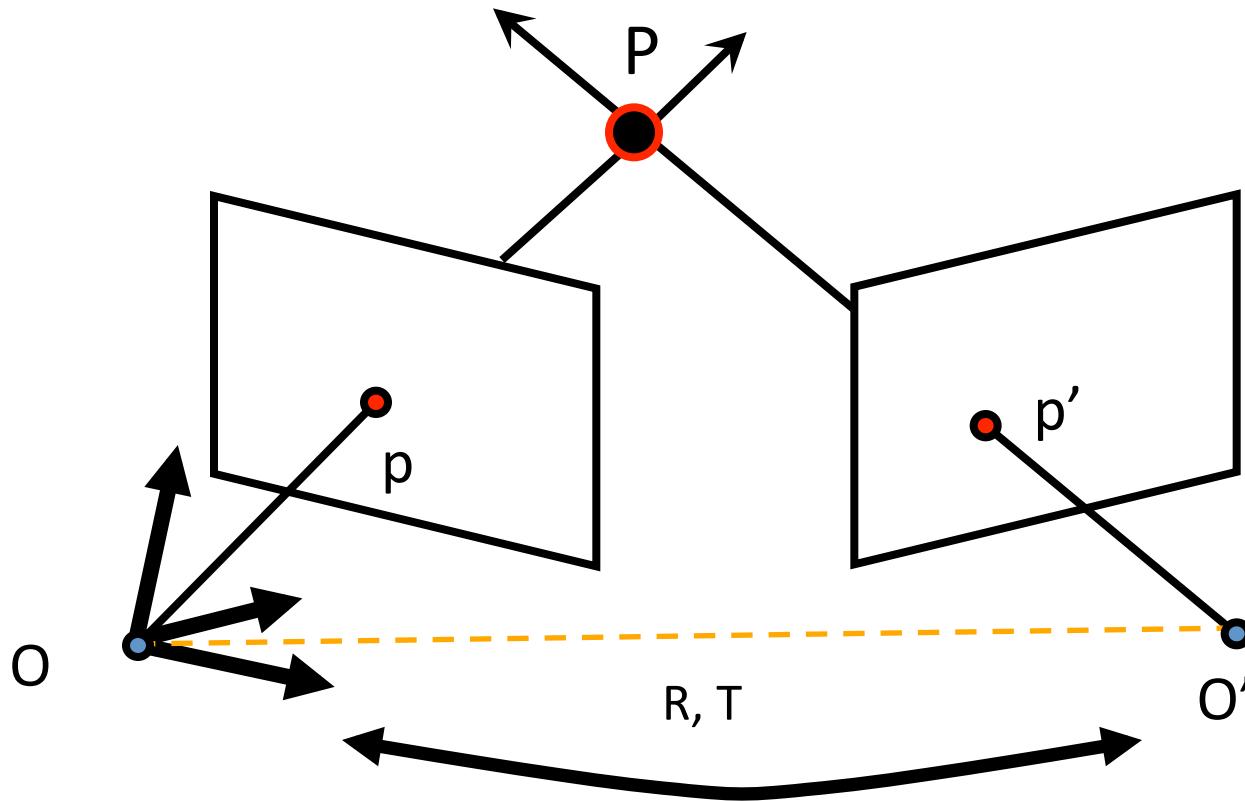
Cross product as matrix multiplication

$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix} \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} = [\mathbf{a}_x] \mathbf{b}$$



“skew symmetric matrix”

Epipolar Constraint

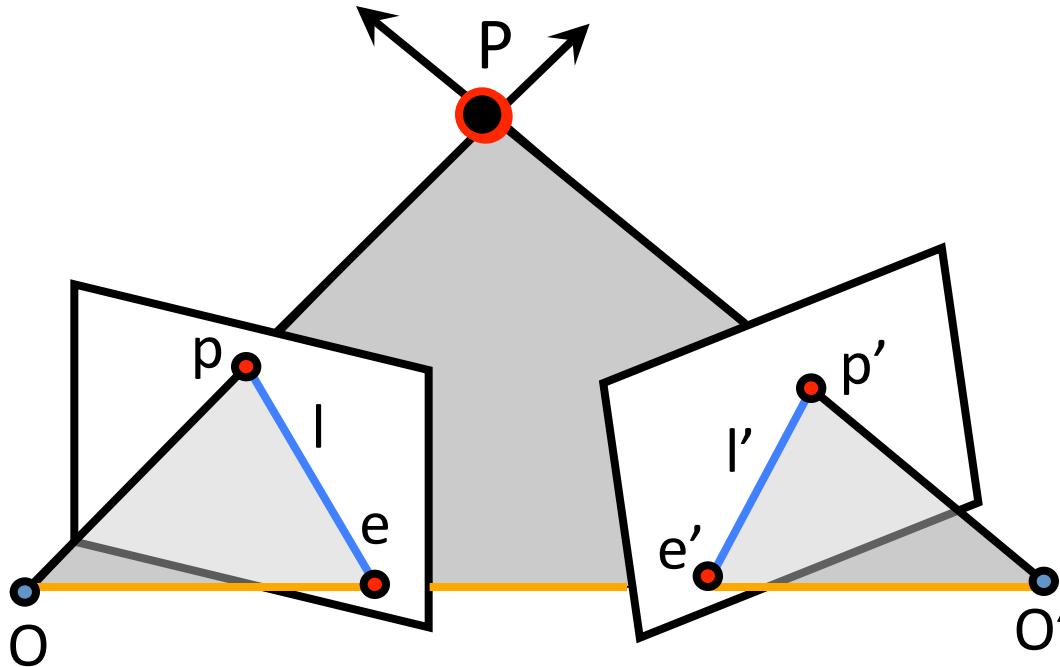


$$p^T \cdot [T \times (R p')] = 0 \rightarrow p^T \cdot [T_x] \cdot R p' = 0$$

(Longuet-Higgins, 1981)

E = essential matrix

Epipolar Constraint



- $E p'$ is the epipolar line associated with p' ($l = E p'$)
- $E^T p$ is the epipolar line associated with p ($l' = E^T p$)
- E is singular (rank two)
- $E e' = 0$ and $E^T e = 0$
- E is 3×3 matrix; 5 DOF

What we will learn today?

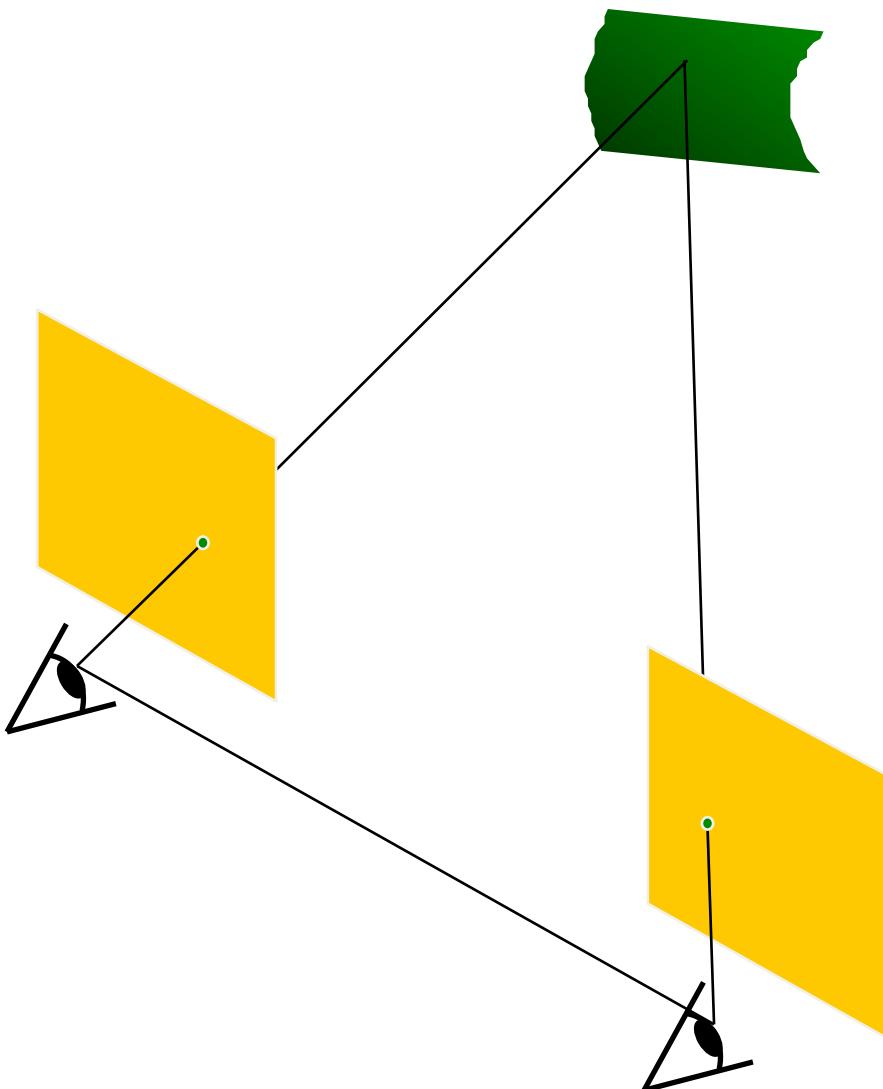
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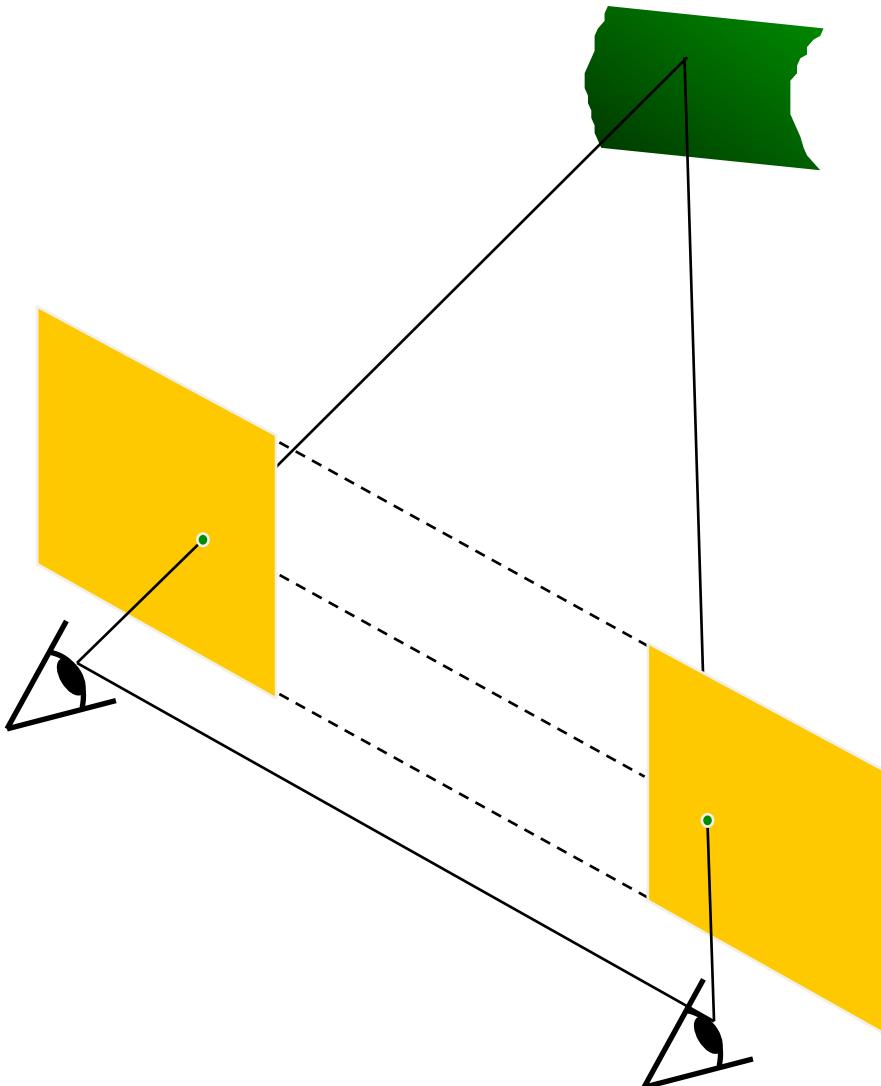
[FP] Chapters: 10

Simplest Case: Parallel images



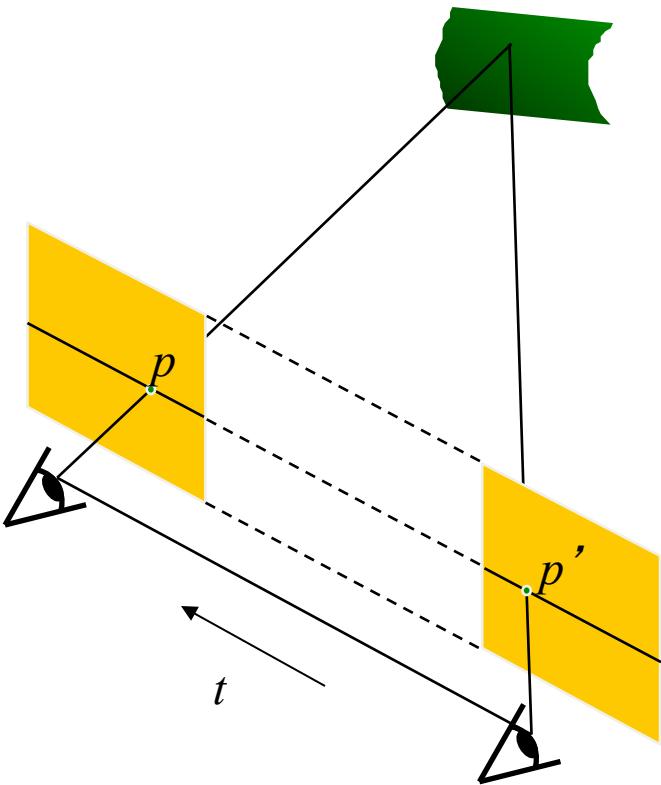
- Image planes of cameras are parallel to each other and to the baseline
- Camera centers are at same height
- Focal lengths are the same

Simplest Case: Parallel images



- Image planes of cameras are parallel to each other and to the baseline
- Camera centers are at same height
- Focal lengths are the same
- Then, epipolar lines fall along the horizontal scan lines of the images

Essential matrix for parallel images



Epipolar constraint:

$$R = I \quad t = (T, 0, 0)$$

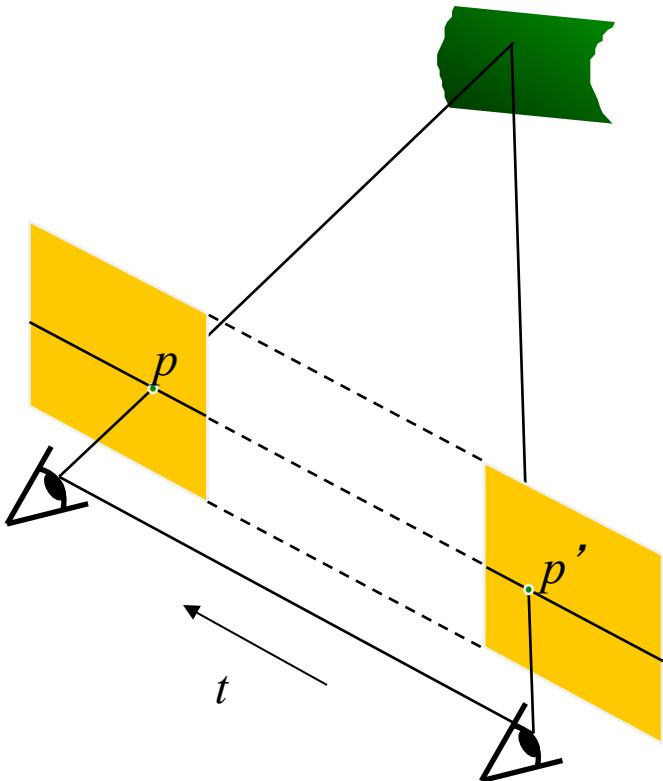
$$p^T E p' = 0, \quad E = [t_x]R$$

$$E = [t_x]R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

Reminder: skew symmetric matrix

$$[a_x] = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix}$$

Essential matrix for parallel images



Epipolar constraint:

$$R = I \quad t = (T, 0, 0)$$

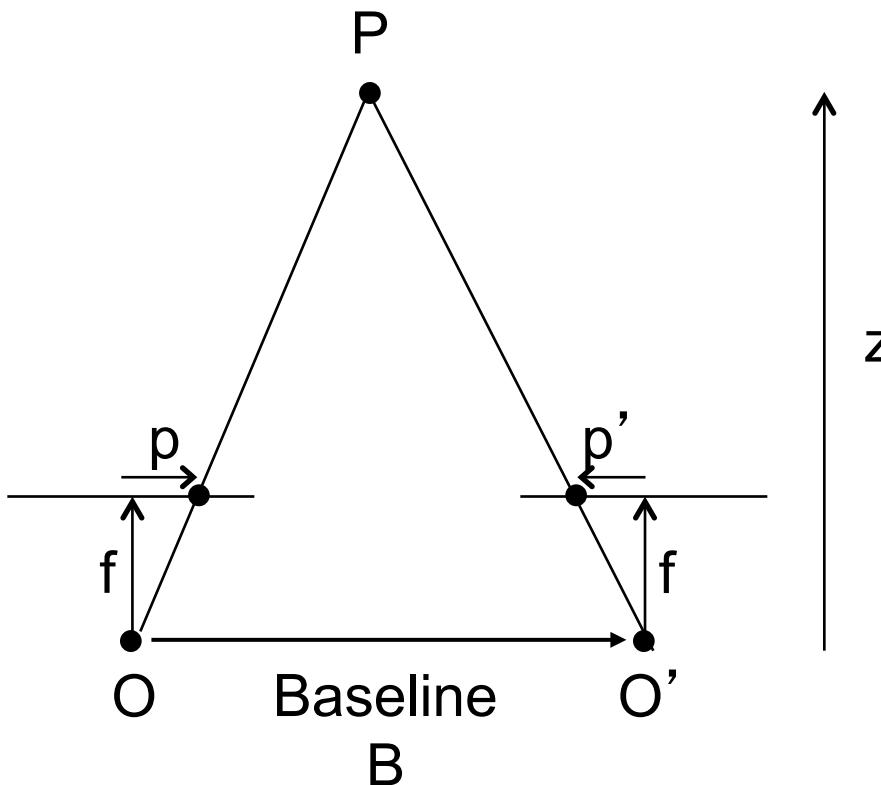
$$p^T E p' = 0, \quad E = [t_x]R$$

$$E = [t_x]R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

$$(u \quad v \quad 1) \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix} \begin{pmatrix} u' \\ v' \\ 1 \end{pmatrix} = 0 \quad (u \quad v \quad 1) \begin{pmatrix} 0 \\ -T \\ Tv' \end{pmatrix} = 0 \quad Tv = Tv'$$

The y-coordinates of corresponding points are the same!

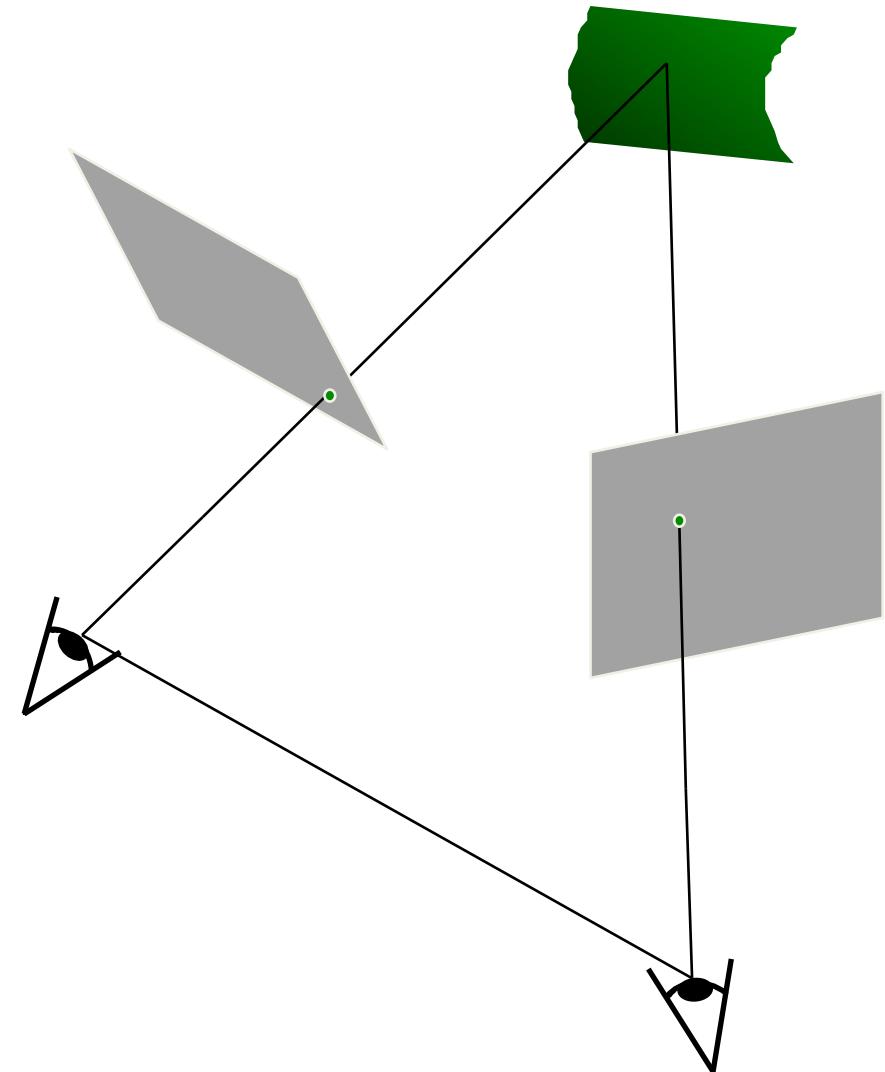
Triangulation -- depth from disparity



$$\text{disparity} = u - u' = \frac{B \cdot f}{z}$$

Disparity is inversely proportional to depth!

Stereo image rectification

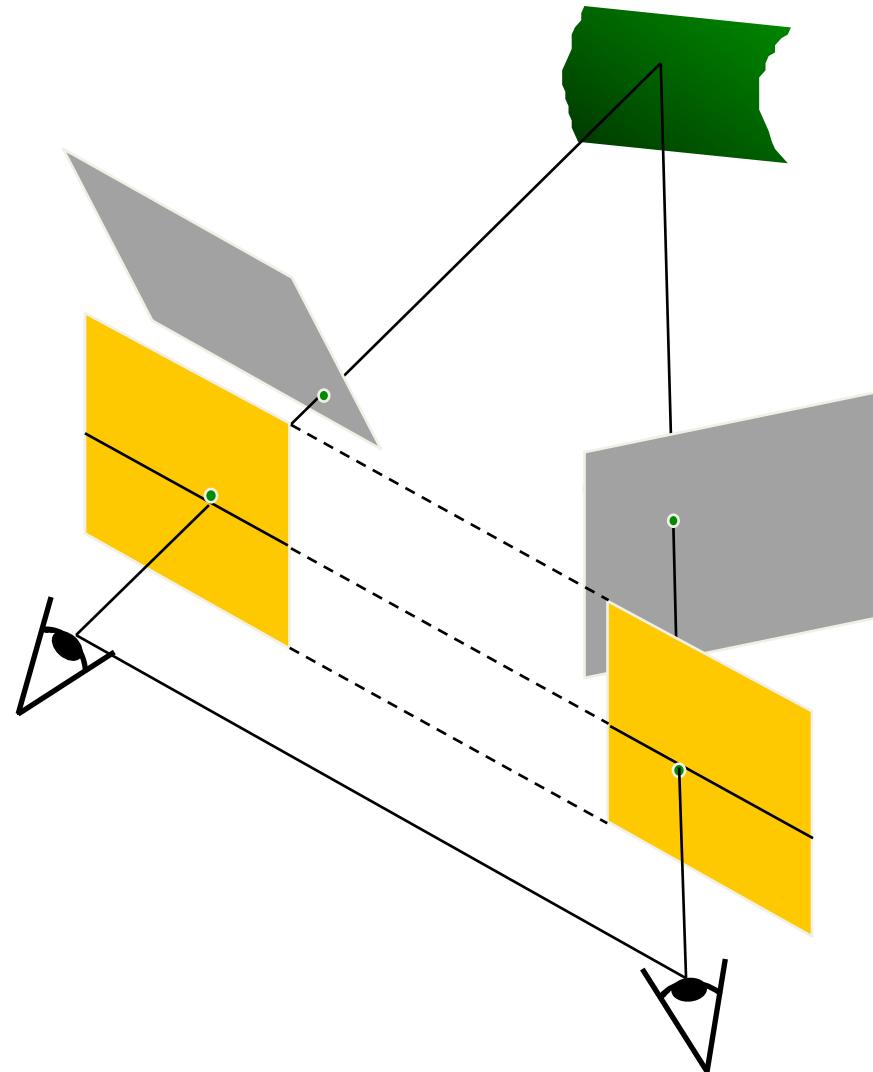


Slide credit: J. Hayes

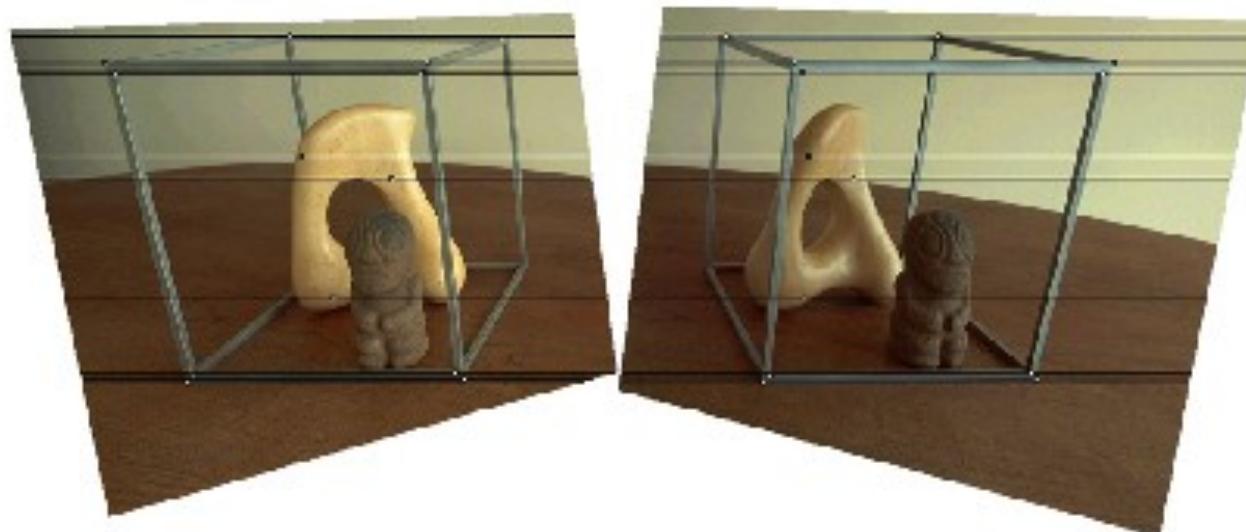
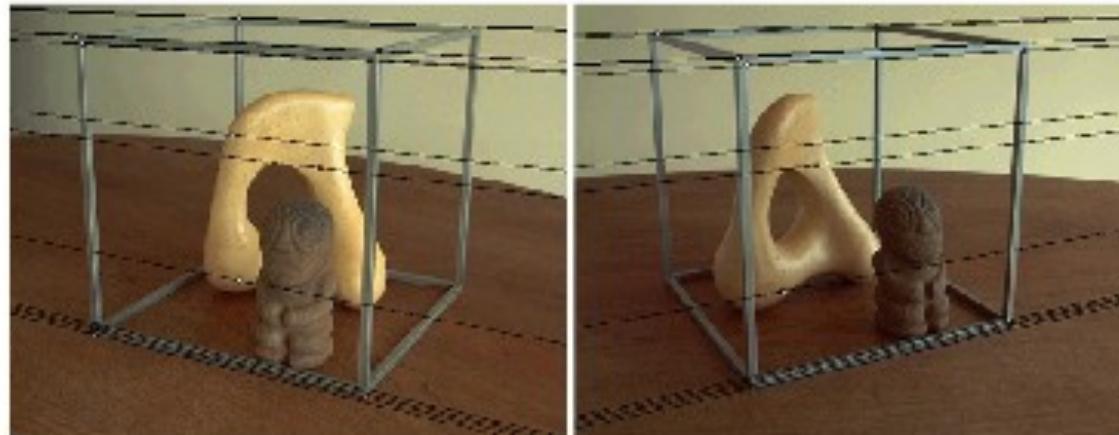
Stereo image rectification

Algorithm:

- Re-project image planes onto a common plane parallel to the line between optical centers
 - Pixel motion is horizontal after this transformation
 - Two transformation matrices, one for each input image reprojection
- C. Loop and Z. Zhang,
[Computing Rectifying Homographies for Stereo Vision](#). IEEE Conf. Computer Vision and Pattern Recognition, 1999.

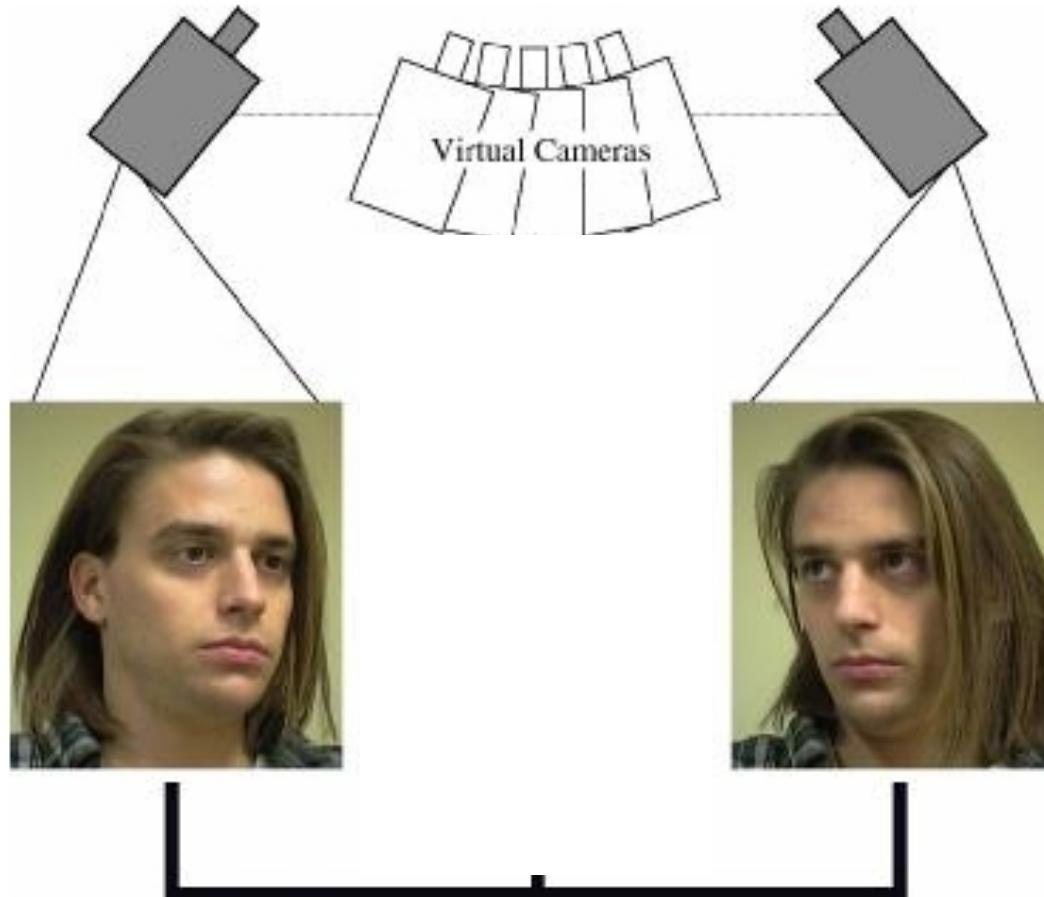


Rectification example

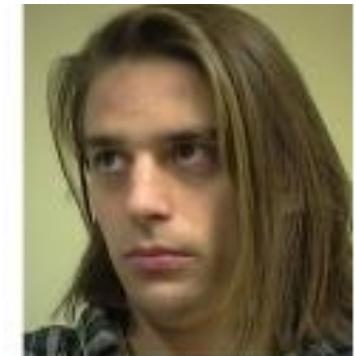


Application: view morphing

S. M. Seitz and C. R. Dyer, *Proc. SIGGRAPH 96*, 1996, 21-30



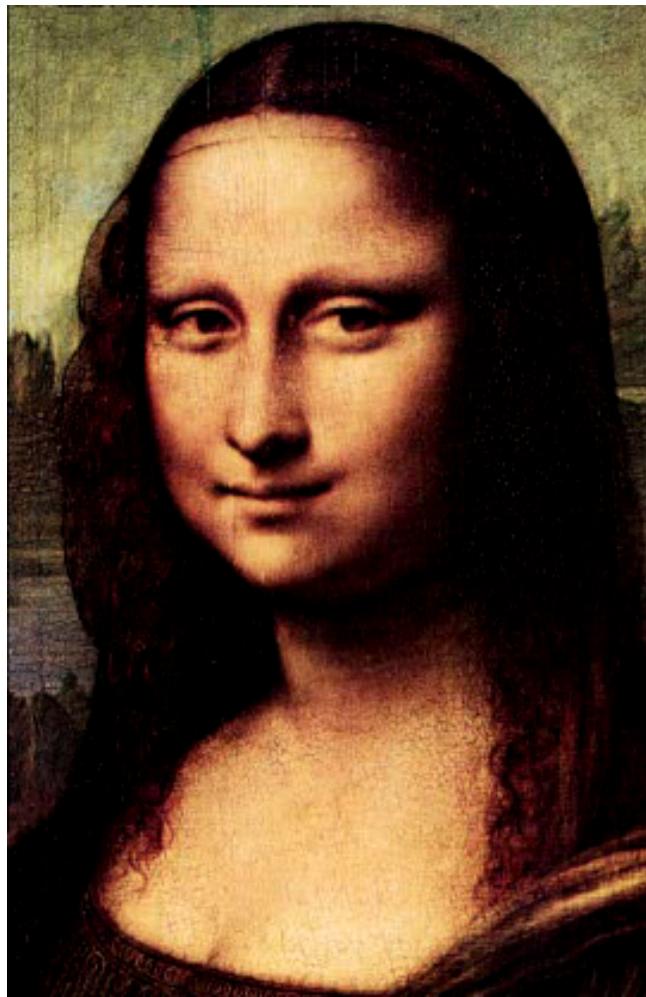
Application: view morphing



Application: view morphing

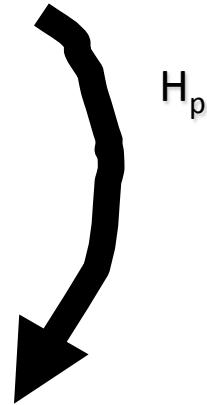


Application: view morphing



Removing perspective distortion

(rectification)



What we will learn today?

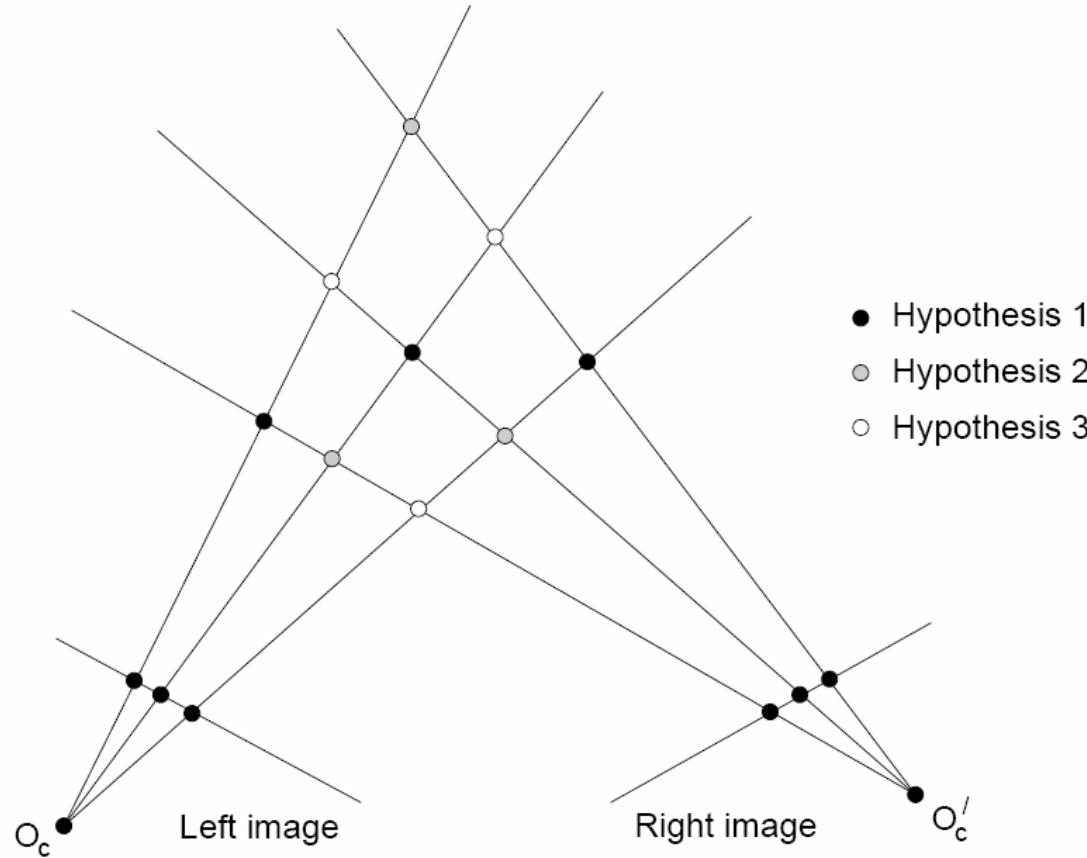
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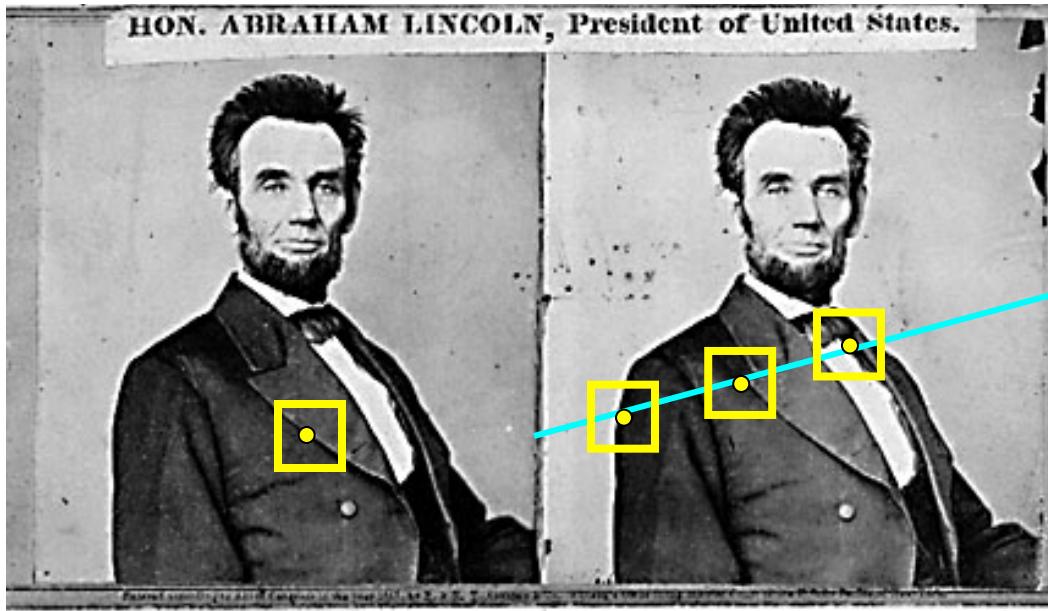
[FP] Chapters: 10

Stereo matching: solving the correspondence problem



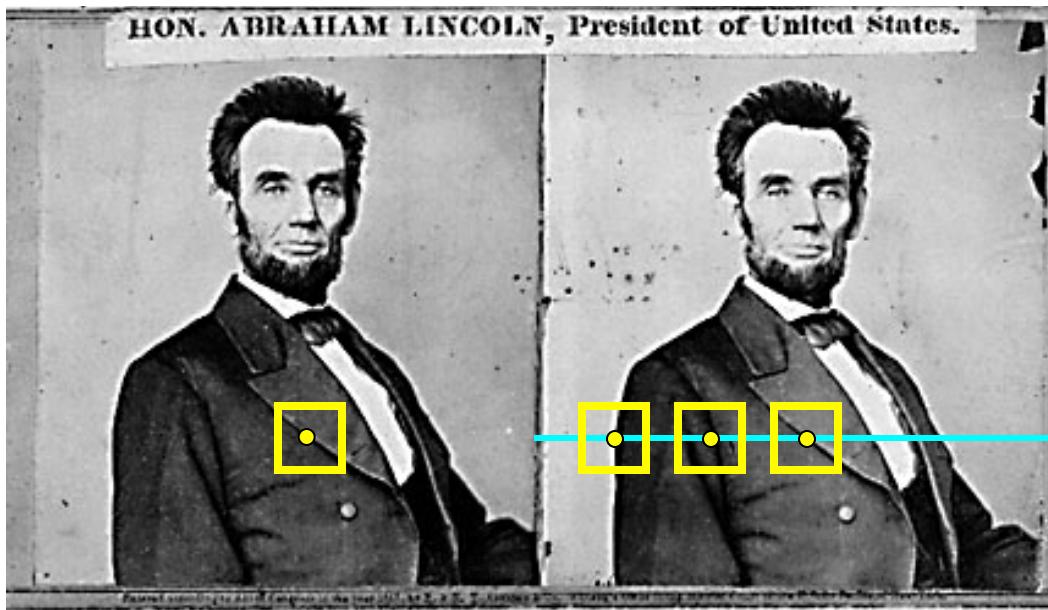
- Goal: finding matching points between two images

Basic stereo matching algorithm



- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Examine all pixels on the epipolar line and pick the best match
 - Triangulate the matches to get depth information
- Simplest case: epipolar lines are scanlines
 - When does this happen?

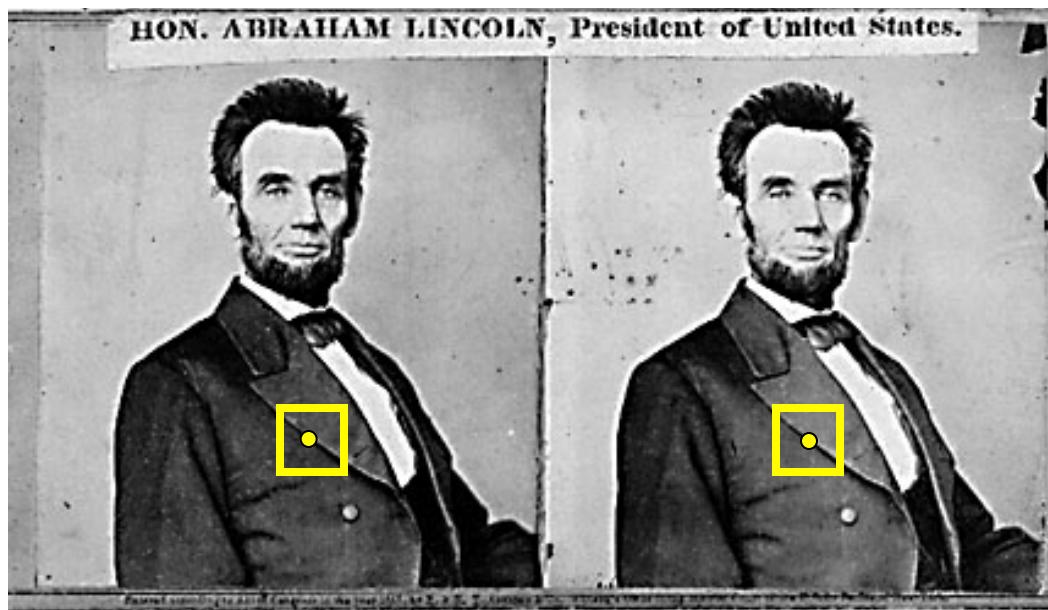
Basic stereo matching algorithm



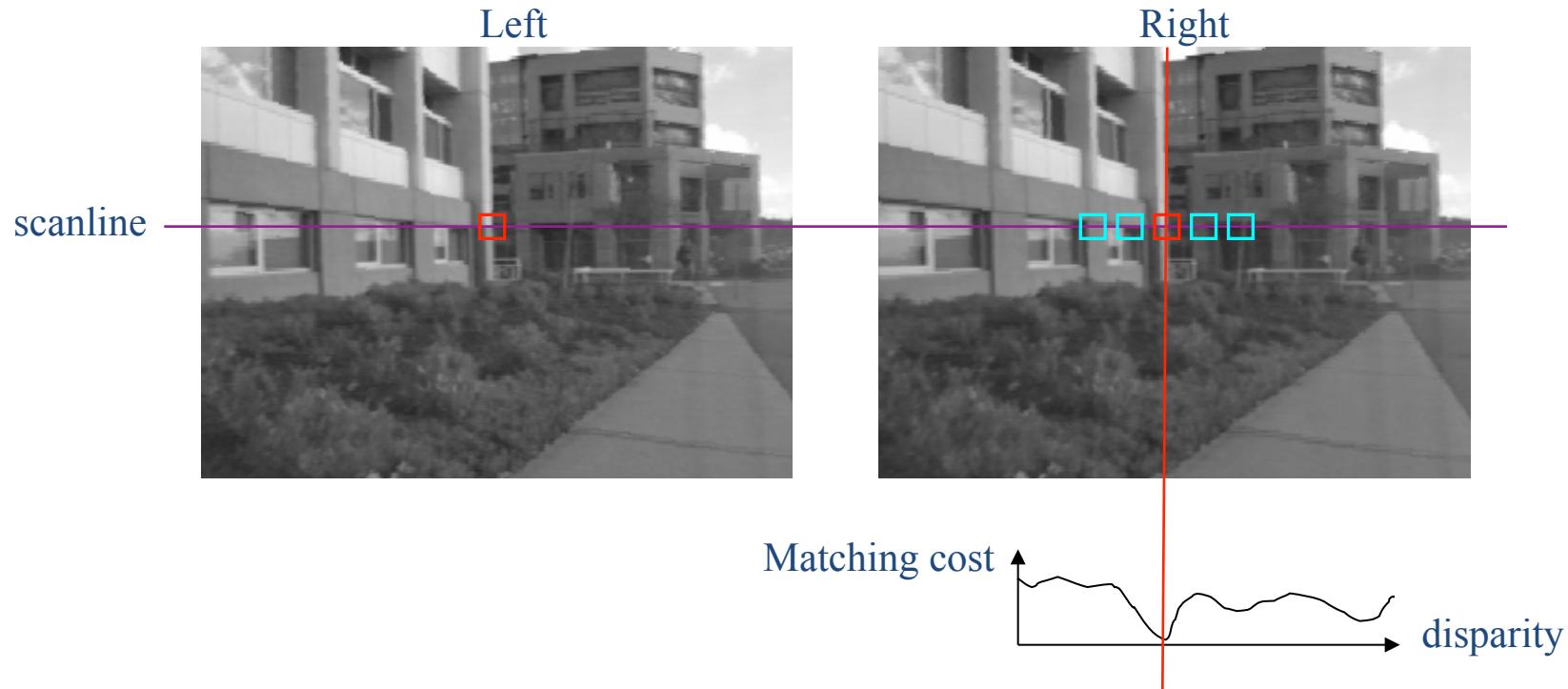
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find **corresponding** epipolar scanline in the right image
 - Examine all pixels on the scanline and pick the best match x'
 - Compute disparity $x-x'$ and set $\text{depth}(x) = 1/(x-x')$

Correspondence problem

- Let's make some assumptions to simplify the matching problem
 - The baseline is relatively small (compared to the depth of scene points)
 - Then most scene points are visible in both views
 - Also, matching regions are similar in appearance

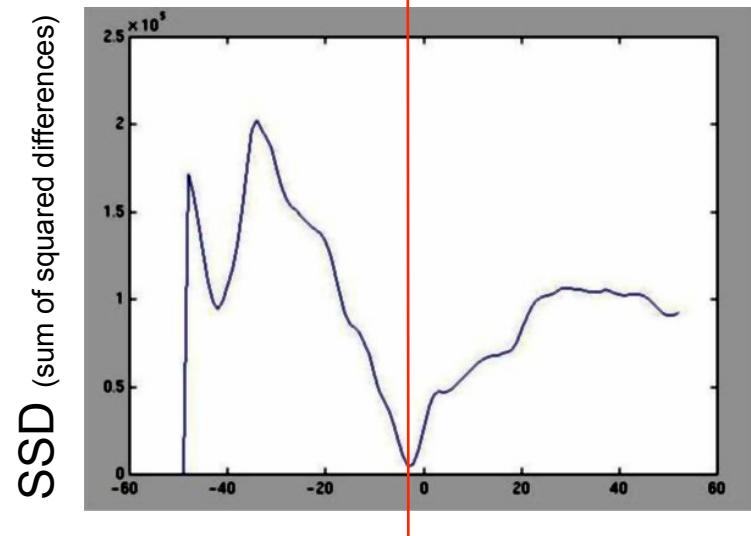
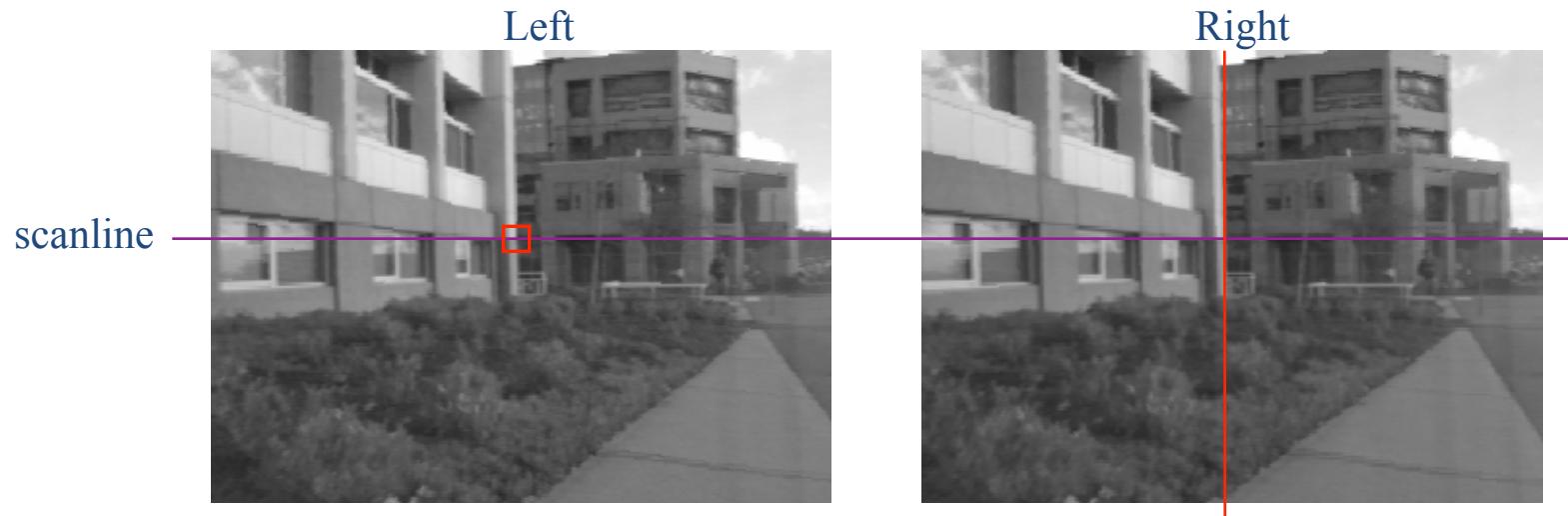


Correspondence search with similarity constraint

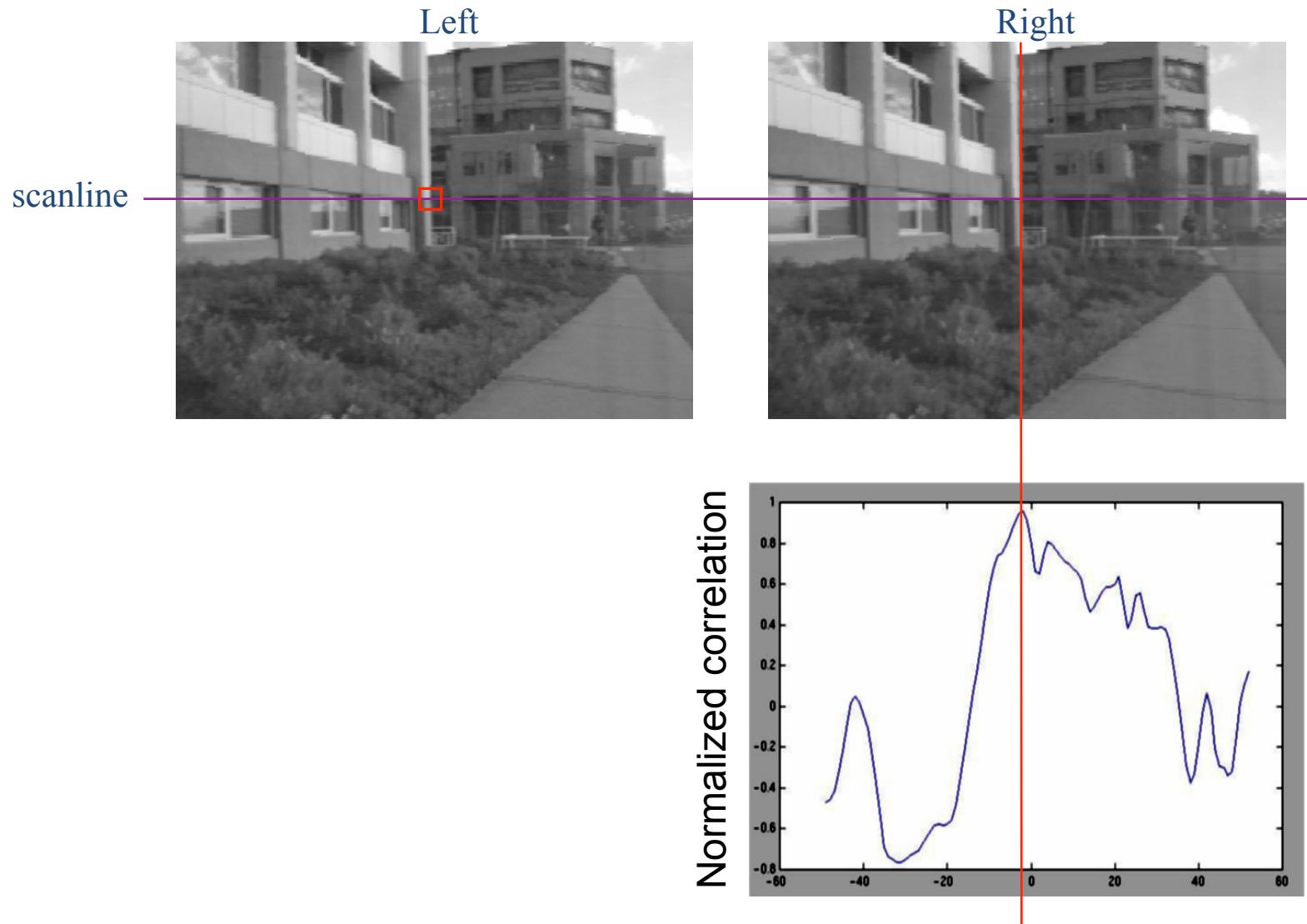


- Slide a window along the right scanline and compare contents of that window with the reference window in the left image
- Matching cost: SSD or normalized correlation

Correspondence search with similarity constraint



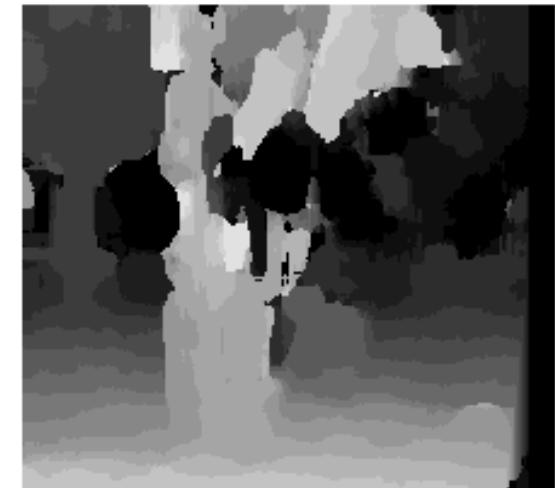
Correspondence search with similarity constraint



Effect of window size



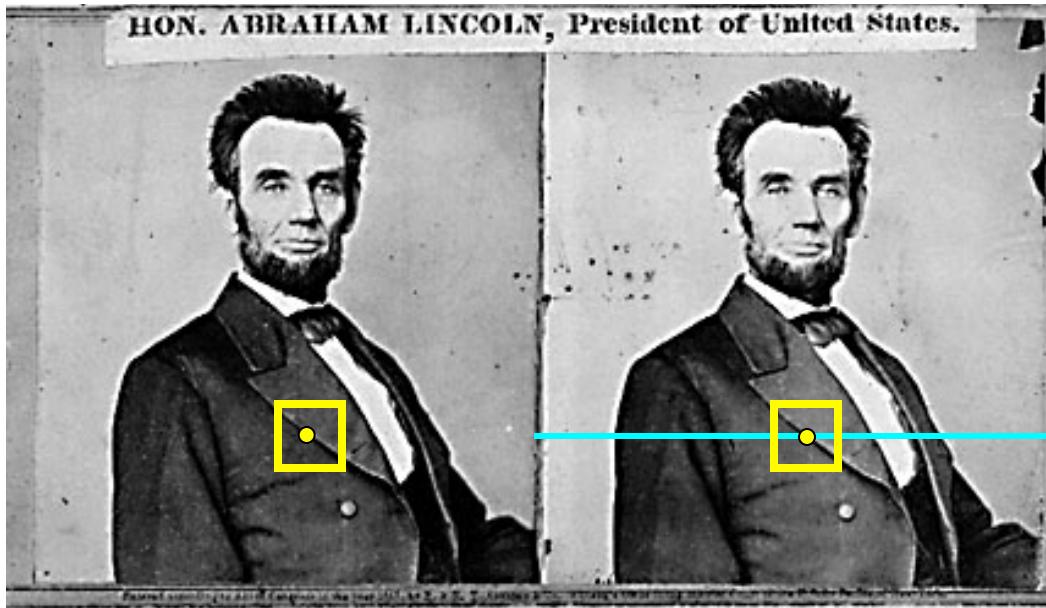
$$W = 3$$



$$W = 20$$

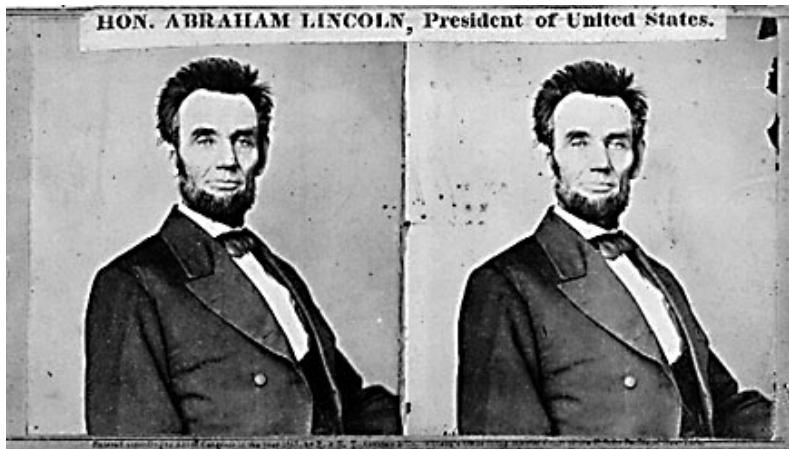
- Smaller window
 - + More detail
 - More noise
- Larger window
 - + Smoother disparity maps
 - Less detail

The similarity constraint



- Corresponding regions in two images should be similar in appearance
- ...and non-corresponding regions should be different
- When will the similarity constraint fail?

Limitations of similarity constraint



Textureless surfaces



Occlusions, repetition



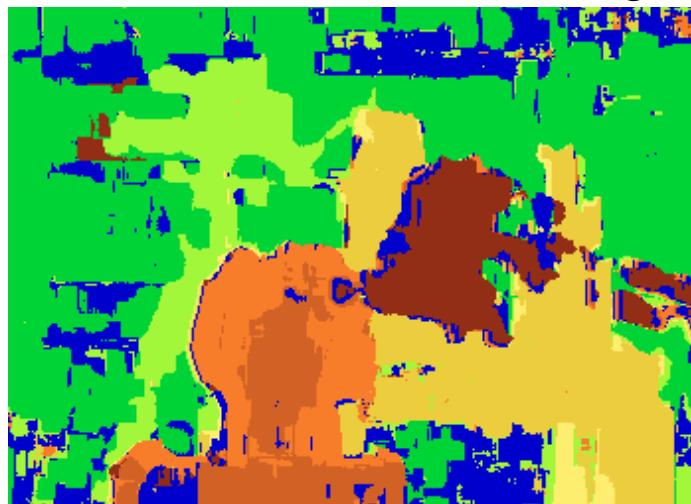
Specular surfaces



Results with window search



Window-based matching



Ground truth



Better methods exist... (CS231a)



Graph cuts

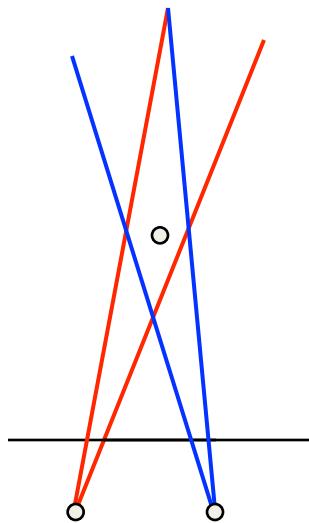


Ground truth

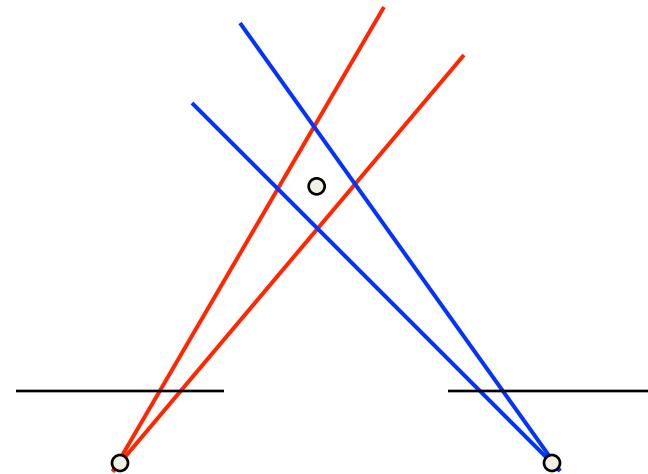
Y. Boykov, O. Veksler, and R. Zabih,

Fast Approximate Energy Minimization via Graph Cuts, PAMI 2001

The role of the baseline



Small Baseline

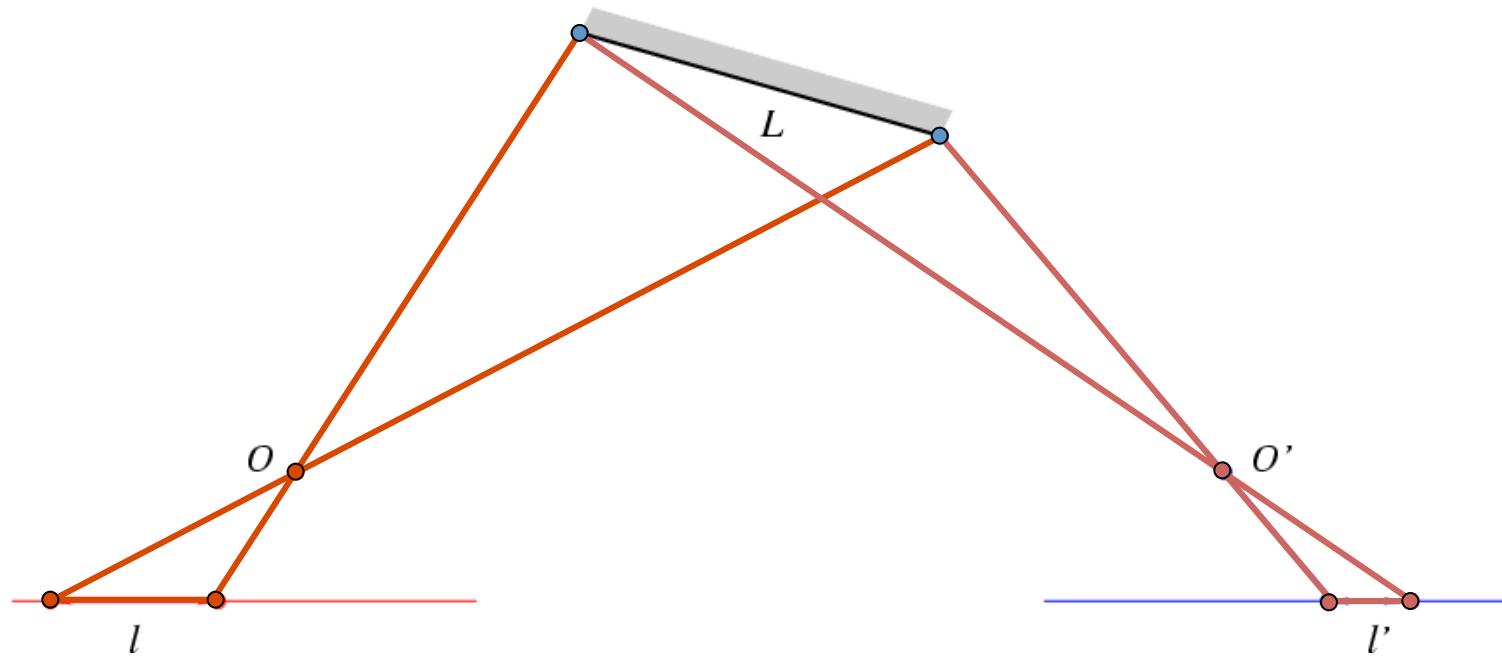


Large Baseline

- Small baseline: large depth error
- Large baseline: difficult search problem

Slide credit: S. Seitz

Problem for wide baselines: Foreshortening



- Matching with fixed-size windows will fail!
- Possible solution: adaptively vary window size
- Another solution: *model-based stereo* (CS231a)

Slide credit: J. Hayes

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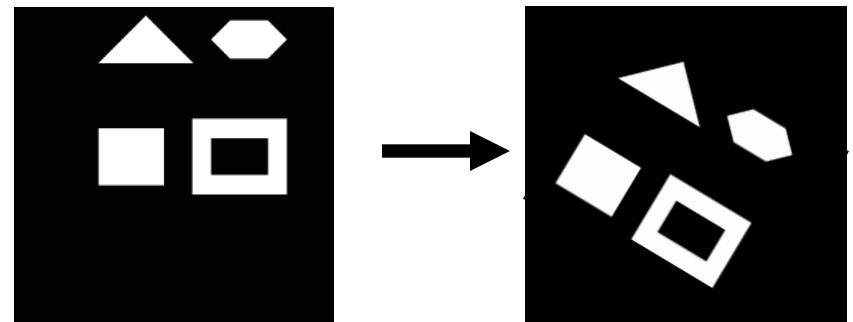
[HZ] Chapters: 4, 9, 11
[FP] Chapters: 10

Reminder: transformations in 2D

Special case
from lecture 2
(planar rotation
& translation)

$$\begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = \begin{bmatrix} R & t \\ 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = H_e \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

- 3 DOF
- Preserve distance (areas)
- Regulate motion
of rigid object

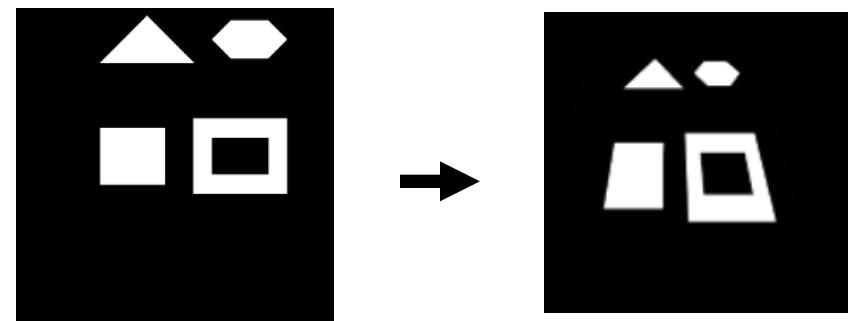


Reminder: transformations in 2D

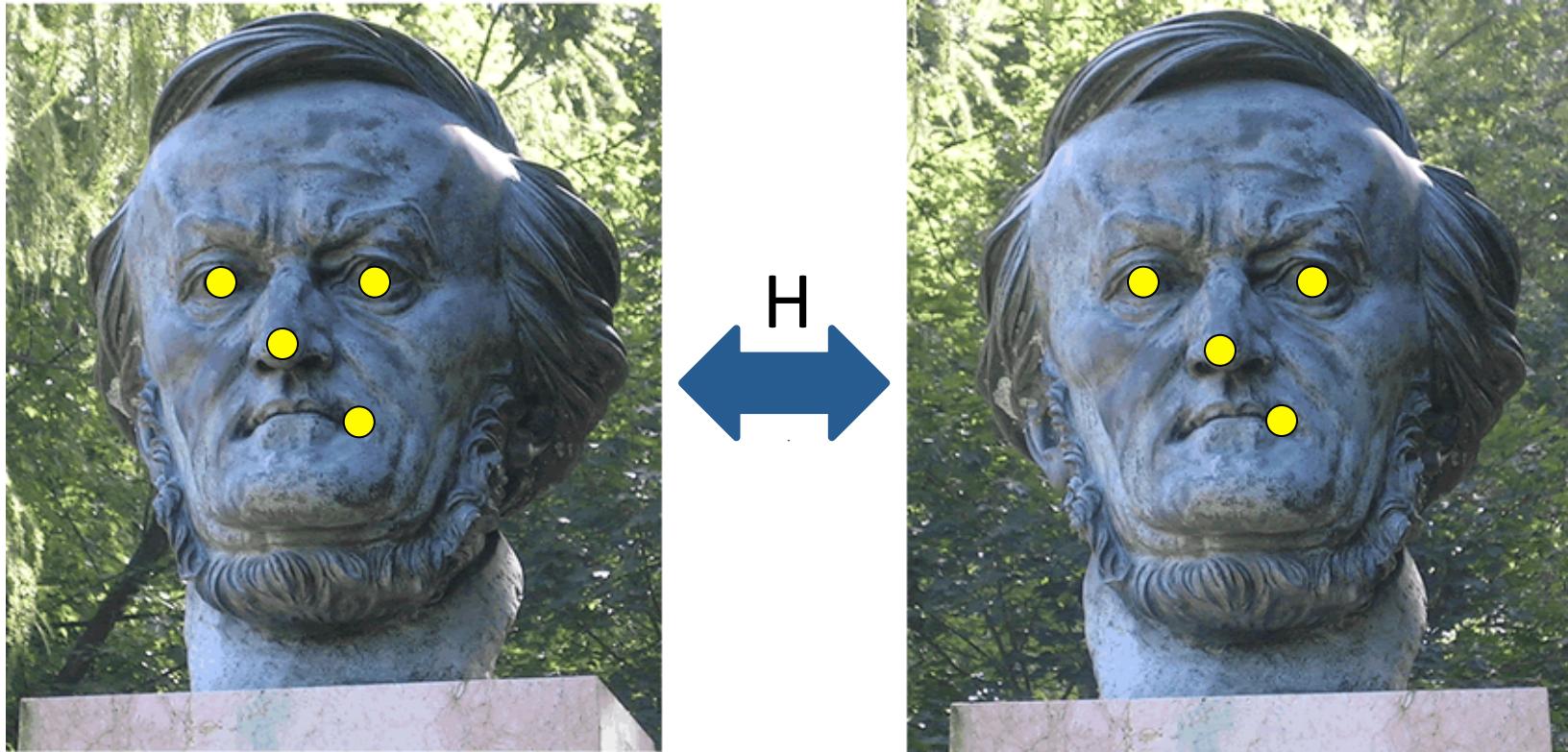
Generic case
(rotation in 3D, scale
& translation)

$$\begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = \begin{bmatrix} a_1 & a_2 & a_3 \\ a_4 & a_5 & a_6 \\ a_7 & a_8 & a_9 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = H \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$

- 8 DOF
- Preserve colinearity

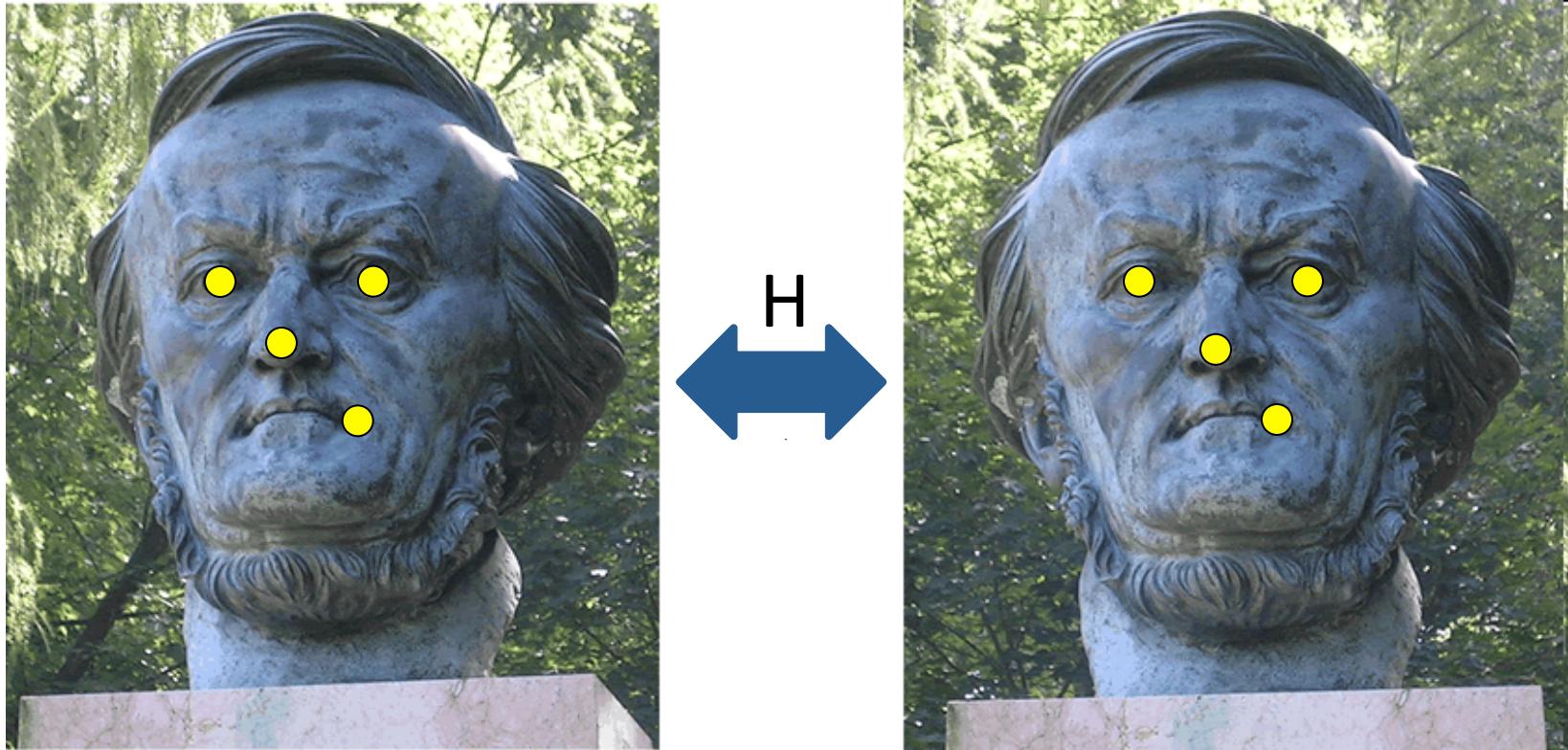


Goal: estimate the homographic transformation between two images



Assumption: Given a set of corresponding points.

Goal: estimate the homographic transformation between two images



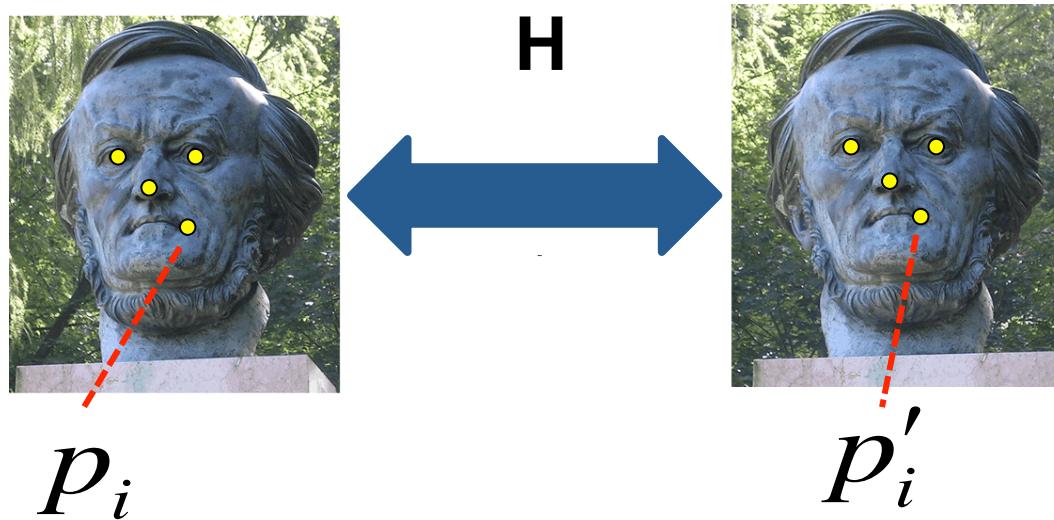
Assumption: Given a set of corresponding points.

Question: How many points are needed?

Hint: DoF for H ? **8!**

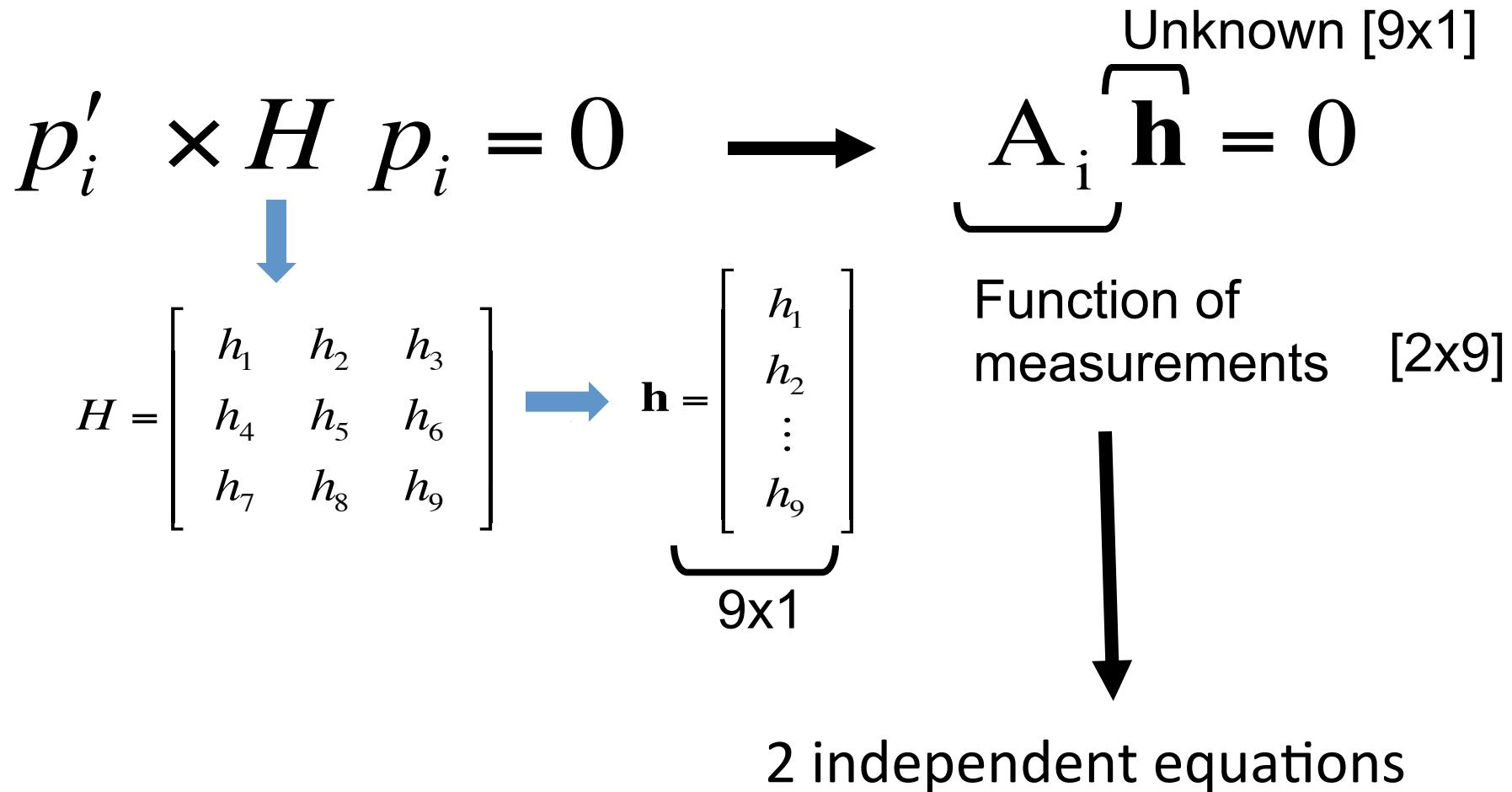
At least 4 points
(8 equations)

DLT algorithm (Direct Linear Transformation)



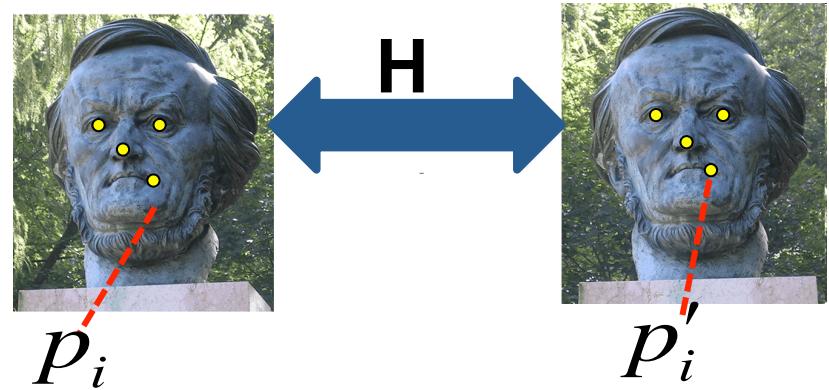
$$p'_i = H p_i$$

DLT algorithm (direct Linear Transformation)



DLT algorithm (direct Linear Transformation)

$$A_{2 \times 9} \quad h_{9 \times 1}$$
$$\boxed{A_i} \boxed{h} = 0$$



$$\left\{ \begin{array}{l} A_1 h = 0 \\ A_2 h = 0 \\ \vdots \\ A_N h = 0 \end{array} \right. \rightarrow A_{2N \times 9} h_{9 \times 1} = 0$$

Over determined
Homogenous system

DLT algorithm (direct Linear Transformation)

How to solve $A_{2N \times 9} h_{9 \times 1} = 0$?

Singular Value Decomposition (SVD)!

DLT algorithm (direct Linear Transformation)

How to solve $A_{2N \times 9} h_{9 \times 1} = 0$?

Singular Value Decomposition (SVD)!



$$U_{2n \times 9} \Sigma_{9 \times 9} V^T_{9 \times 9}$$

Last column of V gives h! $\rightarrow H!$

Why? See pag 593 of AZ

DLT algorithm (direct Linear Transformation)

How to solve $A_{2N \times 9} h_{9 \times 1} = 0$?

```
[U,D,V] = svd(A,0);  
x = V(:,end);
```

Clarification about SVD

$$P_{m \times n} = \boxed{U}_{m \times n} D_{n \times n} \boxed{V}^T_{n \times n}$$

Has n orthogonal columns

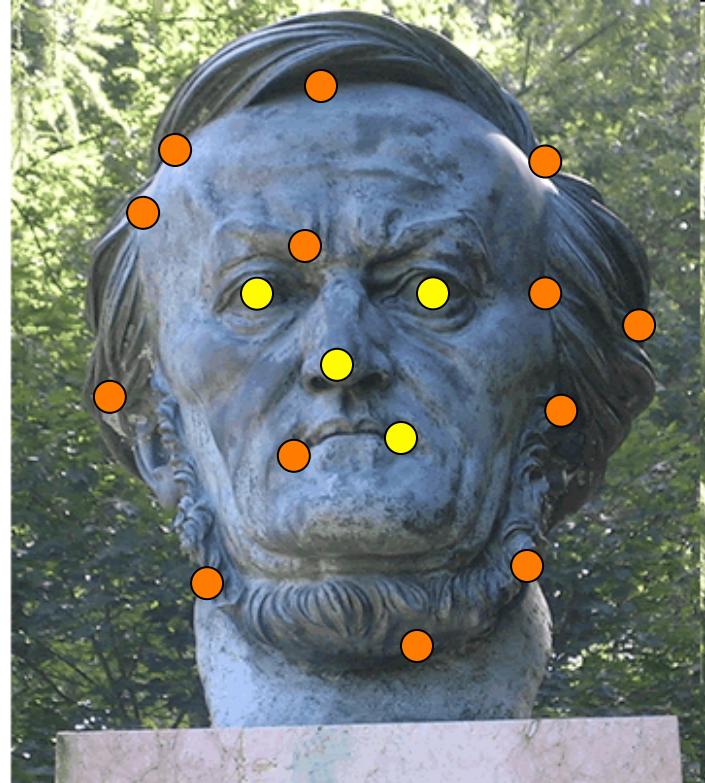
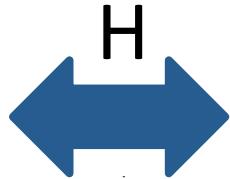
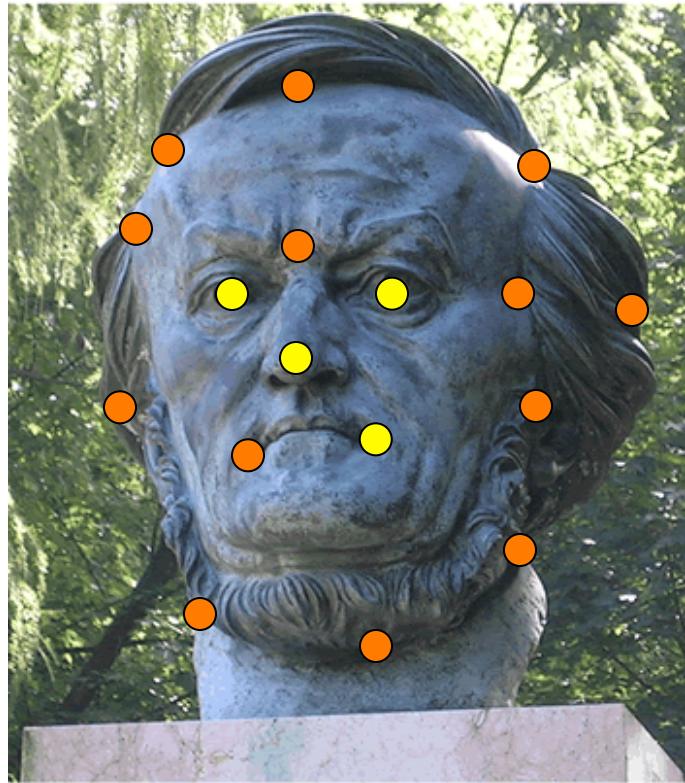
Orthogonal matrix

- This is one of the possible SVD decompositions
- This is typically used for efficiency
- The classic SVD is actually:

$$P_{m \times n} = \boxed{U}_{m \times m} D_{m \times n} \boxed{V}^T_{n \times n}$$

orthogonal

Orthogonal



What we will learn today?

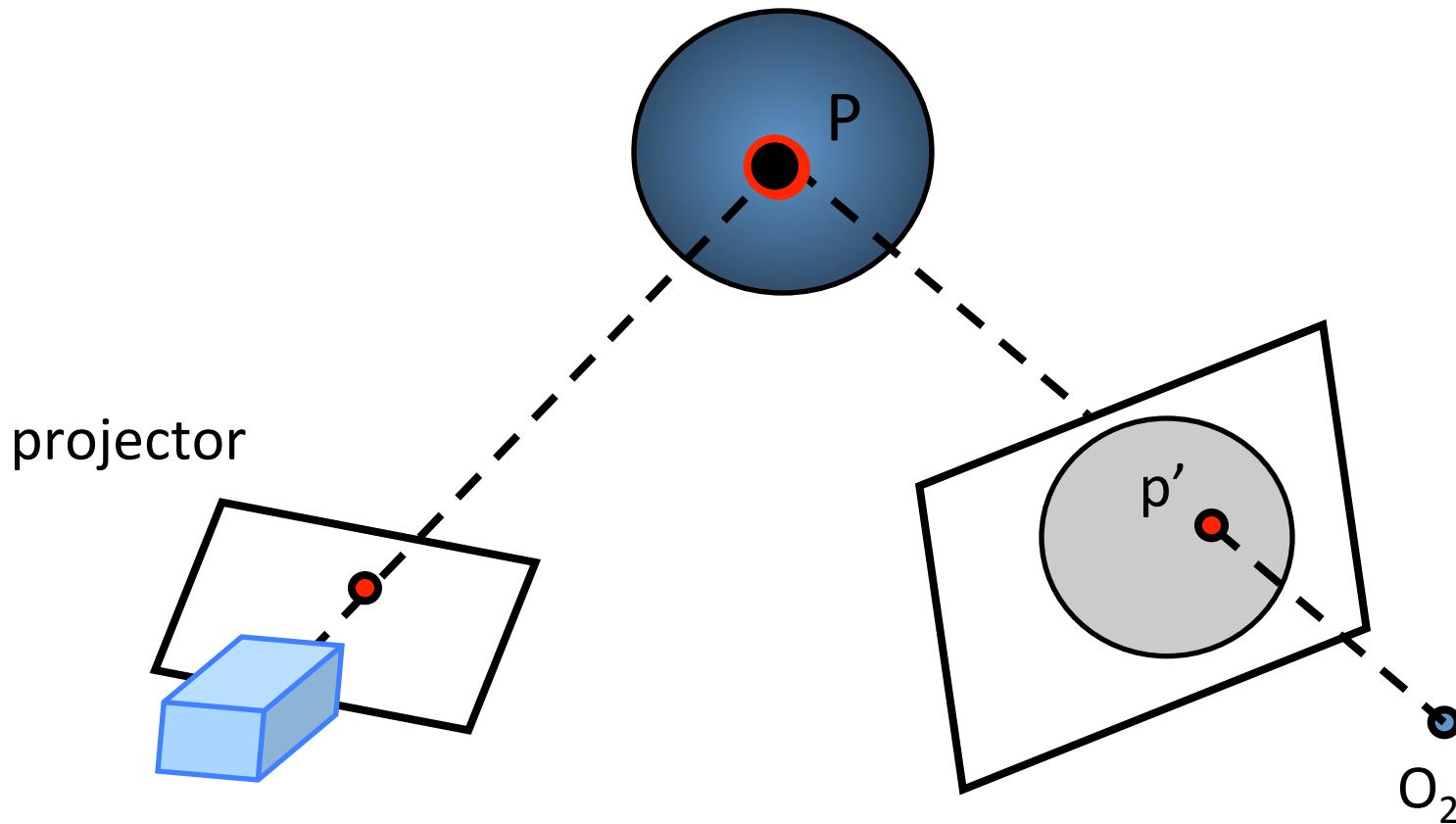
- Introduction to stereo vision
- Epipolar geometry: a gentle intro
- Parallel images & image rectification
- Solving the correspondence problem
- Homographic transformation
- Active stereo vision system

Reading:

[HZ] Chapters: 4, 9, 11

[FP] Chapters: 10

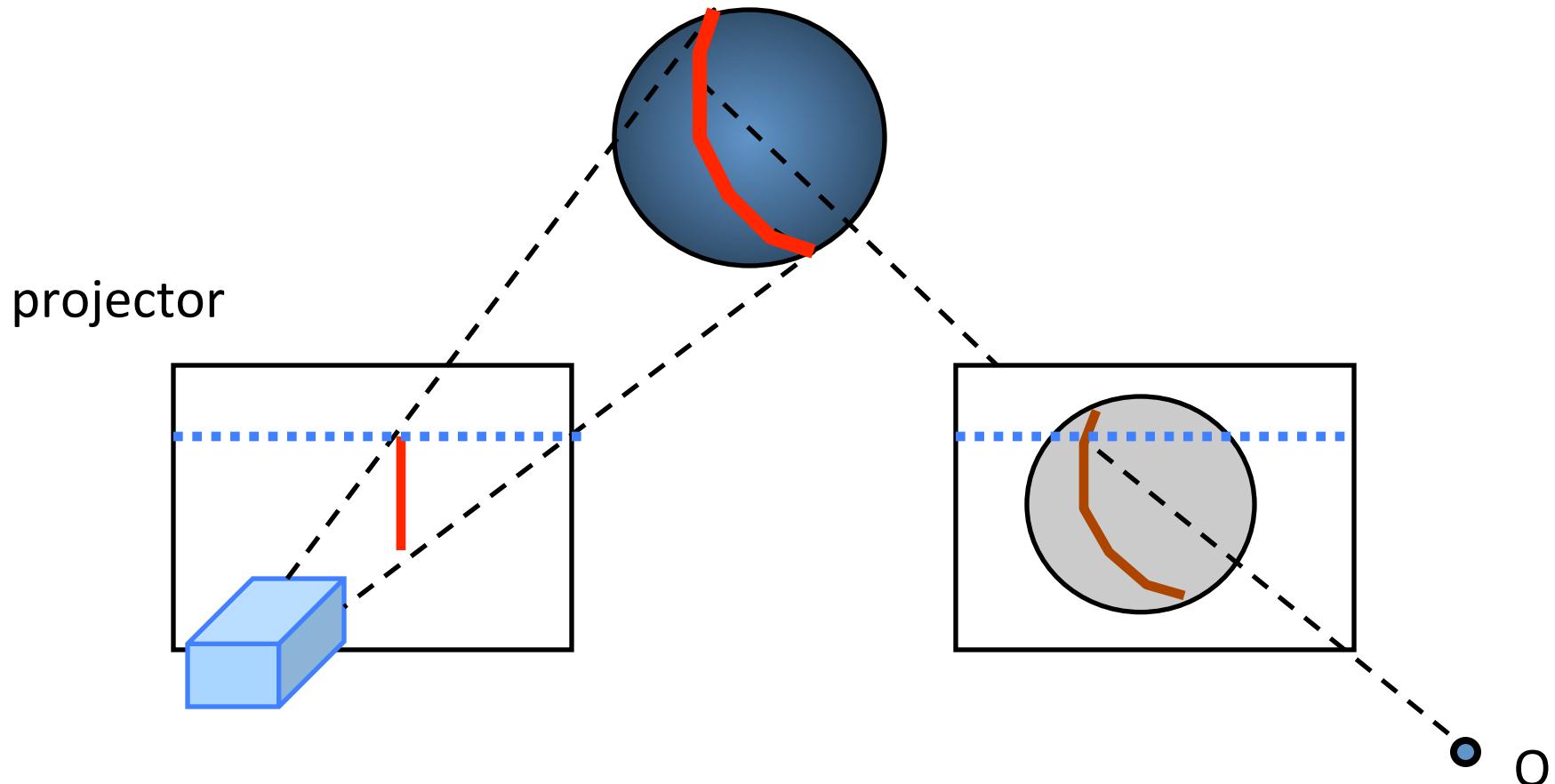
Active stereo (point)



Replace one of the two cameras by a projector

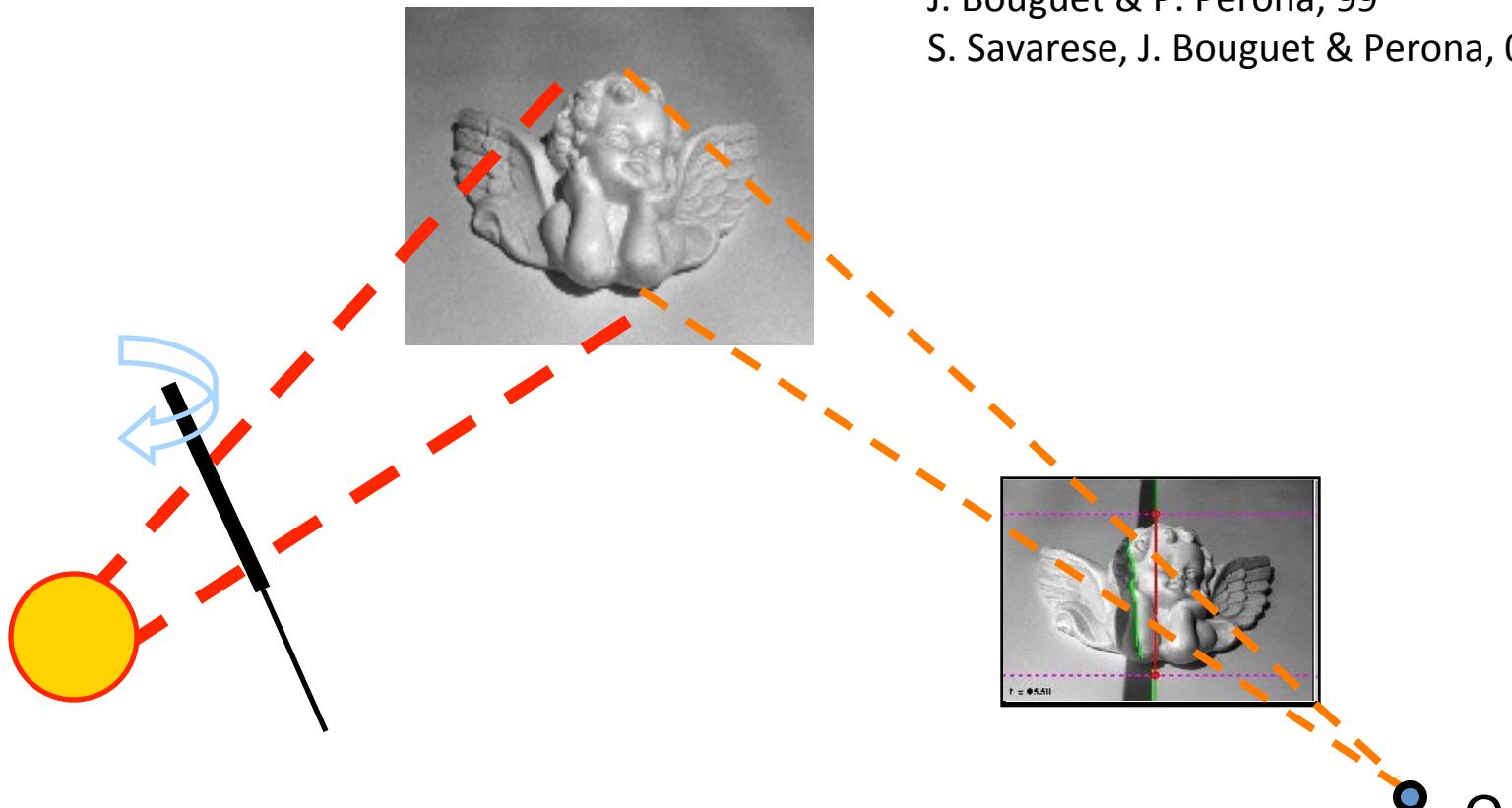
- Single camera
- Projector geometry calibrated
- What's the advantage of having the projector? Correspondence problem solved!

Active stereo (stripe)



- Projector and camera are parallel
- Correspondence problem solved!

Active stereo (shadows)



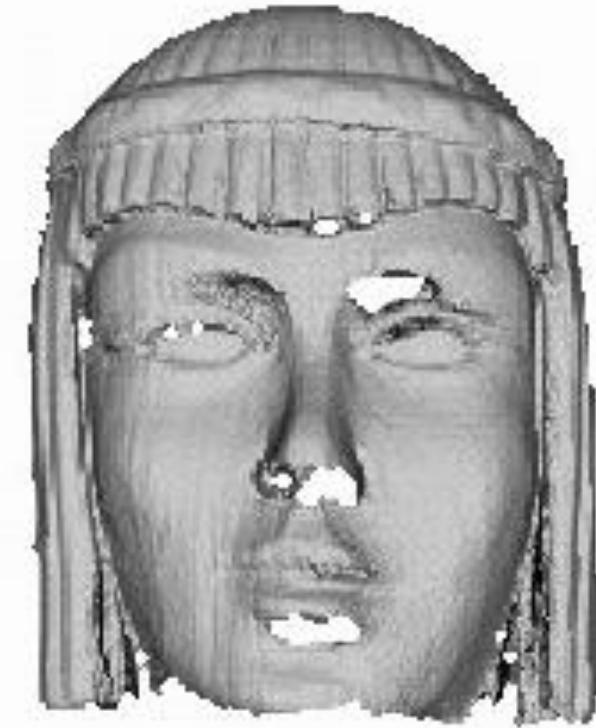
Light source

- 1 camera, 1 light source
- very cheap setup
- calibrated light source

J. Bouguet & P. Perona, 99
S. Savarese, J. Bouguet & Perona, 00

Active stereo (shadows)

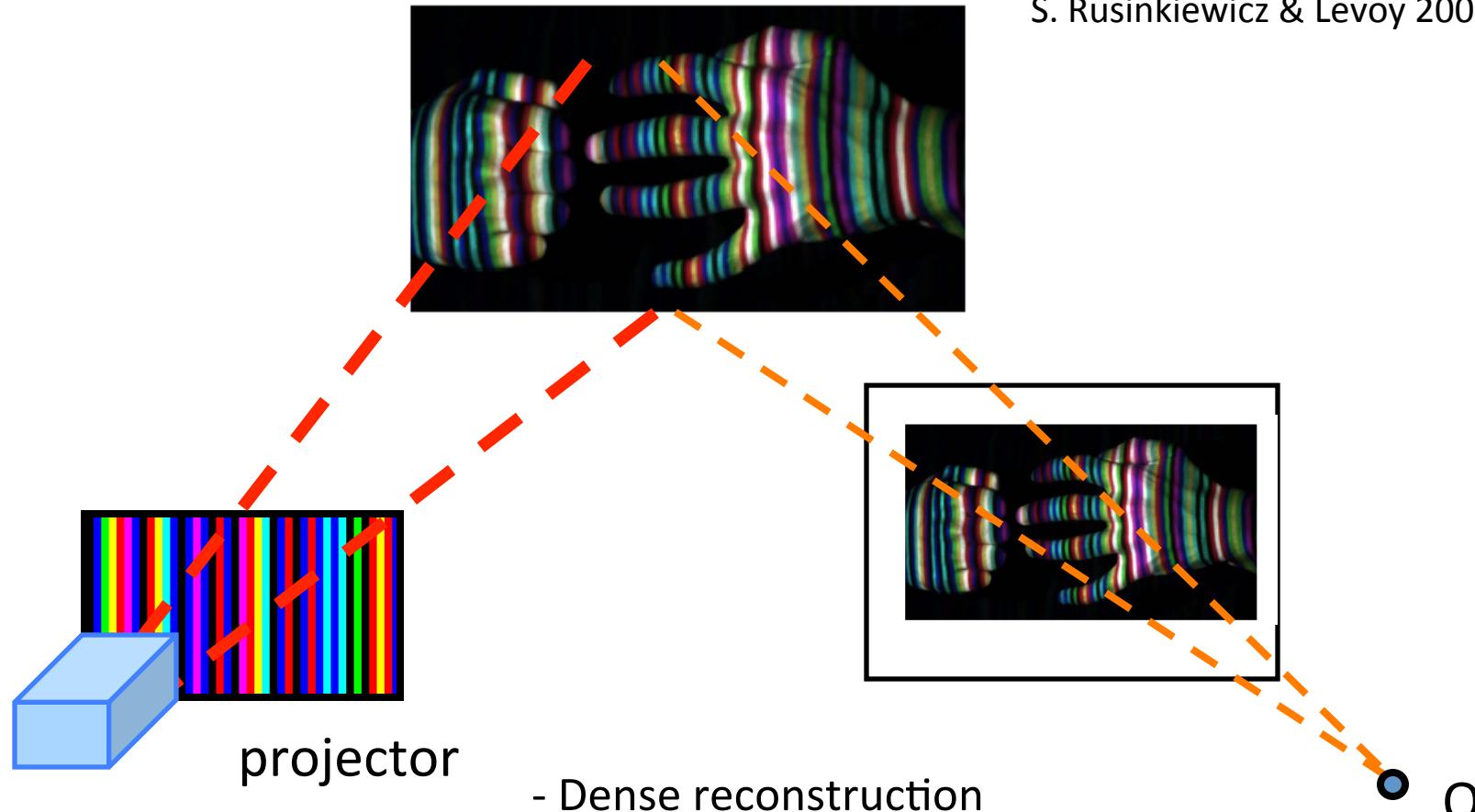
J. Bouguet & P. Perona, 99
S. Savarese, J. Bouguet & Perona, 00



Active stereo (color-coded stripes)

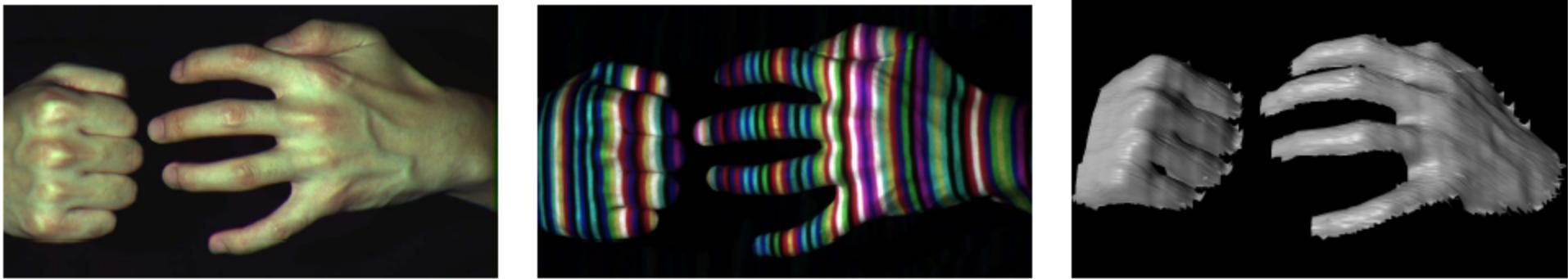
L. Zhang, B. Curless, and S. M. Seitz 2002

S. Rusinkiewicz & Levoy 2002



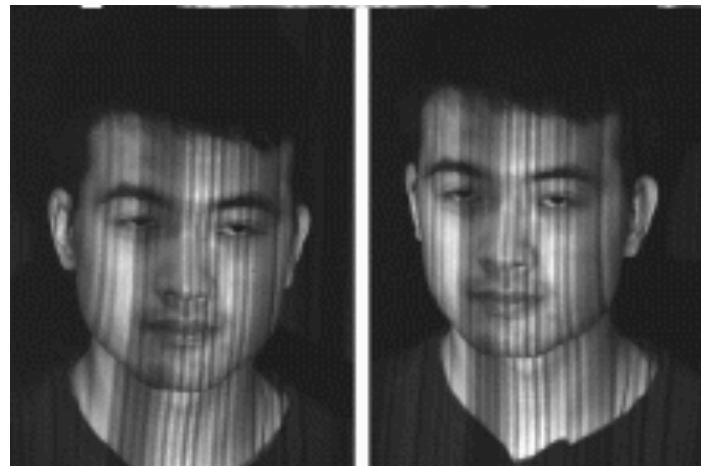
- Dense reconstruction
- Correspondence problem again
- Get around it by using color codes

Active stereo (color-coded stripes)

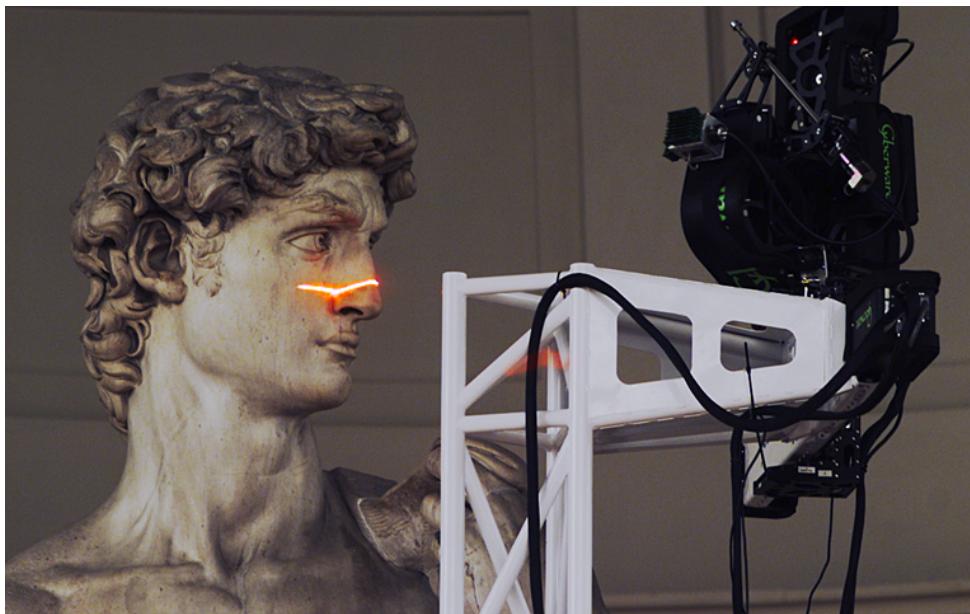


Rapid shape acquisition: Projector + stereo cameras

L. Zhang, B. Curless, and S. M. Seitz. Rapid Shape Acquisition Using Color Structured Light and Multi-pass Dynamic Programming. *3DPVT* 2002



Active stereo (stripe)



Digital Michelangelo Project
<http://graphics.stanford.edu/projects/mich/>

- Optical triangulation
 - Project a single stripe of laser light
 - Scan it across the surface of the object
 - This is a very precise version of structured light scanning

Laser scanned models



The Digital Michelangelo Project, Levoy et al.

Slide credit: S. Seitz

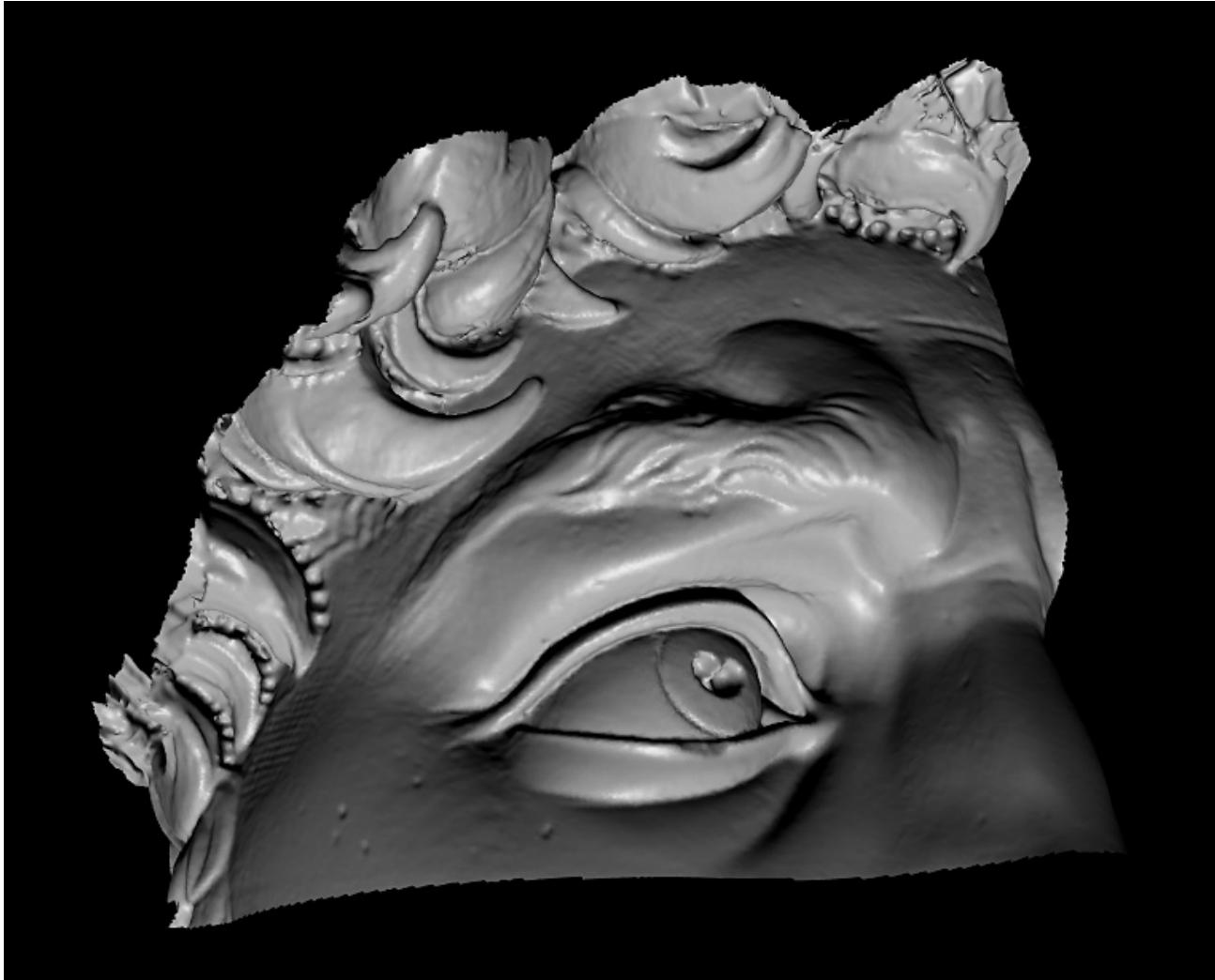
Laser scanned models



The Digital Michelangelo Project, Levoy et al.

Slide credit: S. Seitz

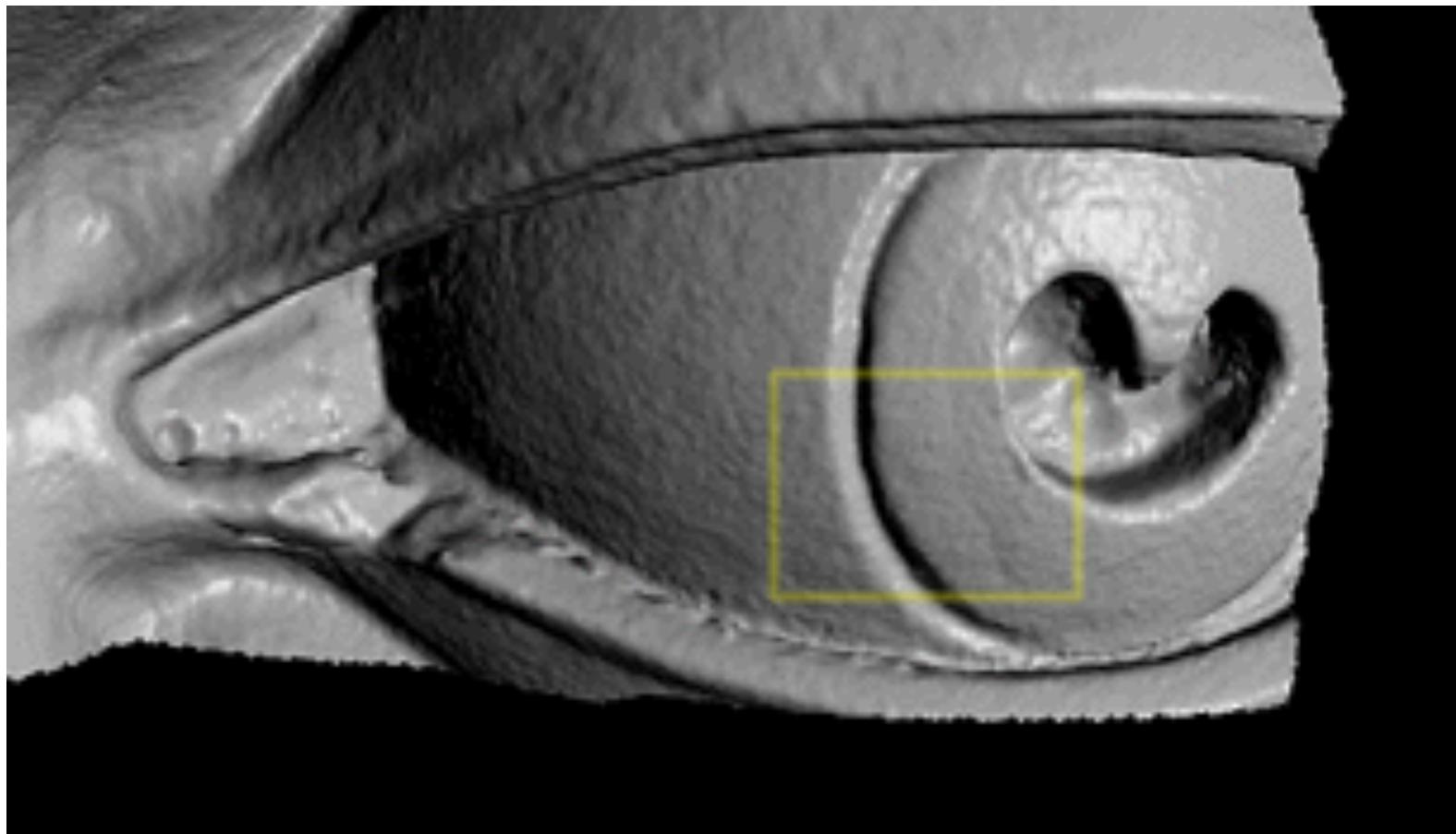
Laser scanned models



The Digital Michelangelo Project, Levoy et al.

Slide credit: S. Seitz

Laser scanned models

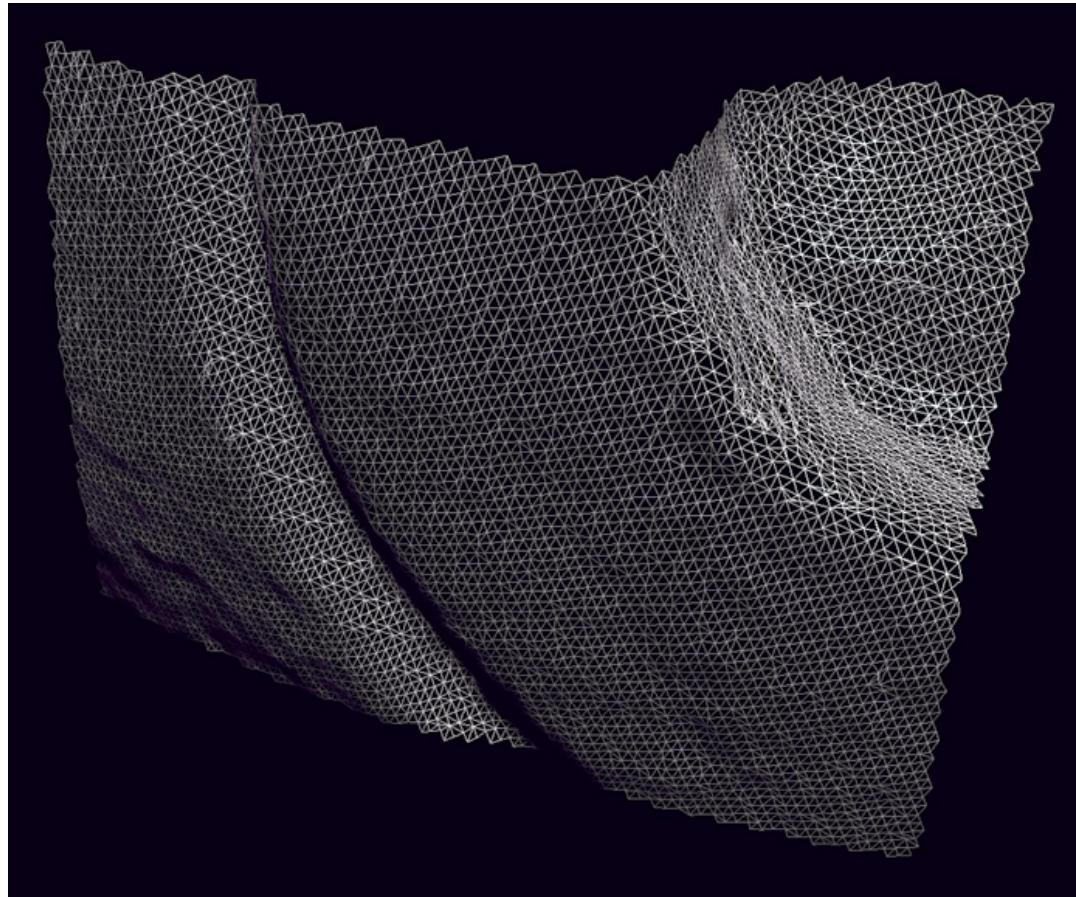


The Digital Michelangelo Project, Levoy et al.

Slide credit: S. Seitz

Laser scanned models

1.0 mm resolution (56 million triangles)



The Digital Michelangelo Project, Levoy et al.

Slide credit: S. Seitz

What we have learned today

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Reading:

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