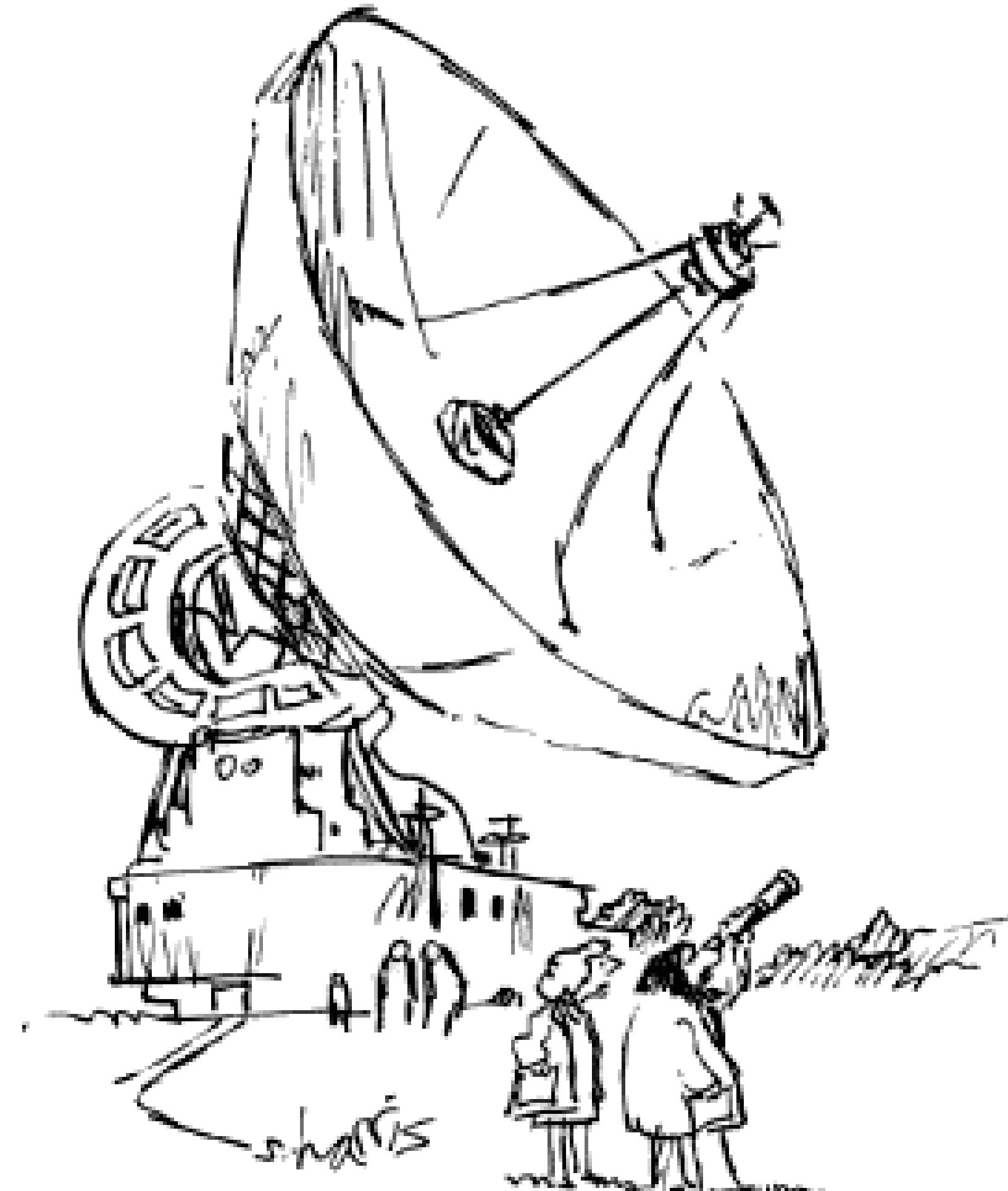


Stereopsis and Epipolar Geometry



"Just checking."

CS180: : Intro to Comp. Vision and Comp. Photo
Alexei Efros, UC Berkeley, Fall 2024

Vision systems

One camera



Two cameras

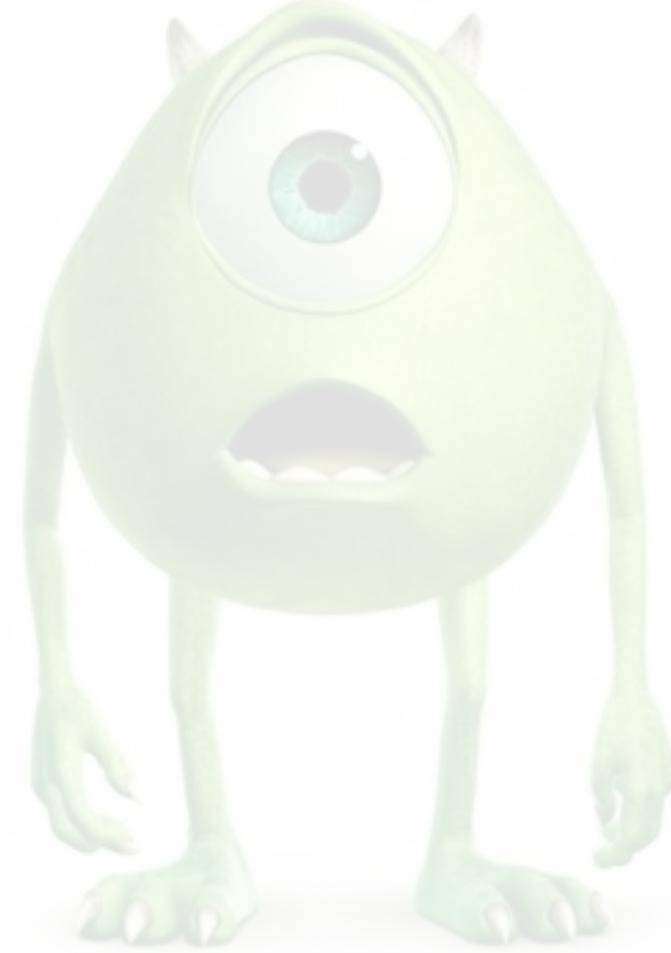


N cameras

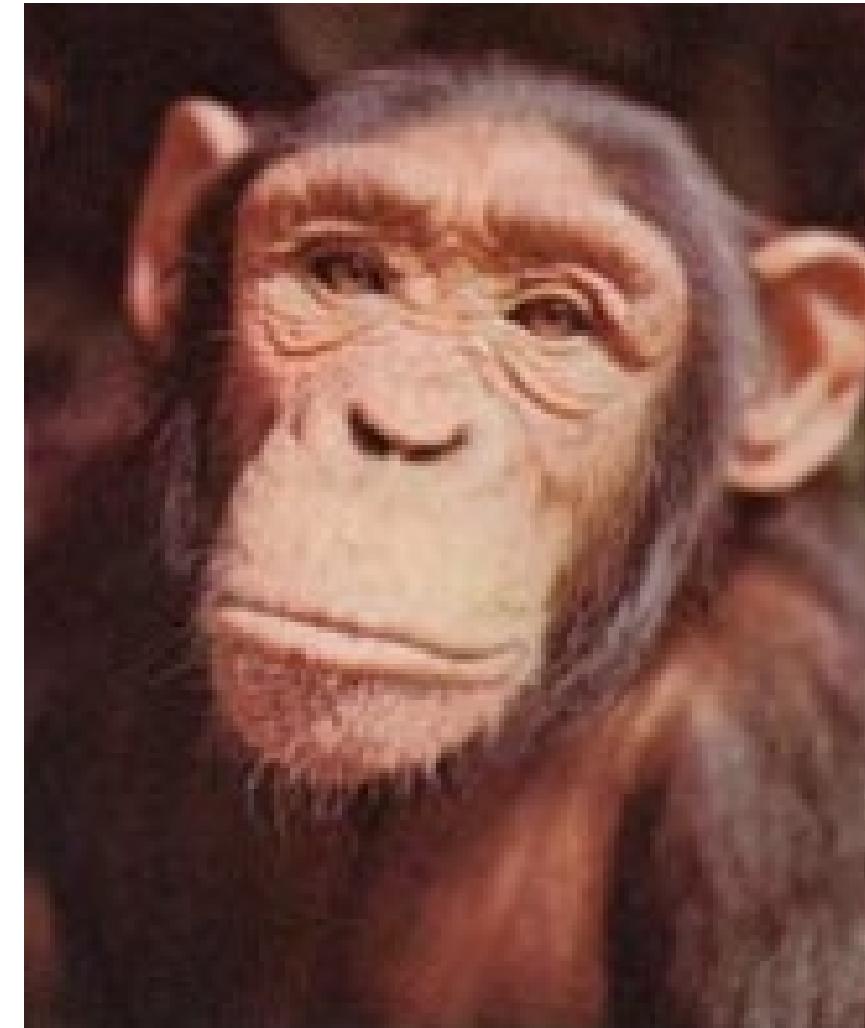


Let's consider two eyes

One camera



Two cameras



N cameras



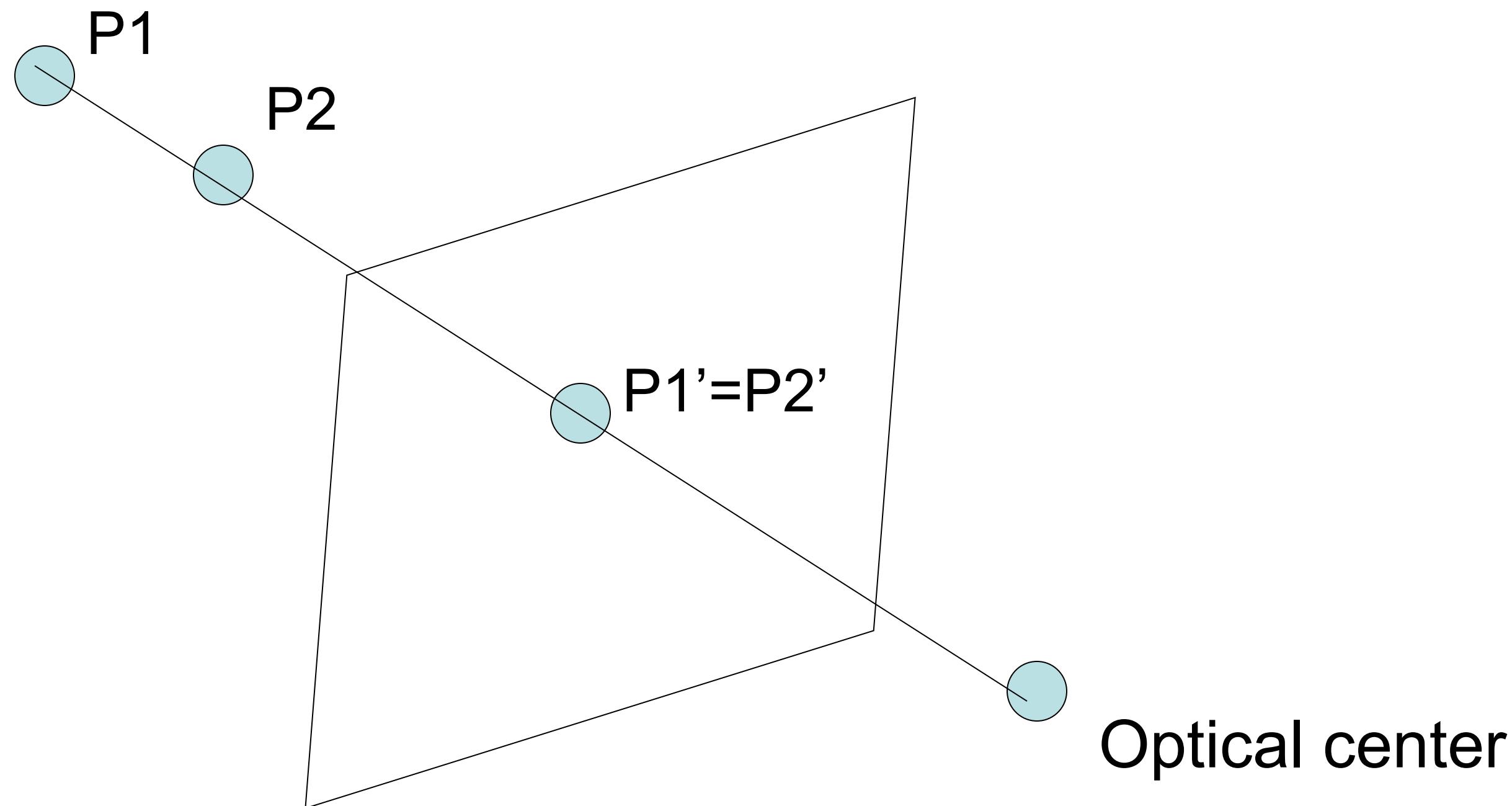
Why multiple views?

- Structure and depth are inherently ambiguous from single views.



Why multiple views?

- Structure (geometry) and depth are inherently ambiguous from single views.



Stereo images



(a)



(b)

Figure 1.1: (a) Stereo anaglyph of the ocean liner, the Titanic [McManus2022]. The red image shows the right eye's view, and cyan the left eye's view. When viewed through stereo red/cyan stereo glasses, as in (b), the cyan contrast appears in the left eye image and the red variations appear to the right eye, creating a the perception of 3d.

Stereoscope



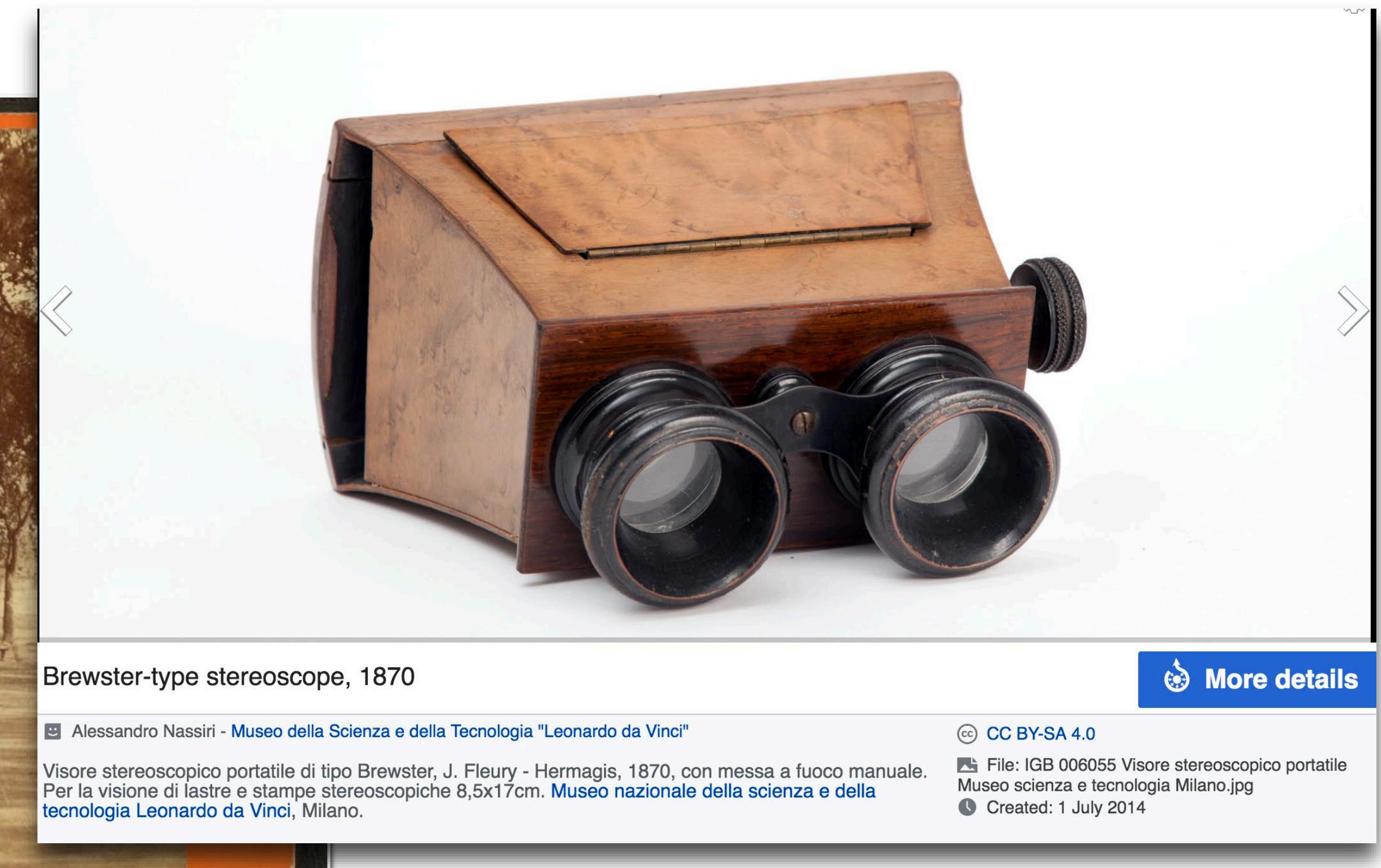
View of [Boston](#), c. 1860; an early stereoscopic card for viewing a scene from nature

[More details](#)

Smiley Soule, John P., 1827-1904 -- Photographer - This image is available from the [New York Public Library's Digital Library](#) under the digital ID G90F336_113F: [digitalgallery.nypl.org](#) → [digitalcollections.nypl.org](#)

CC Public Domain

Image File: Charles Street Mall, Boston Common, by Soule, John P., 1827-1904 3.jpg
Created: Coverage: 1860?-1890?. Source Imprint: 1860?-1890?. Digital item published 7-28-2005; updated 4-23-2009.



Brewster-type stereoscope, 1870

Alessandro Nassiri - [Museo della Scienza e della Tecnologia "Leonardo da Vinci"](#)

Visore stereoscopico portatile di tipo Brewster, J. Fleury - Hermagis, 1870, con messa a fuoco manuale. Per la visione di lastre e stampe stereoscopiche 8,5x17cm. [Museo nazionale della scienza e della tecnologia Leonardo da Vinci](#), Milano.

[More details](#)

CC BY-SA 4.0

File: IGB 006055 Visore stereoscopico portatile Museo scienza e tecnologia Milano.jpg

Created: 1 July 2014

Depth without objects

Random dot stereograms (Bela Julesz)



| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 0 | 1 | 0 | Y | A | A | S | S | 0 | 1 |
| 1 | 1 | 1 | X | S | A | S | A | 0 | 1 |
| 0 | 0 | 1 | X | A | A | S | A | 1 | 0 |
| 1 | 1 | 1 | Y | S | S | A | S | 0 | 1 |
| 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 |
| 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 1 | 0 | 1 | 0 | 1 | 0 | 0 | 1 | 0 | 1 |
| 1 | 0 | 0 | 1 | 0 | 1 | 0 | 1 | 0 | 0 |
| 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 | 0 |
| 0 | 1 | 0 | 4 | A | S | S | X | 0 | 1 |
| 1 | 1 | 1 | S | A | S | A | Y | 0 | 1 |
| 0 | 0 | 1 | A | A | S | A | Y | 1 | 0 |
| 1 | 1 | 1 | S | S | A | S | X | 0 | 1 |
| 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 0 | 1 |
| 1 | 1 | 0 | 0 | 1 | 1 | 0 | 1 | 1 | 1 |
| 0 | 1 | 0 | 0 | 0 | 1 | 1 | 1 | 1 | 0 |

Julesz, 1971

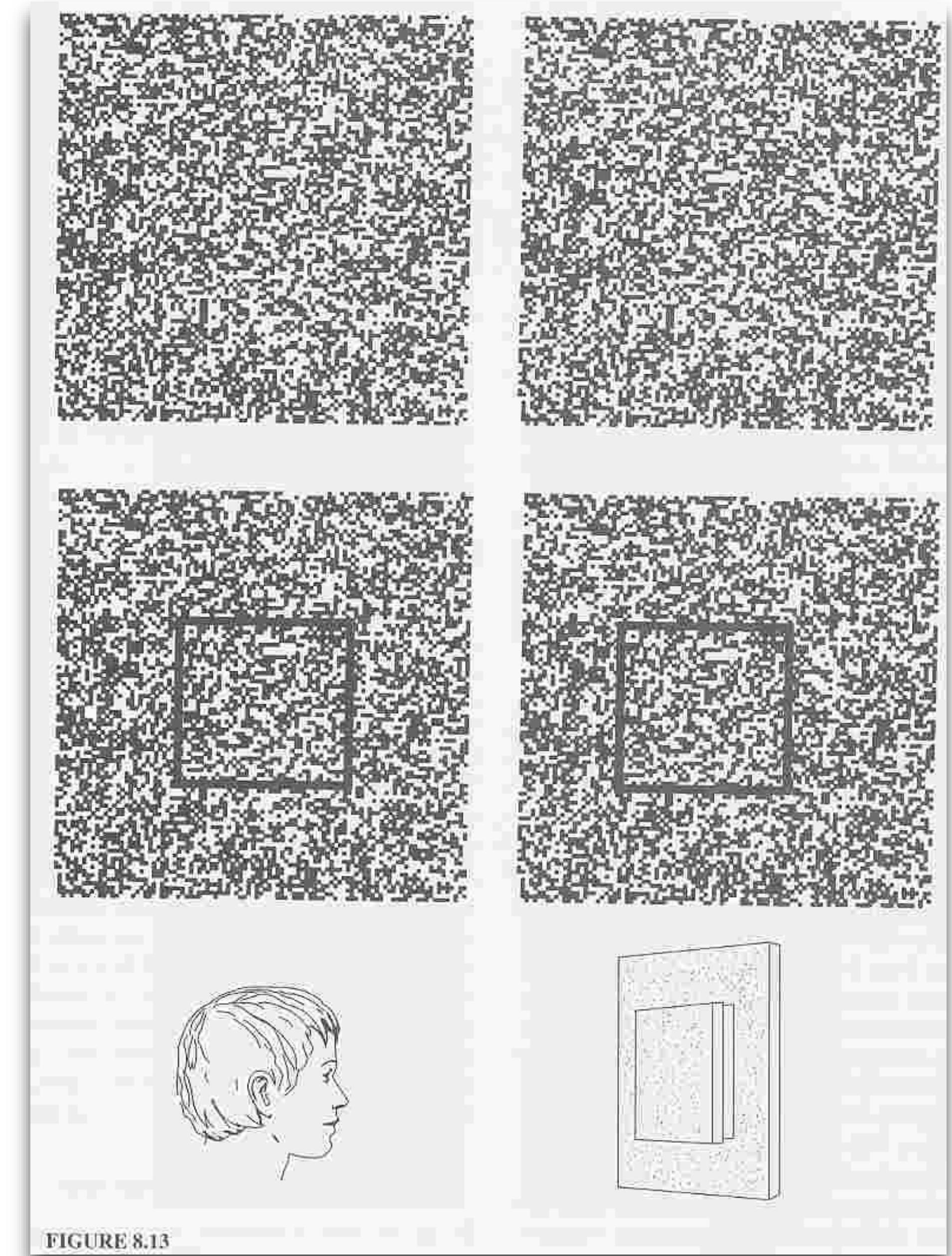
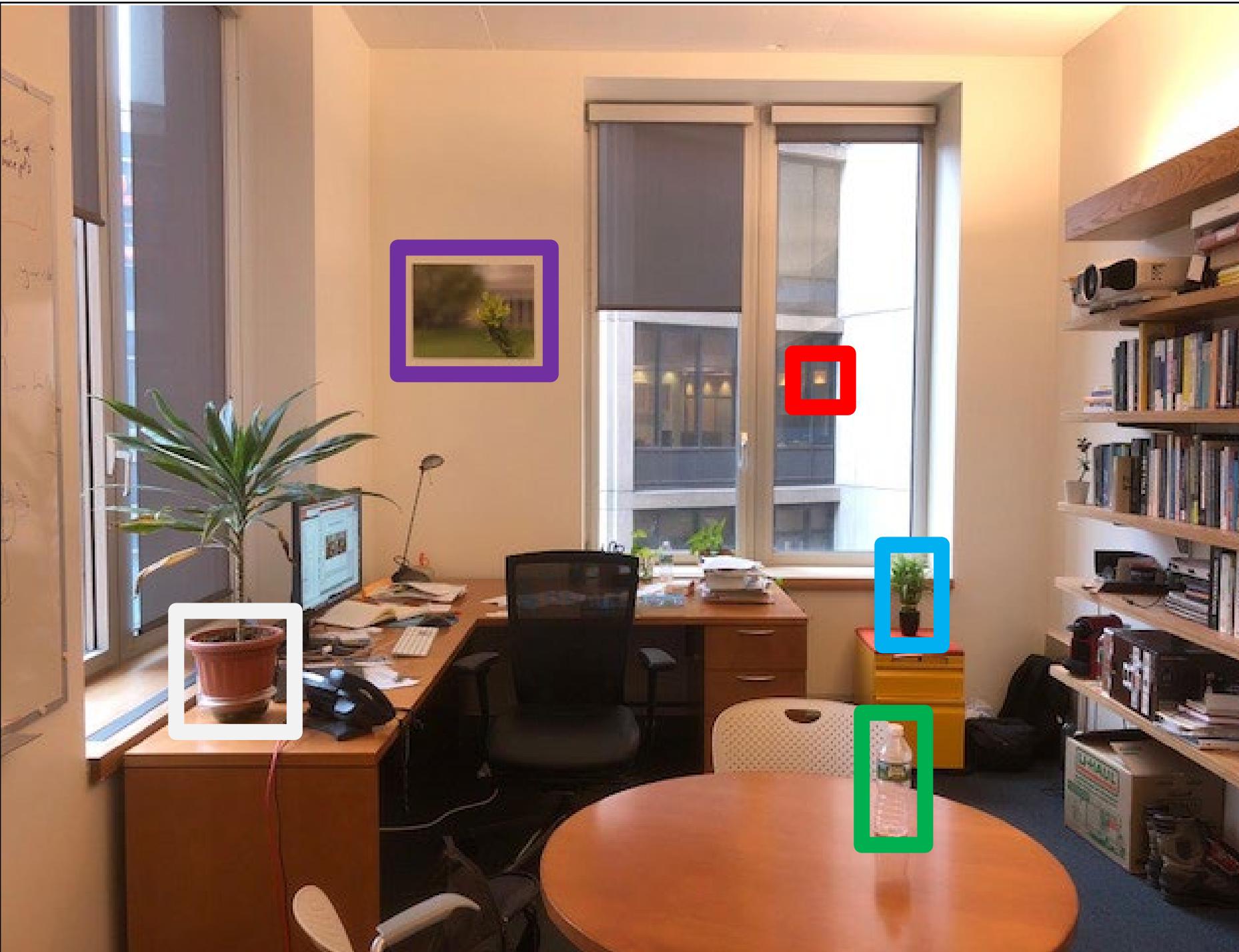
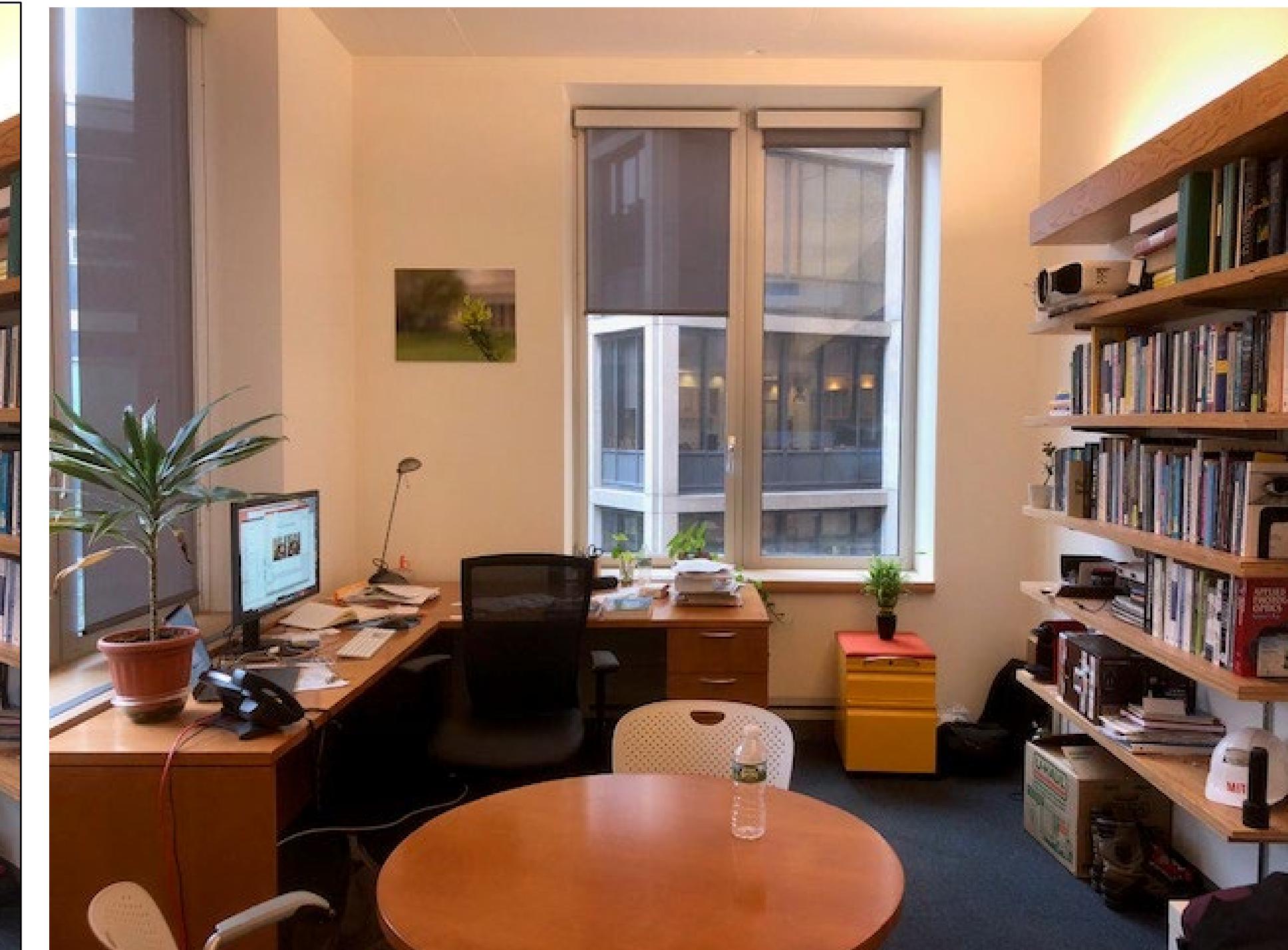


FIGURE 8.13

disparity



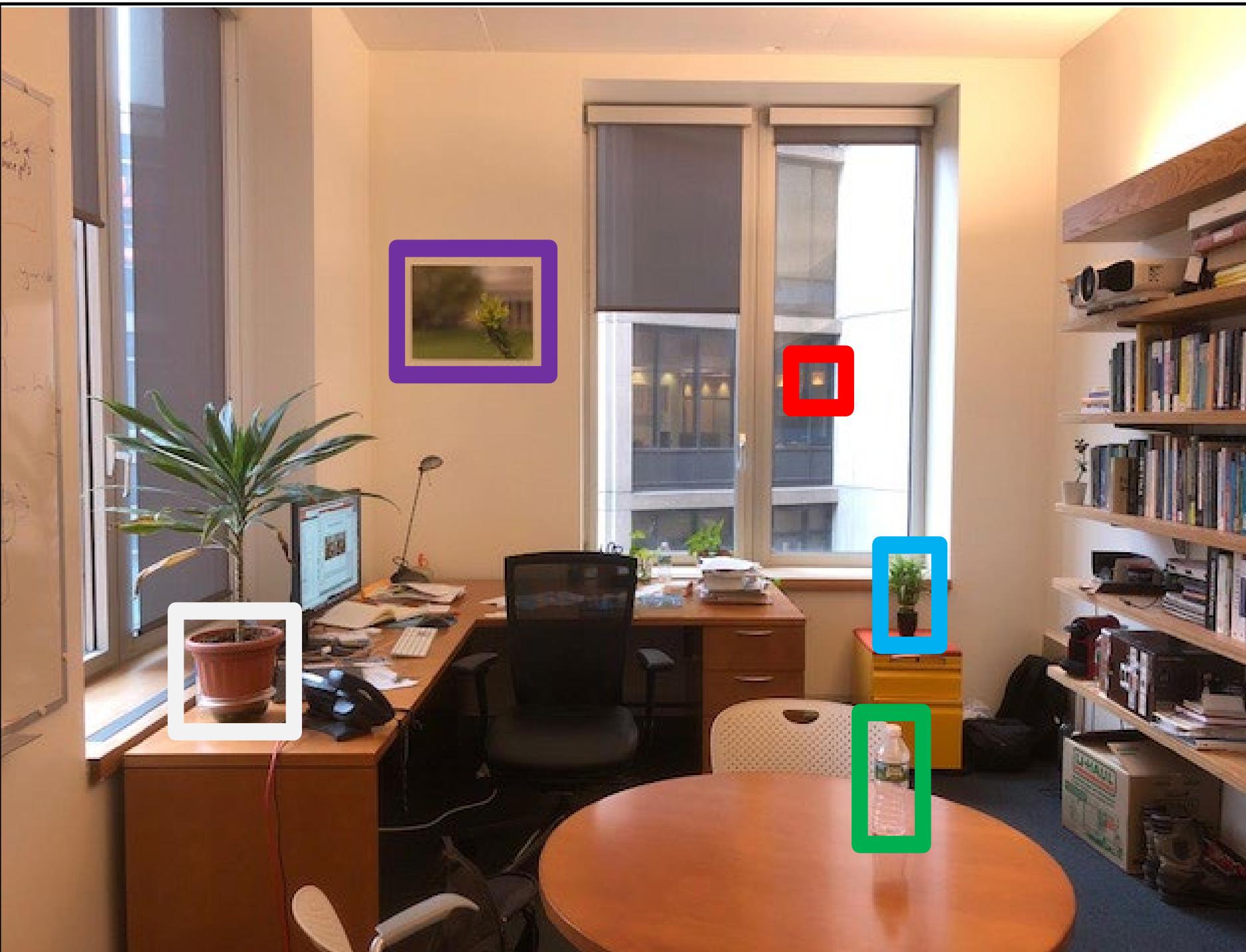
Left image



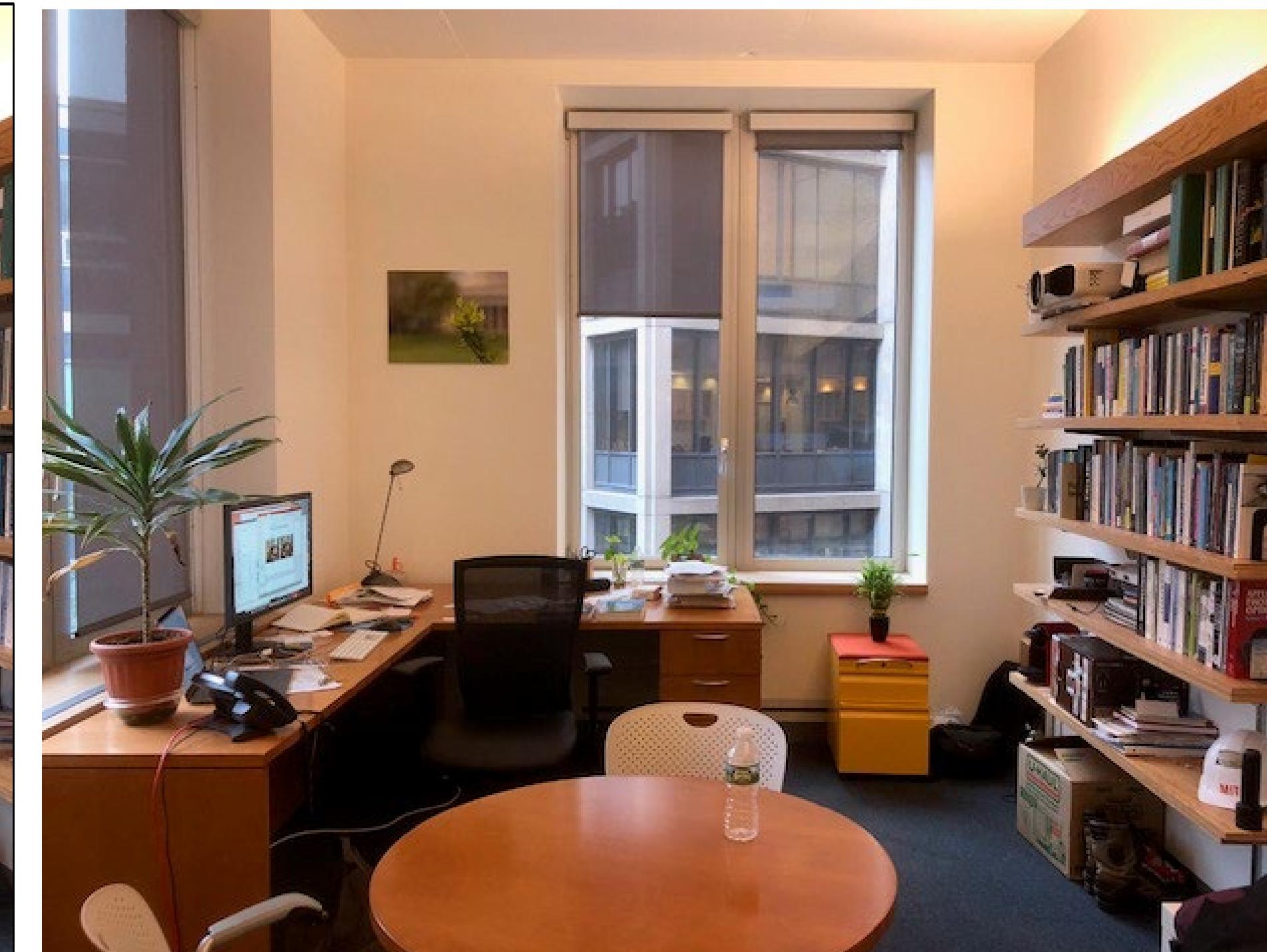
Right image

Antonio took one picture, then he moved ~1m to the right and took a second picture.

disparity

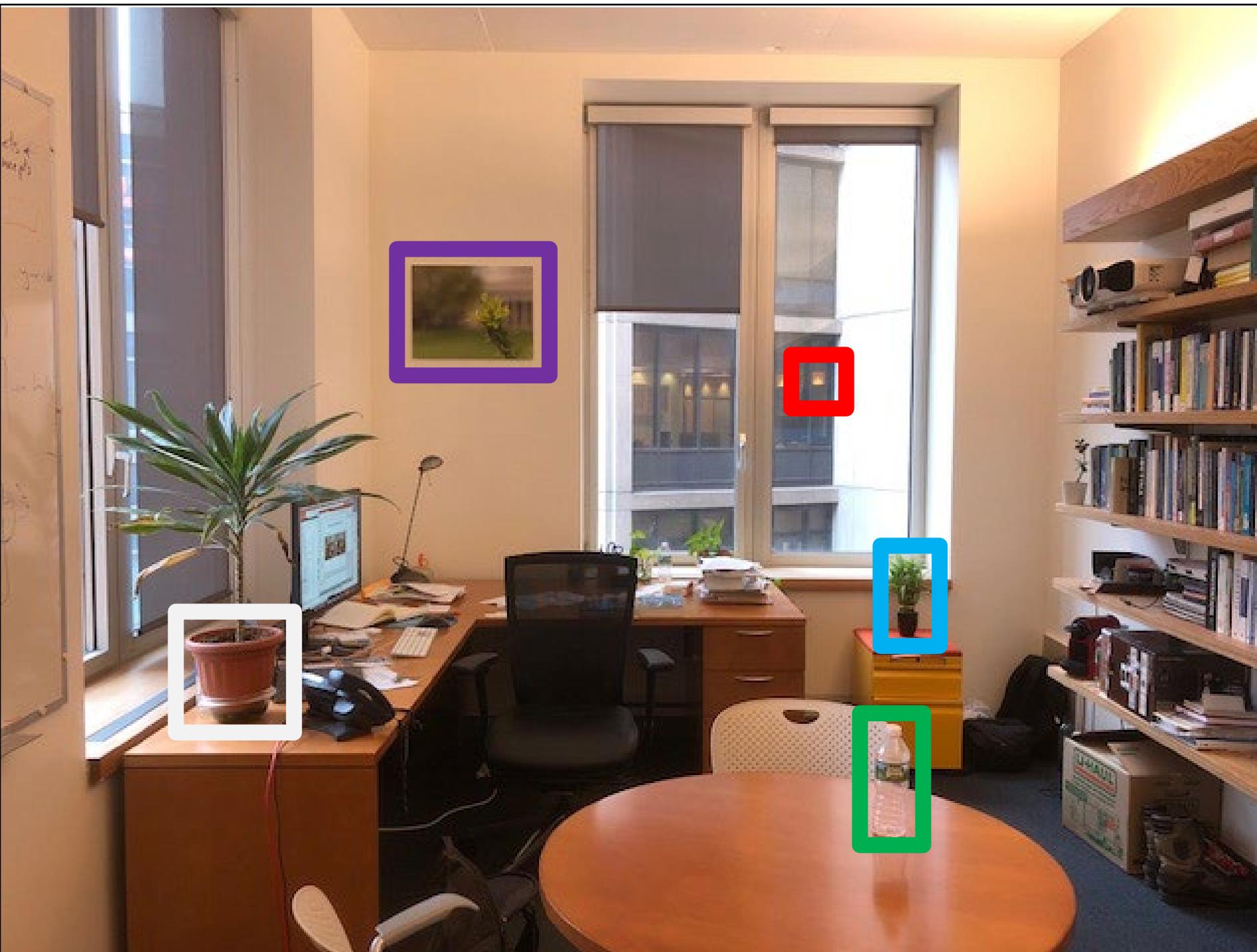


Left image

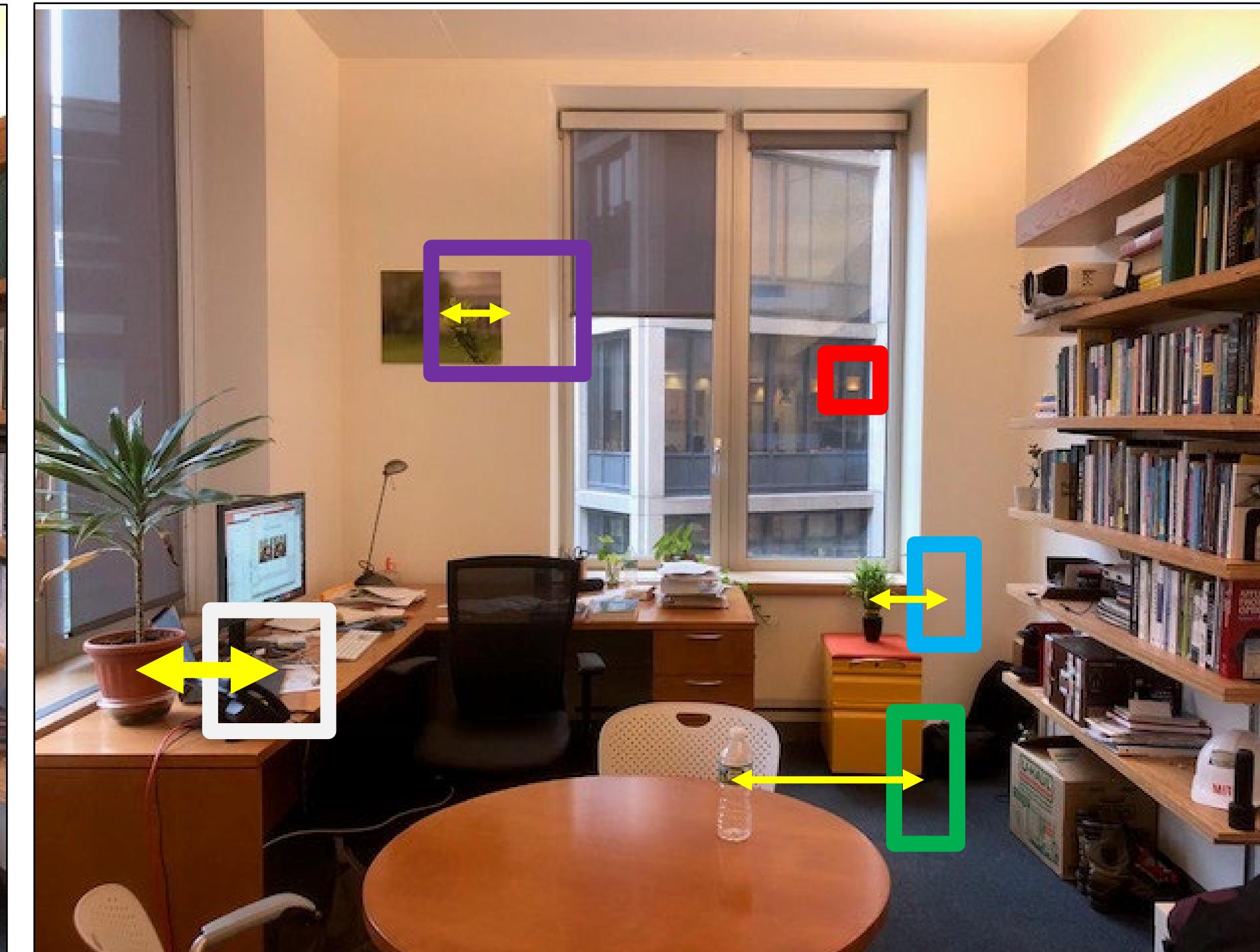


Right image

disparity



Left image



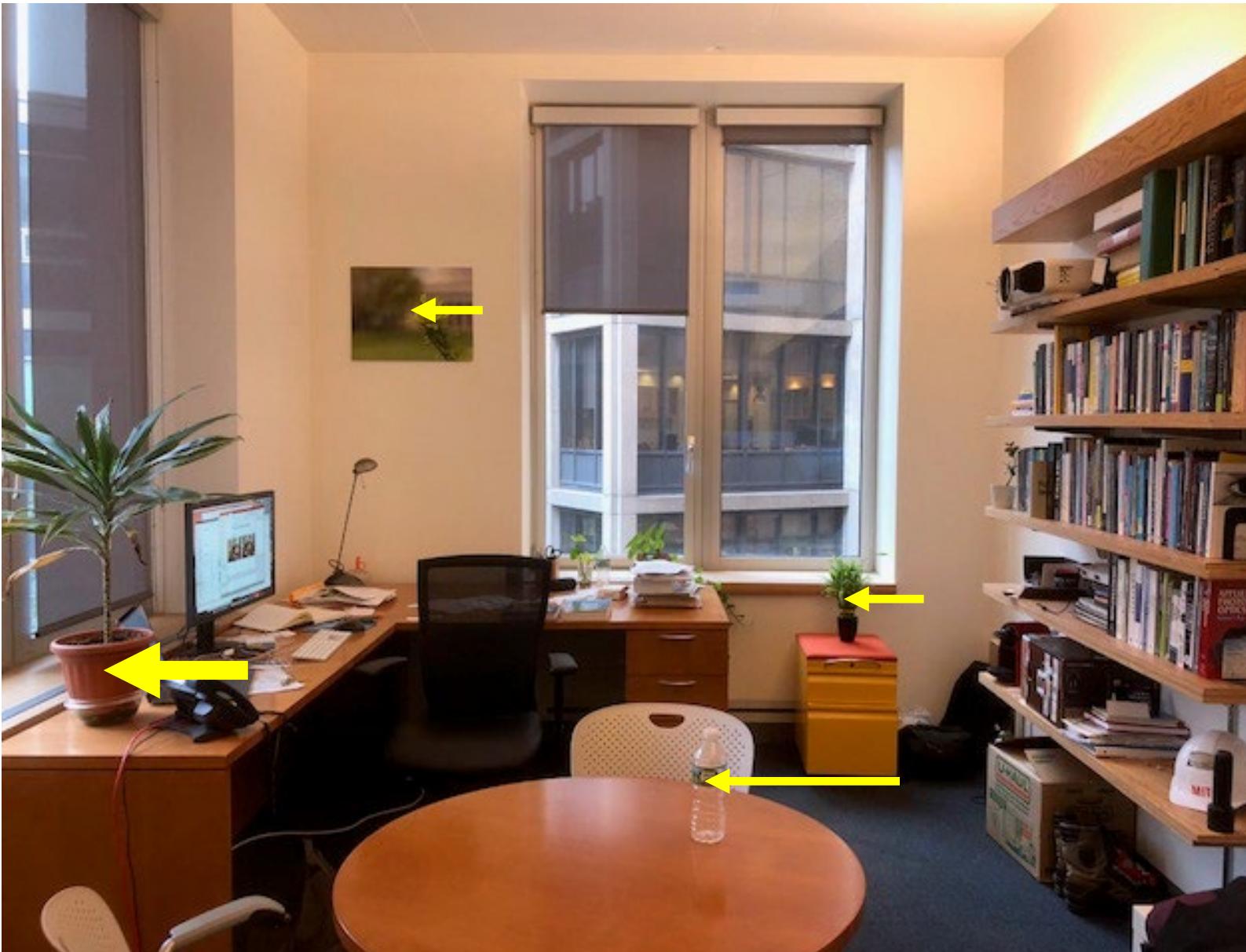
Right image

Disparity map

$I(x,y)$



$I'(x,y) = I(x+D(x,y), y)$

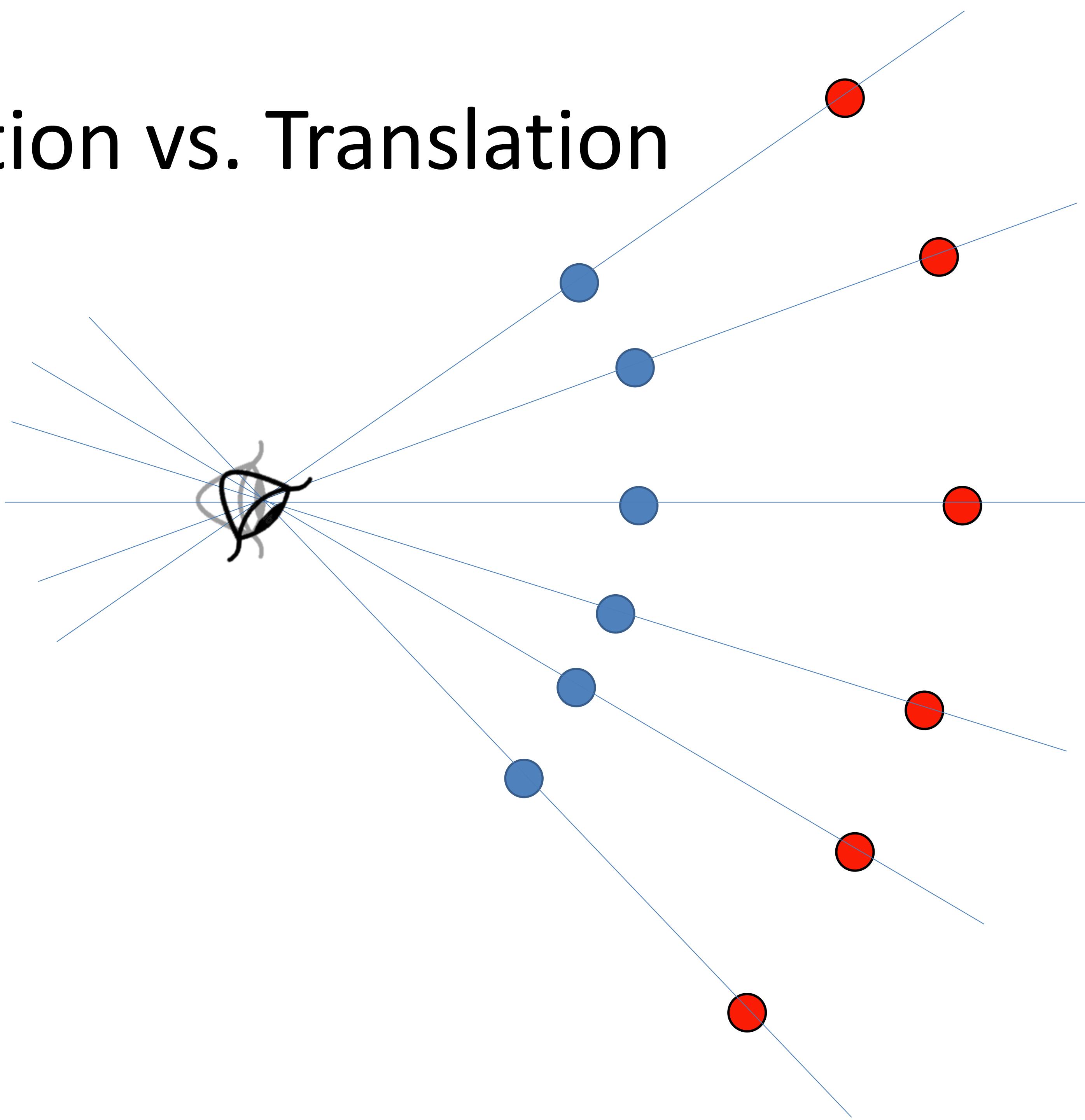


$D(x,y)$

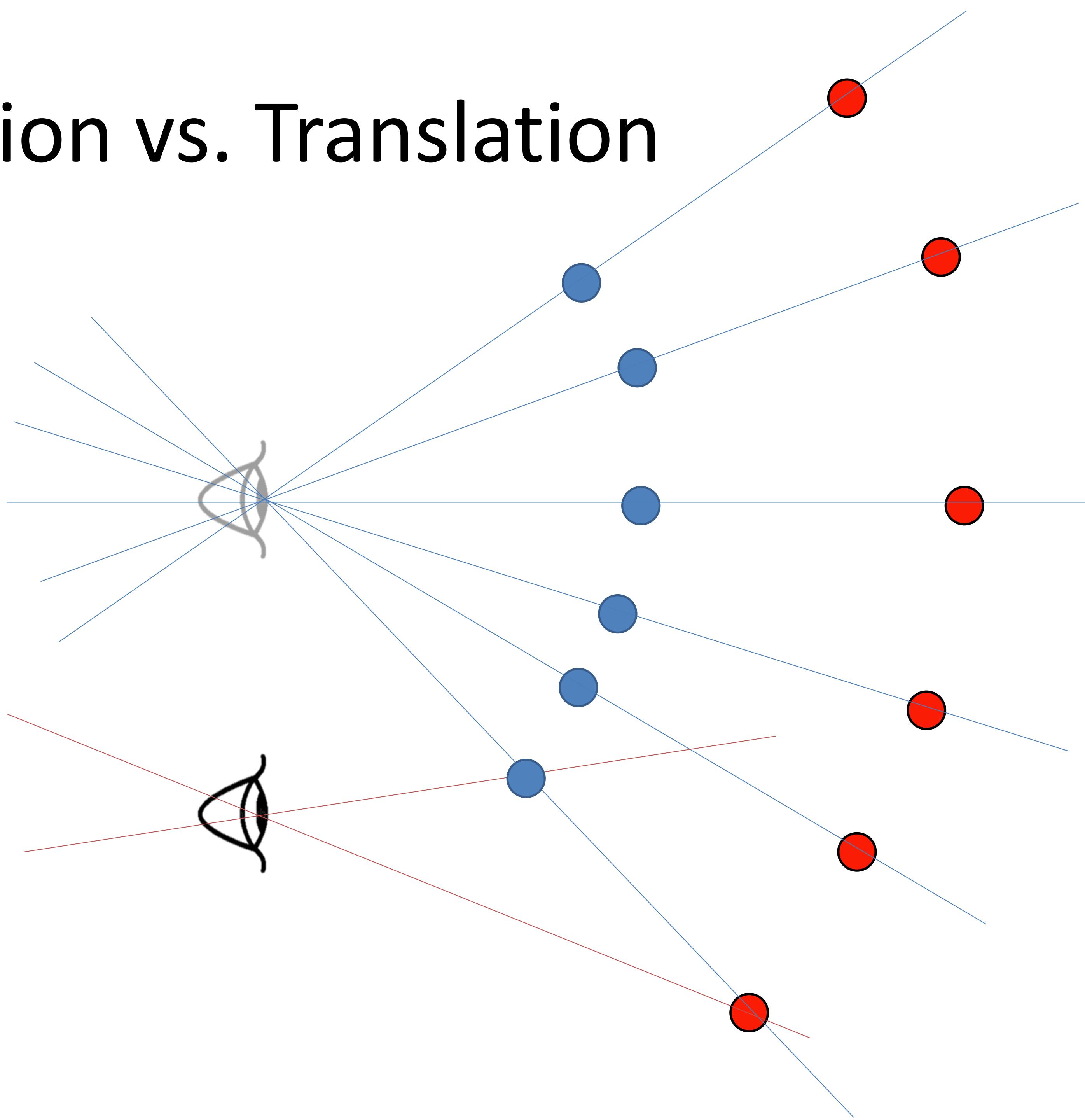


$$Z(x,y) = \frac{a}{D(x,y)}$$

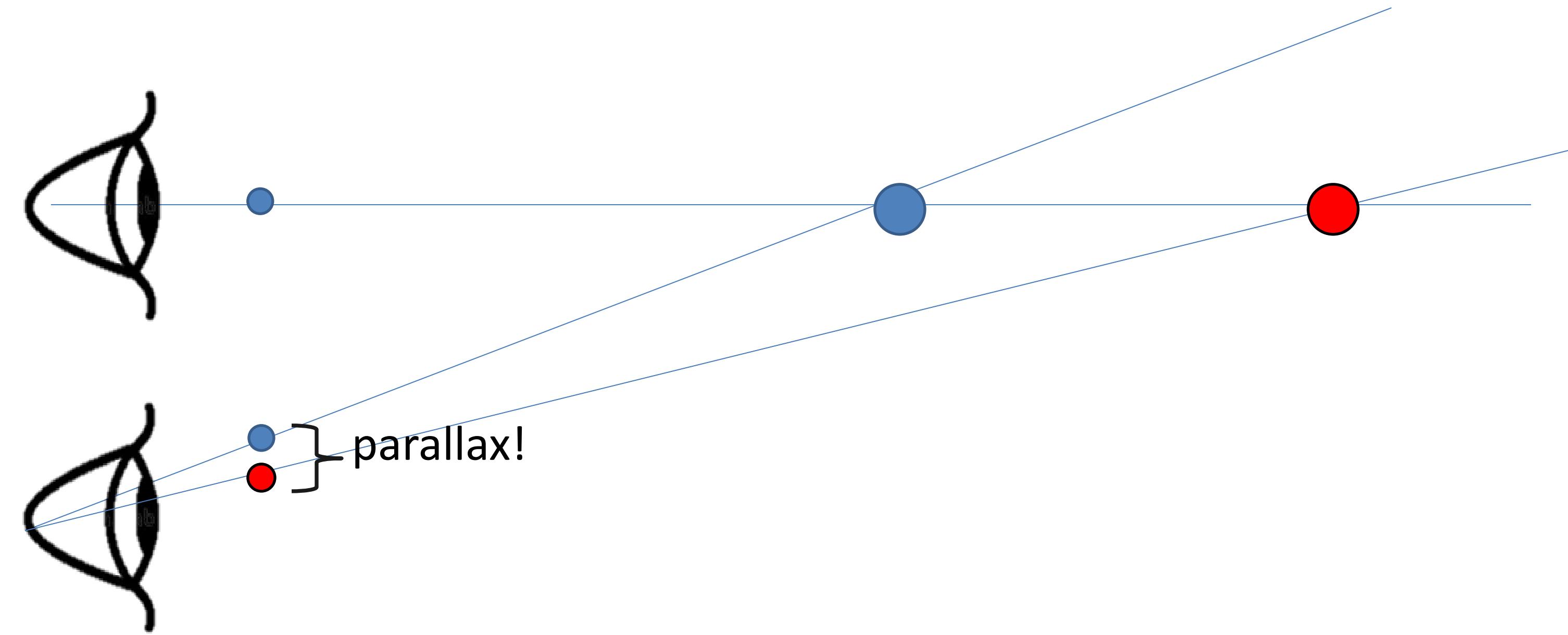
Rotation vs. Translation



Rotation vs. Translation



Parallax



Parallax = *from ancient Greek parállaxis*
 = *Para* (side by side) + *allássō*, (to alter)
 = *Change in position from different view point*

Two eyes give you parallax, you can also move to see more
parallax = “Motion Parallax”

Stereo vision



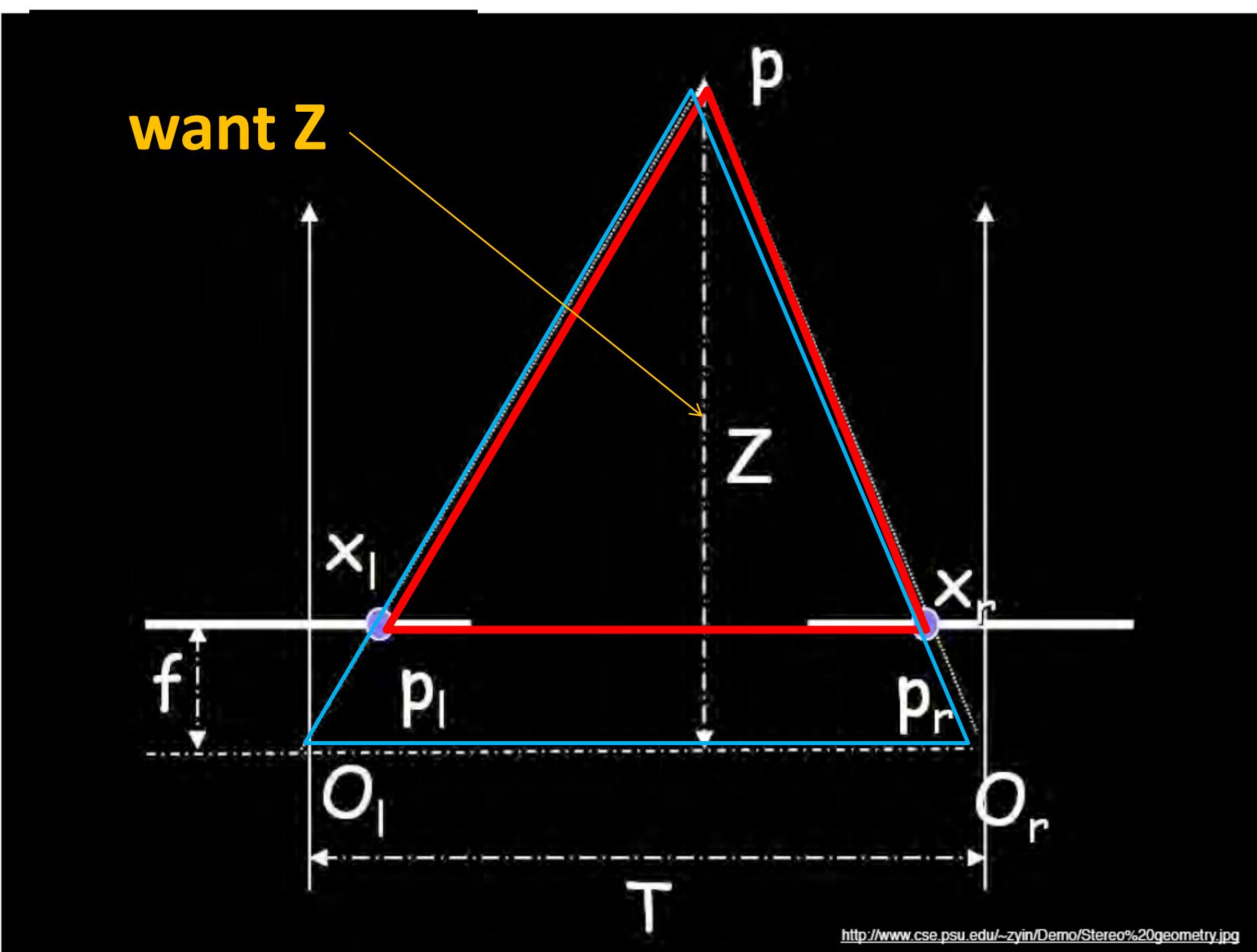
Two cameras, simultaneous views



Single moving camera and static scene

Geometry for a simple stereo system

- Assume **parallel** optical axes, known camera parameters (i.e., calibrated cameras).



Use similar triangles (p_l, P, p_r) and (O_l, P, O_r) :

$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

$$Z = f \frac{T}{x_r - x_l}$$

disparity

Non-parametric transformation!

image $I(x,y)$



Disparity map $D(x,y)$

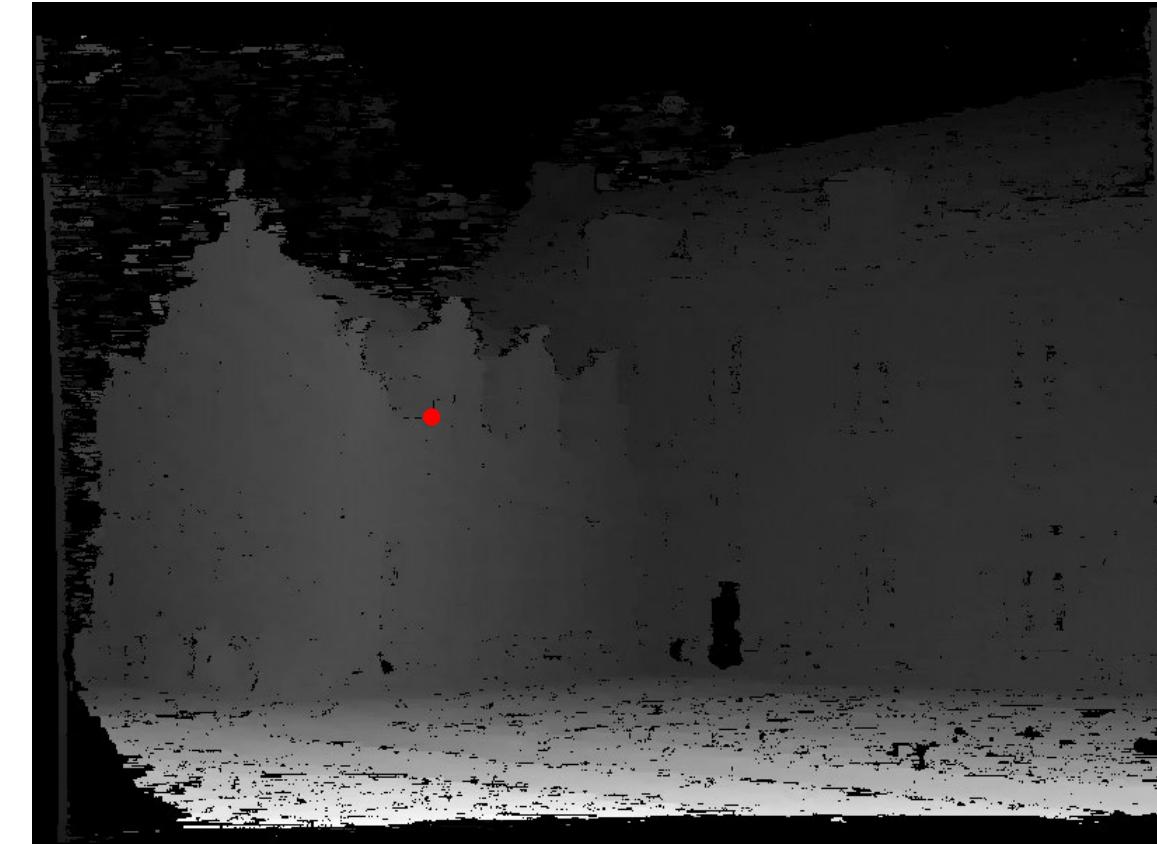


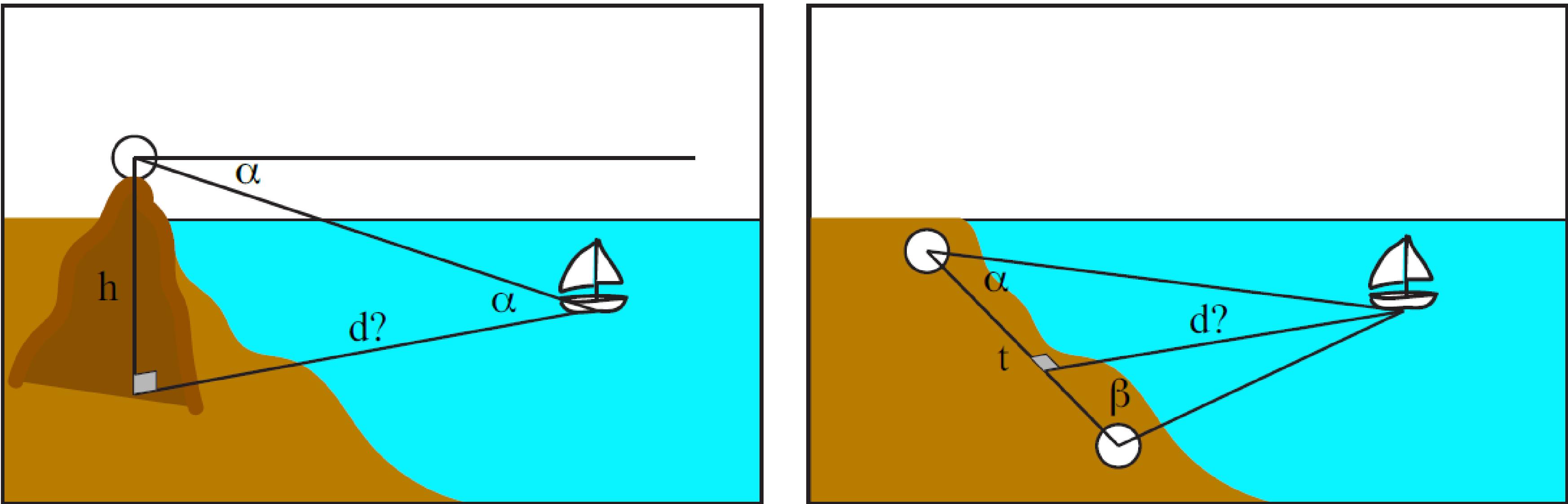
image $I'(x',y')$



$$(x', y') = (x + D(x, y), y)$$

Triangulation for Ship Navigation

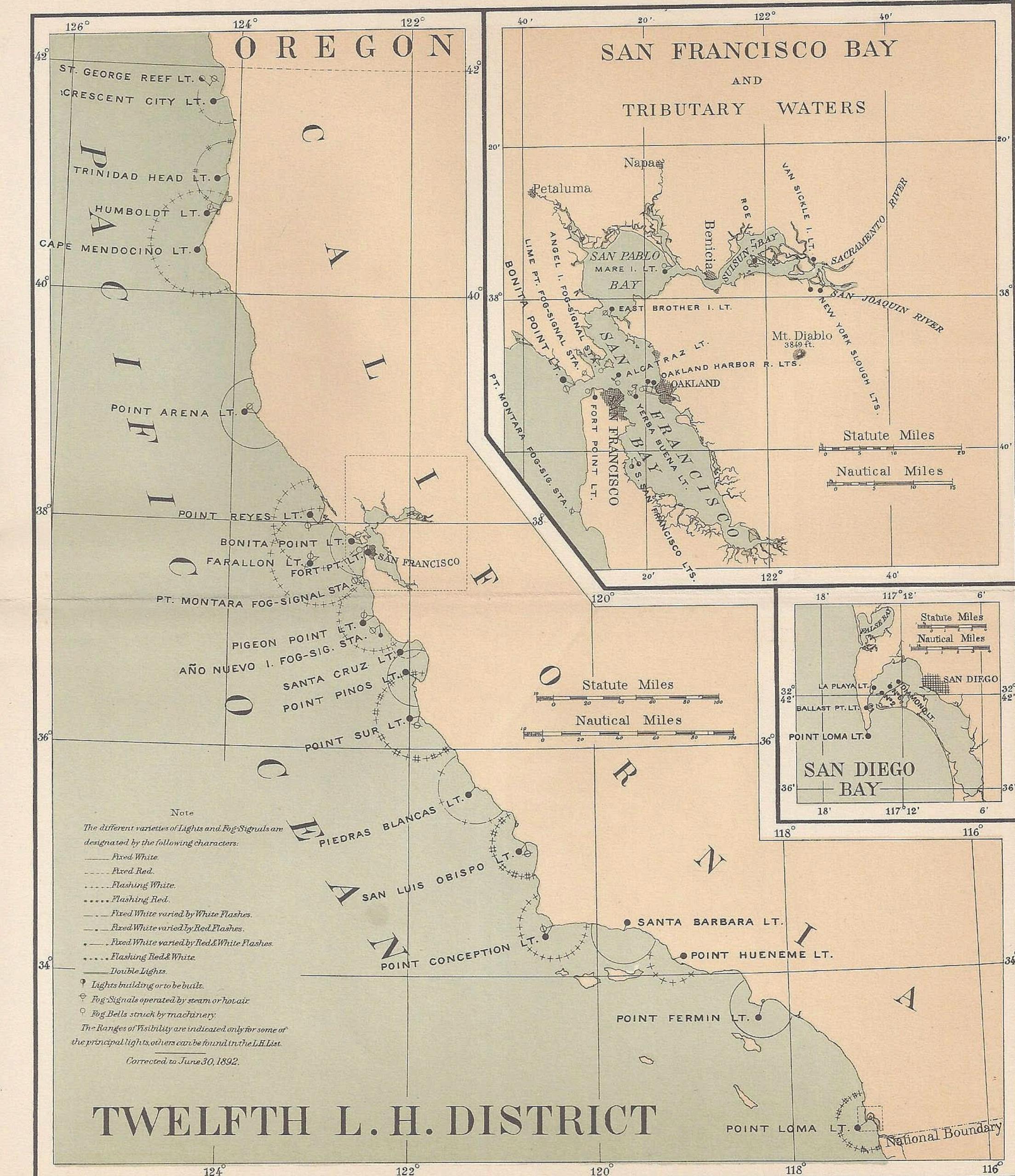
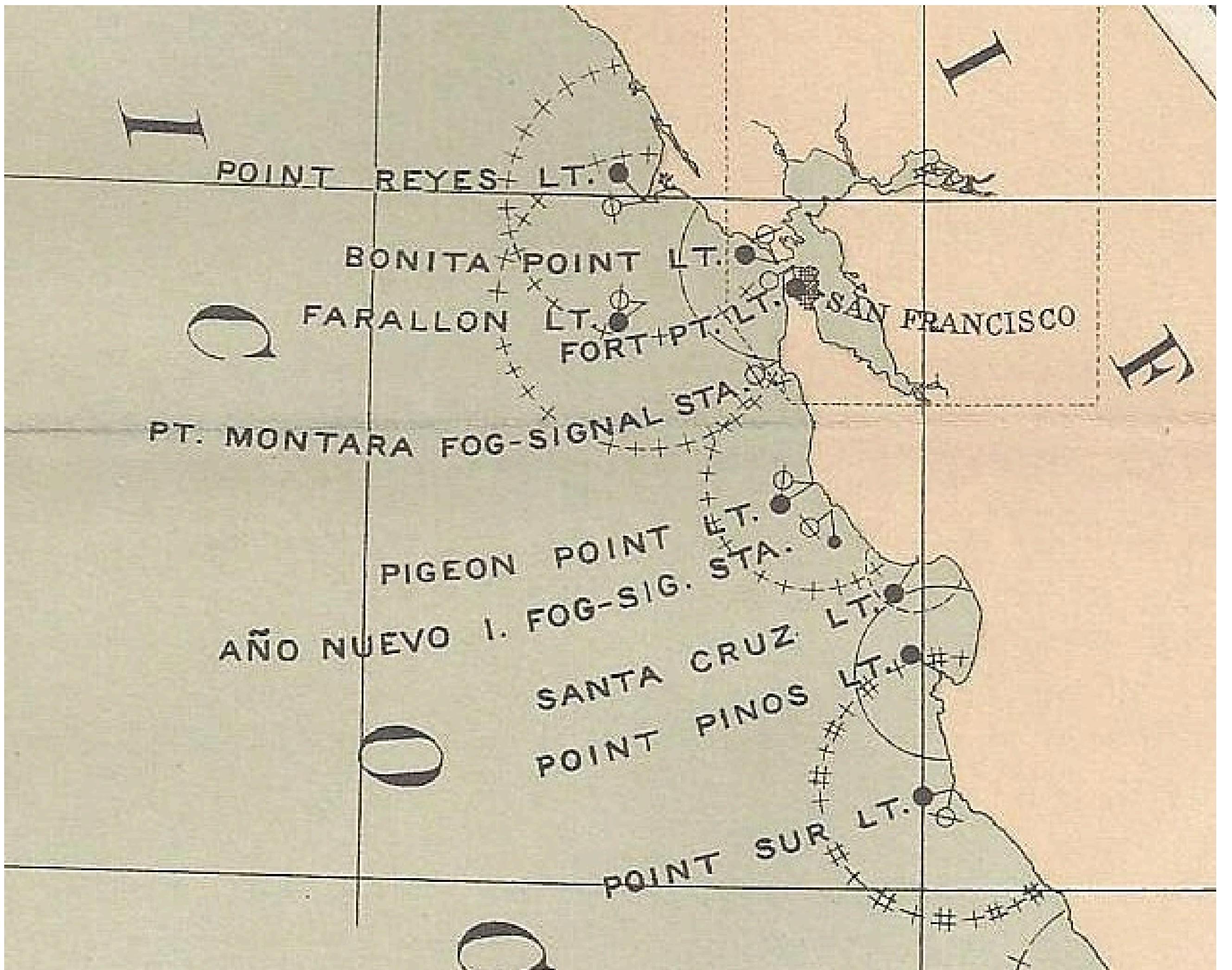
Figure 40.2: Two methods to estimate the distance of a boat from the coast. (left) The first method uses a single observation point, with knowledge of the observer's height above the water. (right) The second method uses two observation points.



$$d = \frac{h}{\tan(\alpha)}$$

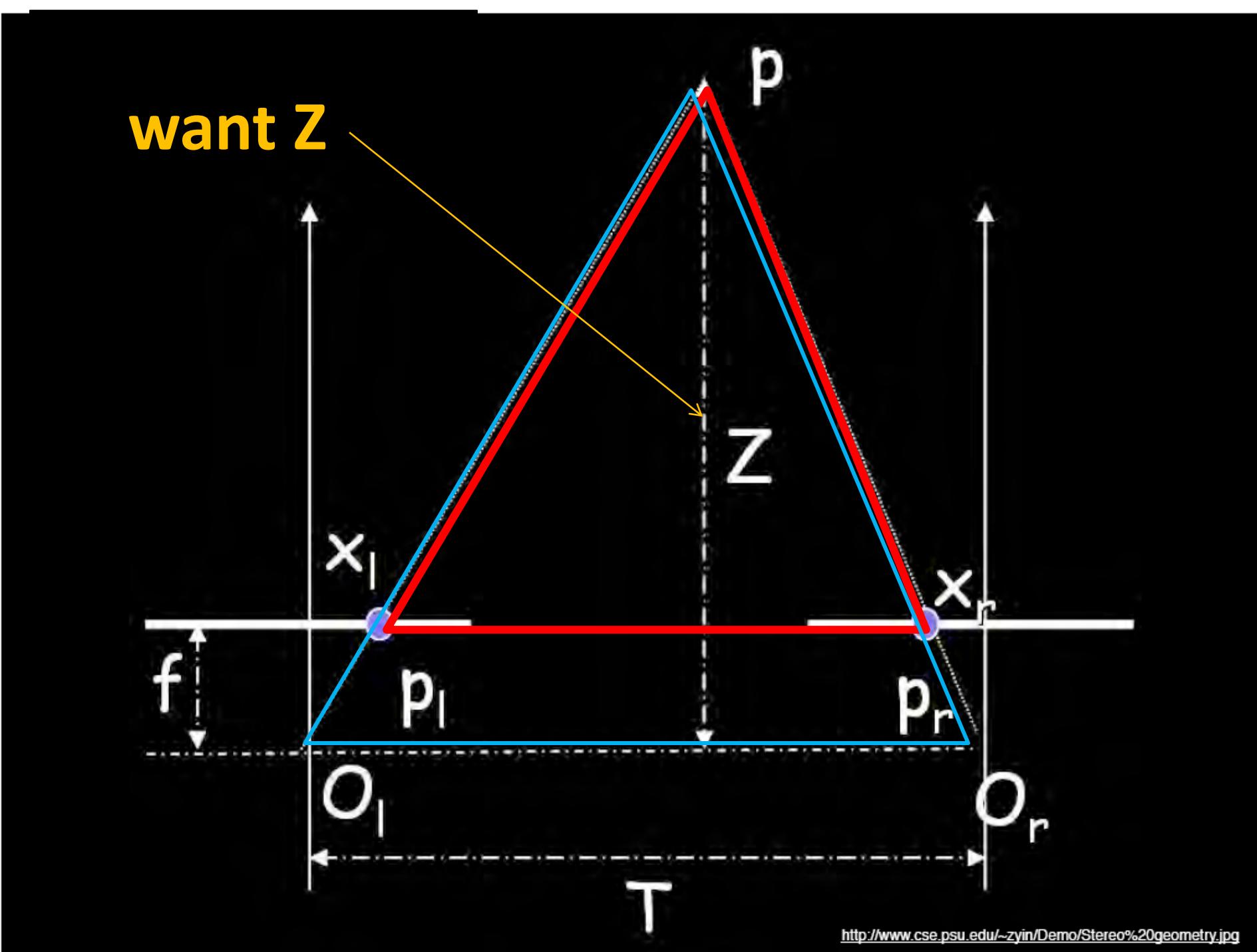
$$d = t \frac{\sin(\alpha) \sin(\beta)}{\sin(\alpha + \beta)}$$

Triangulation



Geometry for a simple stereo system

- Assume **parallel** optical axes, known camera parameters (i.e., calibrated cameras).



Use similar triangles (p_l, P, p_r) and (O_l, P, O_r) :

$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

$$Z = f \frac{T}{x_r - x_l}$$

disparity

Correspondence problem

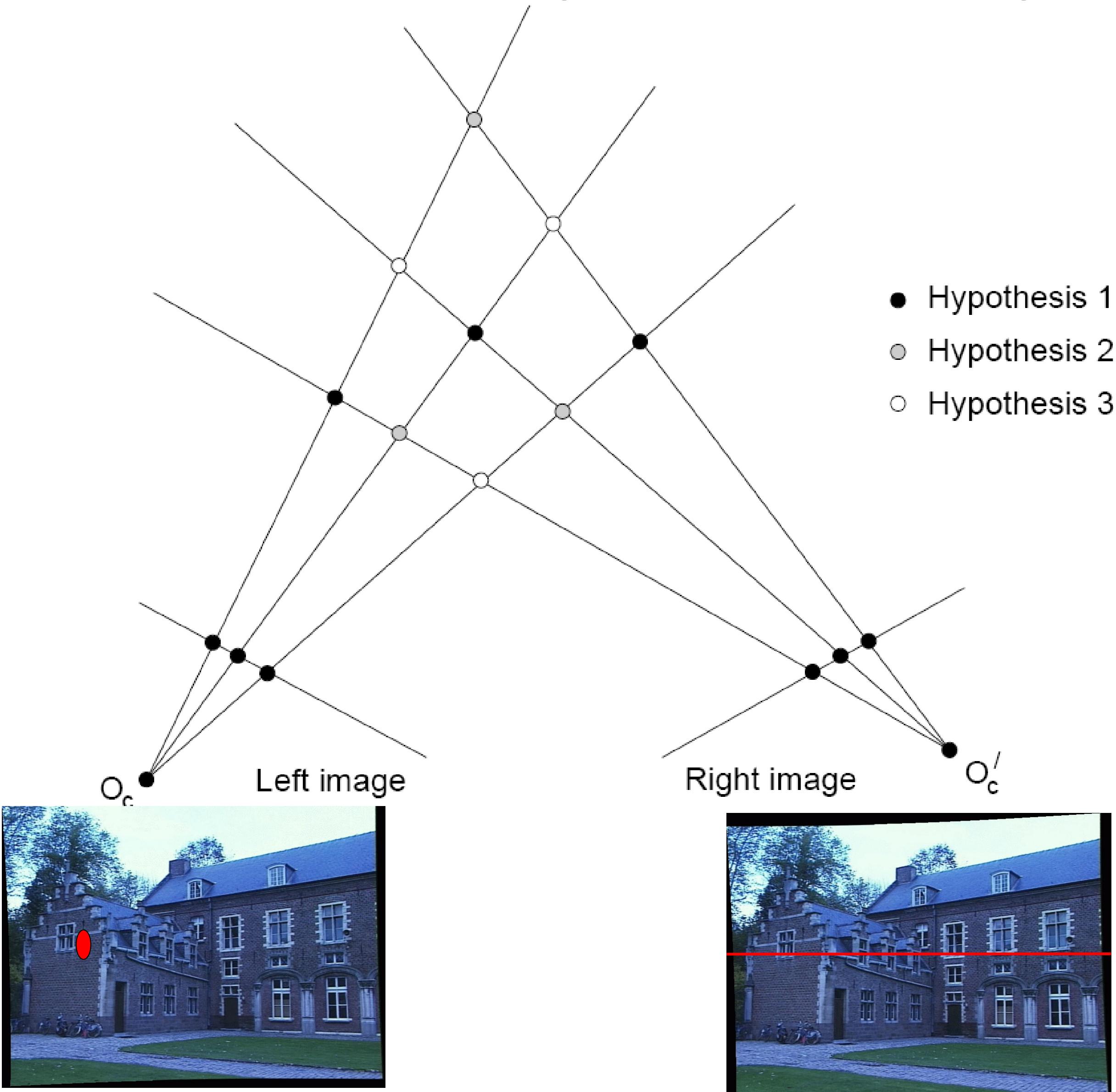
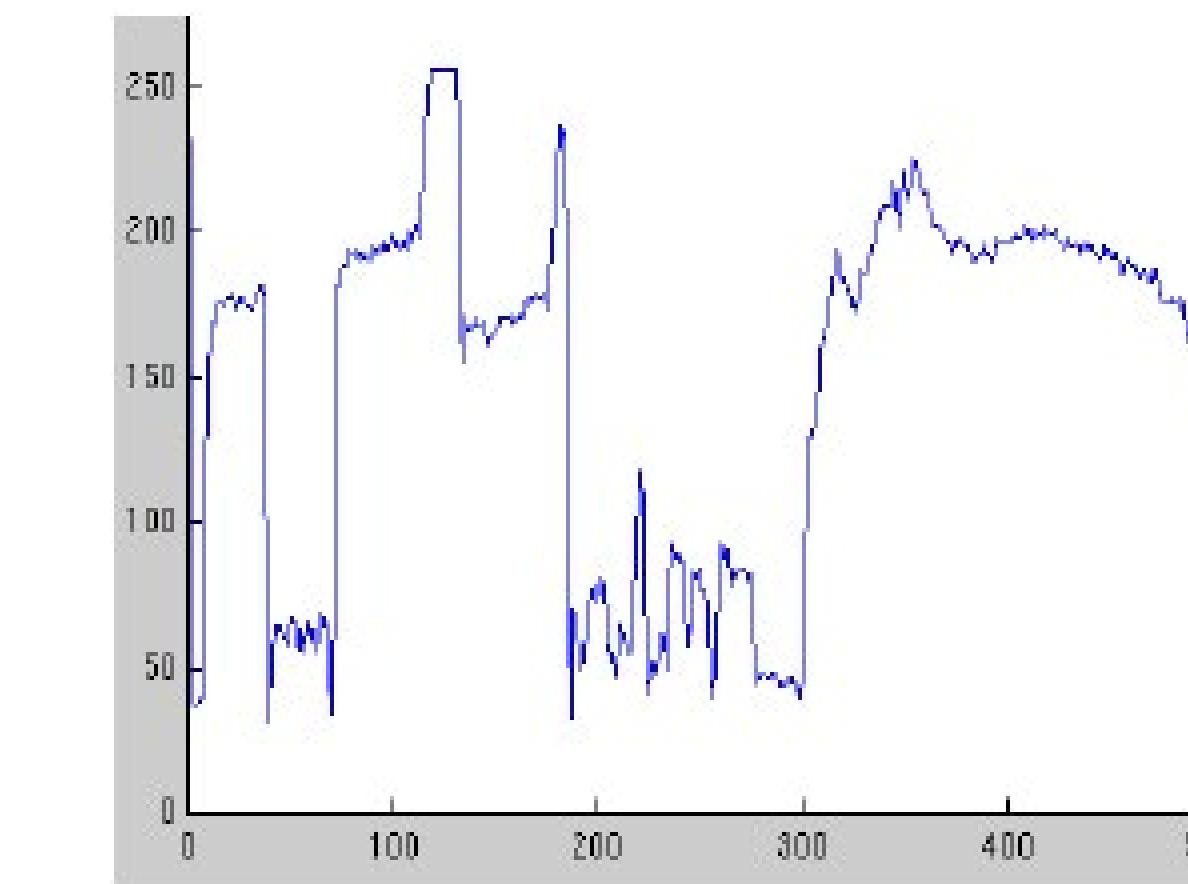
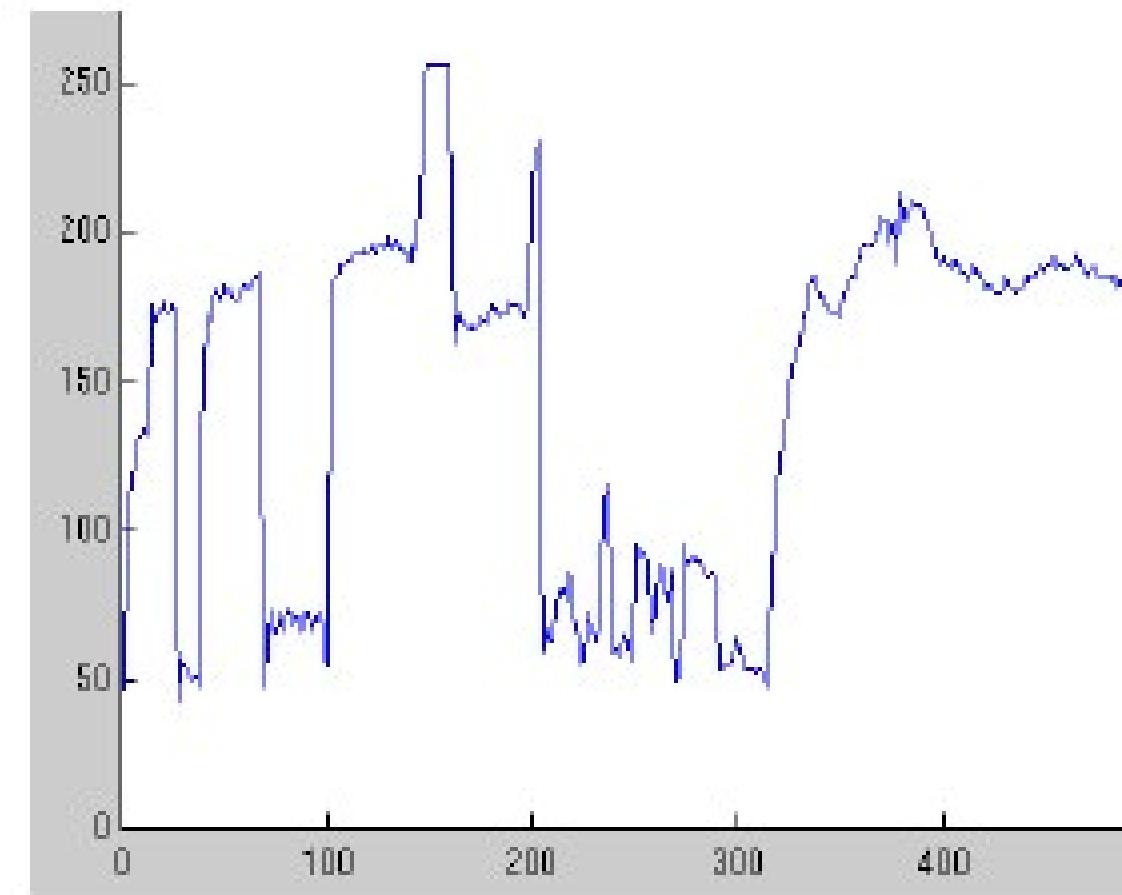
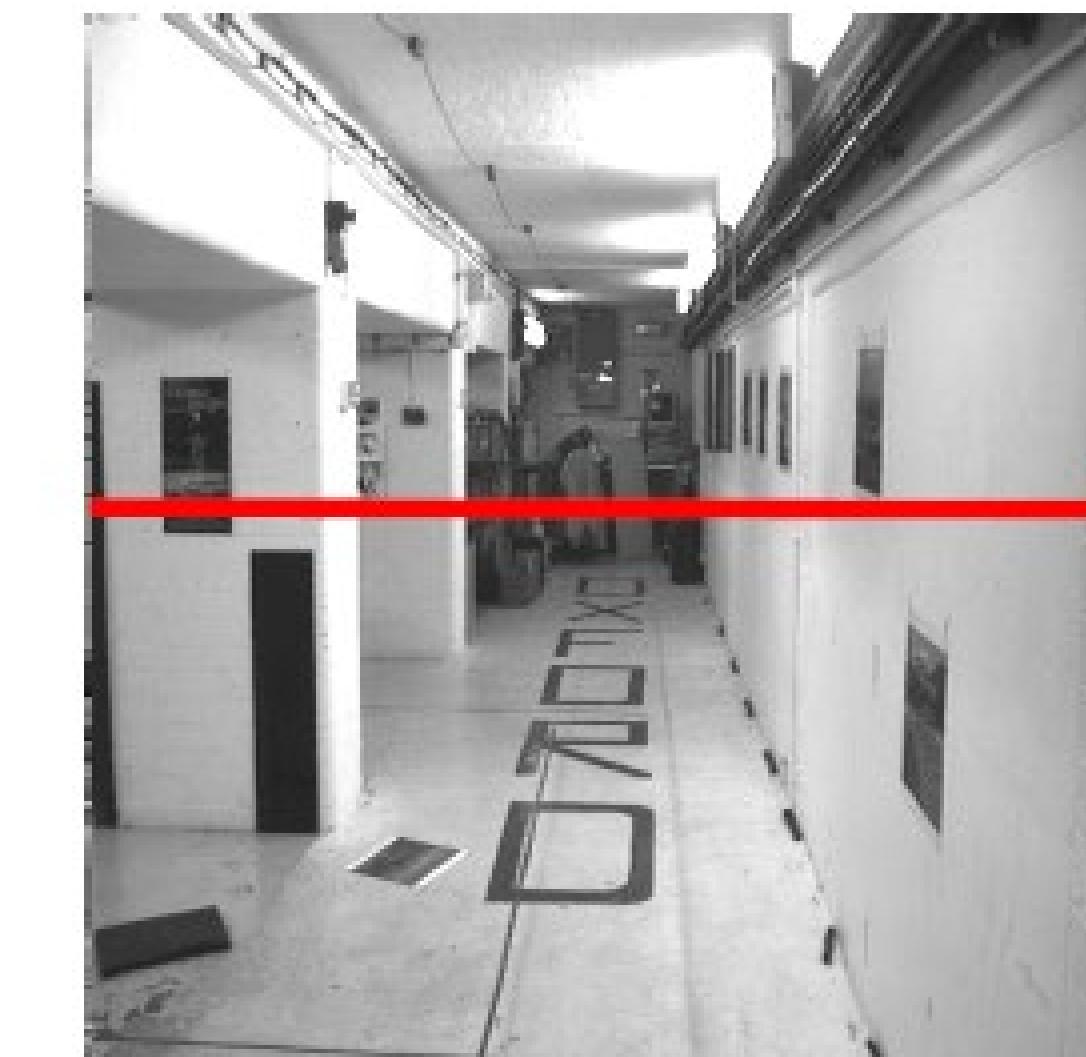


Figure from Gee & Cipolla 1999

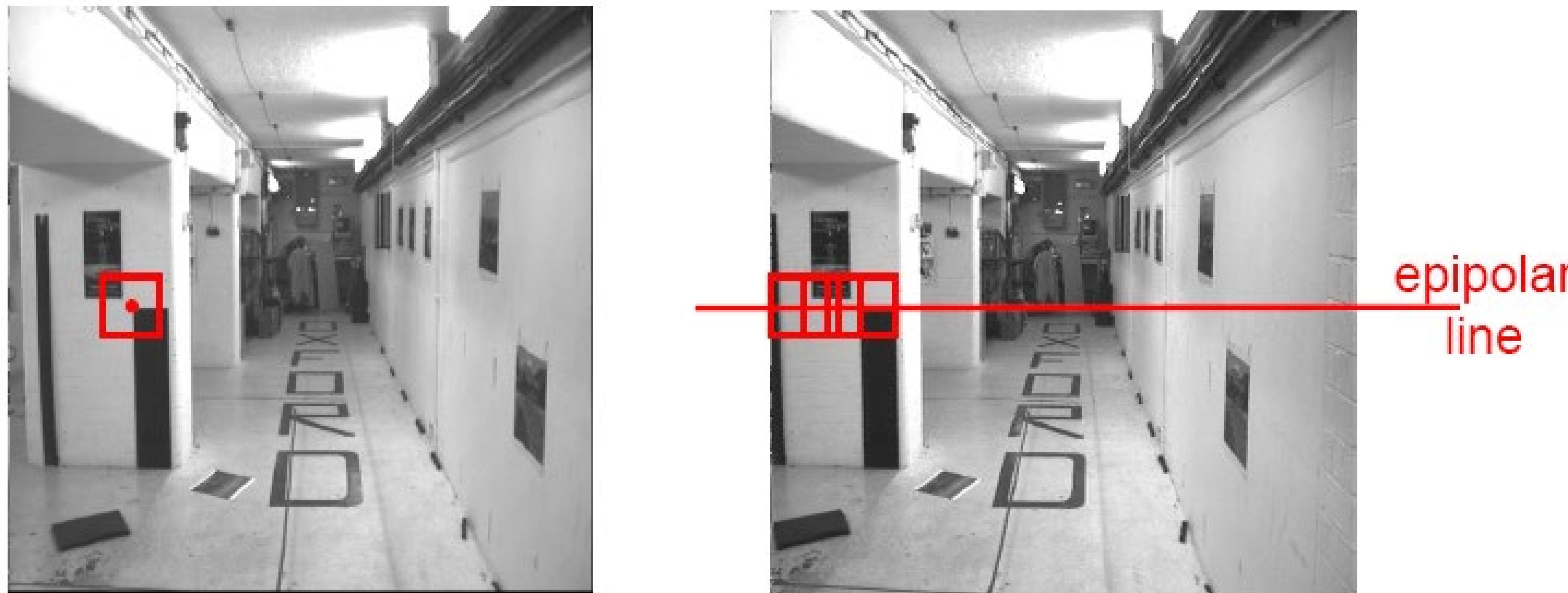
Grauman

Intensity profiles



- Clear correspondence between intensities, but also noise and ambiguity

Correspondence problem

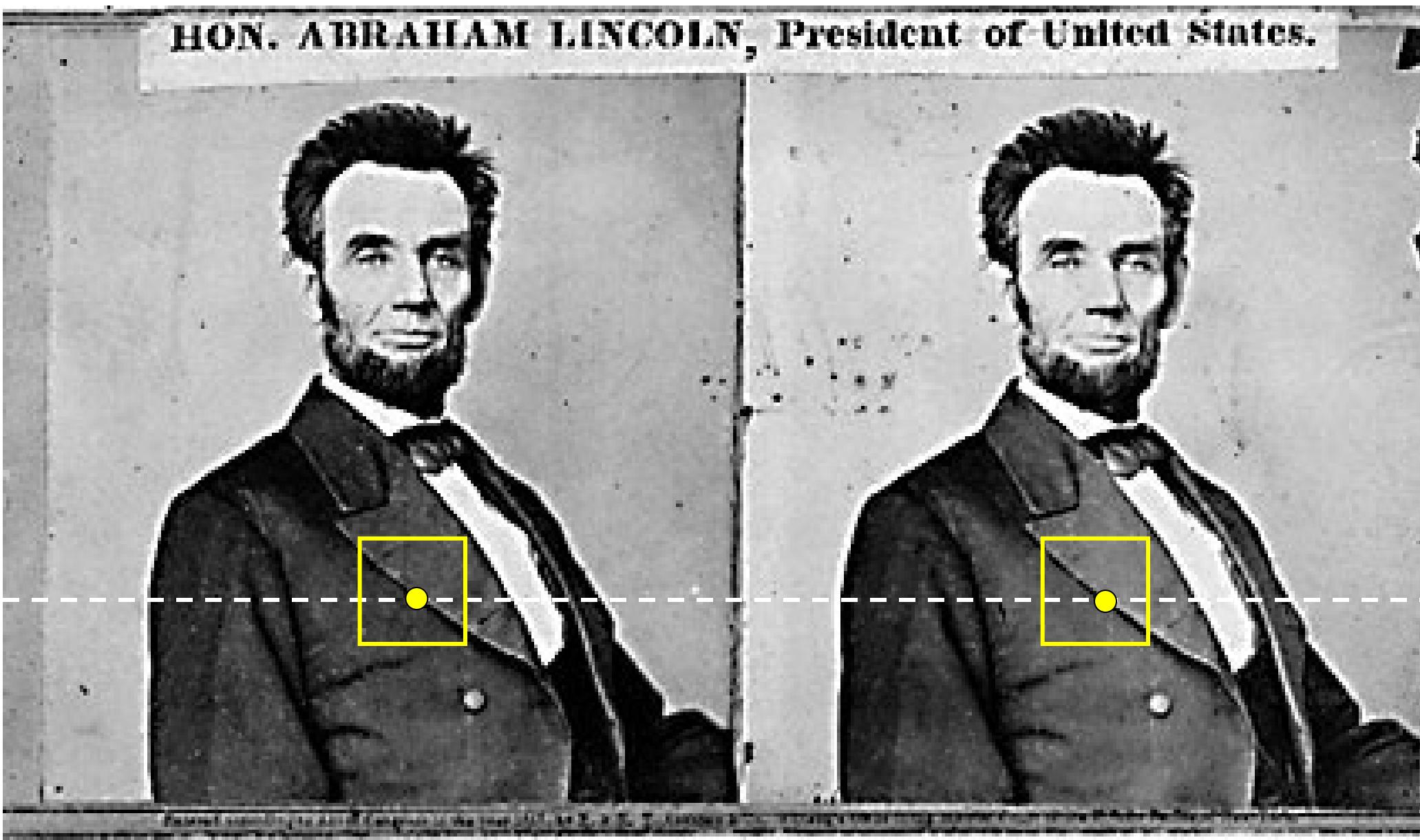


Neighborhood of corresponding points are similar in intensity patterns.

Correlation-based window matching



Dense correspondence search

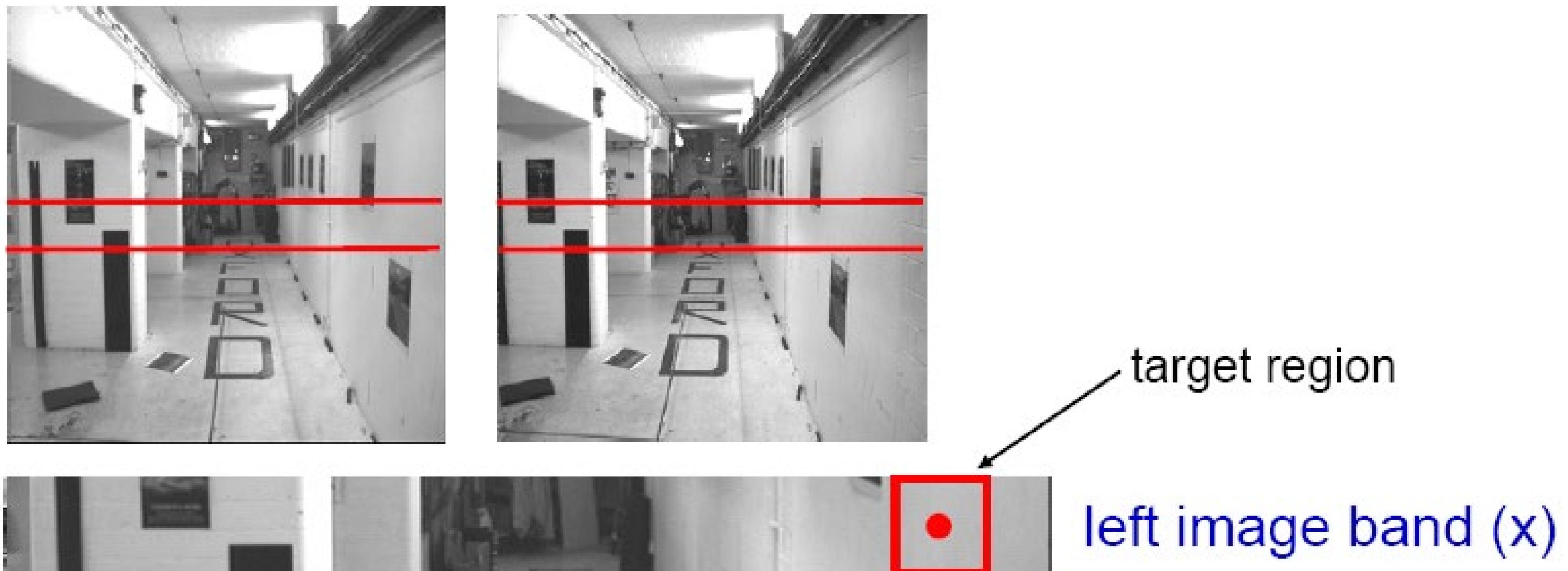


For each epipolar line

For each pixel / window in the left image

- compare with every pixel / window on same epipolar line in right image
- pick position with minimum match cost (e.g., SSD, correlation)

Textureless regions



Failures of Correspondence Search

Repeated Patterns. Why?

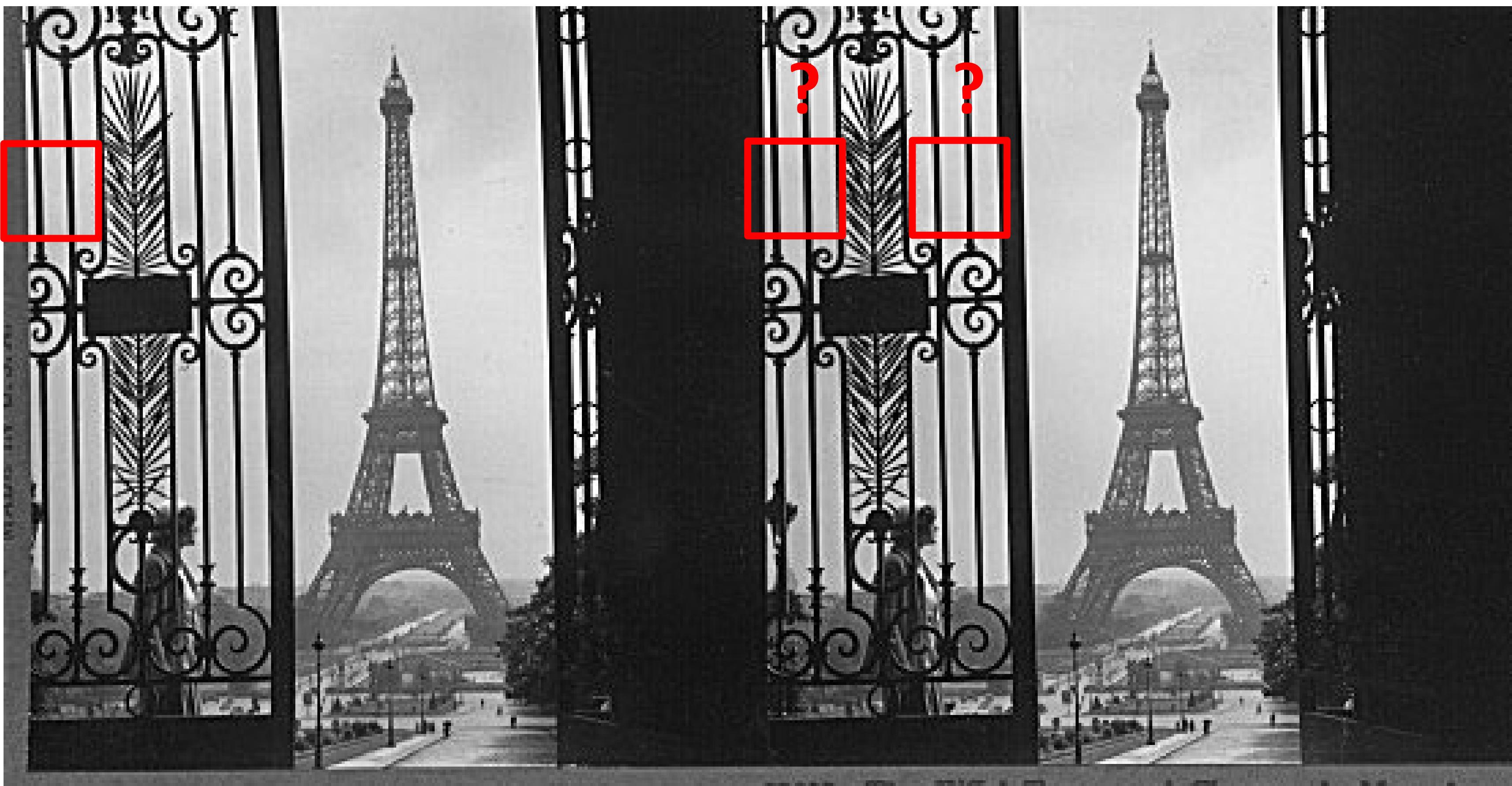
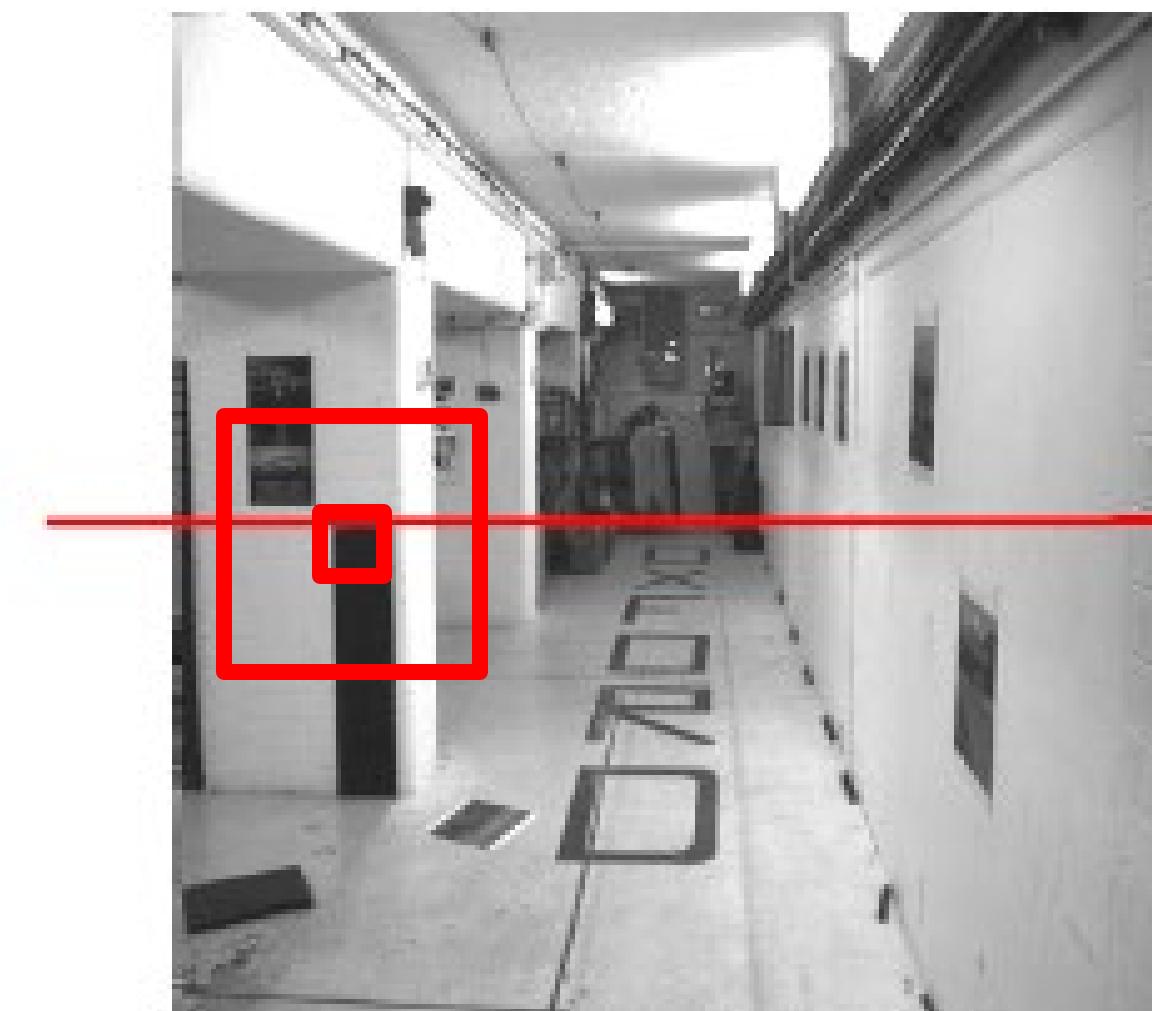


Image credit: S. Lazebnik

Effect of window size

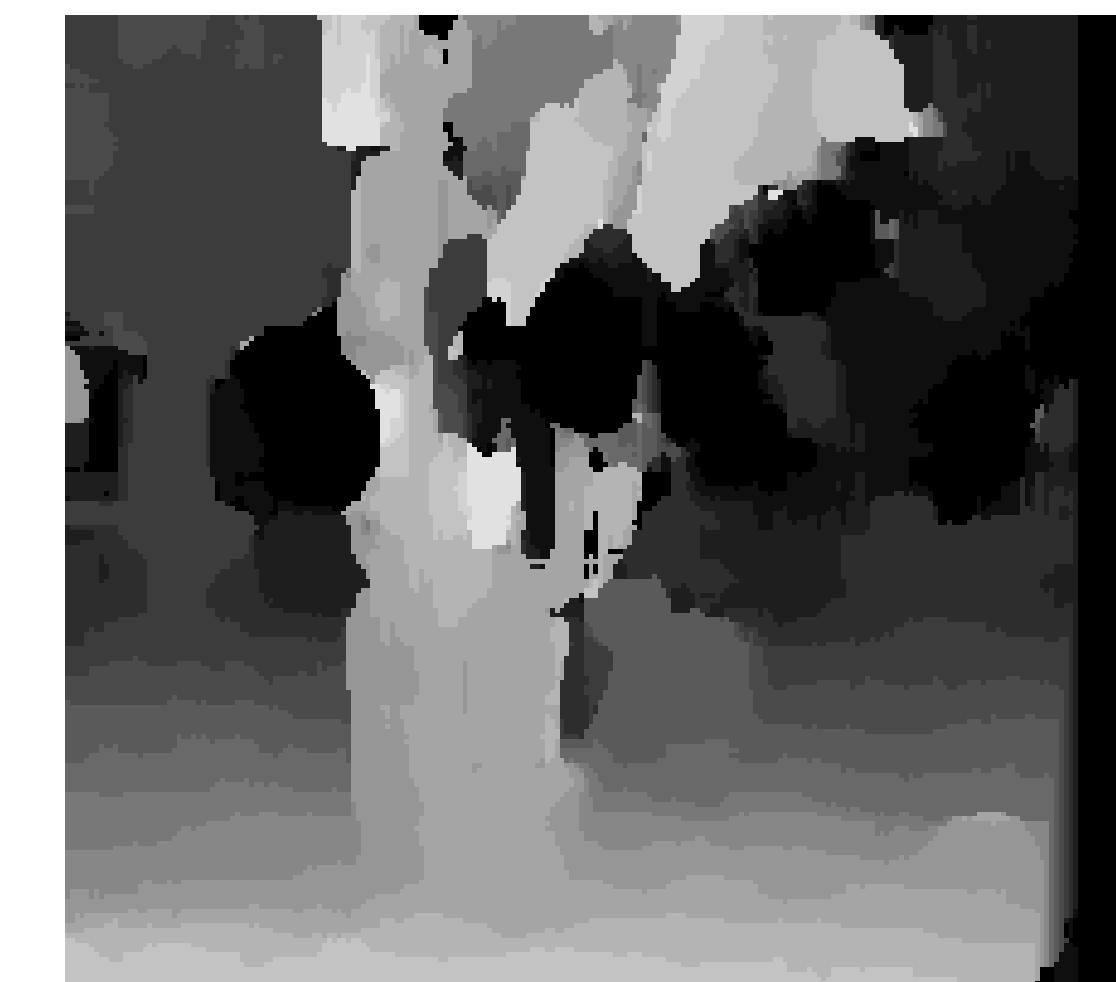


epipolar
line

Effect of window size



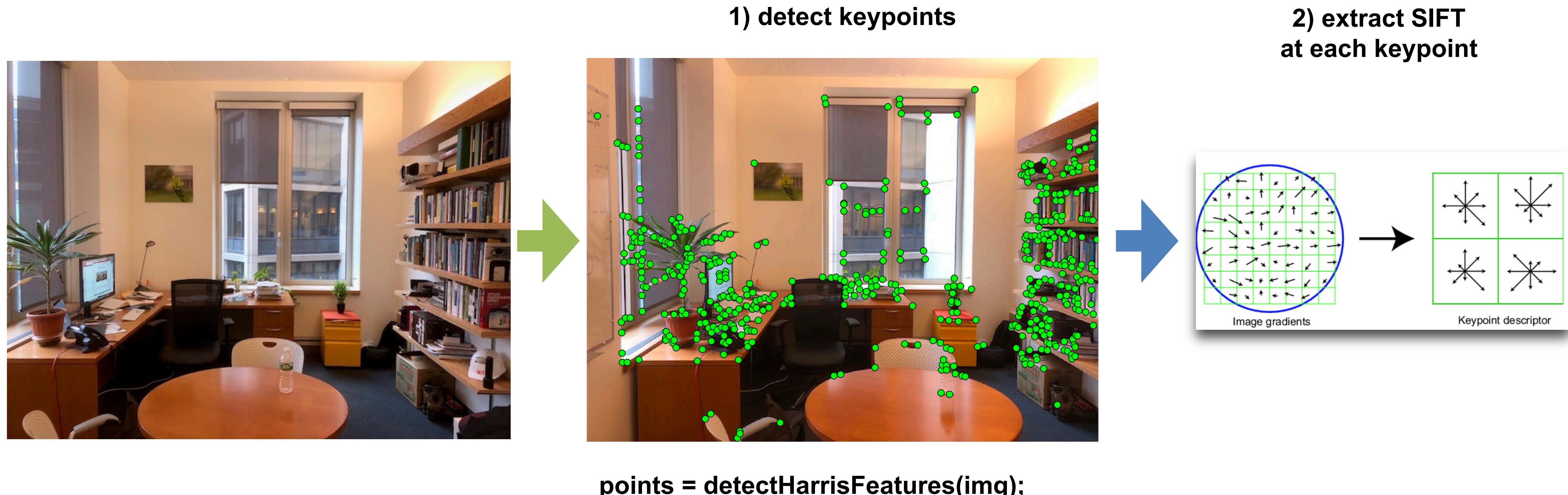
$W = 3$



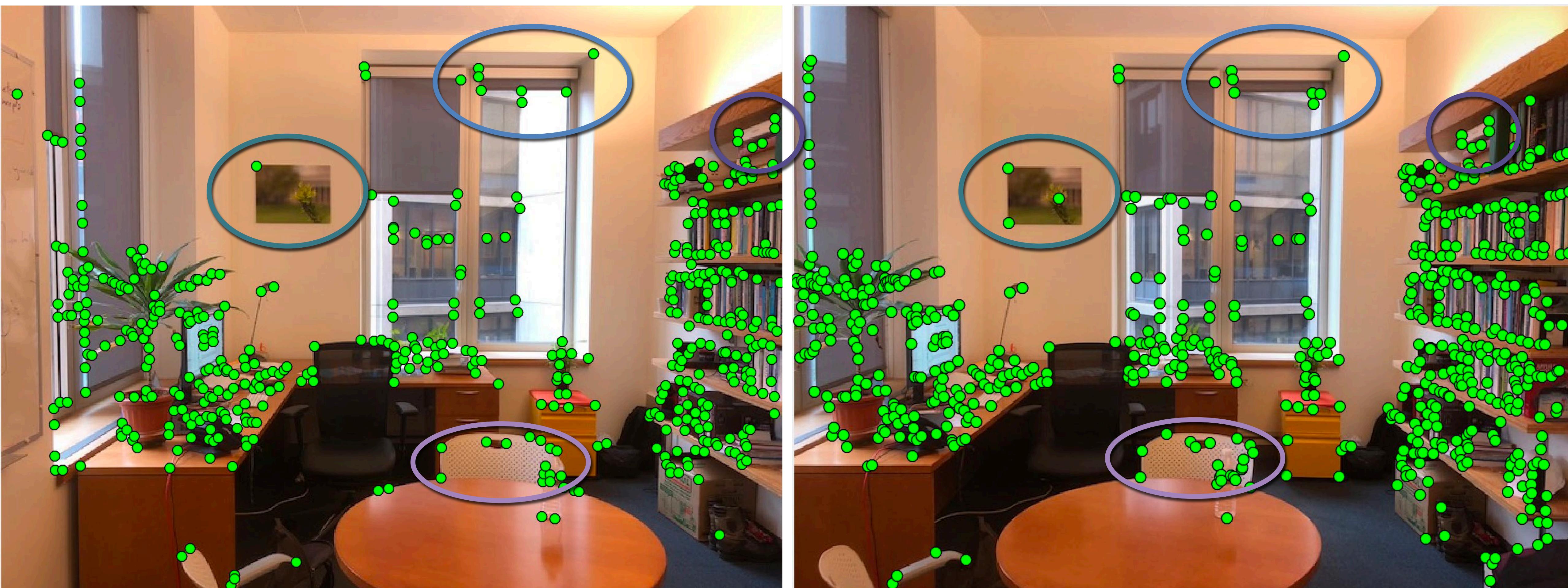
$W = 20$

Want window large enough to have sufficient intensity variation, yet small enough to contain only pixels with about the same disparity.

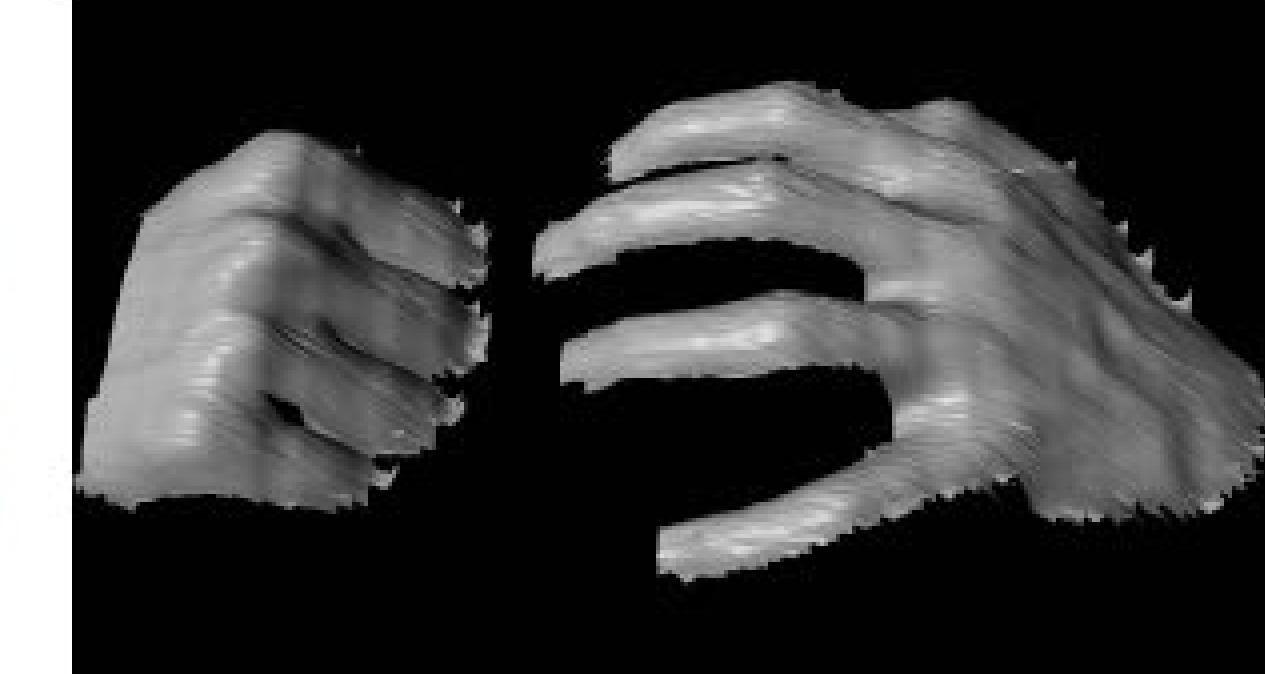
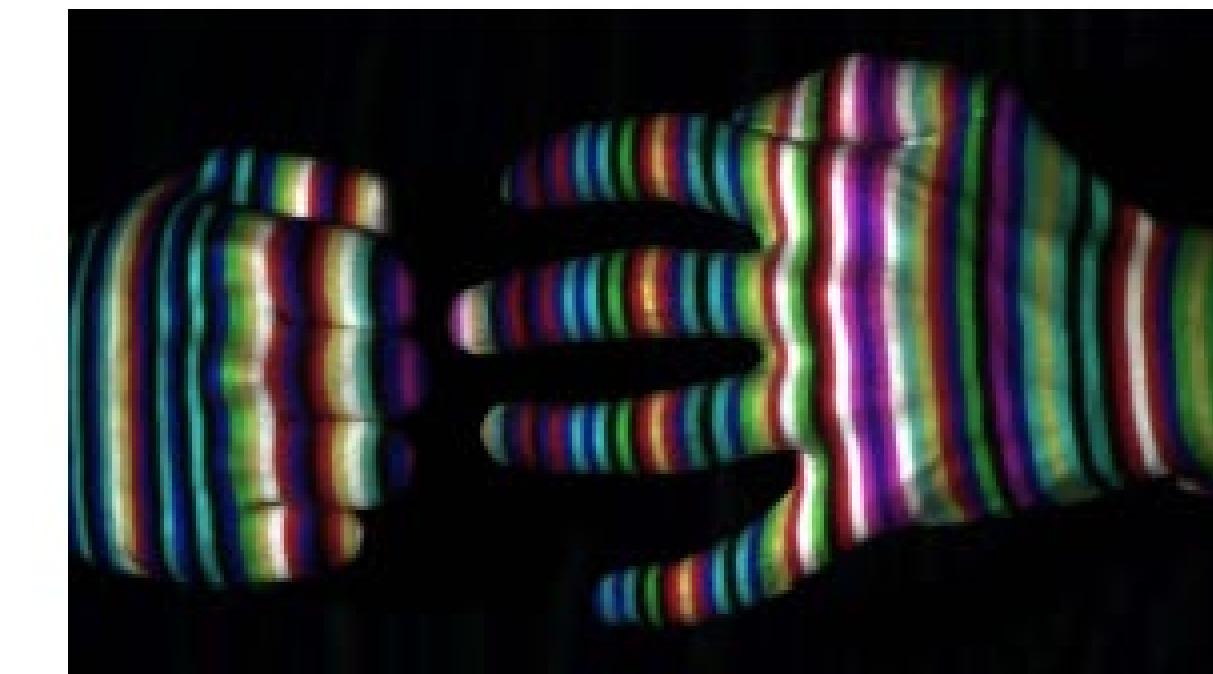
Feature correspondences



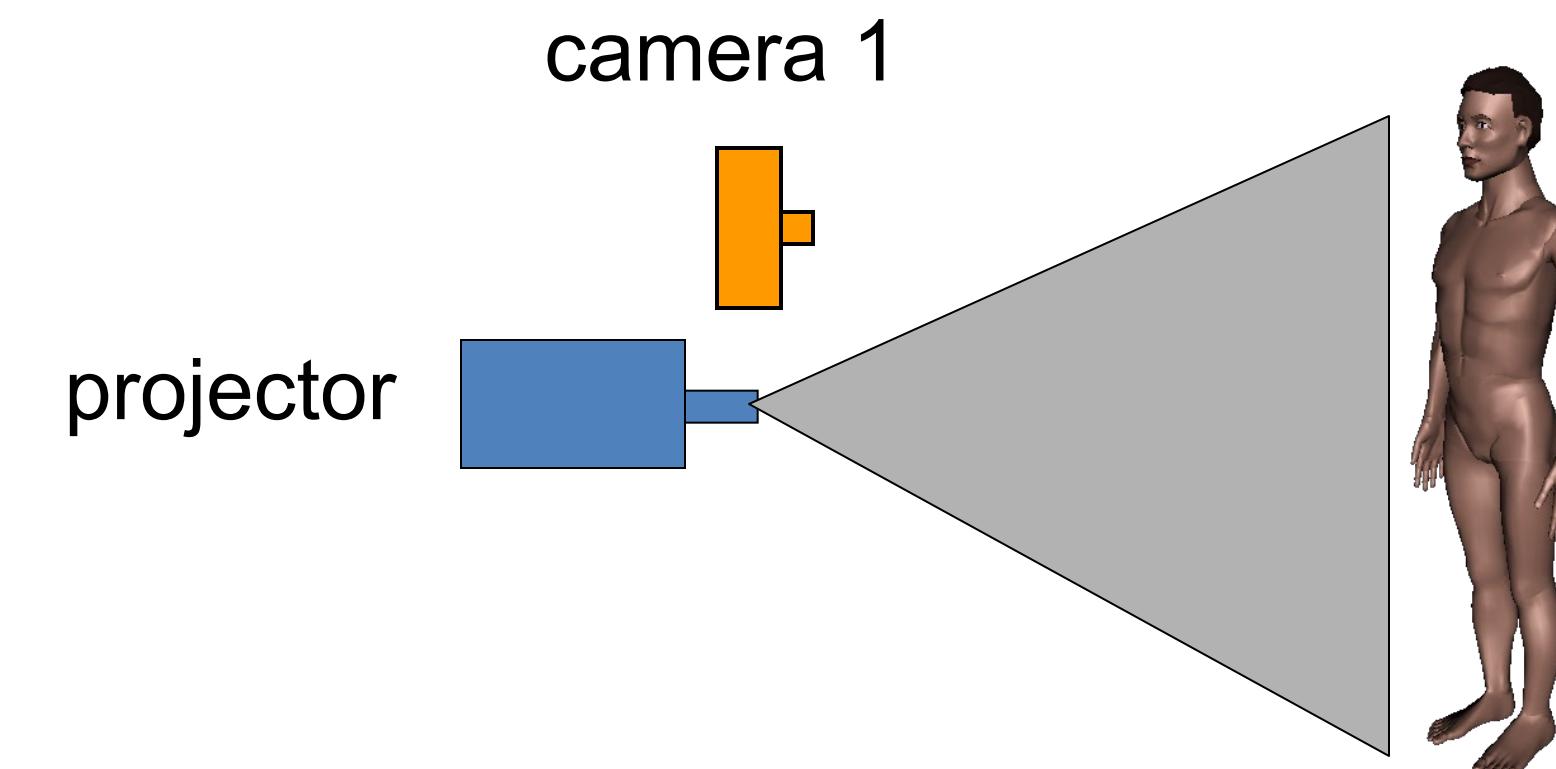
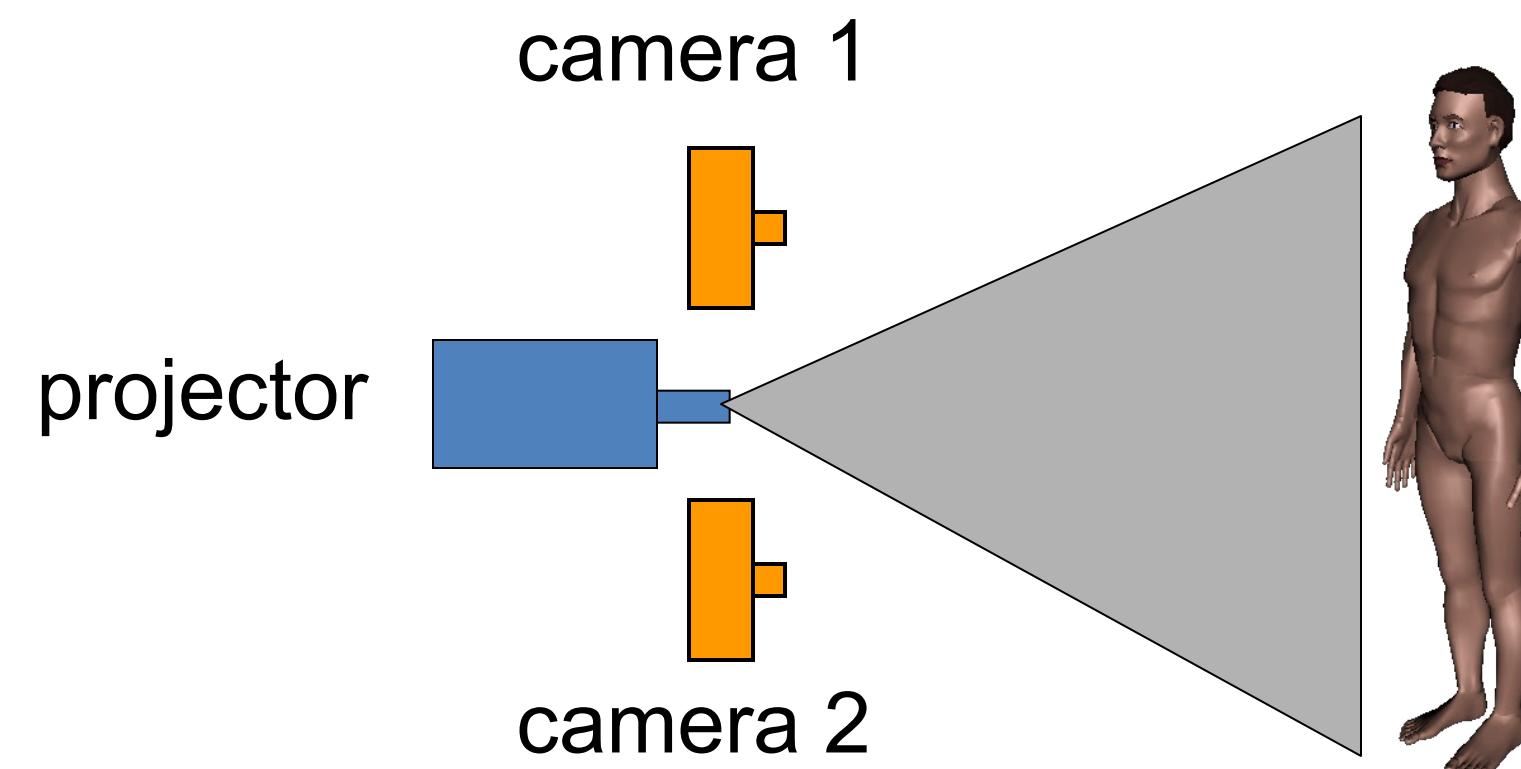
Finding correspondences (SIFT)



Active stereo with structured light

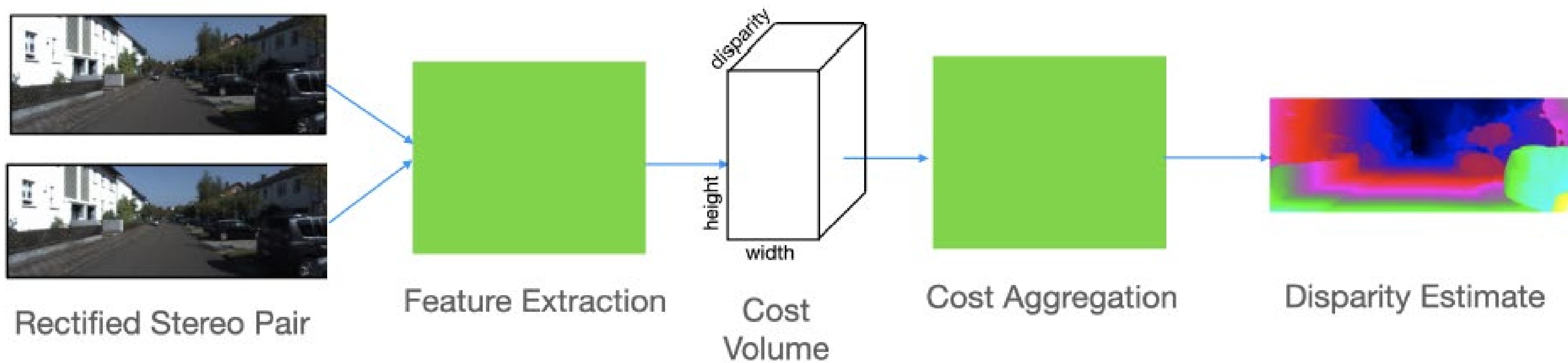


Li Zhang's one-shot stereo

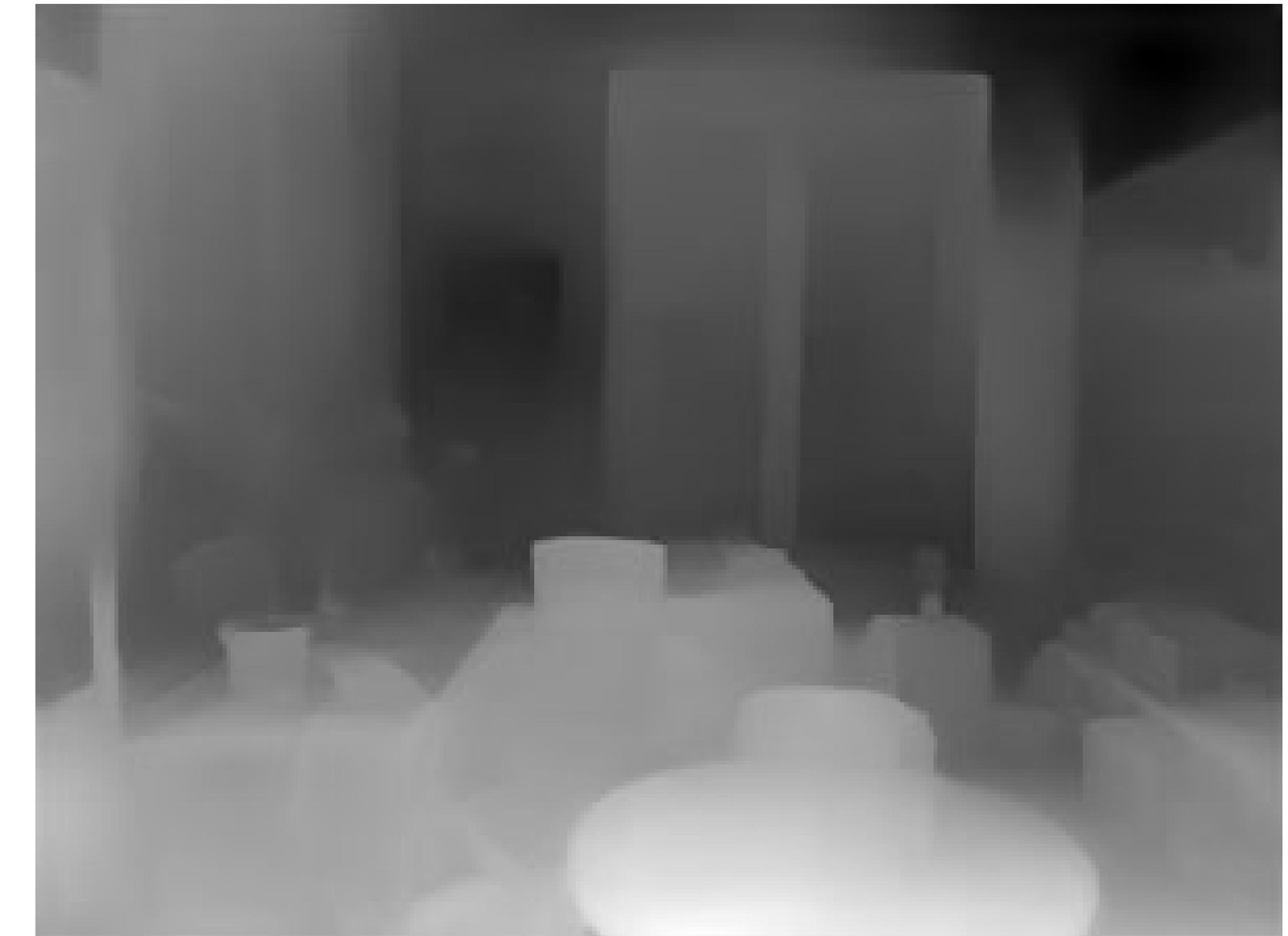


- Project “structured” light patterns onto the object
 - simplifies the correspondence problem

CNN-based Stereo Matching



Can also learn depth from a single image



MegaDepth: Learning Single-View Depth Prediction from Internet Photos

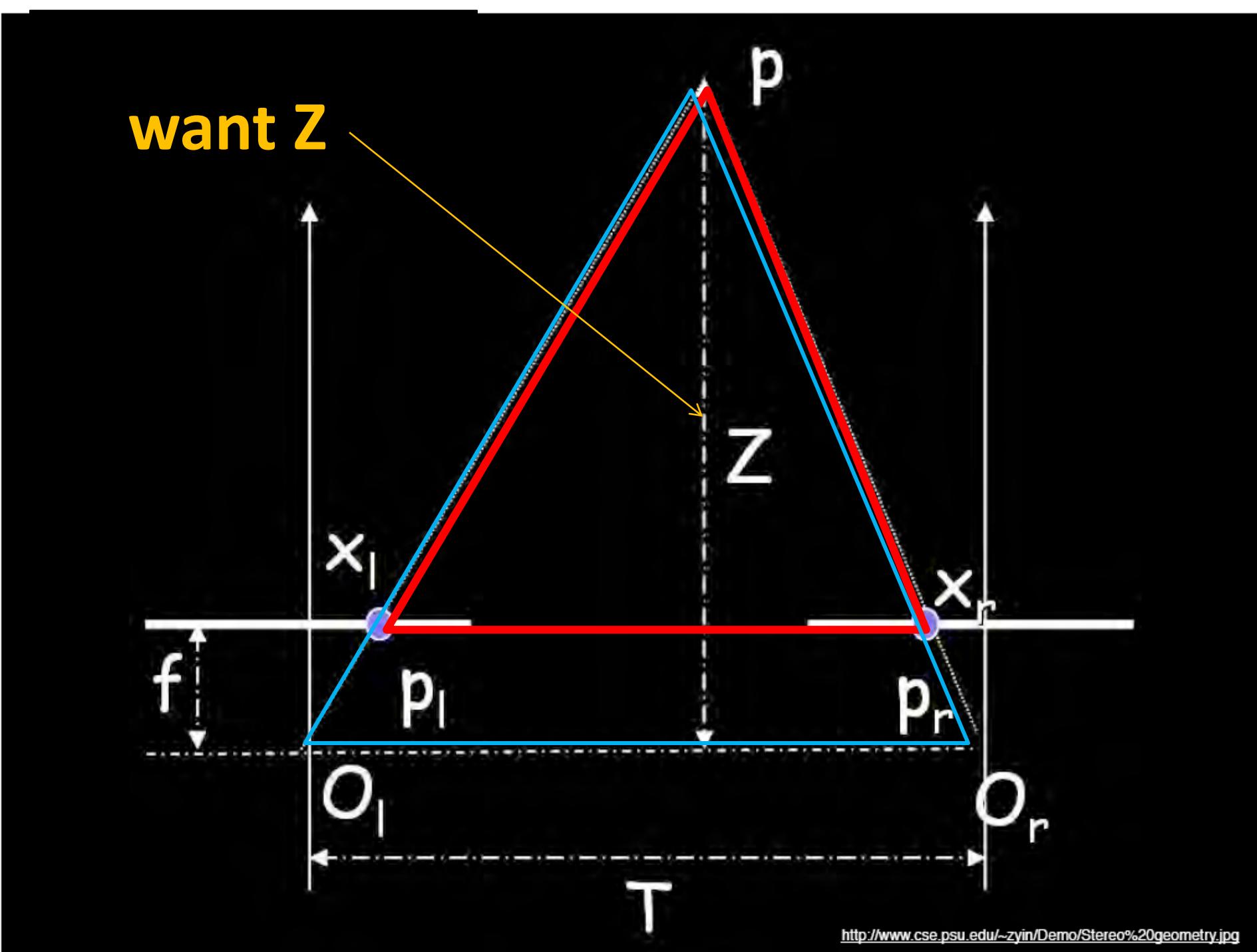
Zhengqi Li Noah Snavely
Department of Computer Science & Cornell Tech, Cornell University

35

Source: Torralba, Isola, Freeman

Geometry for a simple stereo system

- Assume **parallel** optical axes, known camera parameters (i.e., calibrated cameras).



Use similar triangles (p_l, P, p_r) and (O_l, P, O_r):

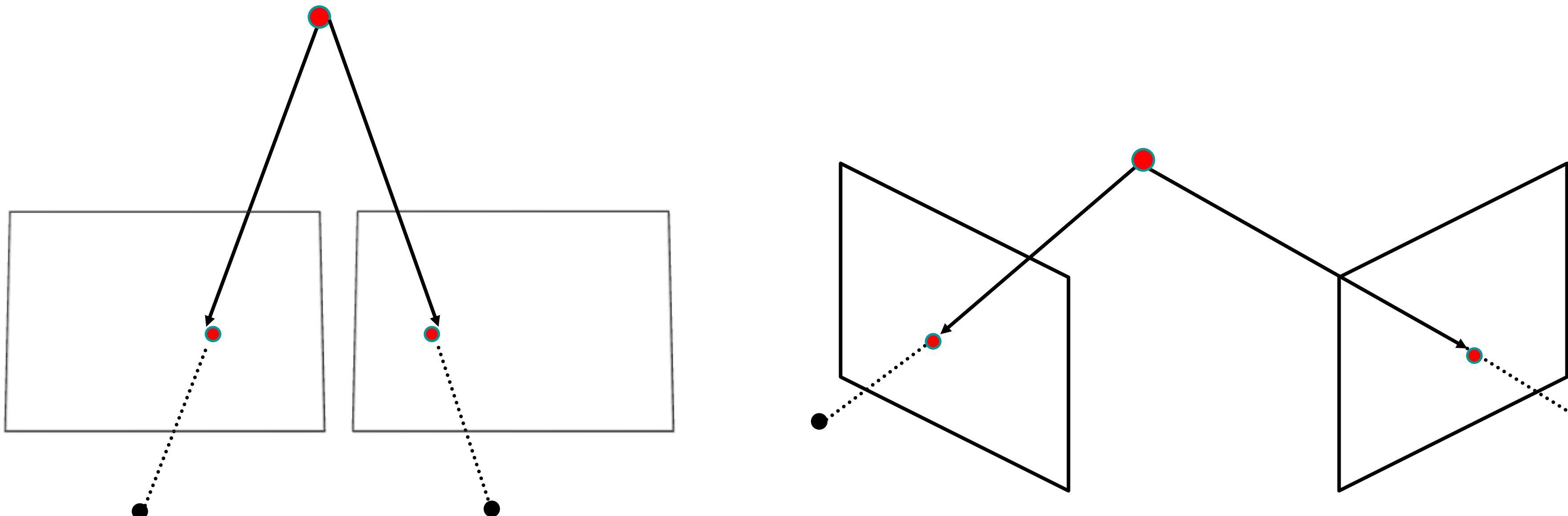
$$\frac{T + x_l - x_r}{Z - f} = \frac{T}{Z}$$

$$Z = f \frac{T}{x_r - x_l}$$

disparity

General case

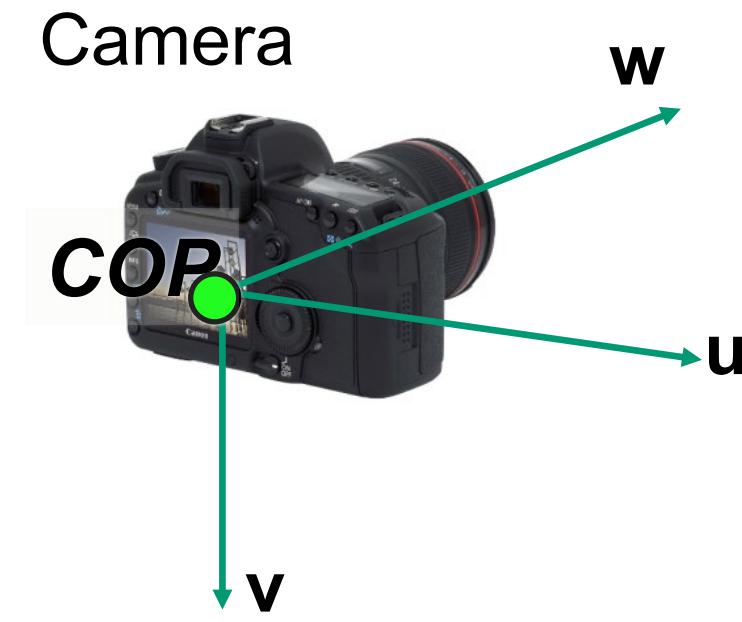
- The two cameras need not have parallel optical axes.



Situating Camera in the world

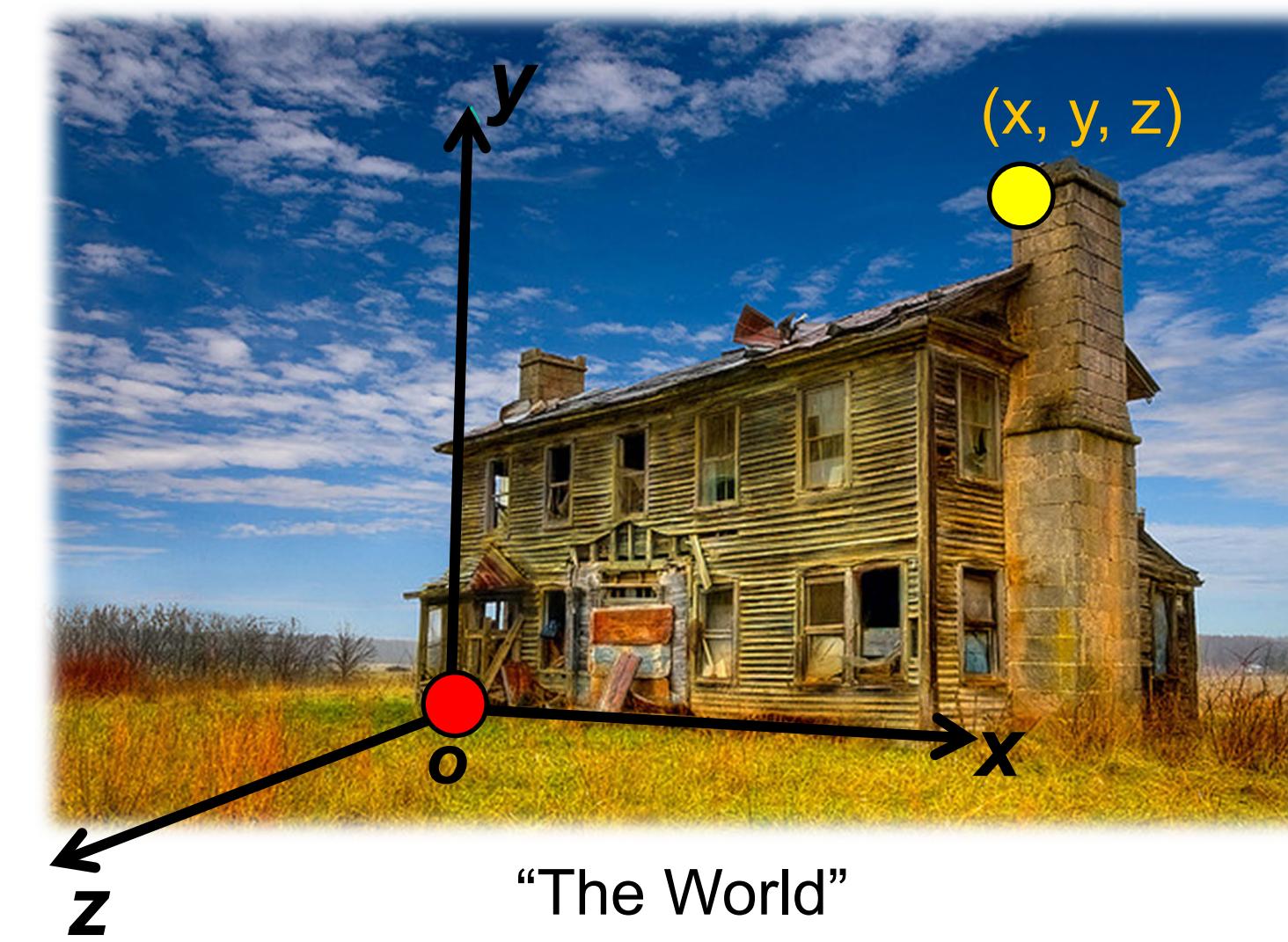
There is a world coordinate frame and camera looking at the world

How can we model the geometry of a camera?

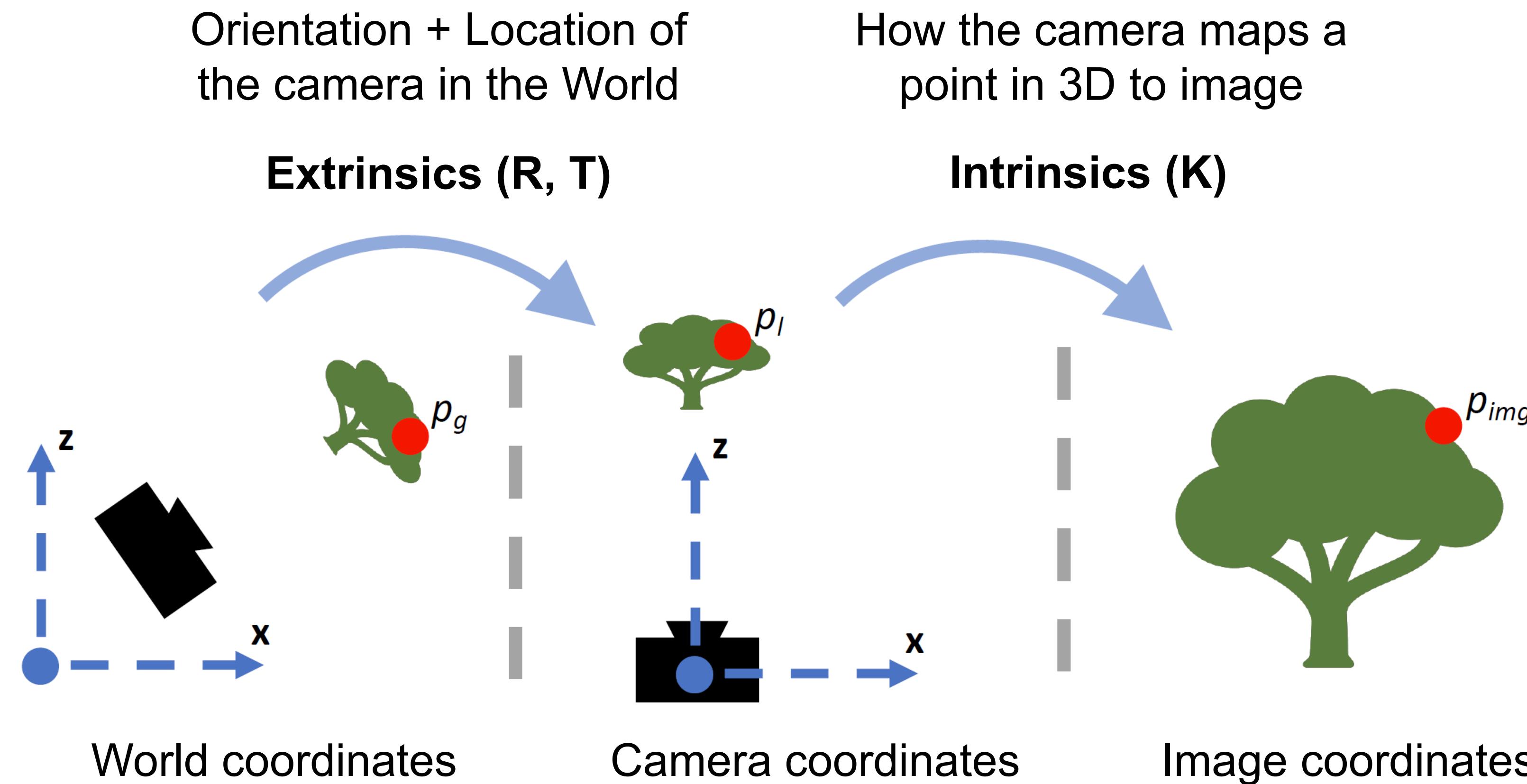


Three important coordinate systems:

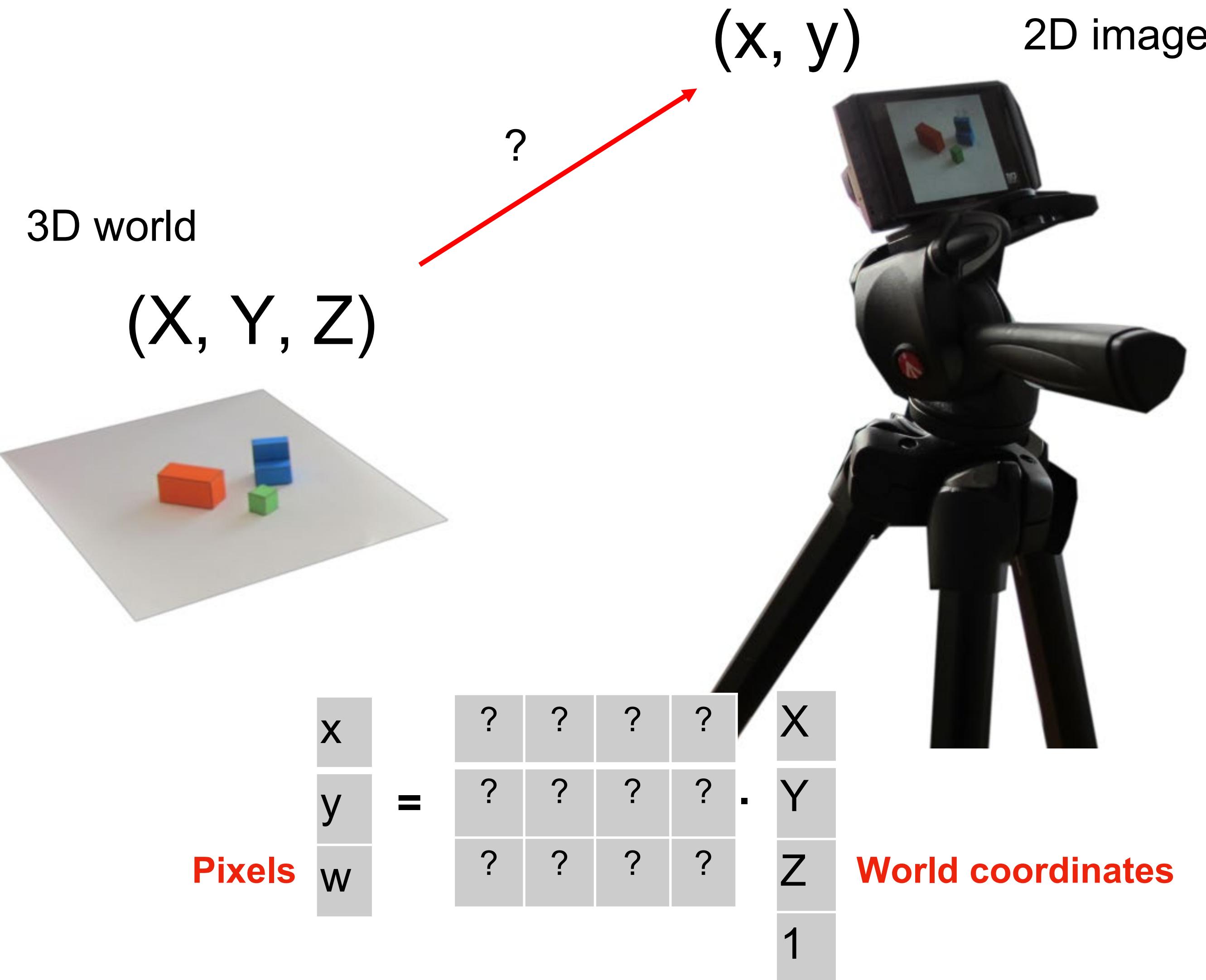
1. *World* coordinates
2. *Camera* coordinates
3. *Image* coordinates



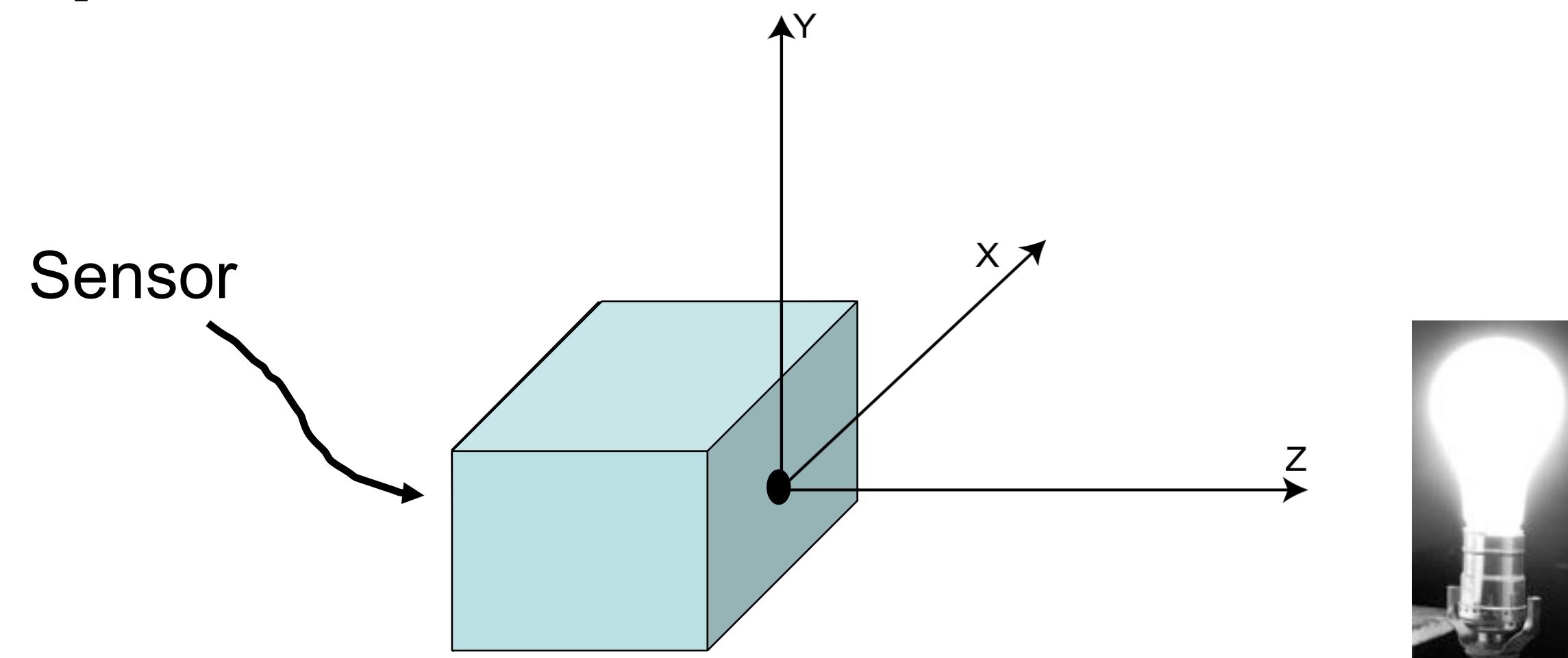
Coordinate frames + Transforms



Review: Camera parameters



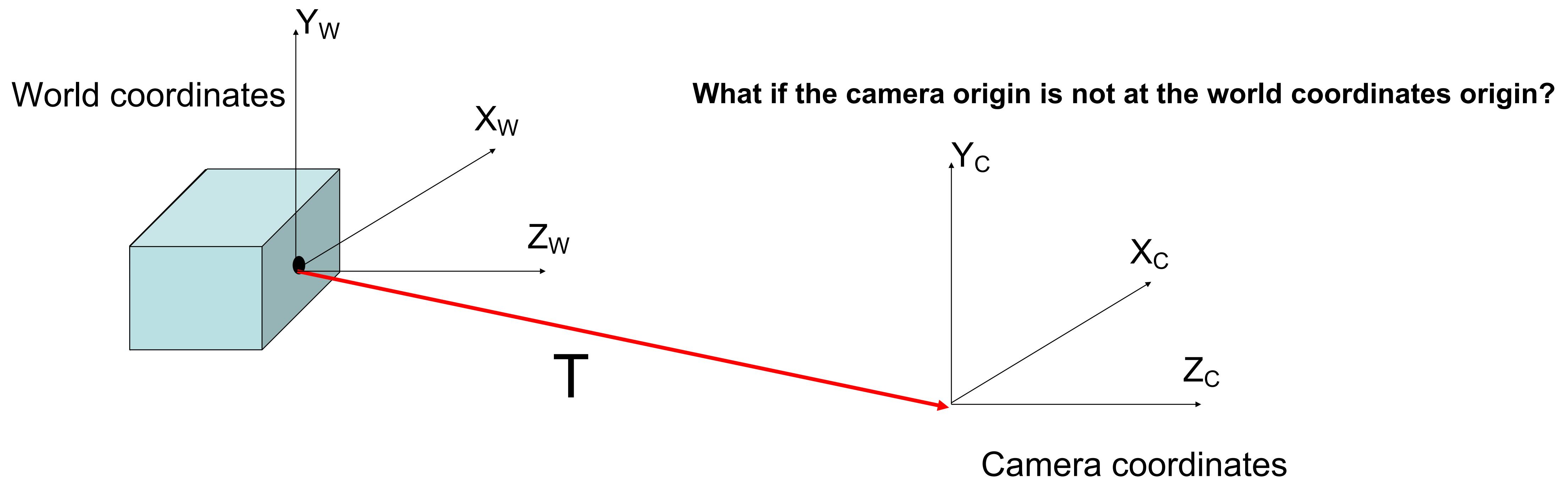
Camera parameters



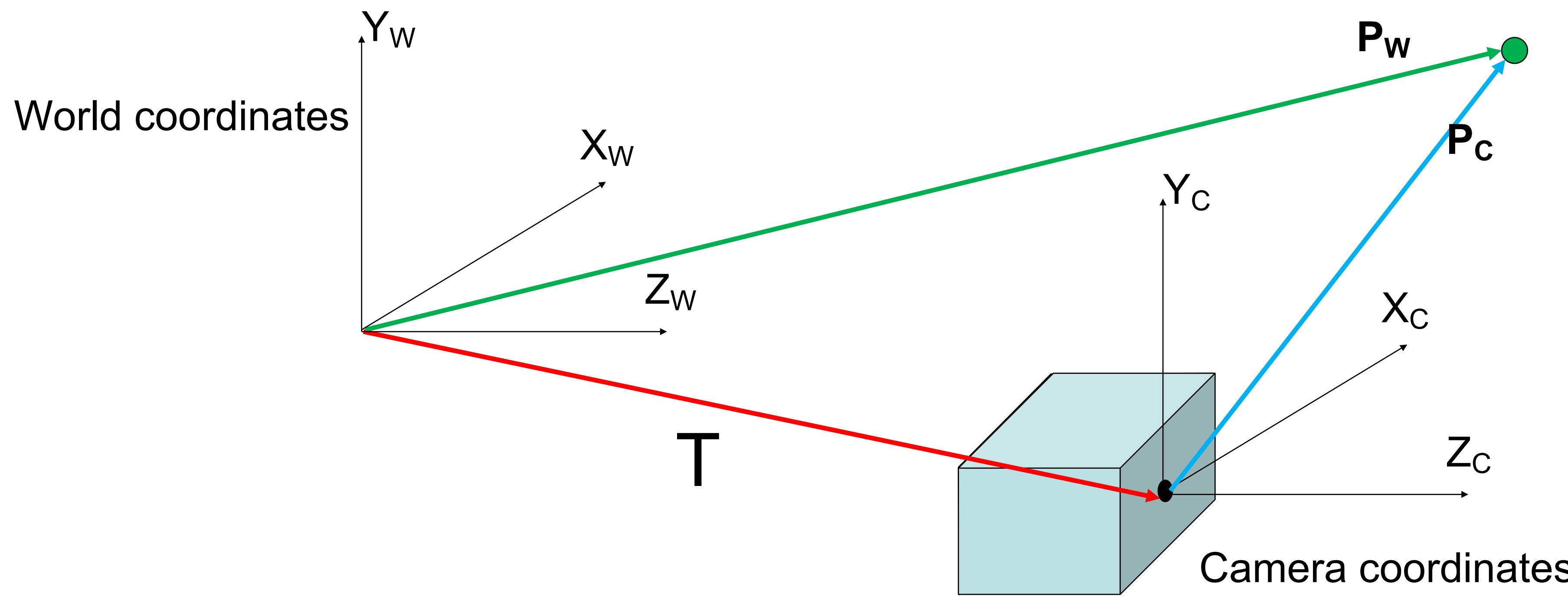
if pixels are rectangular

$$\begin{matrix} \begin{matrix} x \\ y \\ w \end{matrix} & = & \begin{matrix} a & 0 & 0 & 0 \\ 0 & b & 0 & 0 \\ 0 & 0 & 1 & 0 \end{matrix} \cdot \begin{matrix} X \\ Y \\ Z \\ 1 \end{matrix} & = & \begin{matrix} aX \\ bY \\ Z \\ 1 \end{matrix} \longrightarrow (aX/Z, bY/Z) \end{matrix}$$

Camera parameters



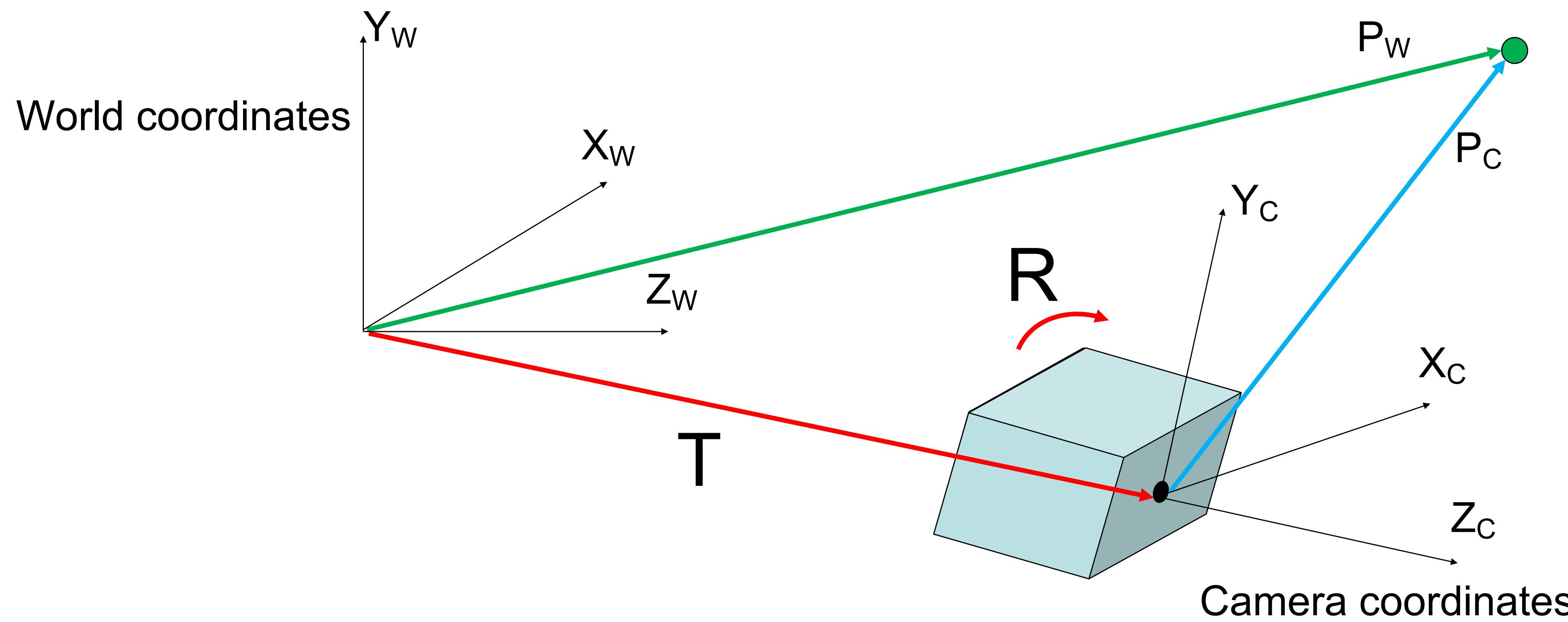
Camera parameters



In heterogeneous coordinates:

$$P_C = P_W - T$$

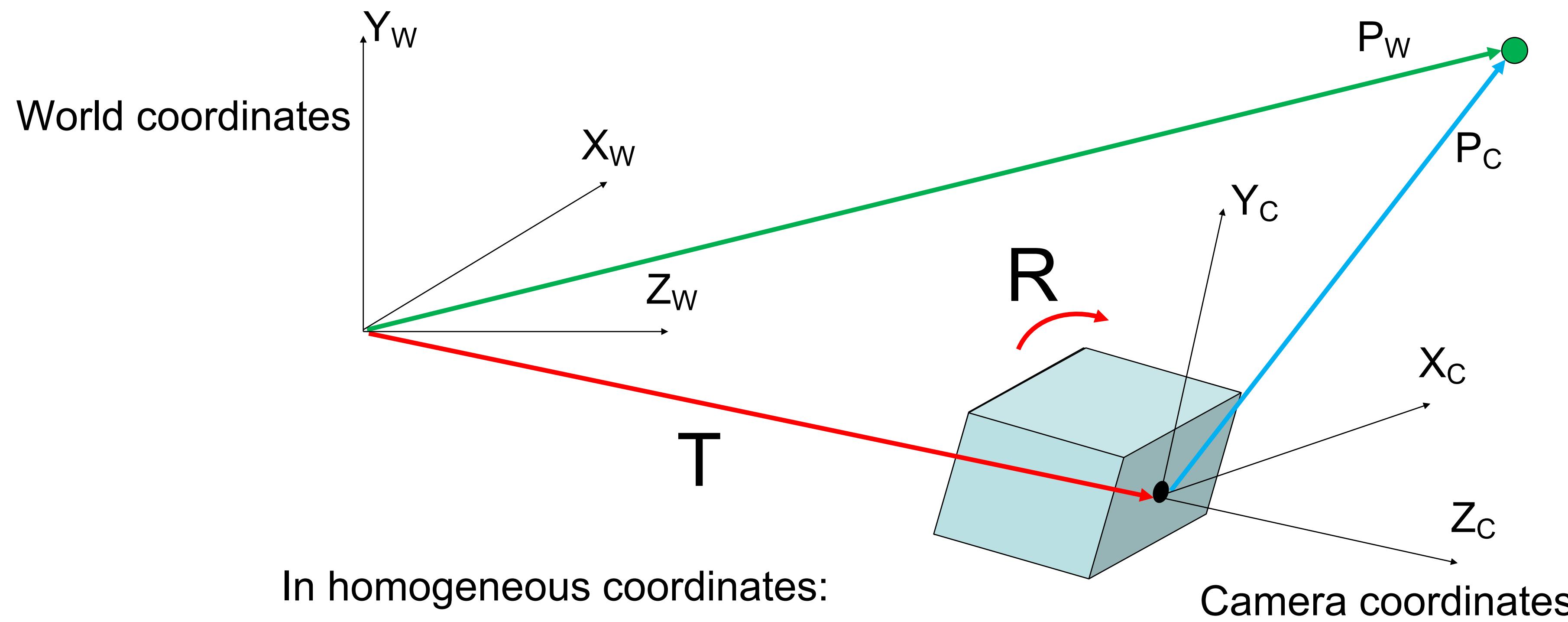
Camera parameters



In heterogeneous coordinates:

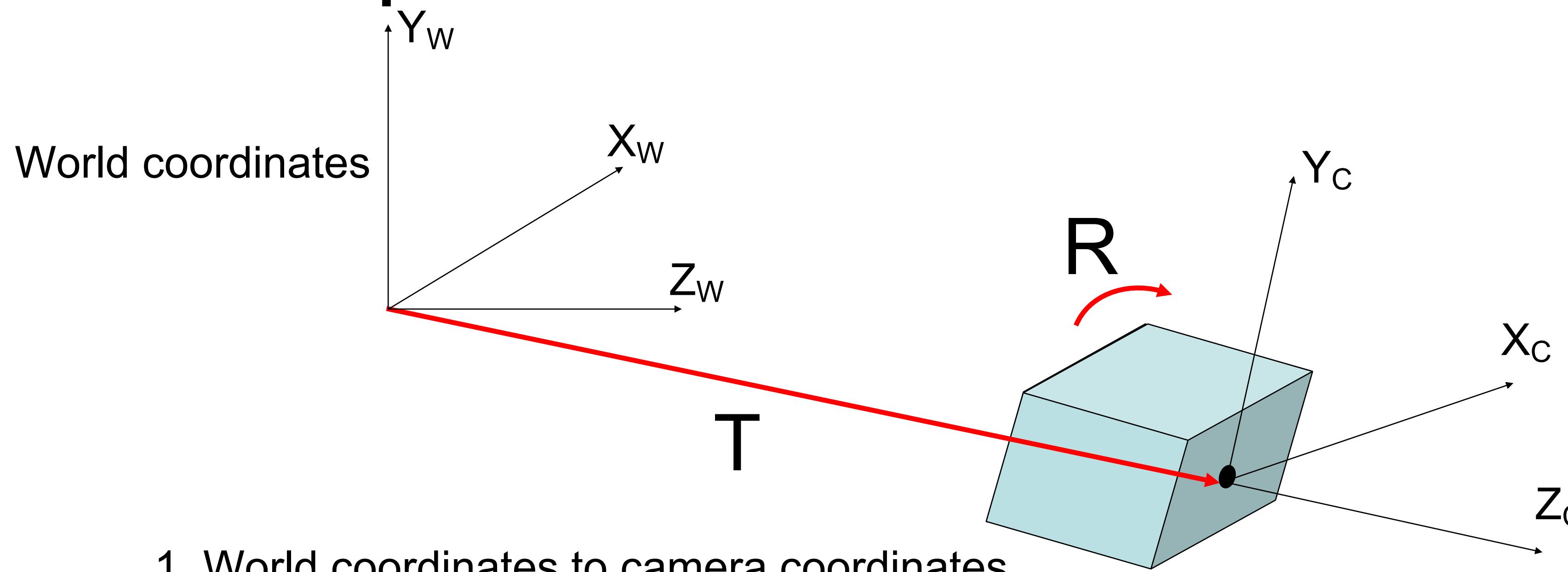
$$P_C = R(P_W - T)$$

Camera parameters



$$\begin{bmatrix} X_C \\ Y_C \\ Z_C \\ 1 \end{bmatrix} = \begin{bmatrix} [3 \times 3] & [3 \times 1] \\ R & -RT \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

Camera parameters



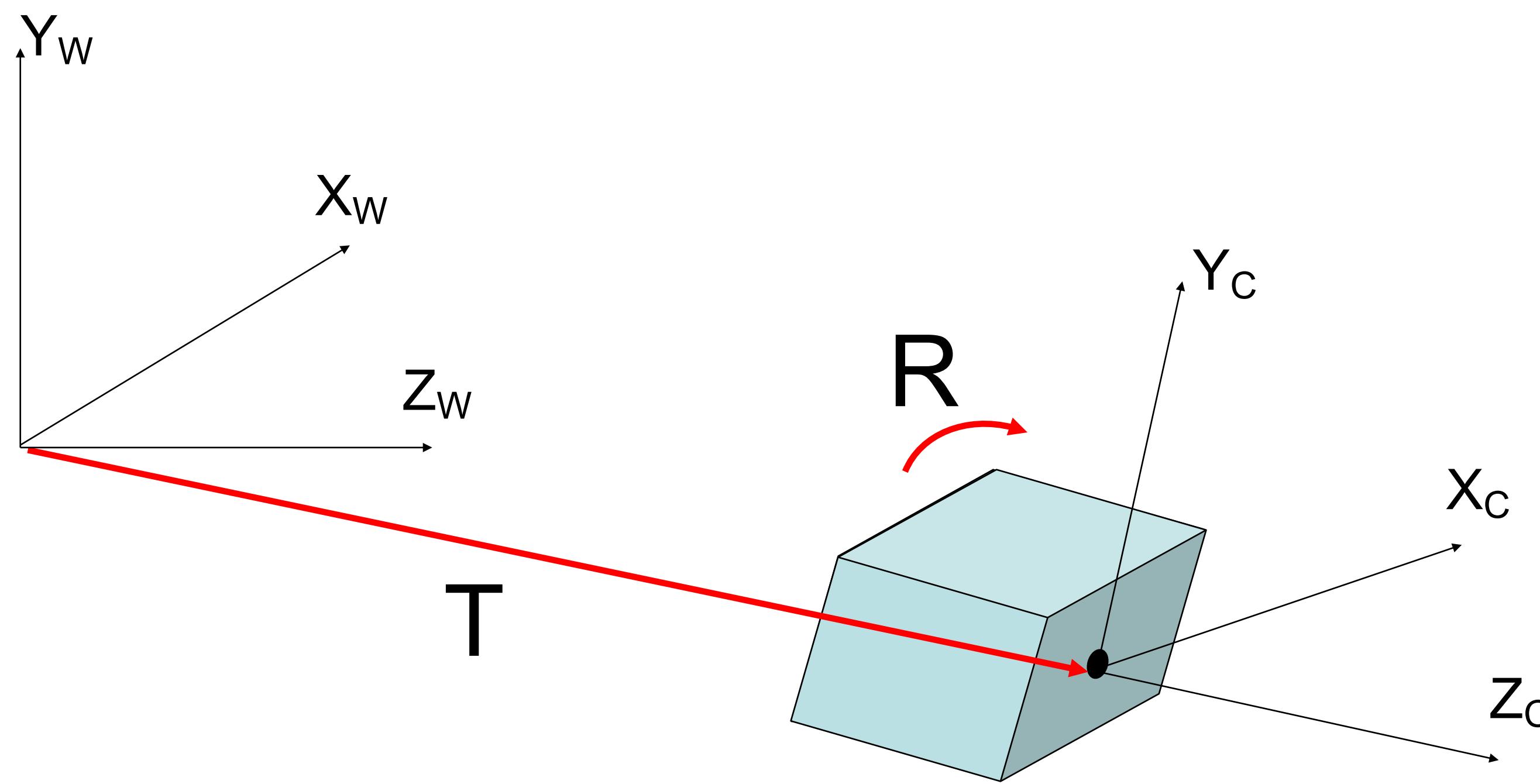
1. World coordinates to camera coordinates

$$\begin{bmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{bmatrix} = \begin{bmatrix} R & -RT \\ 0 & 1 \end{bmatrix} \cdot \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

2. Camera coordinates to image coordinates (square pixels)

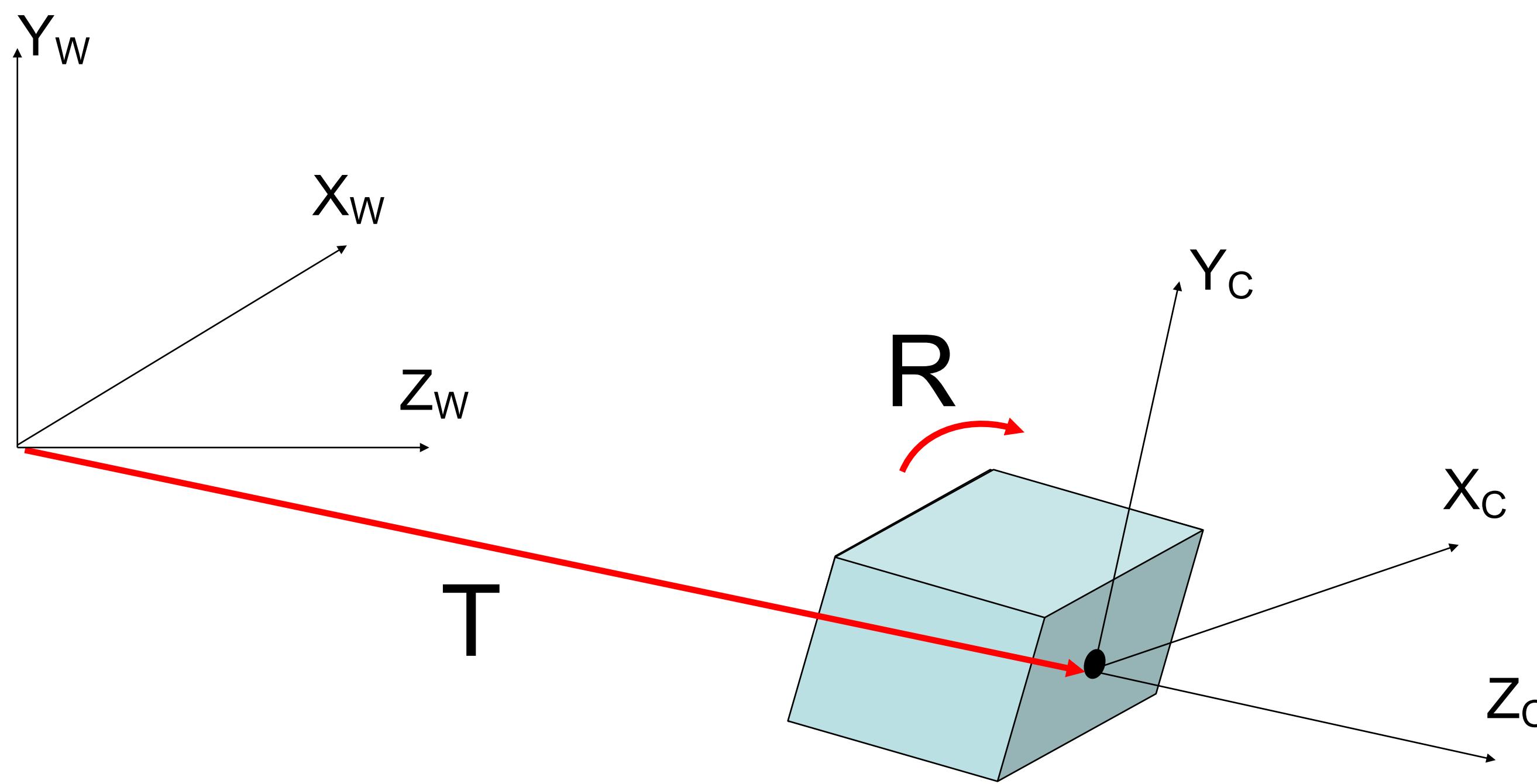
$$\begin{bmatrix} x \\ y \\ w \\ 1 \end{bmatrix} = \begin{bmatrix} a & 0 & 0 & 0 \\ 0 & a & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} \cdot \begin{bmatrix} X_c \\ Y_c \\ Z_c \\ 1 \end{bmatrix}$$

Camera parameters



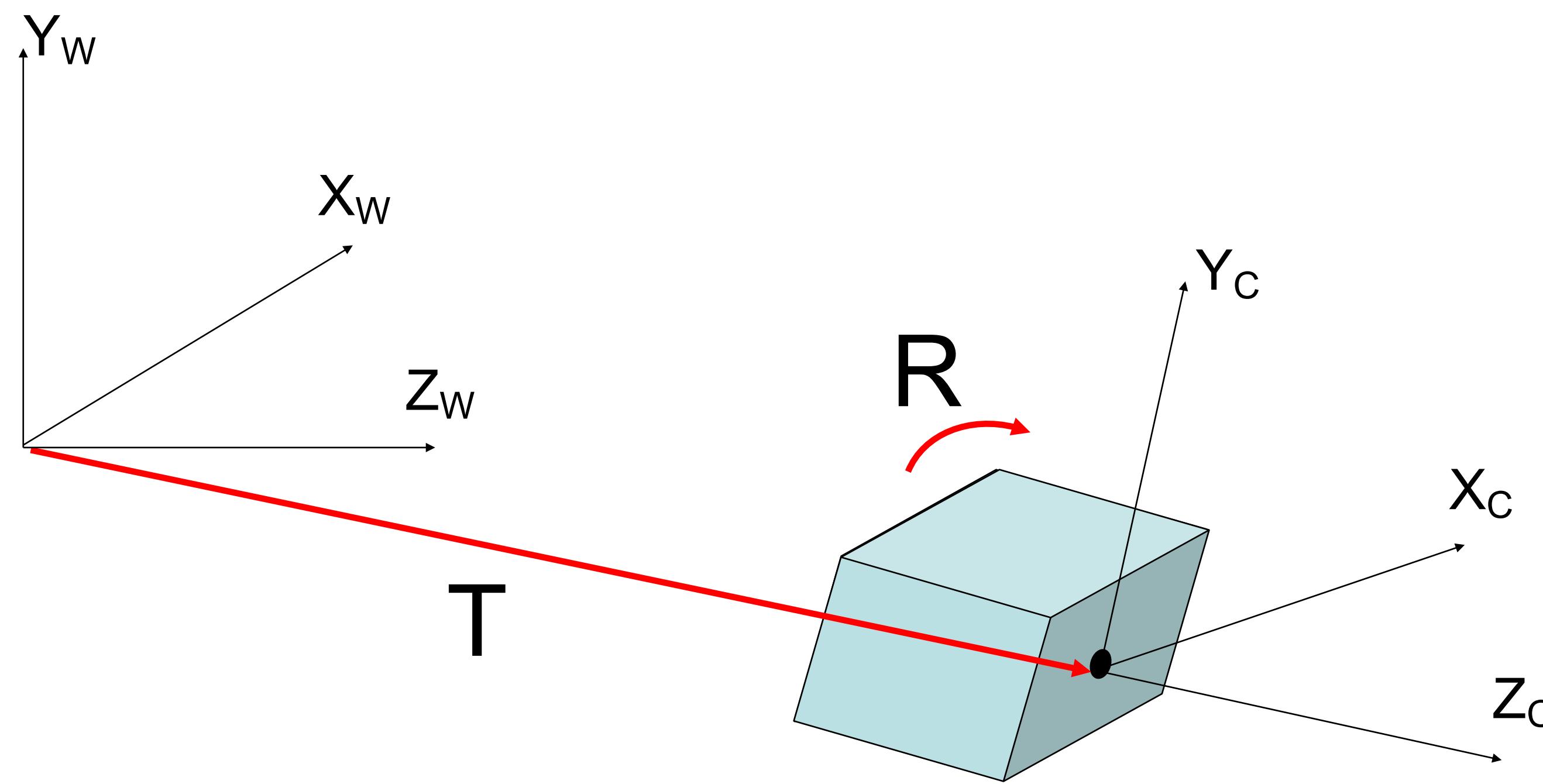
$$\begin{matrix} \mathbf{x} \\ \mathbf{y} \\ \mathbf{w} \end{matrix} = \begin{matrix} ? & ? & ? & ? \\ ? & ? & ? & ? \\ ? & ? & ? & ? \end{matrix} \begin{matrix} X_w \\ Y_w \\ Z_w \\ 1 \end{matrix}$$

Camera parameters



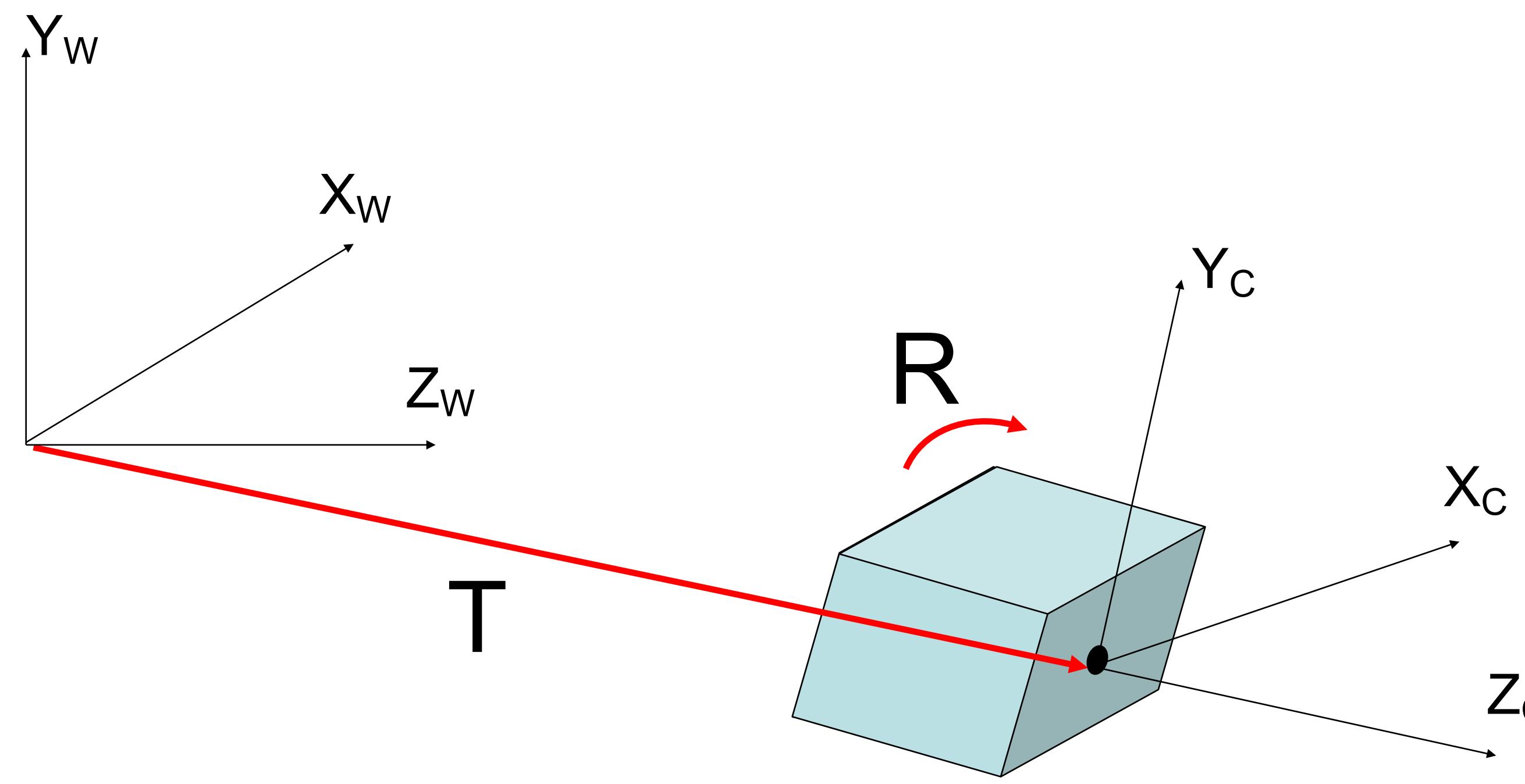
$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} = \begin{bmatrix} [3 \times 4] & [4 \times 4] \\ \begin{matrix} a & 0 & 0 & 0 \\ 0 & a & 0 & 0 \\ 0 & 0 & 1 & 0 \end{matrix} & \begin{matrix} R & -RT \\ 0 & 1 \end{matrix} \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

Camera parameters



$$\begin{matrix} \begin{matrix} x \\ y \\ w \end{matrix} & = & \begin{matrix} [3 \times 3] \\ a & 0 & 0 \\ 0 & a & 0 \\ 0 & 0 & 1 \end{matrix} & \cdot & \begin{matrix} [3 \times 4] \\ R & -RT \end{matrix} & \cdot & \begin{matrix} X_w \\ Y_w \\ Z_w \\ 1 \end{matrix} \end{matrix}$$

Camera parameters



$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} = \underbrace{\begin{bmatrix} [3x3] \\ a & 0 & 0 \\ 0 & a & 0 \\ 0 & 0 & 1 \end{bmatrix}}_{\text{Intrinsic parameters}} \cdot \underbrace{\begin{bmatrix} [3x3] \\ R \end{bmatrix}}_{\text{Extrinsic parameters}} \cdot \underbrace{\begin{bmatrix} [3x4] \\ I & -T \end{bmatrix}}_{\text{Extrinsic parameters}} \cdot \begin{bmatrix} X_w \\ Y_w \\ Z_w \\ 1 \end{bmatrix}$$

Camera Projection Model

$$X = K[R \quad t]X$$



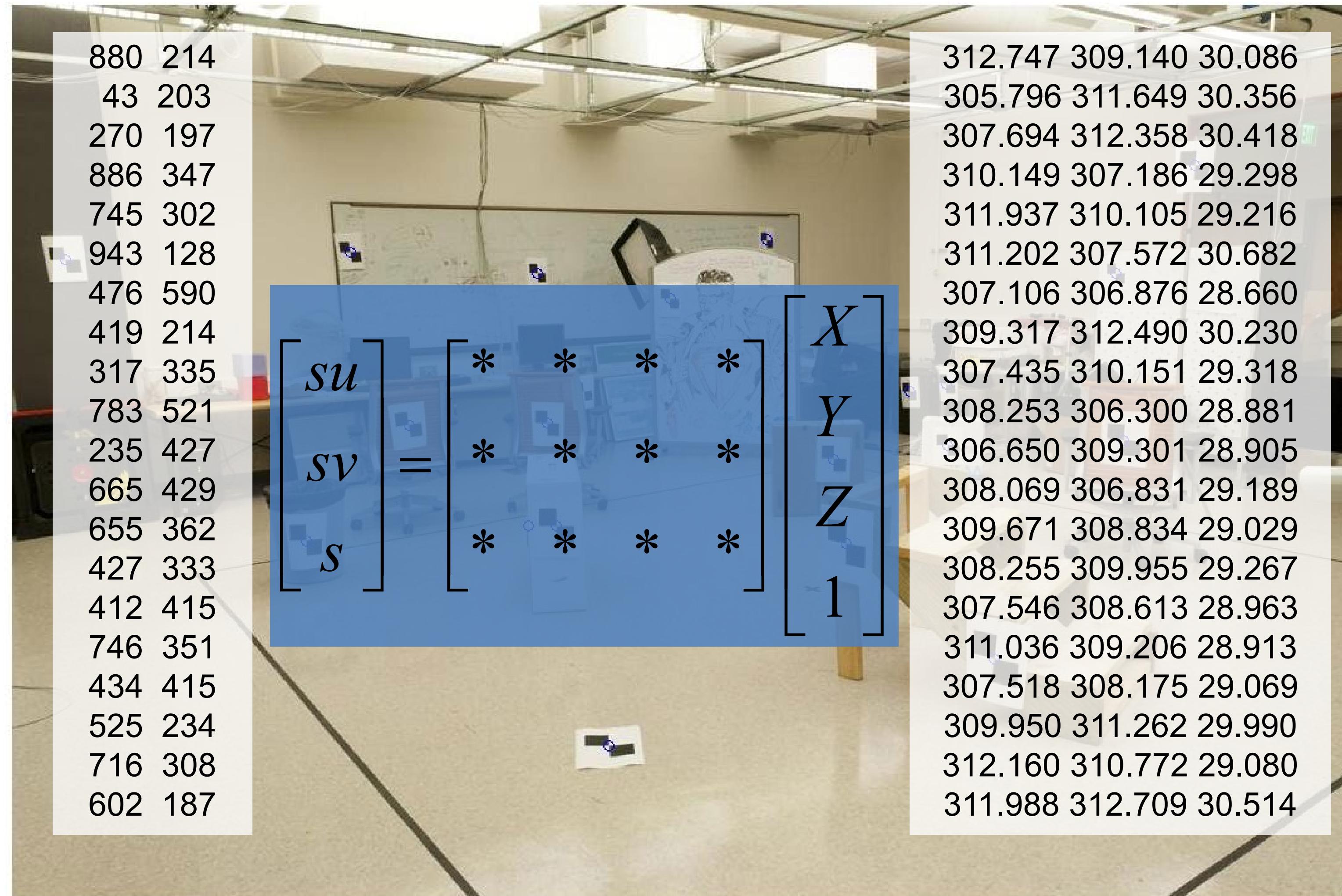
$$w \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \alpha & s & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_x \\ r_{21} & r_{22} & r_{23} & t_y \\ r_{31} & r_{32} & r_{33} & t_z \end{bmatrix} \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

How to calibrate the camera?

$$\mathbf{x} = \mathbf{K}[\mathbf{R} \quad \mathbf{t}] \mathbf{X}$$

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} * & * & * & * \\ * & * & * & * \\ * & * & * & * \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we calibrate a camera? Learning problem!

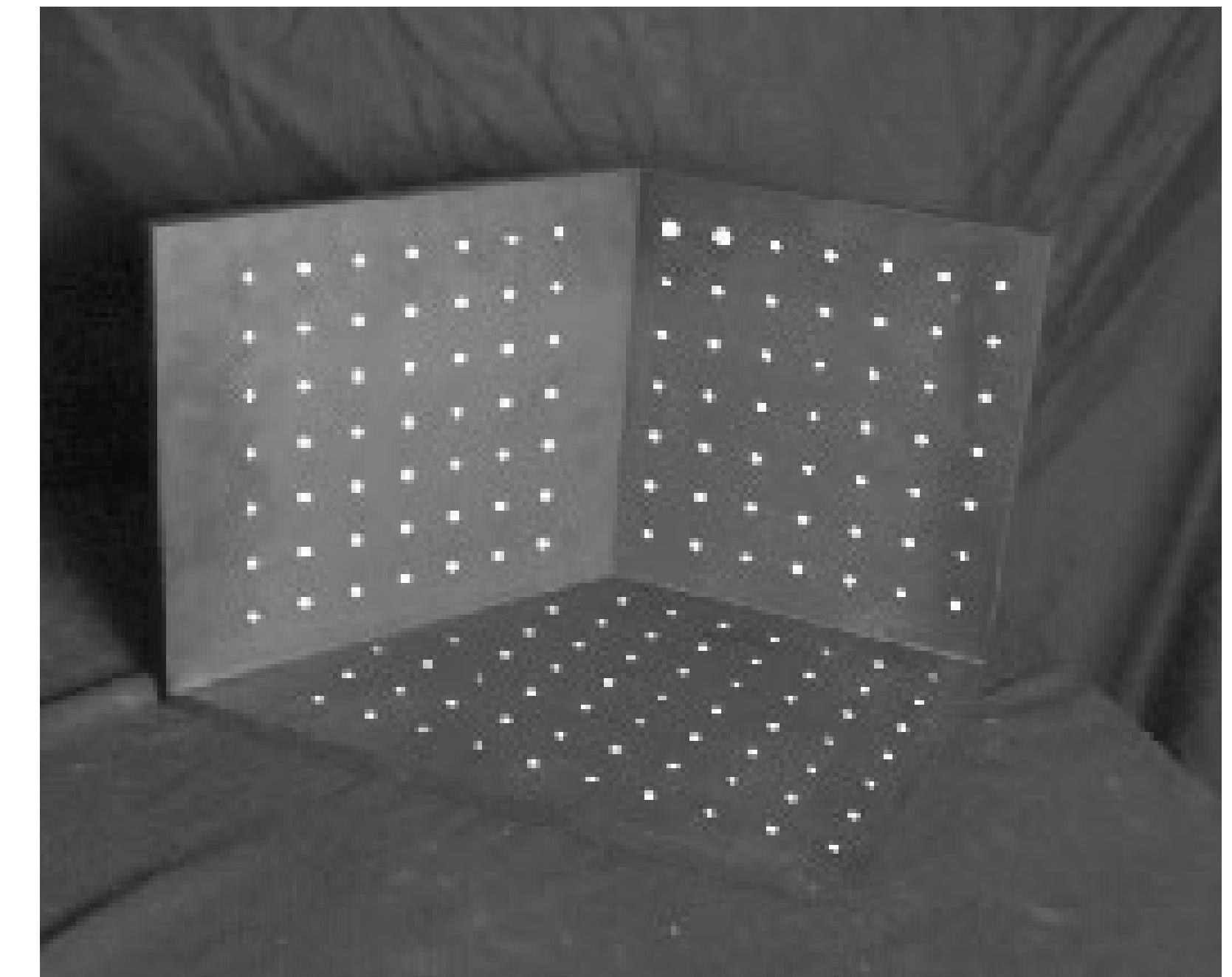


Calibration using a reference object

- Place a known object in the scene
 - identify correspondence between image and scene
 - compute mapping from scene to image

Issues

- must know geometry very accurately
- must know 3D -> 2D correspondence



Method: Setup a linear system

$$\begin{bmatrix} su \\ sv \\ s \end{bmatrix} = \begin{bmatrix} m_{11} & m_{12} & m_{13} & m_{14} \\ m_{21} & m_{22} & m_{23} & m_{24} \\ m_{31} & m_{32} & m_{33} & m_{34} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

- Solve for m's entries using linear least squares

Ax=0 form

$$\begin{bmatrix} X_1 & Y_1 & Z_1 & 1 & 0 & 0 & 0 & -u_1X_1 & -u_1Y_1 & -u_1Z_1 & -u_1 \\ 0 & 0 & 0 & 0 & X_1 & Y_1 & Z_1 & 1 & -v_1X_1 & -v_1Y_1 & -v_1Z_1 & -v_1 \\ & & & & \vdots & & & & & & & \\ X_n & Y_n & Z_n & 1 & 0 & 0 & 0 & -u_nX_n & -u_nY_n & -u_nZ_n & -u_n \\ 0 & 0 & 0 & 0 & X_n & Y_n & Z_n & 1 & -v_nX_n & -v_nY_n & -v_nZ_n & -v_n \end{bmatrix}$$

$$\begin{bmatrix} m_{11} \\ m_{12} \\ m_{13} \\ m_{14} \\ m_{21} \\ m_{22} \\ m_{23} \\ m_{24} \\ m_{31} \\ m_{32} \\ m_{33} \\ m_{34} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ \vdots \\ 0 \\ 0 \\ \vdots \\ 0 \\ 0 \end{bmatrix}$$

Just like how
you solved for
homography!

Can we factorize M back to K [R | T]?

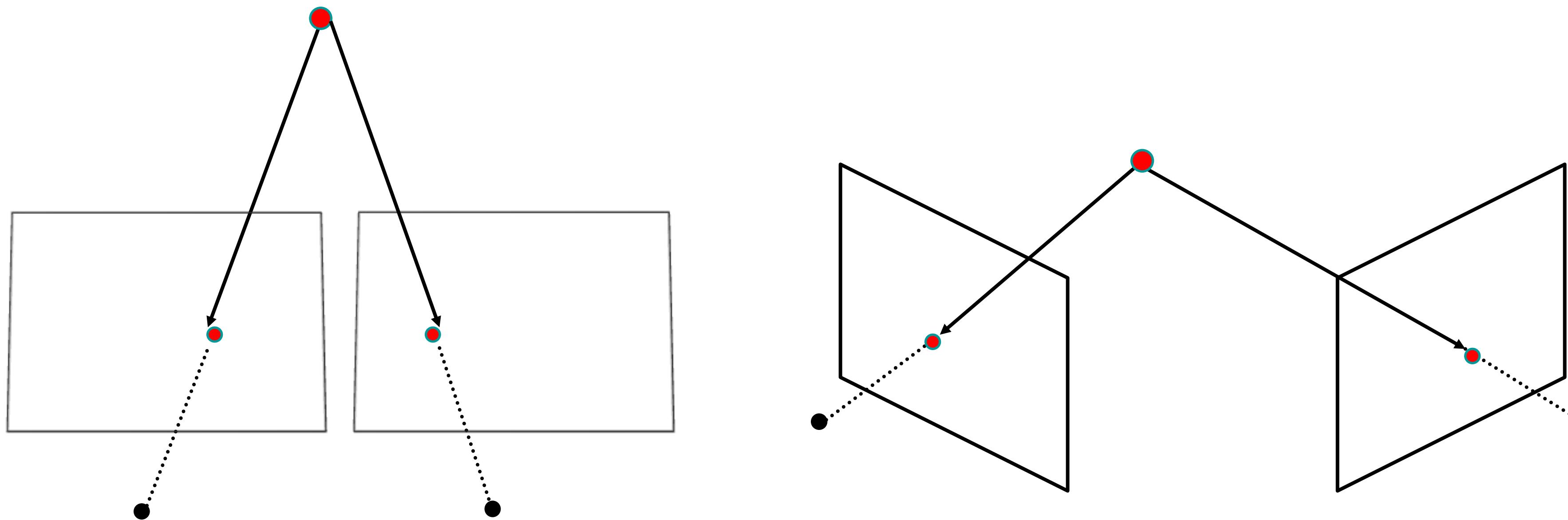
- Yes.
- Why? because K and R have a very special form:

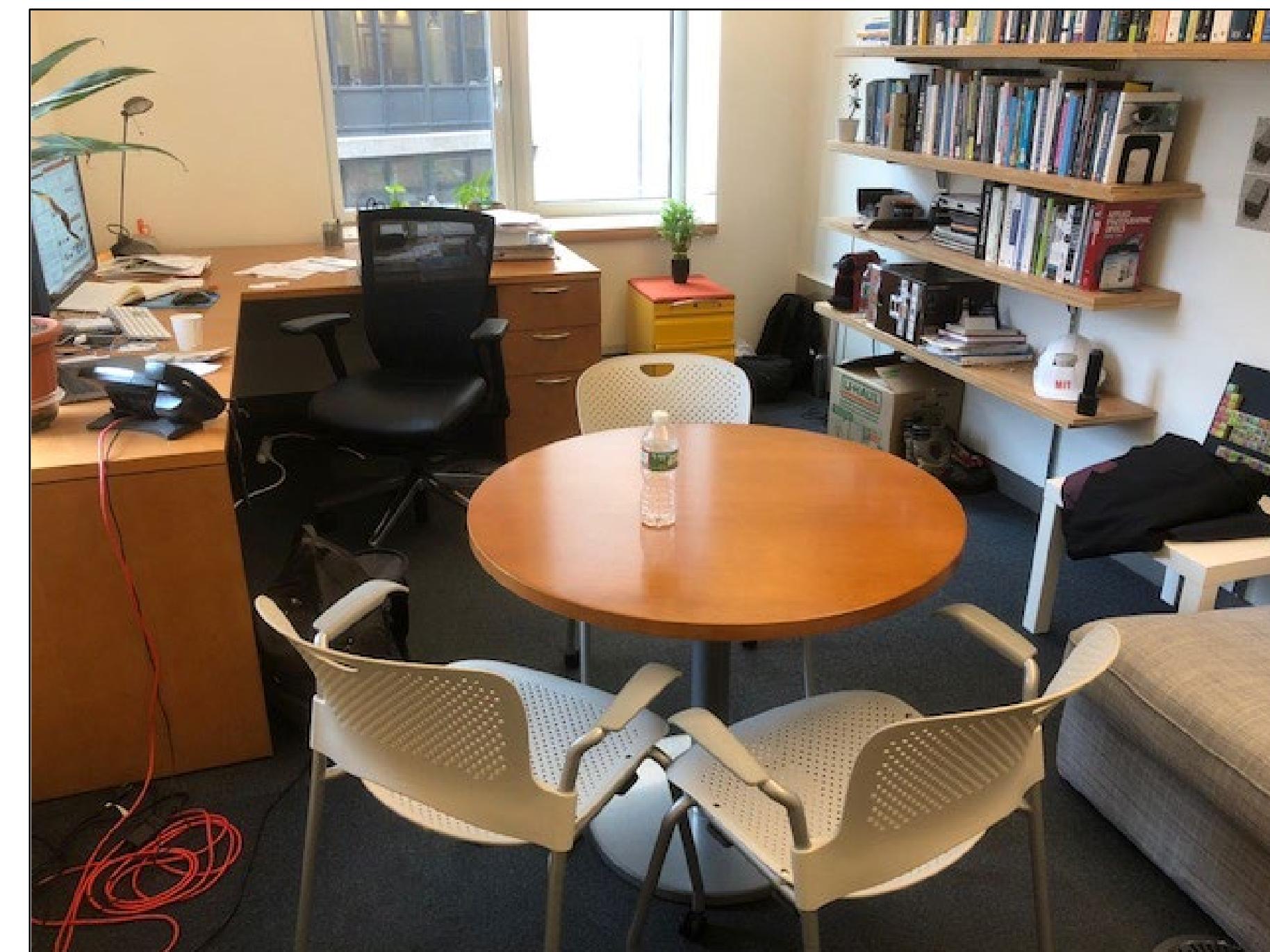
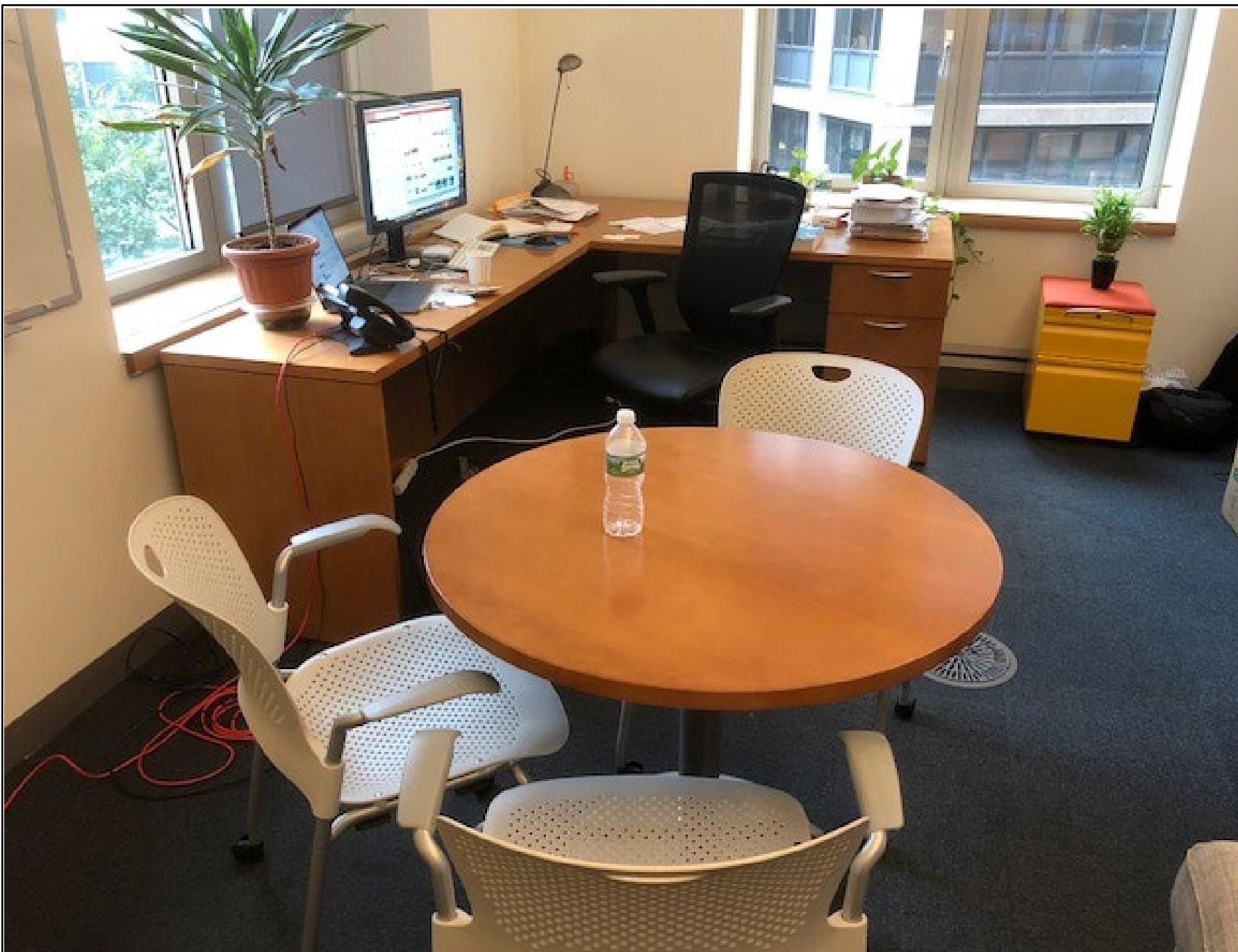
$$\begin{bmatrix} f_x & s & o_x \\ 0 & f_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix}$$

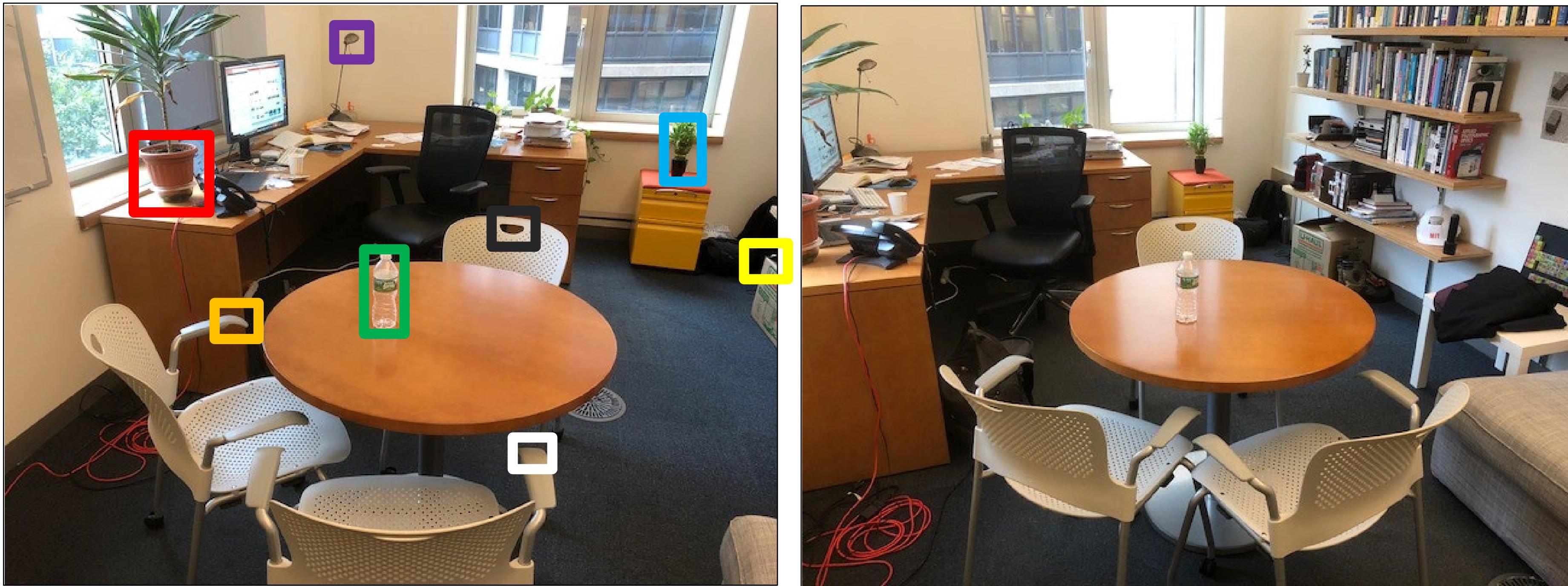
- RQ decomposition
- Practically, use camera calibration packages
(there is a good one in OpenCV)

General case

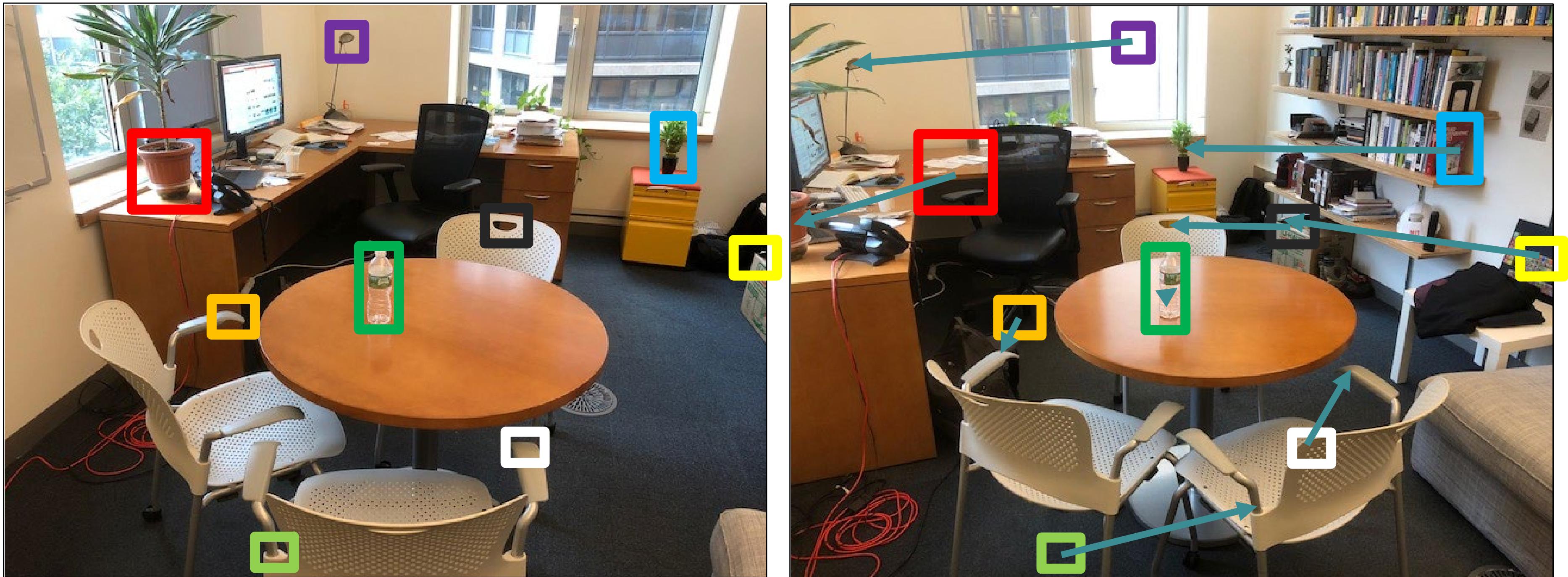
- The two cameras need not have parallel optical axes.



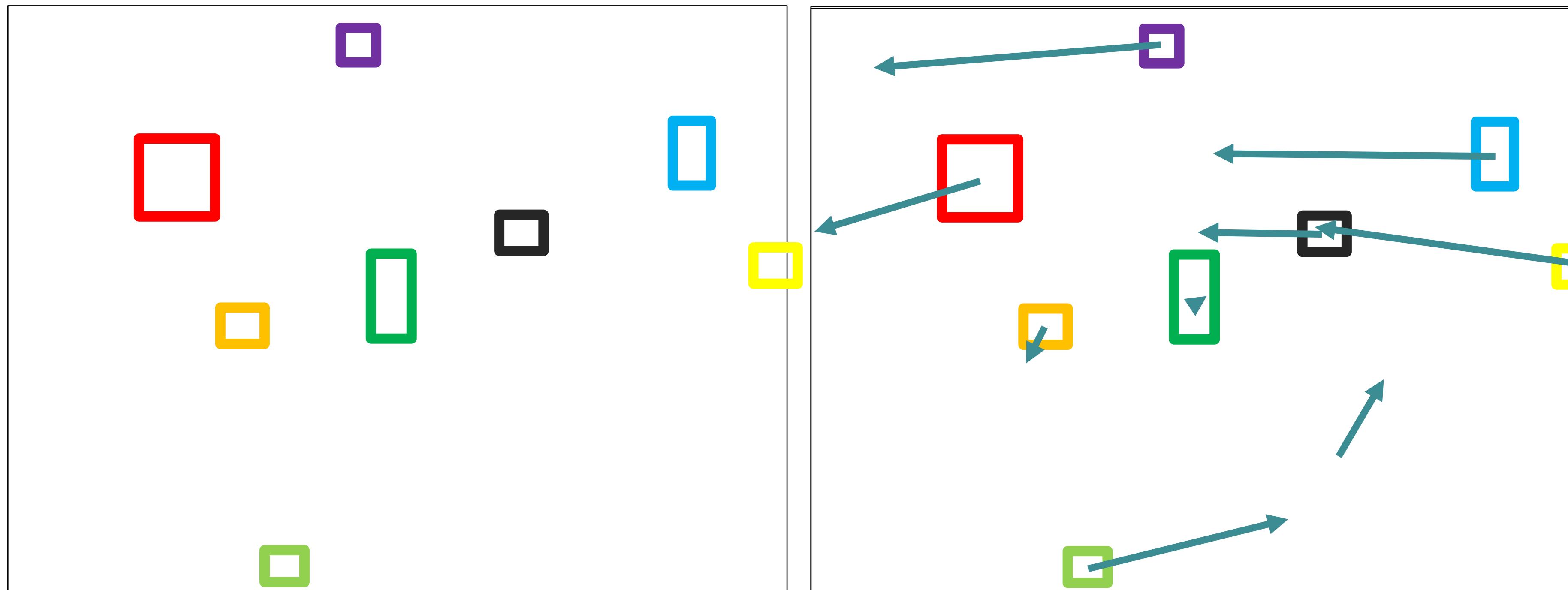




Can we search for matches only along horizontal lines?



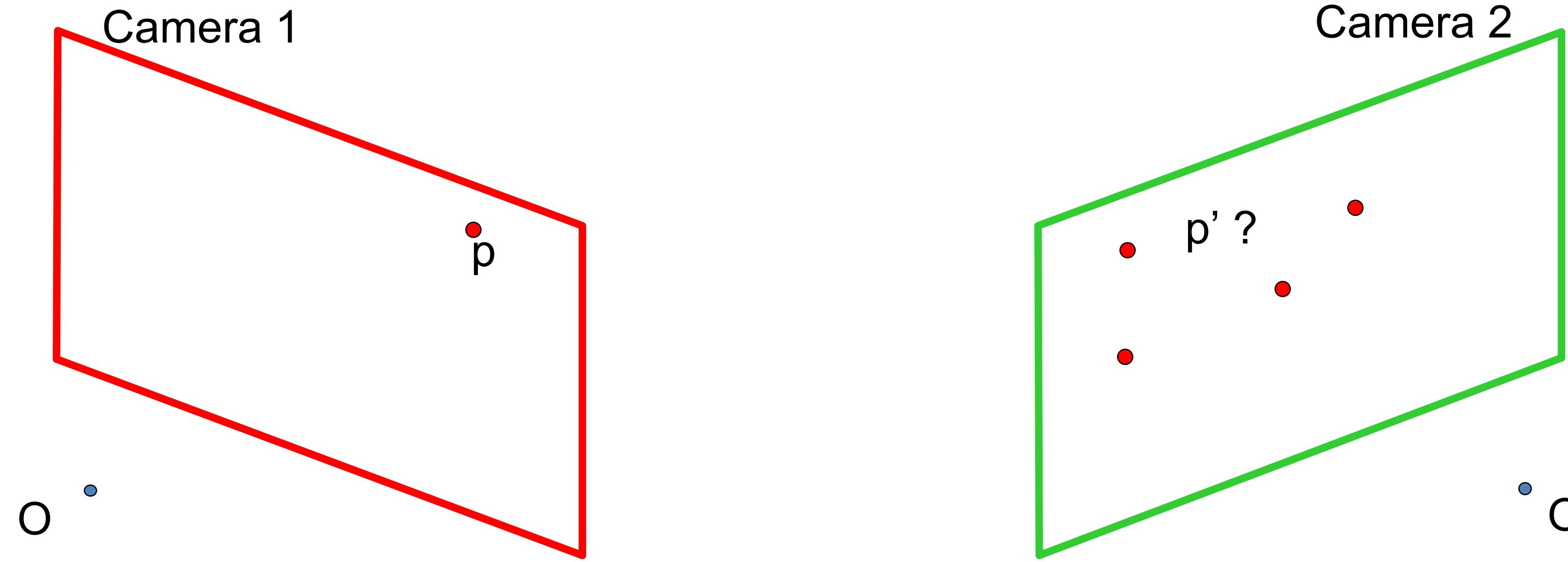
Can we search for matches only along horizontal lines?



Can we search for matches only along horizontal lines?

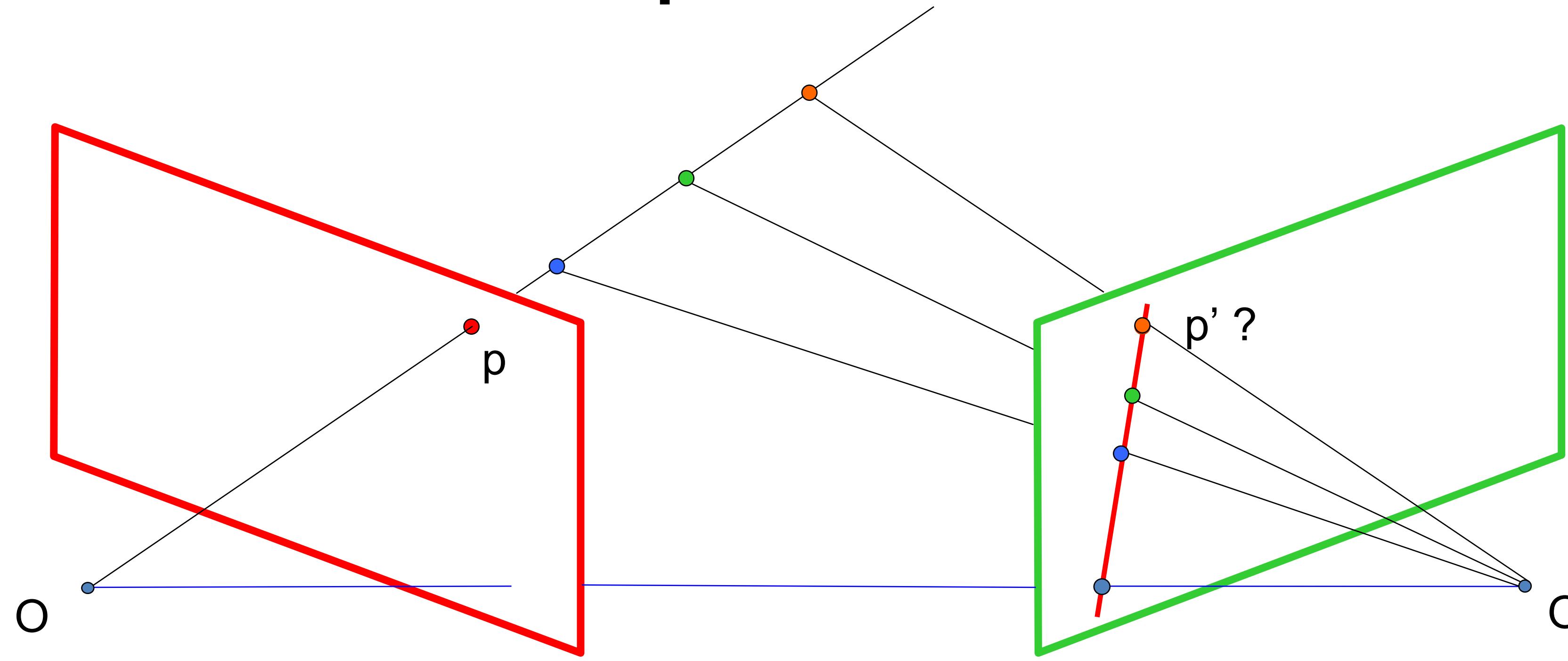
It looks like we might need to search everywhere... are there any constraints that can guide the search?

Stereo correspondence constraints

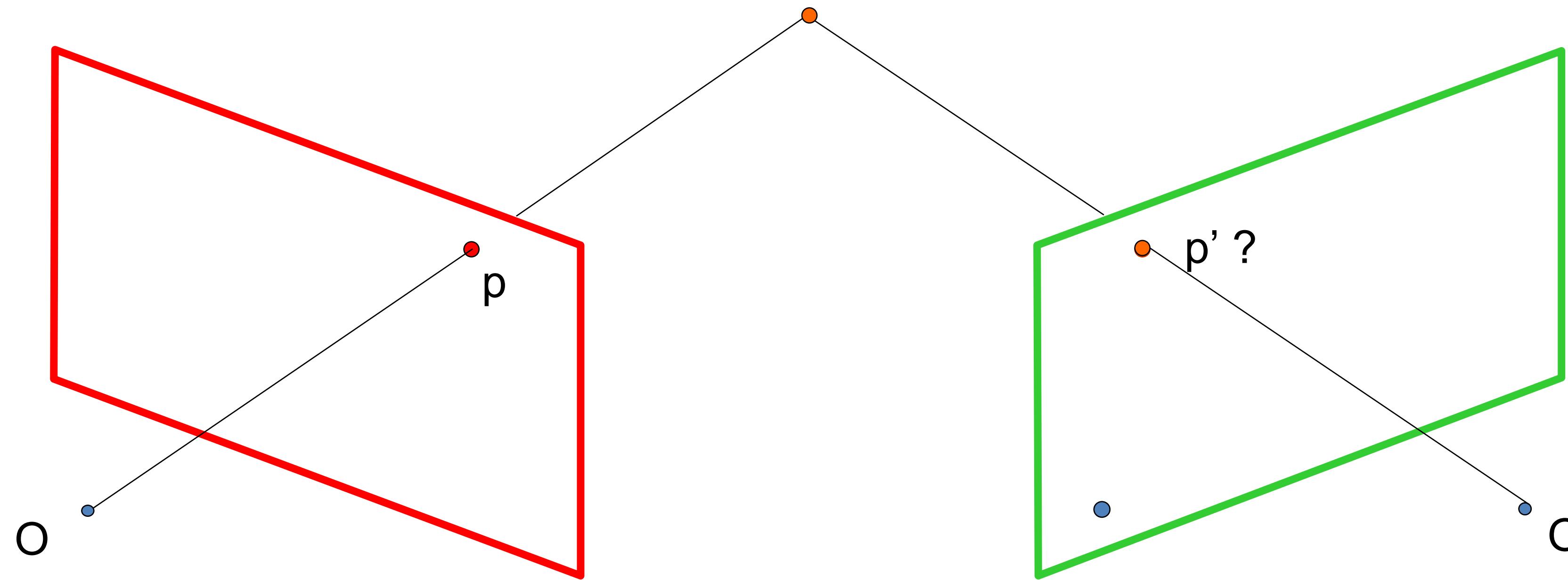


If we see a point in camera 1, are there any constraints on where we will find it on camera 2?

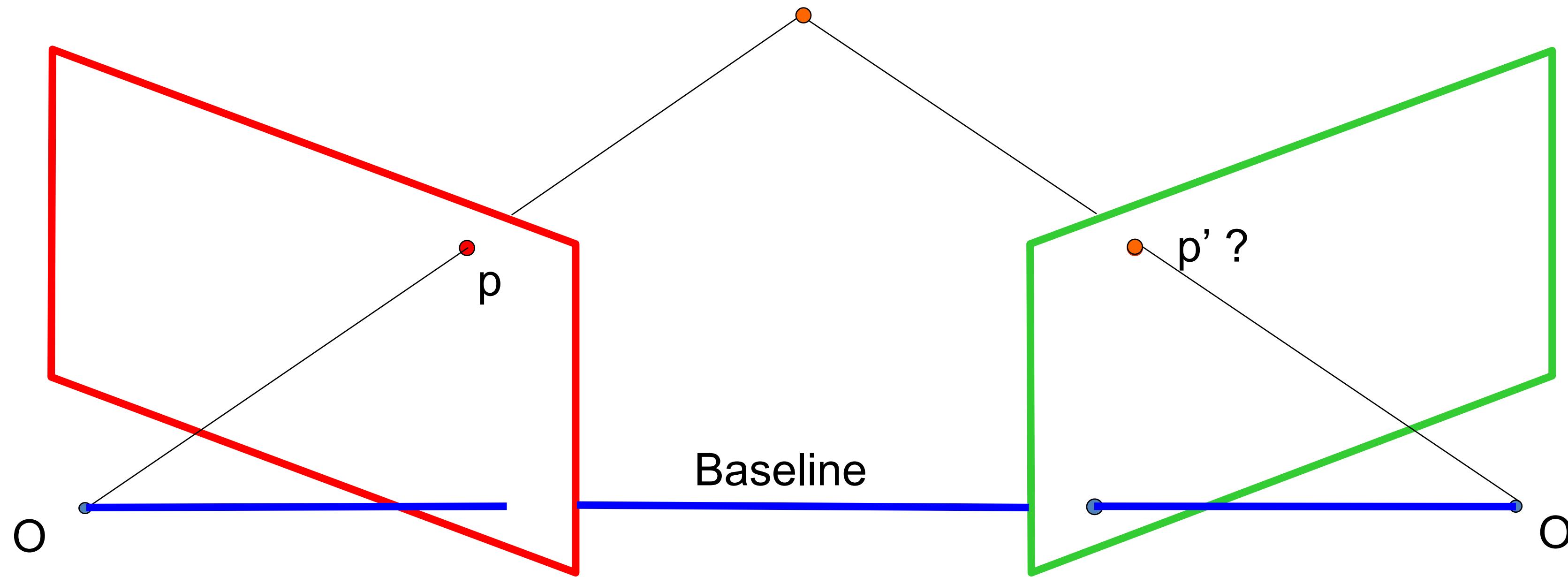
Stereo correspondence constraints



Some terminology



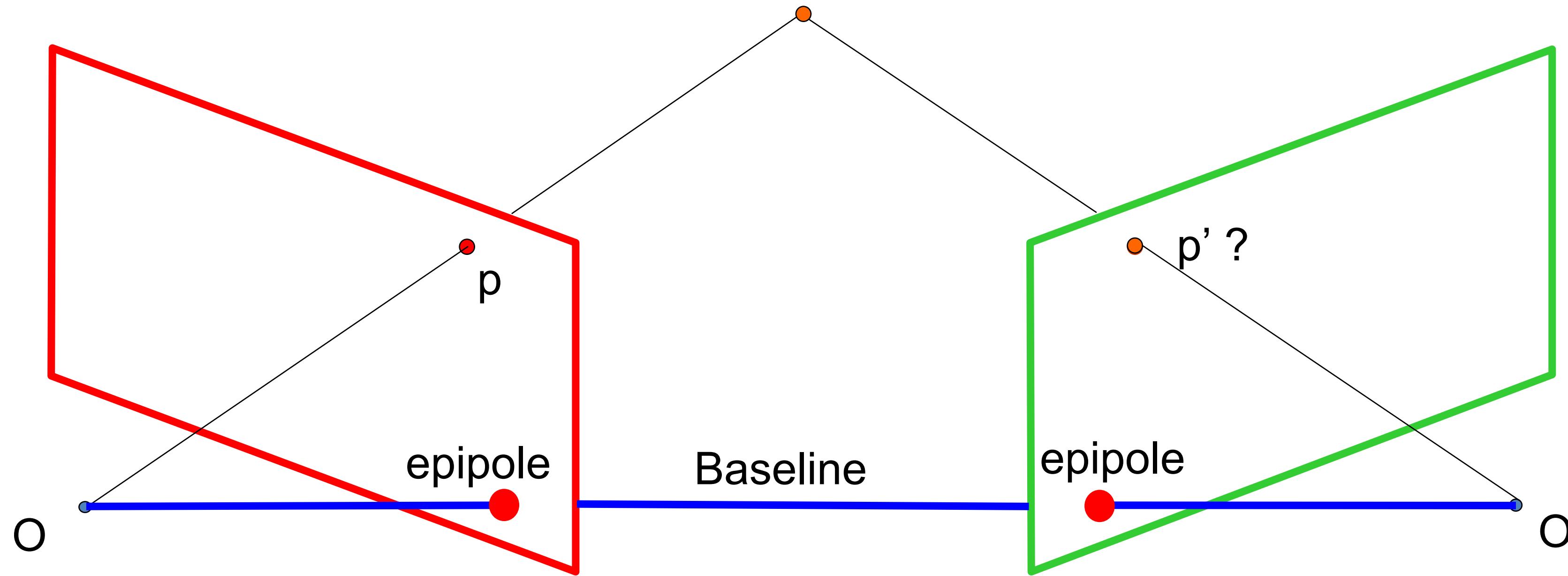
Some terminology



Baseline: the line connecting the two camera centers

Epipole: point of intersection of *baseline* with the image plane

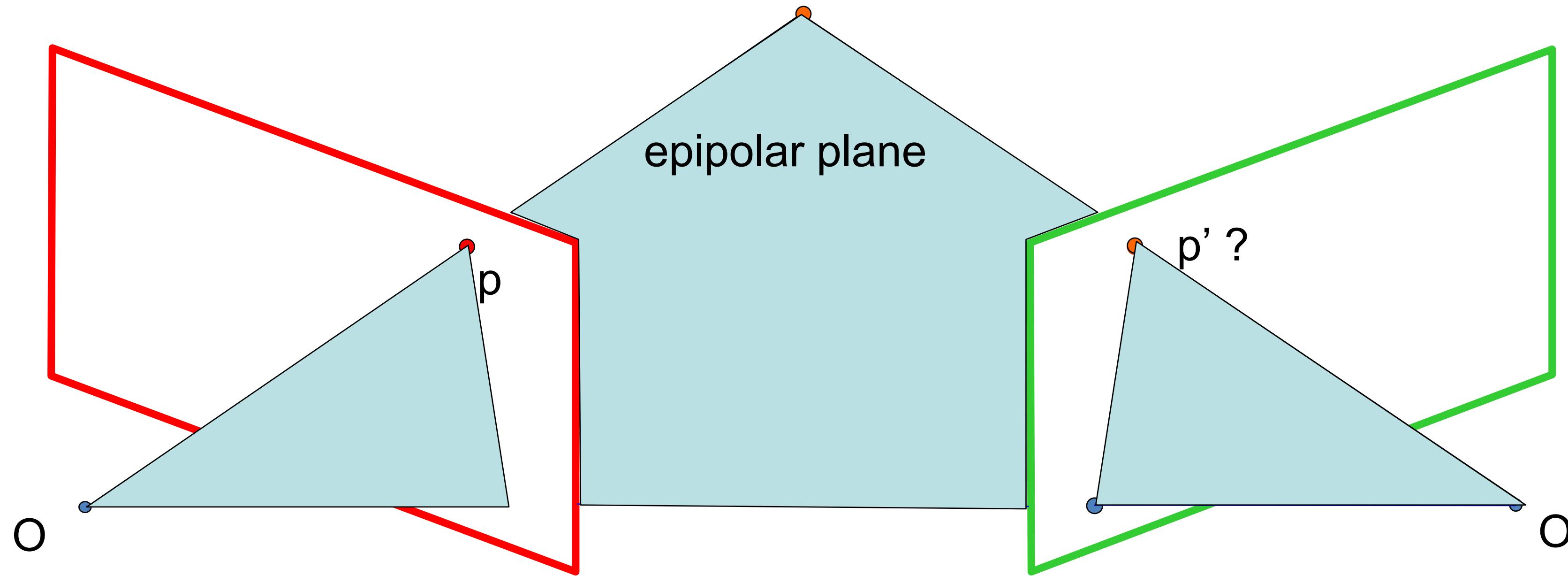
Some terminology



Baseline: the line connecting the two camera centers

Epipole: point of intersection of *baseline* with the image plane

Some terminology

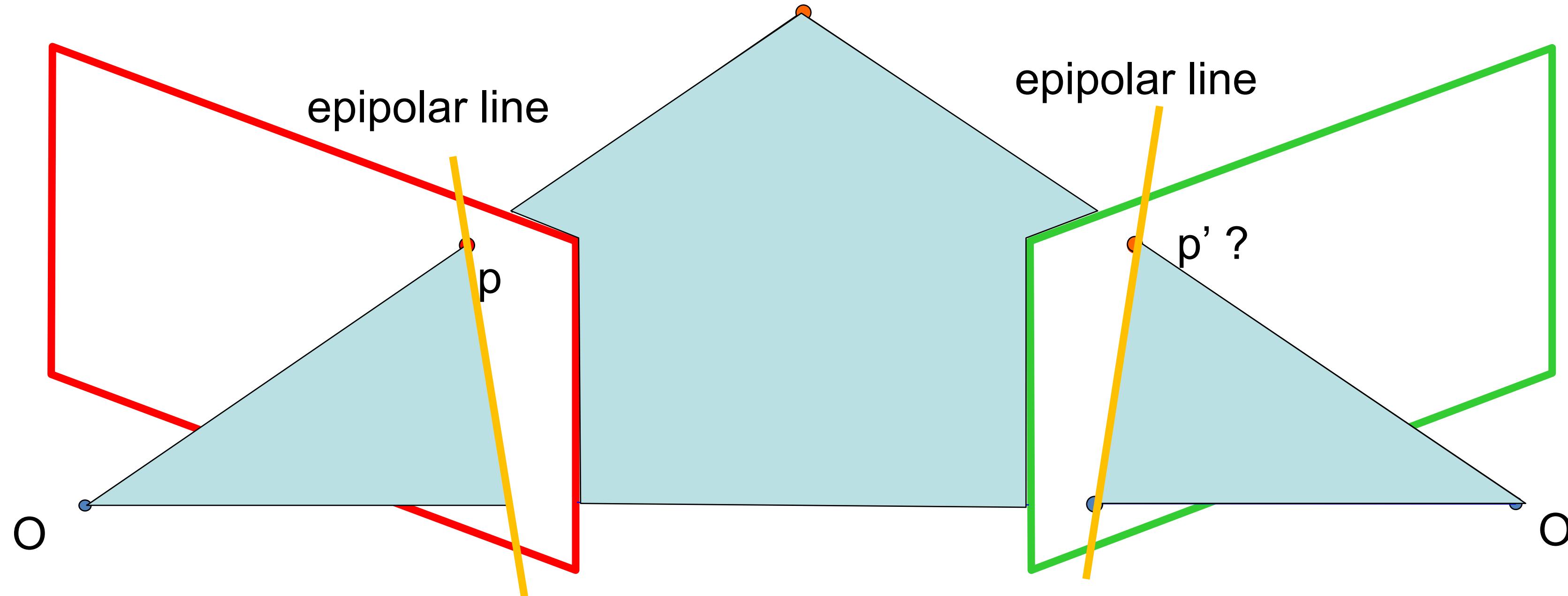


Baseline: the line connecting the two camera centers

Epipole: point of intersection of *baseline* with the image plane

Epipolar plane: the plane that contains the two camera centers and a 3D point in the world

Some terminology



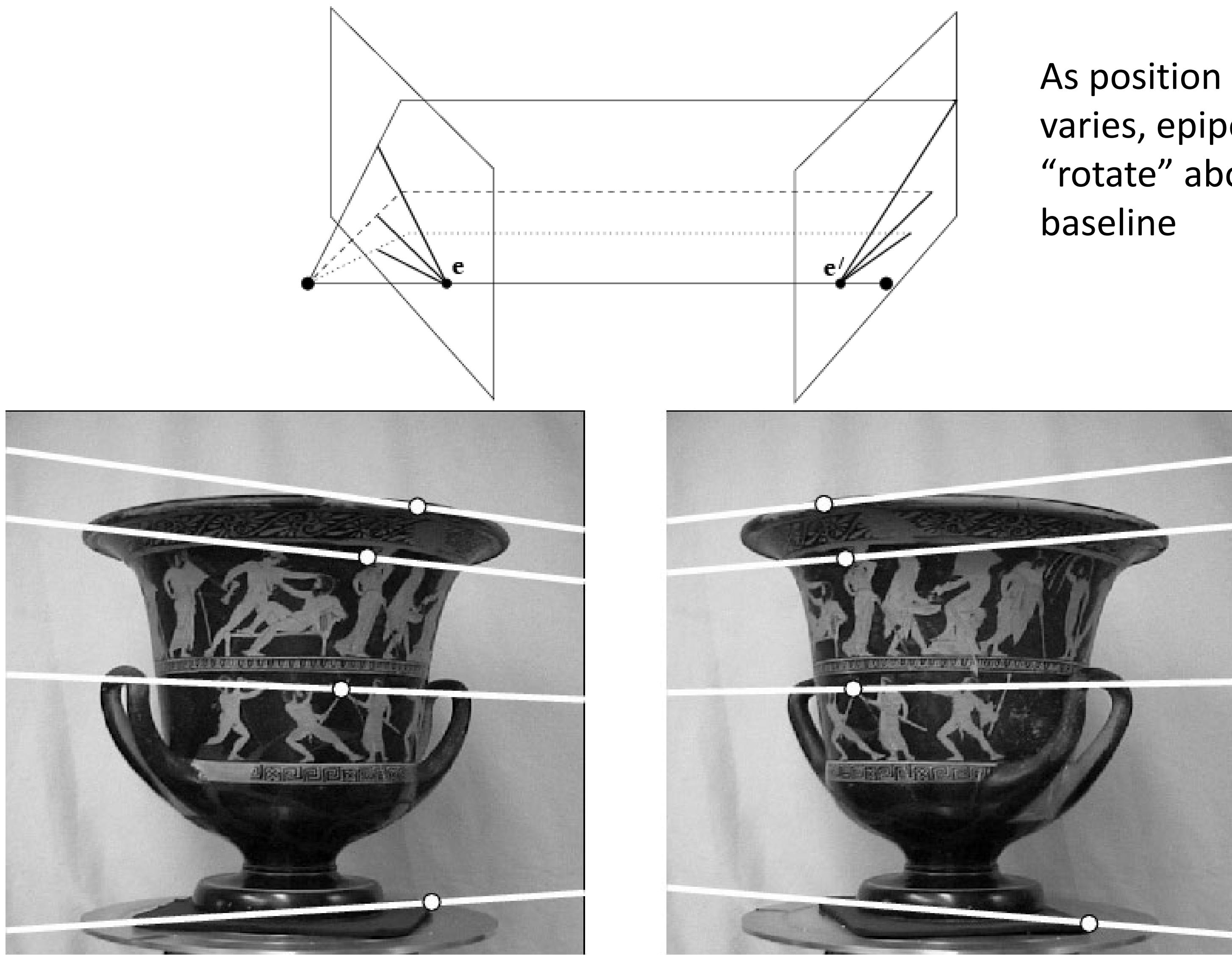
Baseline: the line connecting the two camera centers

Epipole: point of intersection of *baseline* with the image plane

Epipolar plane: the plane that contains the two camera centers and a 3D point in the world

Epipolar line: intersection of the *epipolar plane* with each image plane

Example: converging cameras



As position of 3d point varies, epipolar lines “rotate” about the baseline

Example: motion parallel with image plane

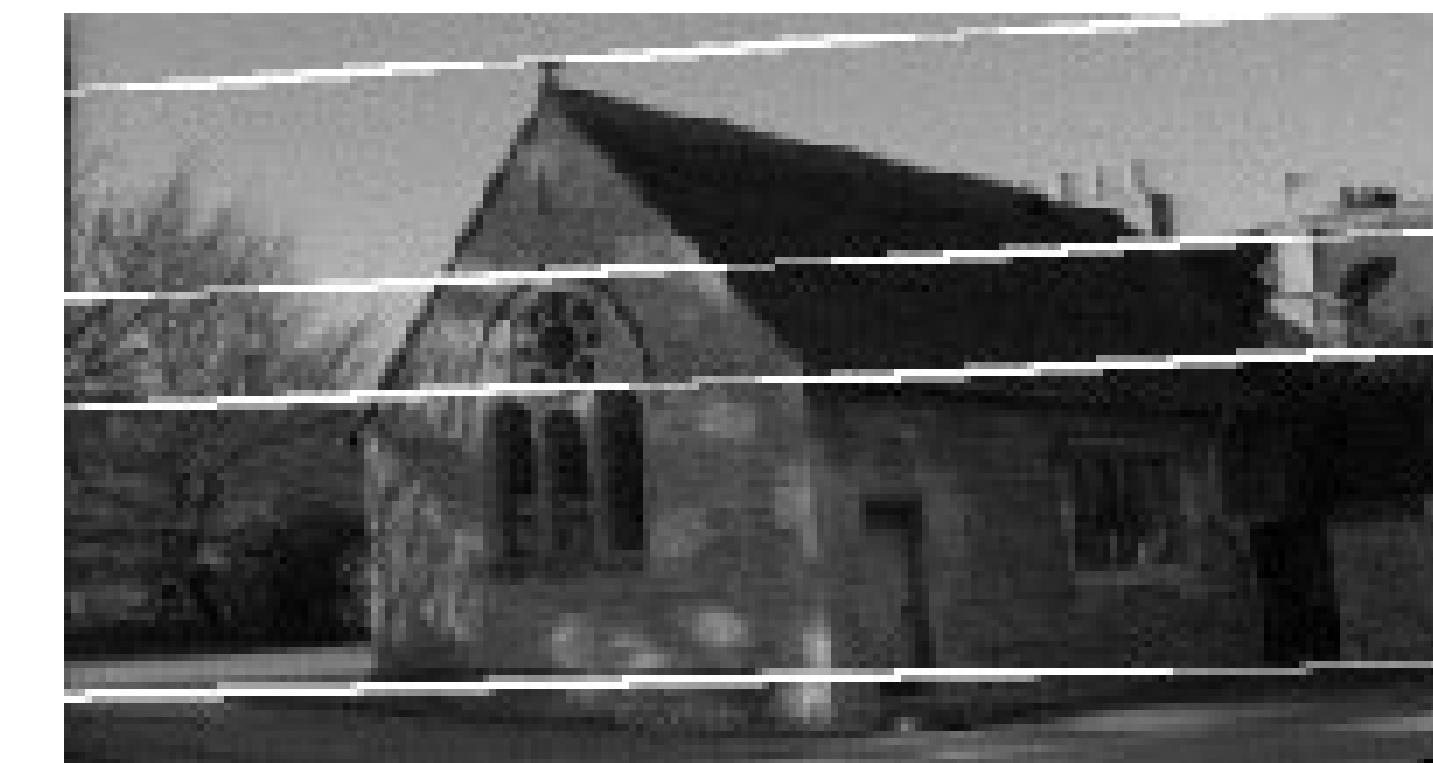
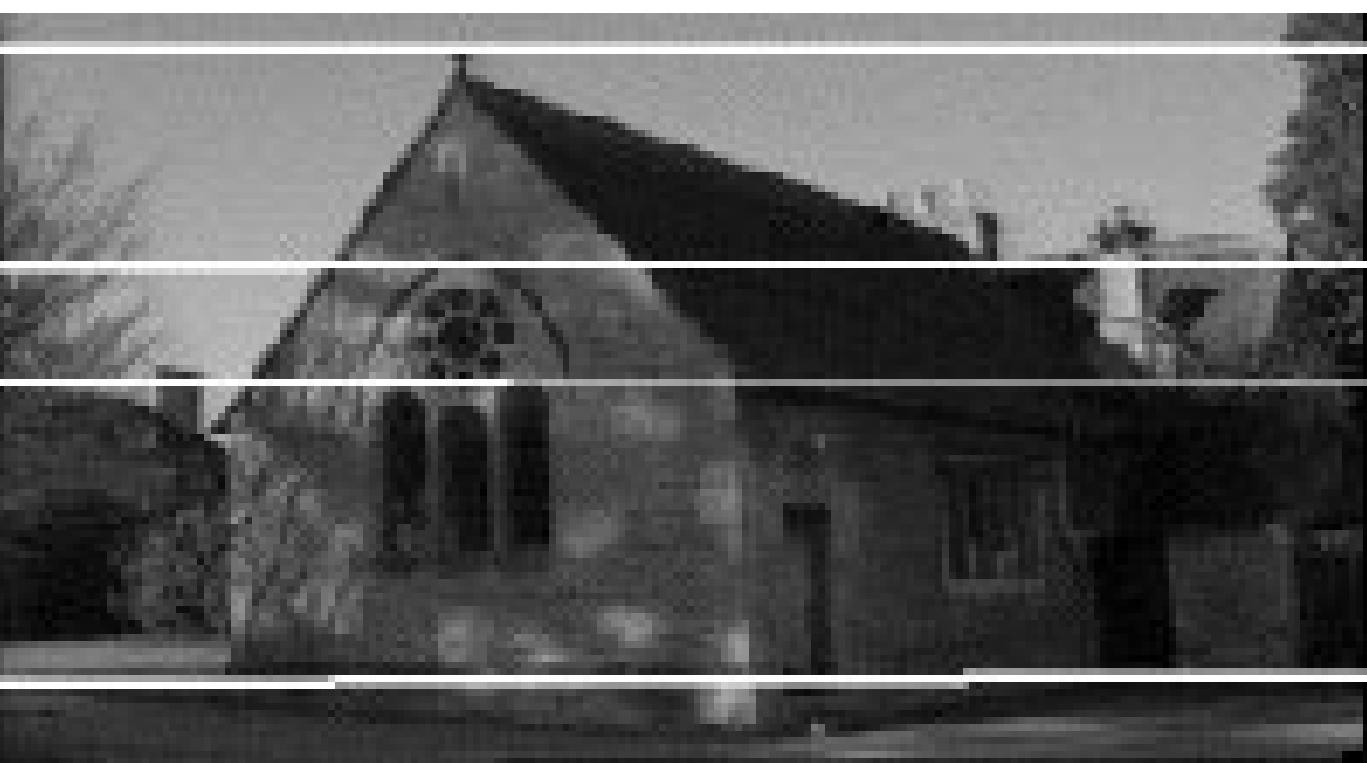
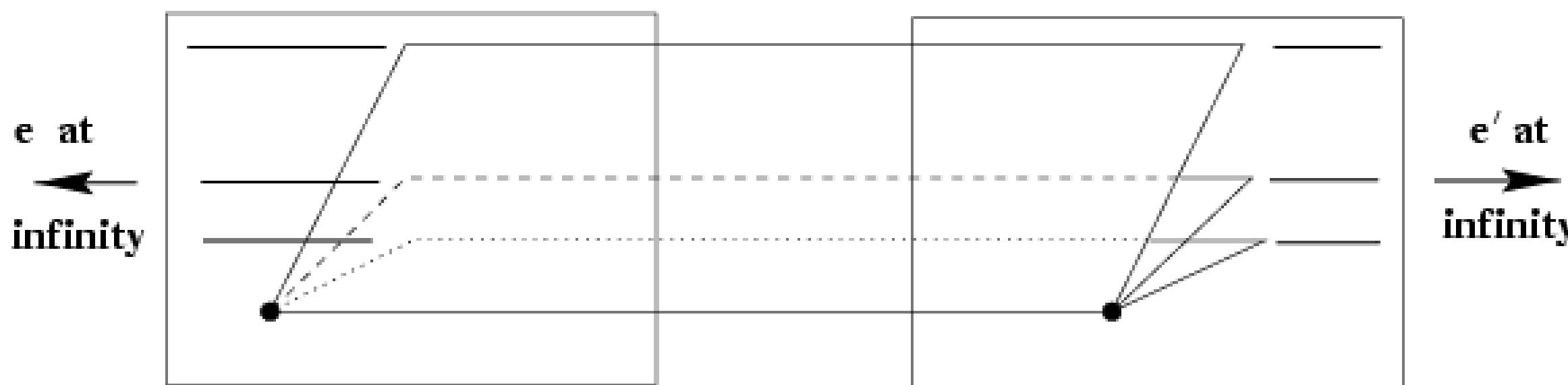
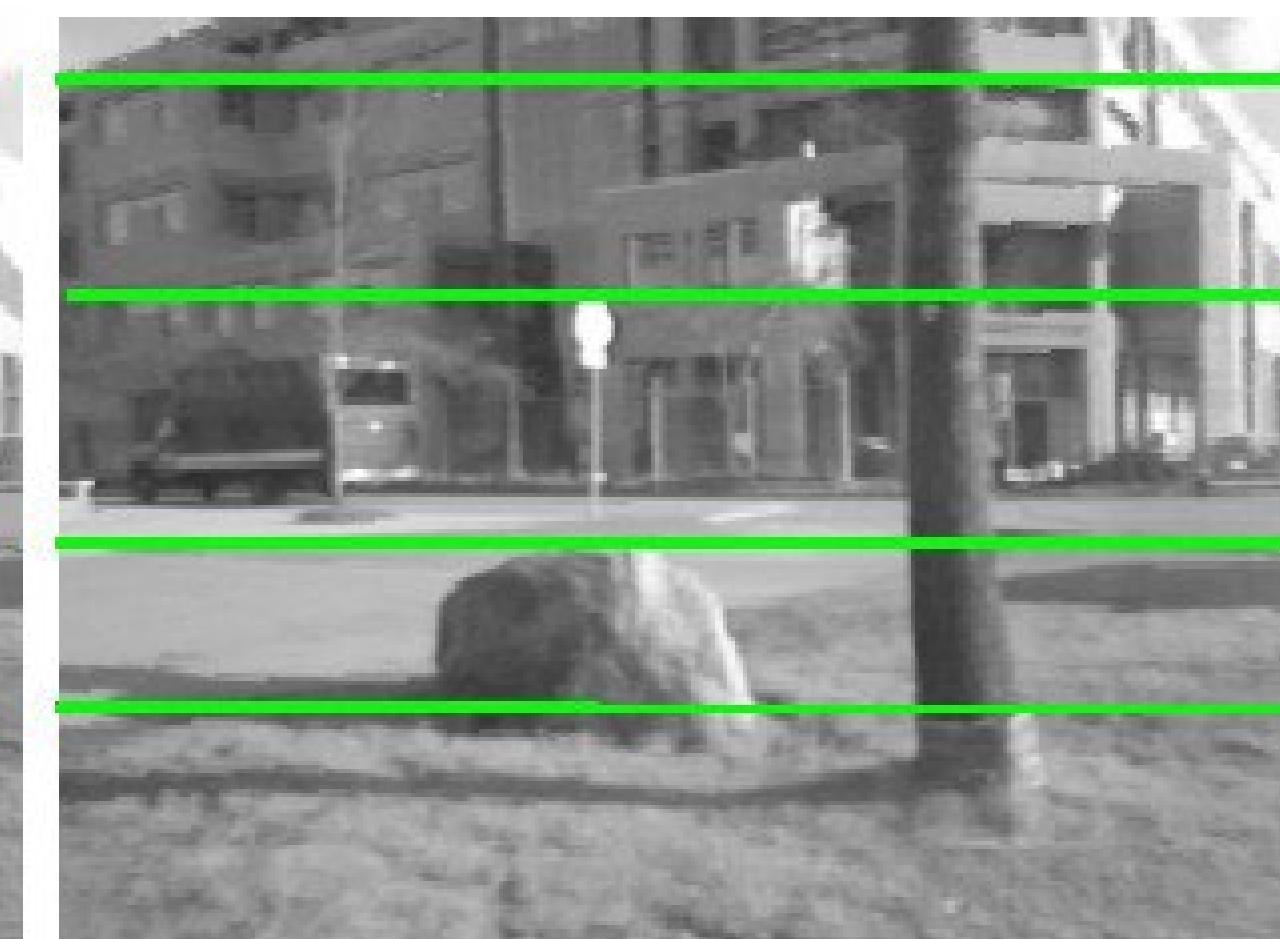
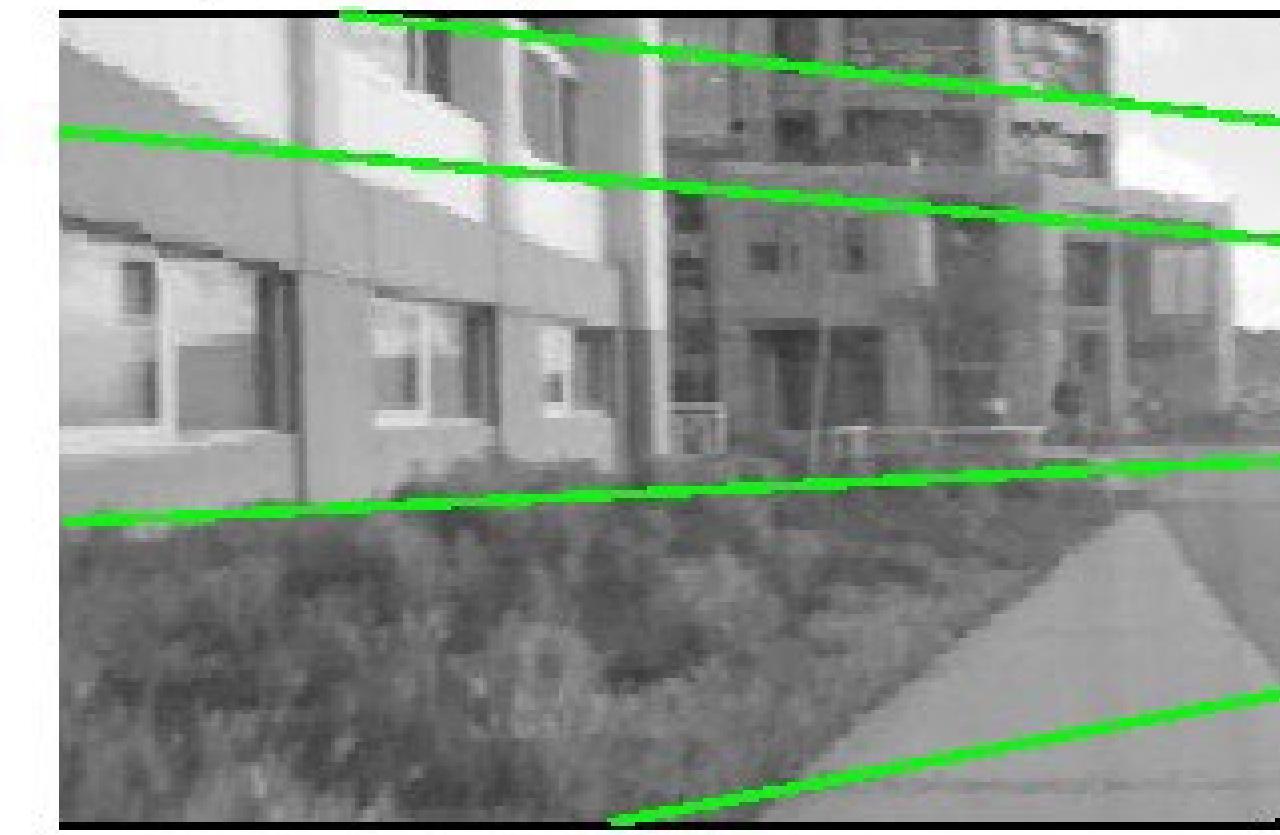
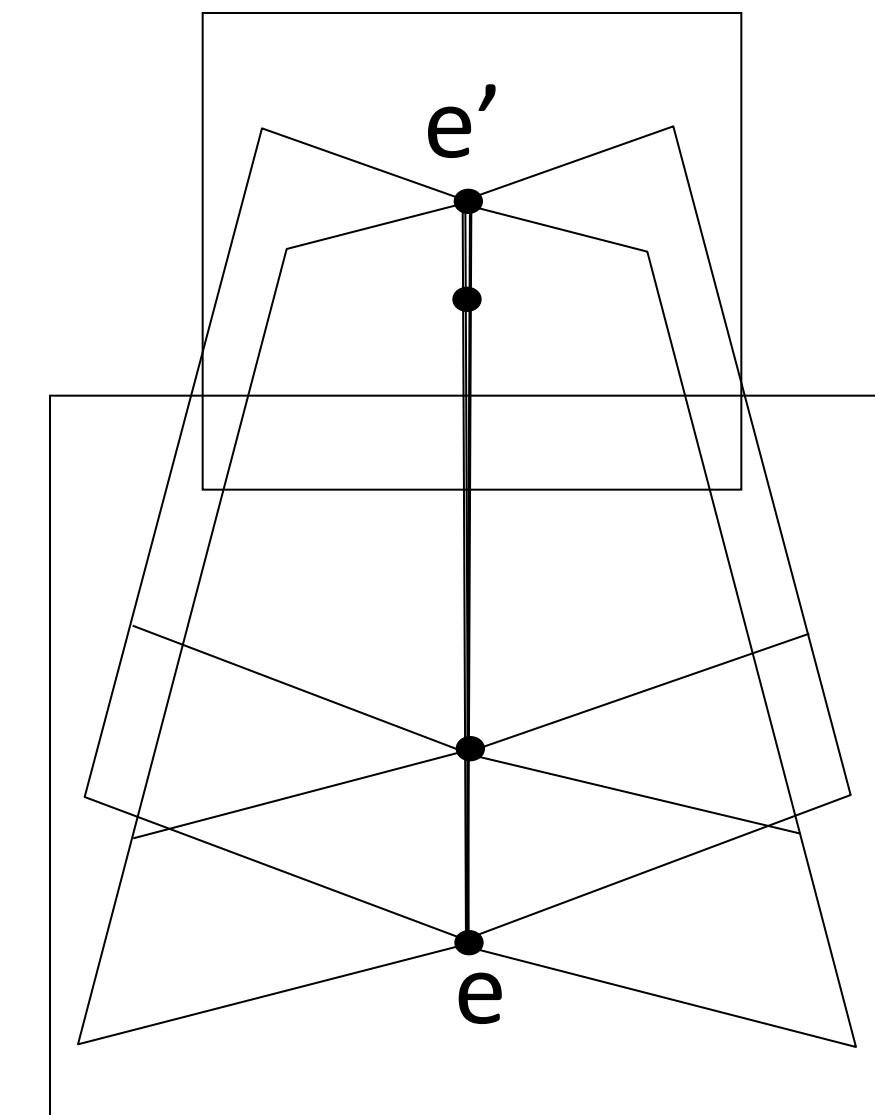
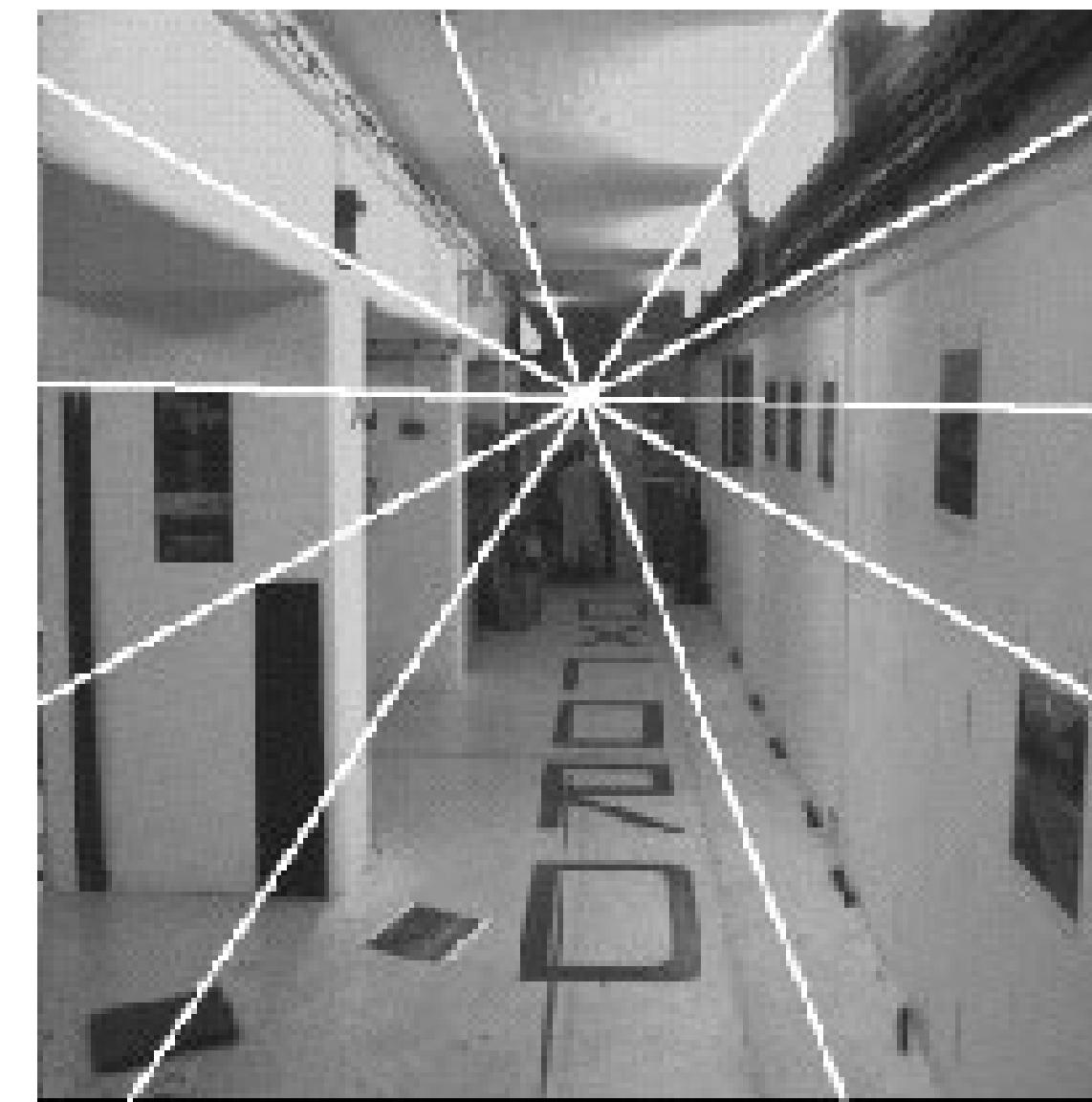
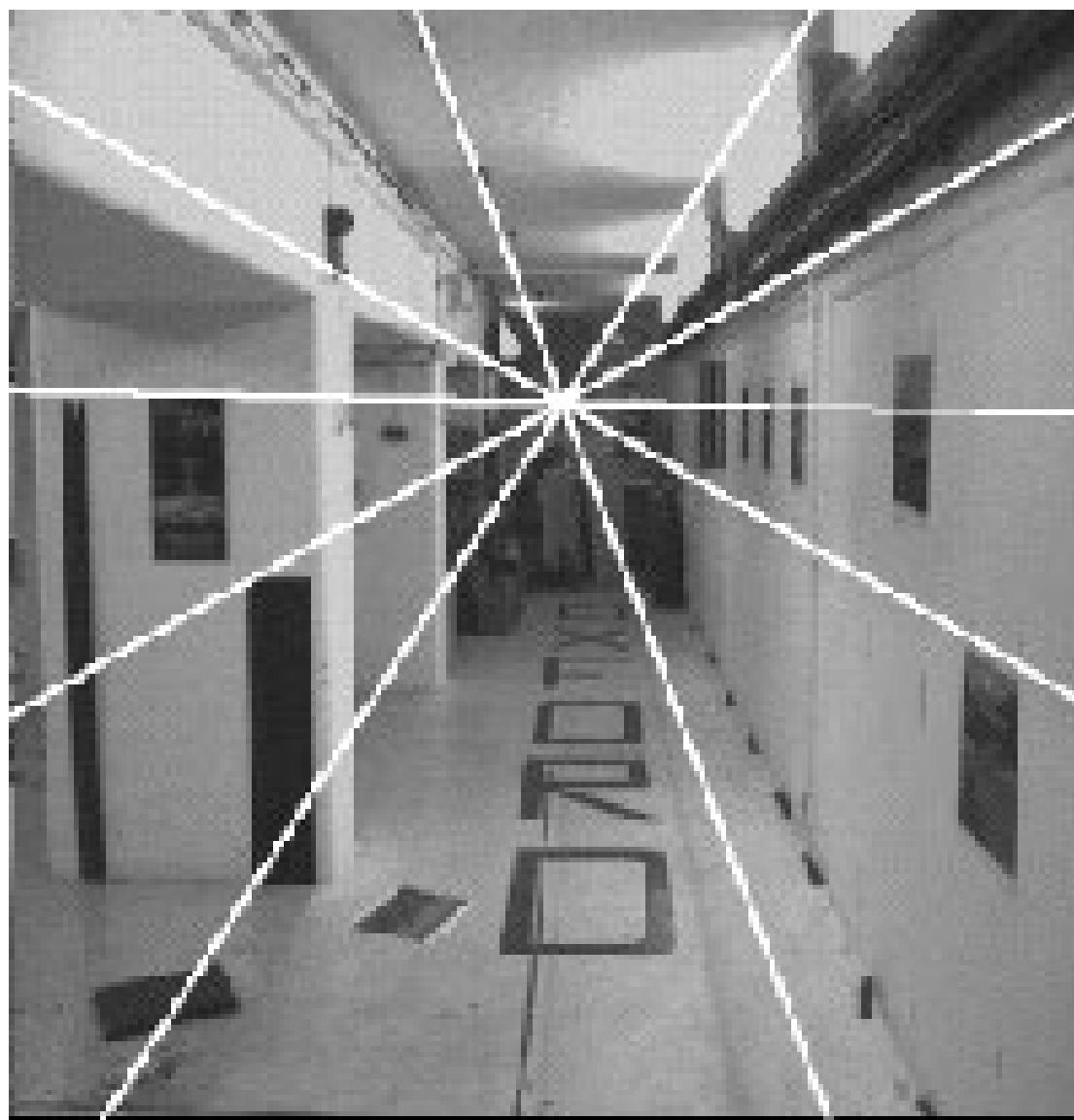


Figure from Hartley & Zisserman

Example



Example: forward motion



Epipole has same coordinates in both images.

Points move along lines radiating from e : “Focus of expansion”

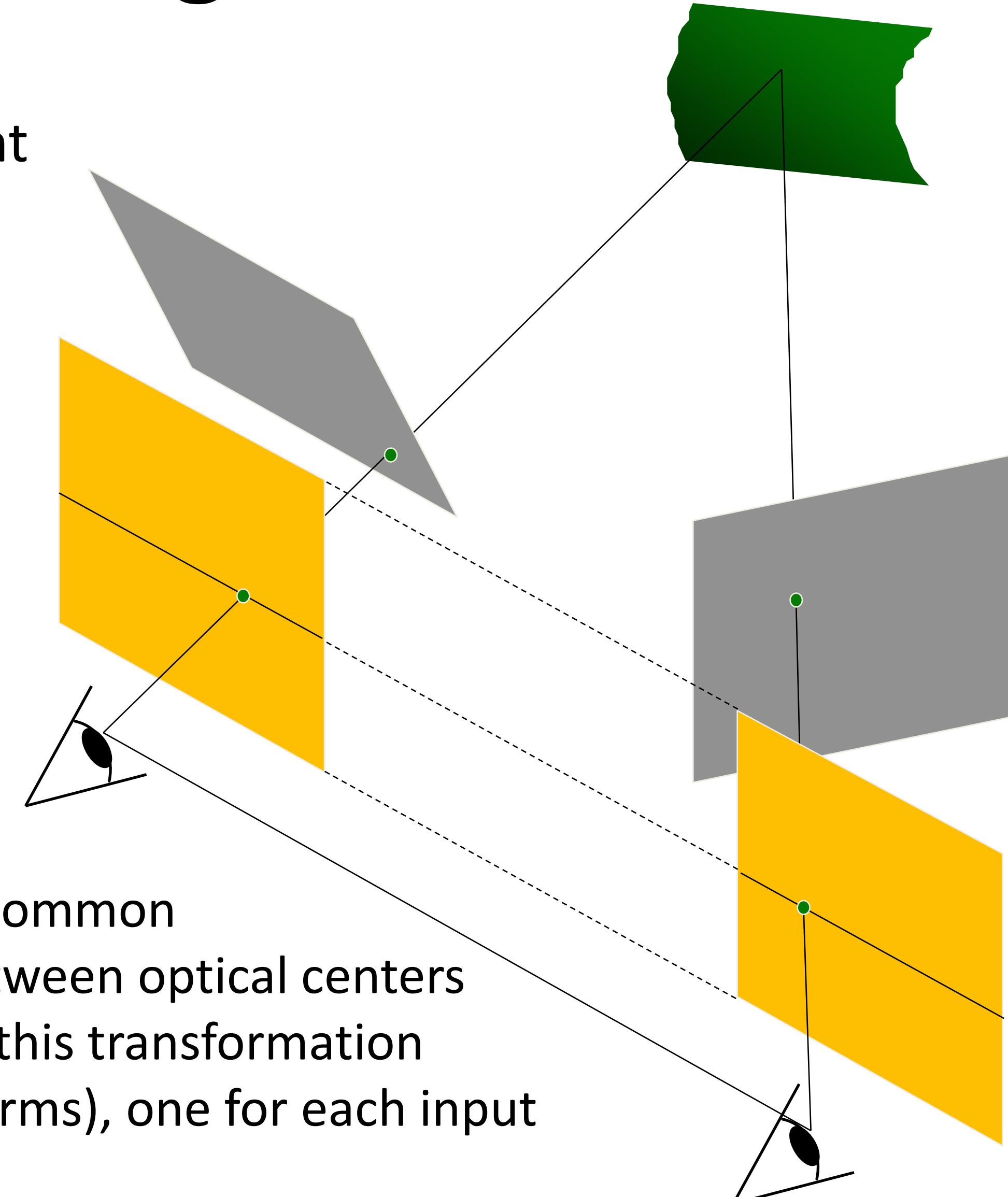
The Epipole



Photo by Frank Dellaert

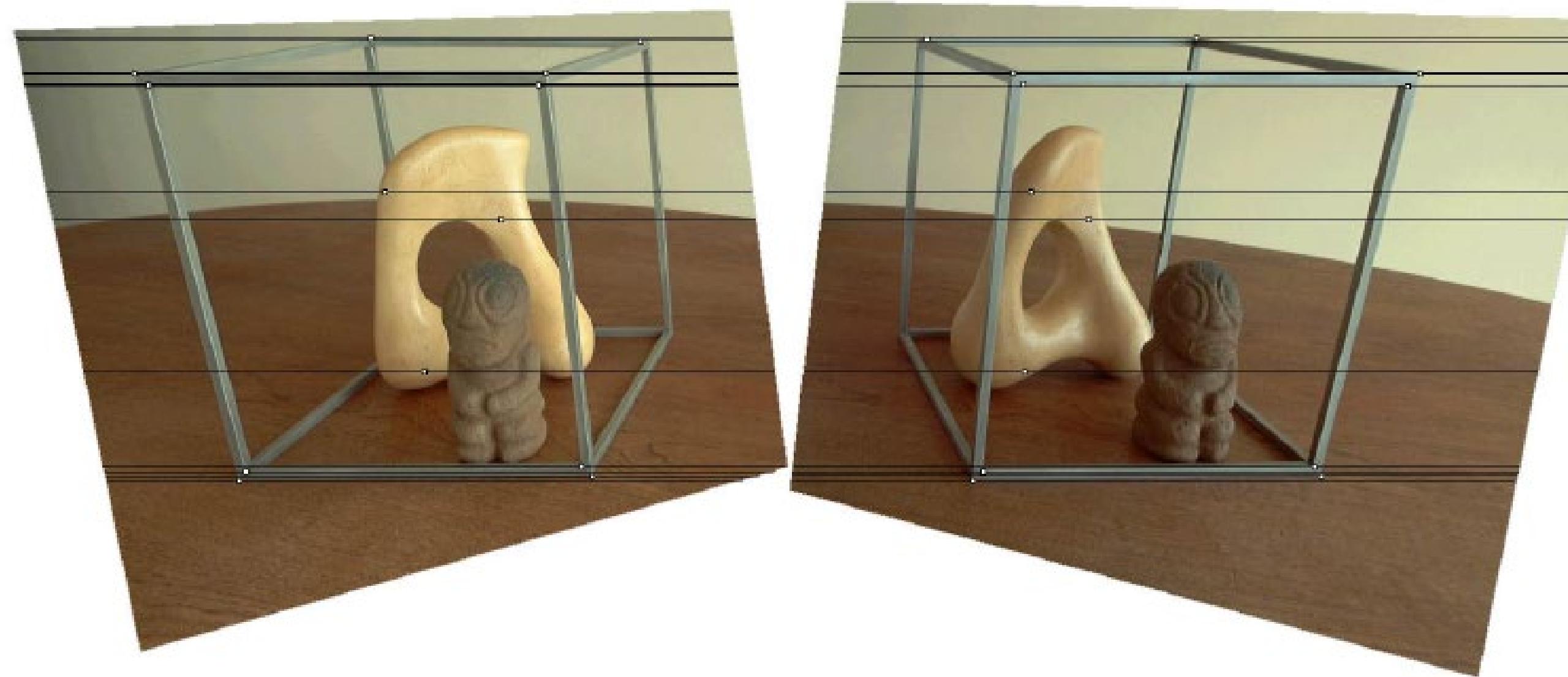
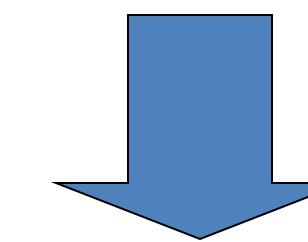
Stereo image rectification

In practice, it is convenient if image scanlines are the epipolar lines.



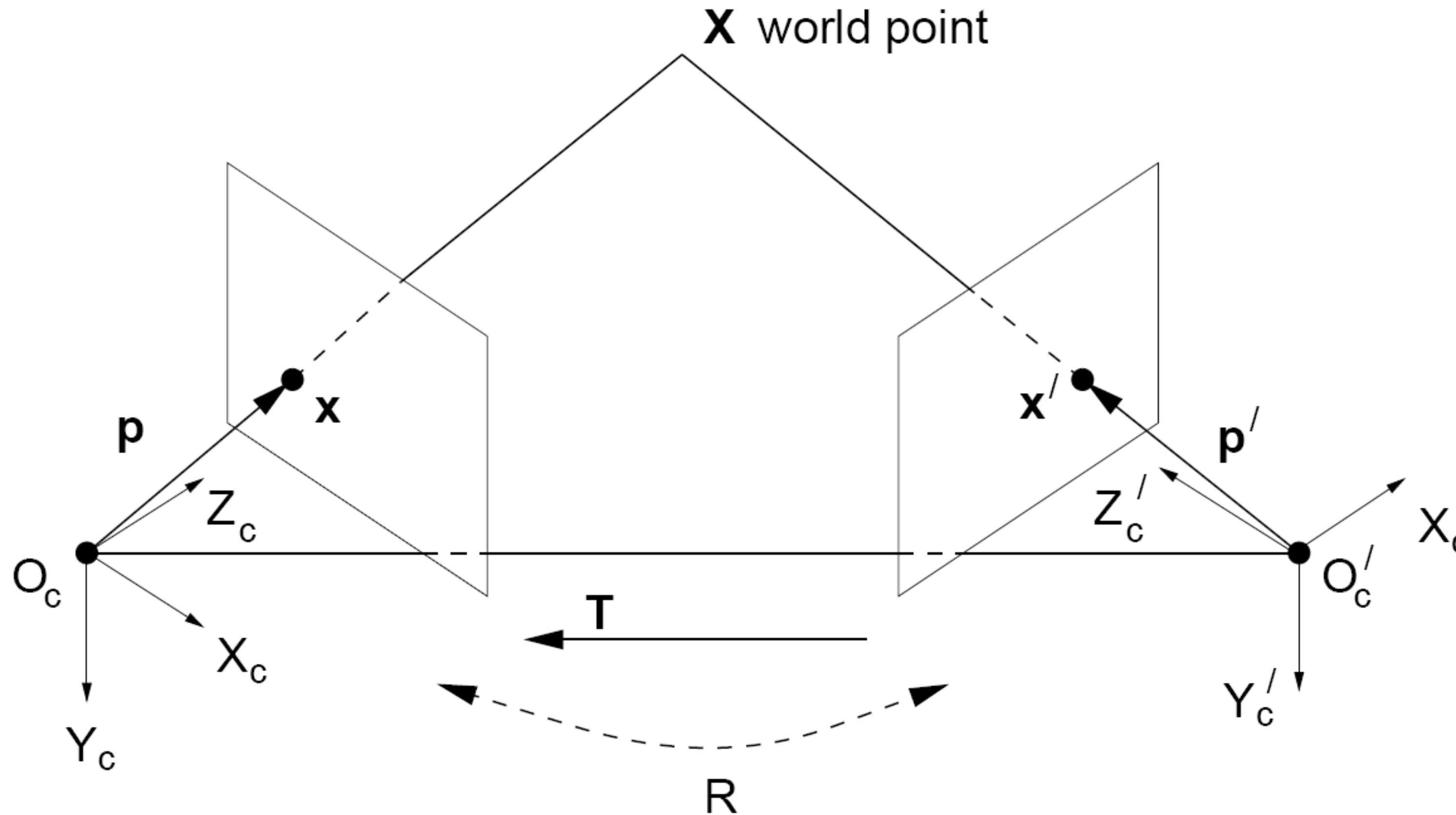
reproject image planes onto a common
plane parallel to the line between optical centers
pixel motion is horizontal after this transformation
two homographies (3x3 transforms), one for each input
image reprojection

Stereo image rectification: example



- For a given stereo rig, how do we express the epipolar constraints algebraically?
 - For calibrated cameras, with **Essential Matrix**
 - For uncalibrated cameras, with **Fundamental Matrix**

Deriving the Essential Matrix: Stereo geometry, with calibrated cameras



If the rig is calibrated, we know :

- how to **rotate** and **translate** camera reference frame 1 to get to camera reference frame 2.

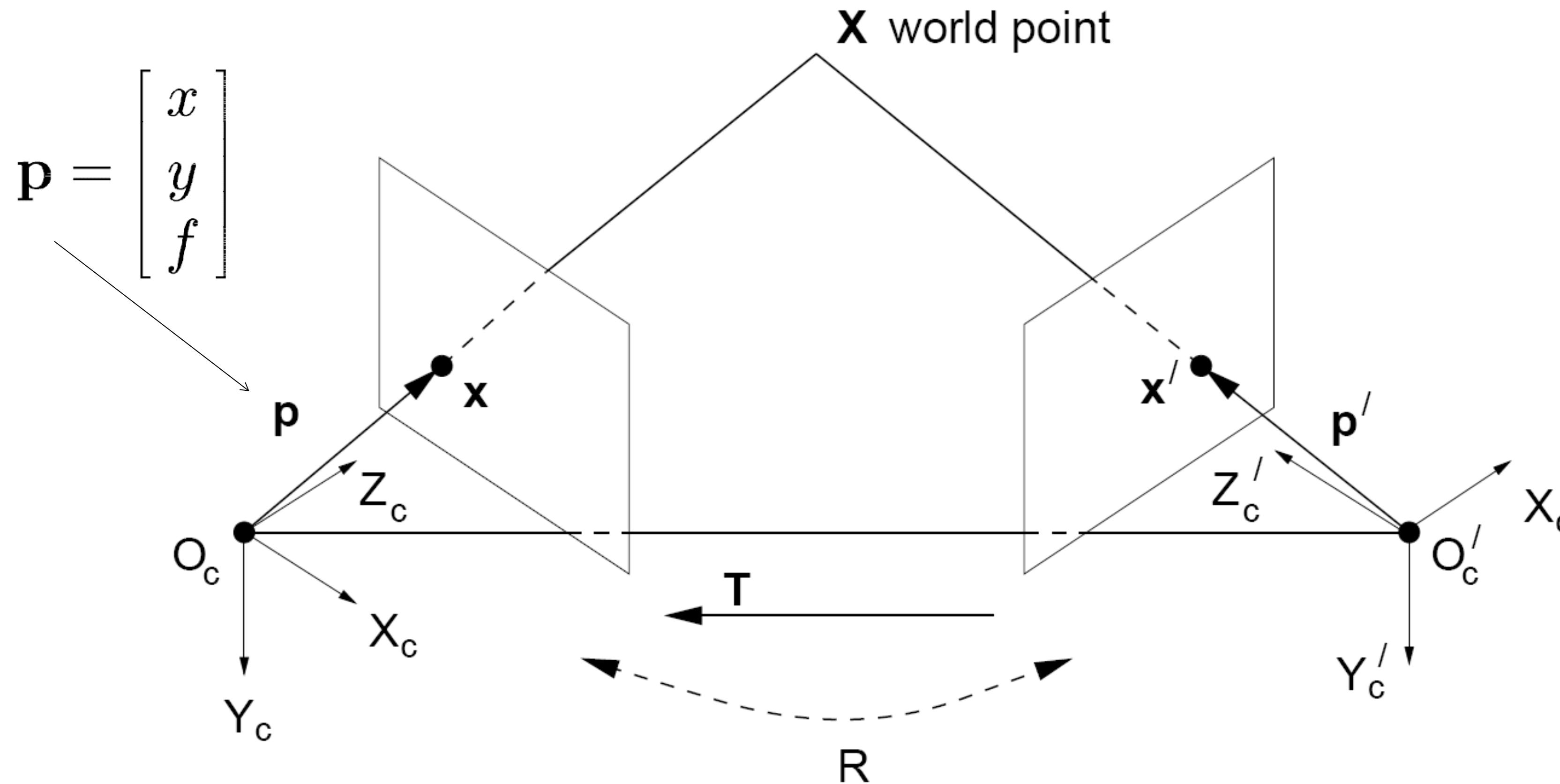
Rotation: 3×3 matrix; translation: 3 vector.

Deriving the Essential Matrix:

3d rigid transformation

$$\begin{bmatrix} x' \\ y' \\ z' \end{bmatrix} = \begin{bmatrix} R & T \end{bmatrix} \begin{bmatrix} x \\ y \\ z \end{bmatrix}$$
$$x' = Rx + T_x$$
$$y' = Ry + T_y$$
$$z' = Rz + T_z$$
$$\mathbf{X}' = \mathbf{R}\mathbf{X} + \mathbf{T}$$

Deriving the Essential Matrix: Stereo geometry, with calibrated cameras



Camera-centered coordinate systems are related by known rotation \mathbf{R} and translation \mathbf{T} :

$$\mathbf{X}' = \mathbf{RX} + \mathbf{T}$$

Deriving the Essential Matrix: Review: Cross product

$$\vec{a} \times \vec{b} = \vec{c}$$

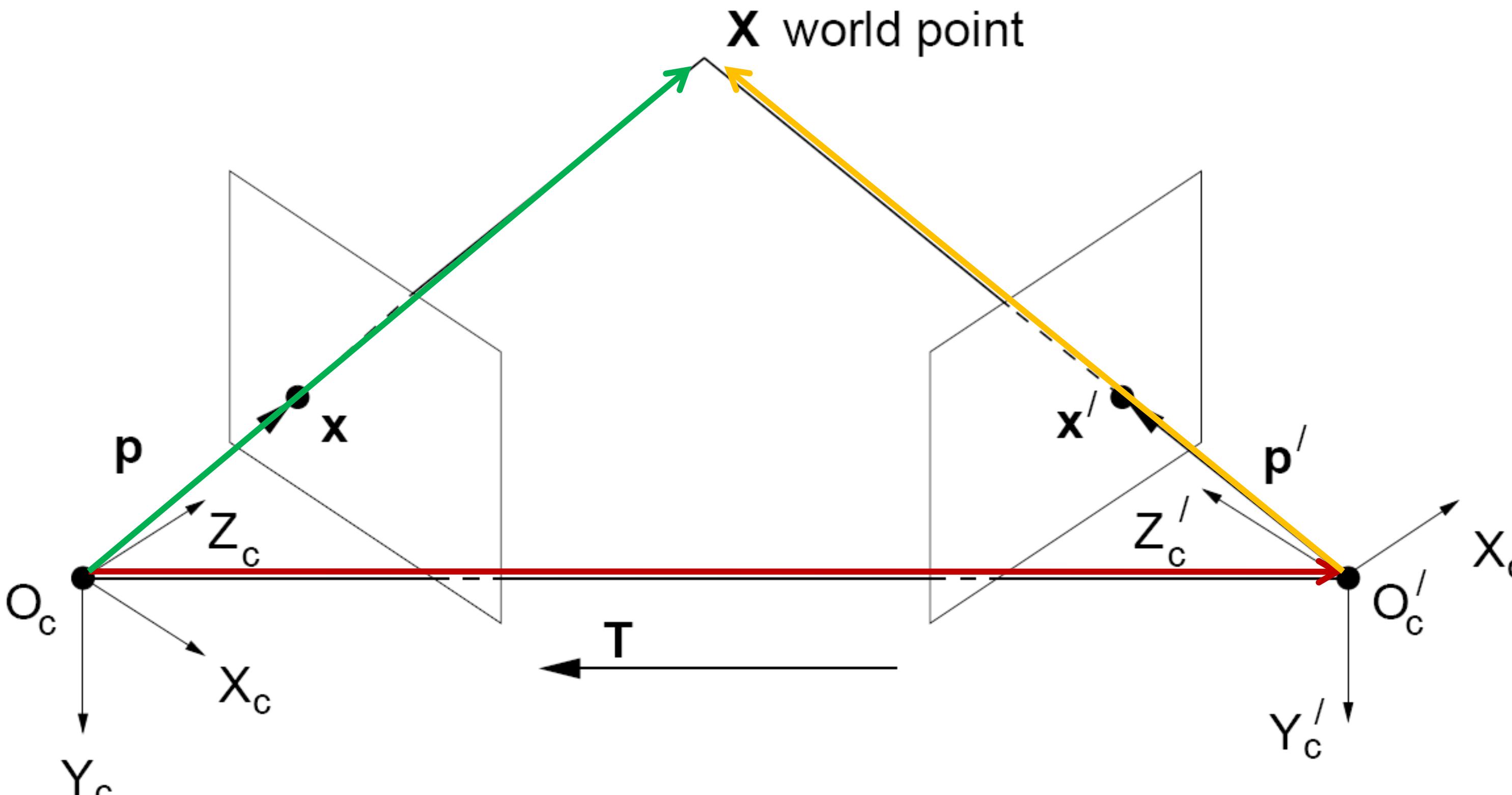
$$\vec{a} \cdot \vec{c} = 0$$

$$\vec{b} \cdot \vec{c} = 0$$

Vector cross product takes two vectors and returns a third vector that's perpendicular to both inputs.

So here, c is perpendicular to both a and b, which means the dot product = 0.

Deriving the Essential Matrix: From geometry to algebra



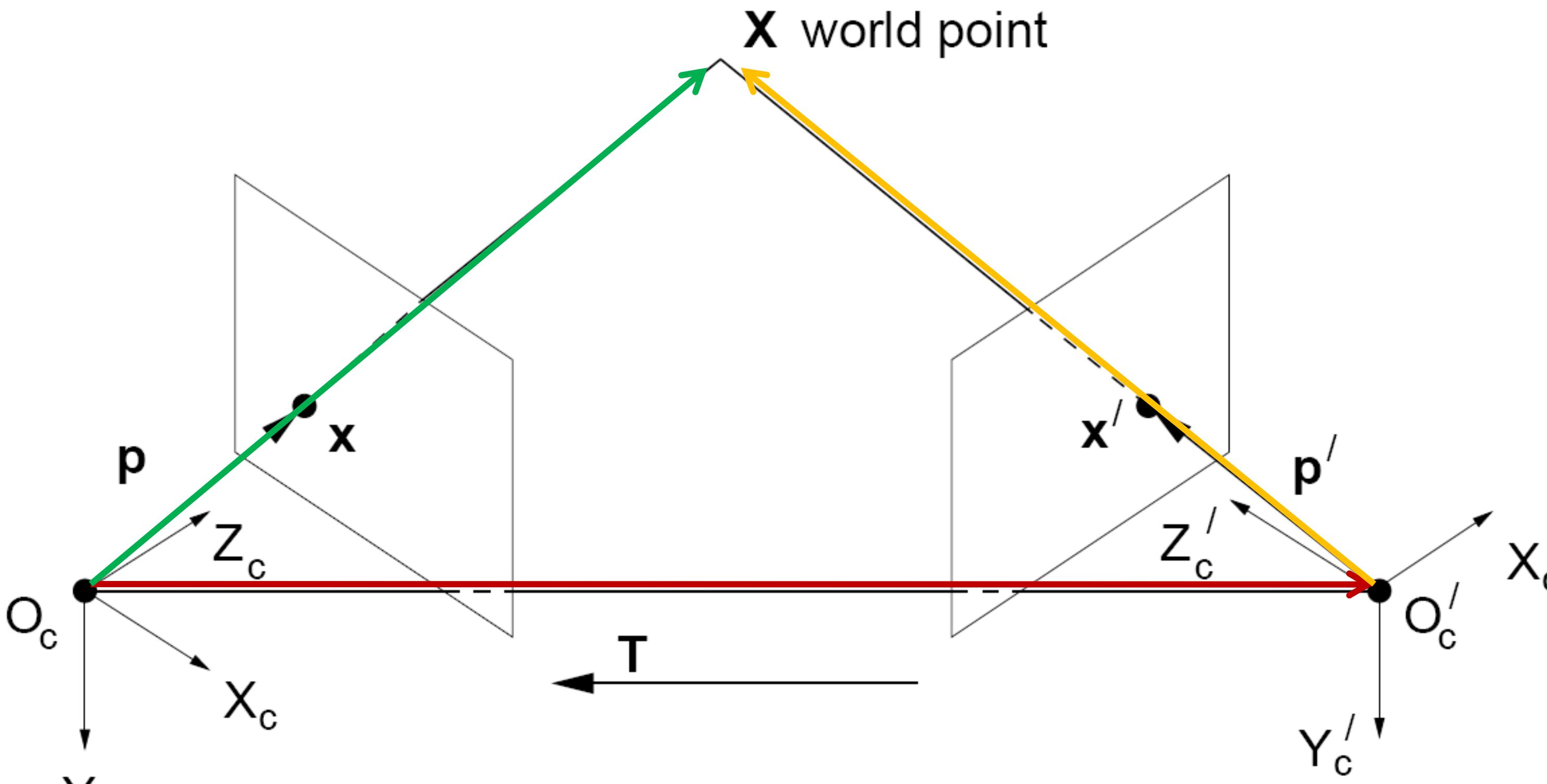
$$\boxed{\mathbf{X}'} = \boxed{\mathbf{R}\mathbf{X}} + \boxed{\mathbf{T}}$$

$$\underbrace{\mathbf{T} \times \mathbf{X}'}_{\text{Normal to the plane}} =$$

$$= \mathbf{T} \times \mathbf{R}\mathbf{X}$$

$$\begin{aligned} \mathbf{X}' \cdot (\mathbf{T} \times \mathbf{X}') &= \mathbf{X}' \cdot (\mathbf{T} \times \mathbf{R}\mathbf{X}) \\ &= 0 \end{aligned}$$

Deriving the Essential Matrix: From geometry to algebra



$$\boxed{X'} = \boxed{RX} + \boxed{T}$$

$$\underbrace{\mathbf{T} \times \mathbf{X}'}_{\text{Normal to the plane}} = \mathbf{T} \times \mathbf{R}\mathbf{X} + \mathbf{T} \times \mathbf{T}$$

Normal to the plane

$$= \mathbf{T} \times \mathbf{R}\mathbf{X}$$

$$\begin{aligned} \mathbf{X}' \cdot (\mathbf{T} \times \mathbf{X}') &= \mathbf{X}' \cdot (\mathbf{T} \times \mathbf{R}\mathbf{X}) \\ &= 0 \end{aligned}$$

Deriving the Essential Matrix:

Matrix form of cross product

$$\vec{a} \times \vec{b}$$

$$= \vec{c} \quad \begin{aligned} \vec{a} \cdot \vec{c} &= 0 \\ \vec{b} \cdot \vec{c} &= 0 \end{aligned}$$

Can be expressed as a matrix multiplication.

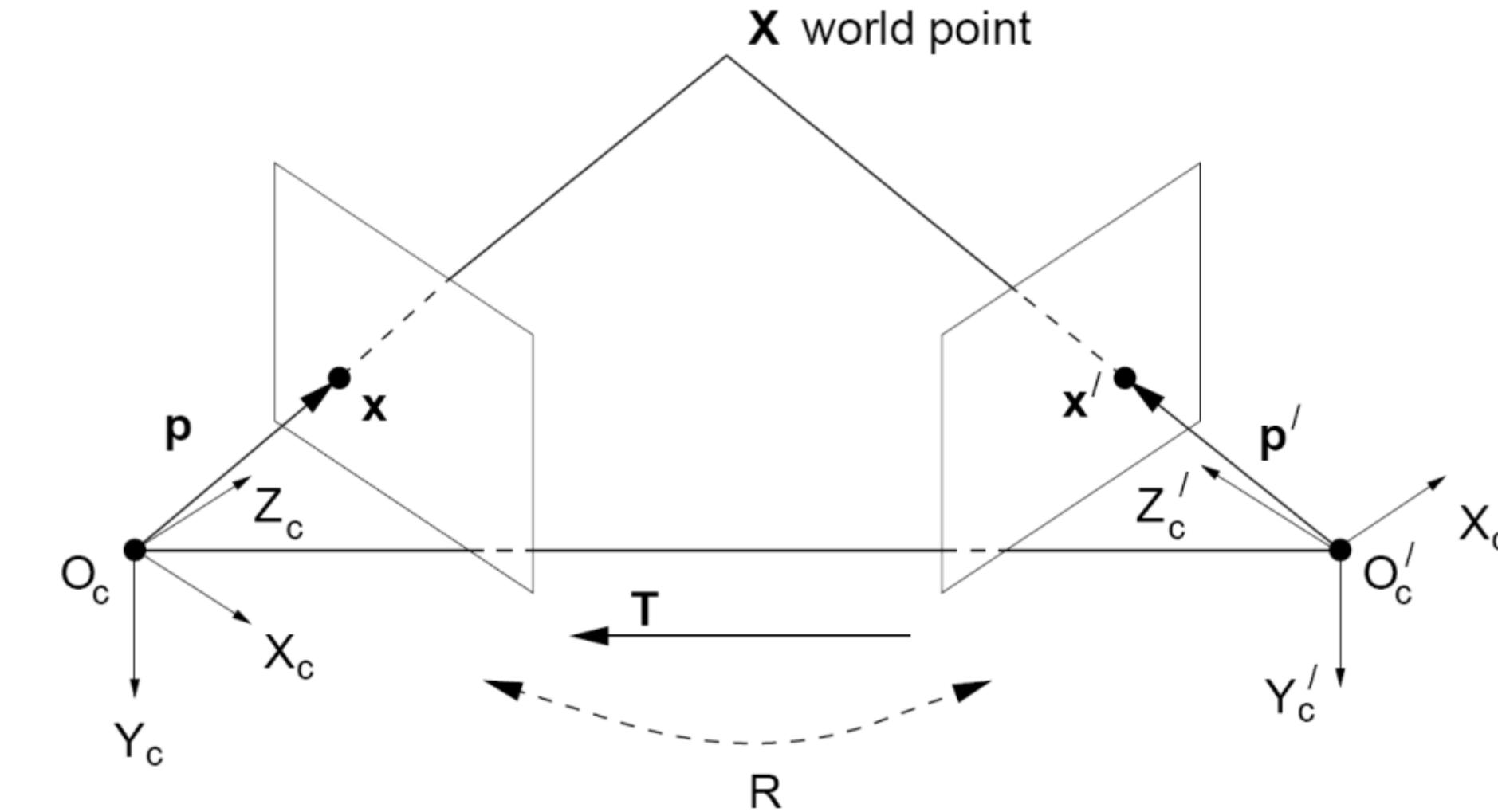
$$[a_x] = \begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix}$$

$$\vec{a} \times \vec{b} = [a_x] \vec{b}$$

Essential matrix

$$\mathbf{X}' \cdot (\mathbf{T}_x \mathbf{R} \mathbf{X}) = 0$$

Let $\mathbf{E} = \mathbf{T}_x \mathbf{R}$



This holds for the rays \mathbf{p} and \mathbf{p}' that are parallel to the camera-centered position vectors \mathbf{X} and \mathbf{X}' , so we have:

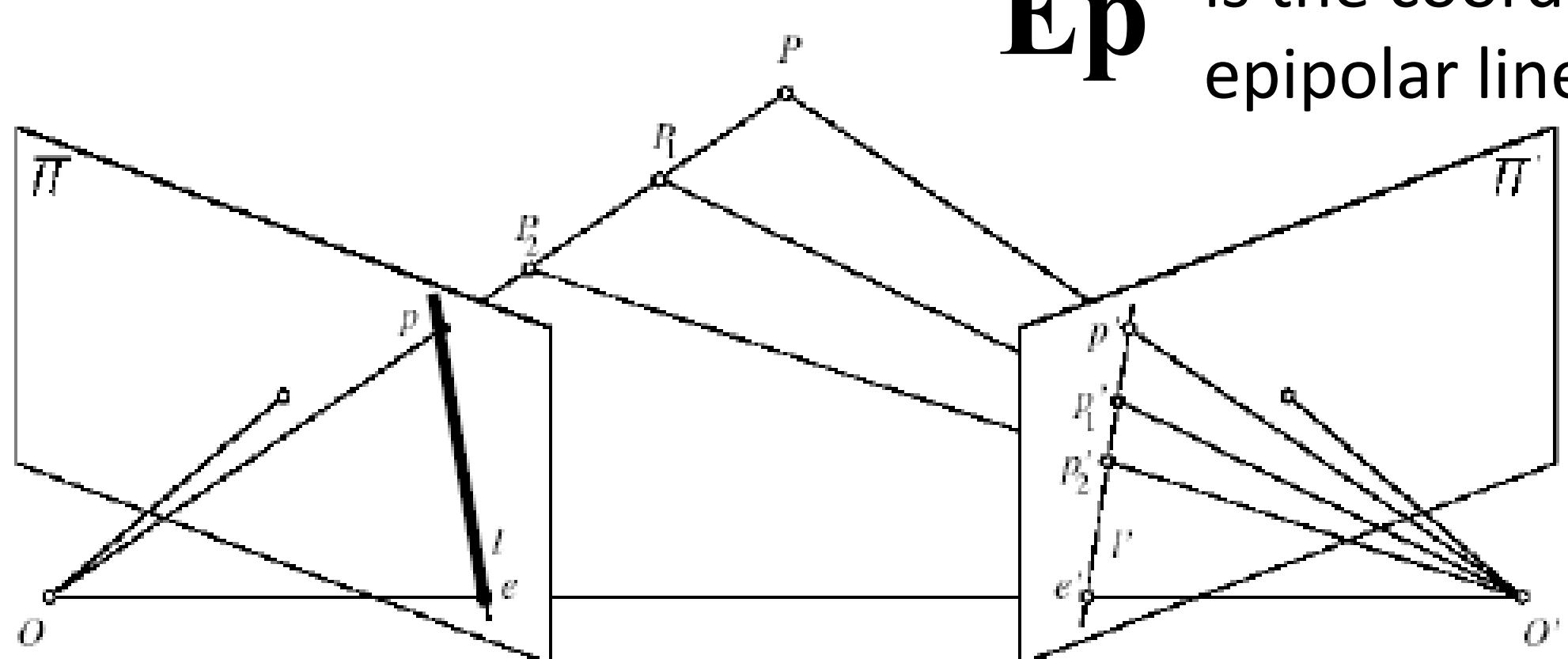
$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$

\mathbf{E} is called the **essential matrix**, which relates corresponding image points [Longuet-Higgins 1981]

Essential matrix and epipolar lines

$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$

Epipolar constraint: if we observe point \mathbf{p} in one image, then its position \mathbf{p}' in second image must satisfy this equation.



$\mathbf{E} \mathbf{p}$ is the coordinate vector representing the epipolar line associated with point p

$\mathbf{E}^T \mathbf{p}'$ is the coordinate vector representing the epipolar line associated with point p'

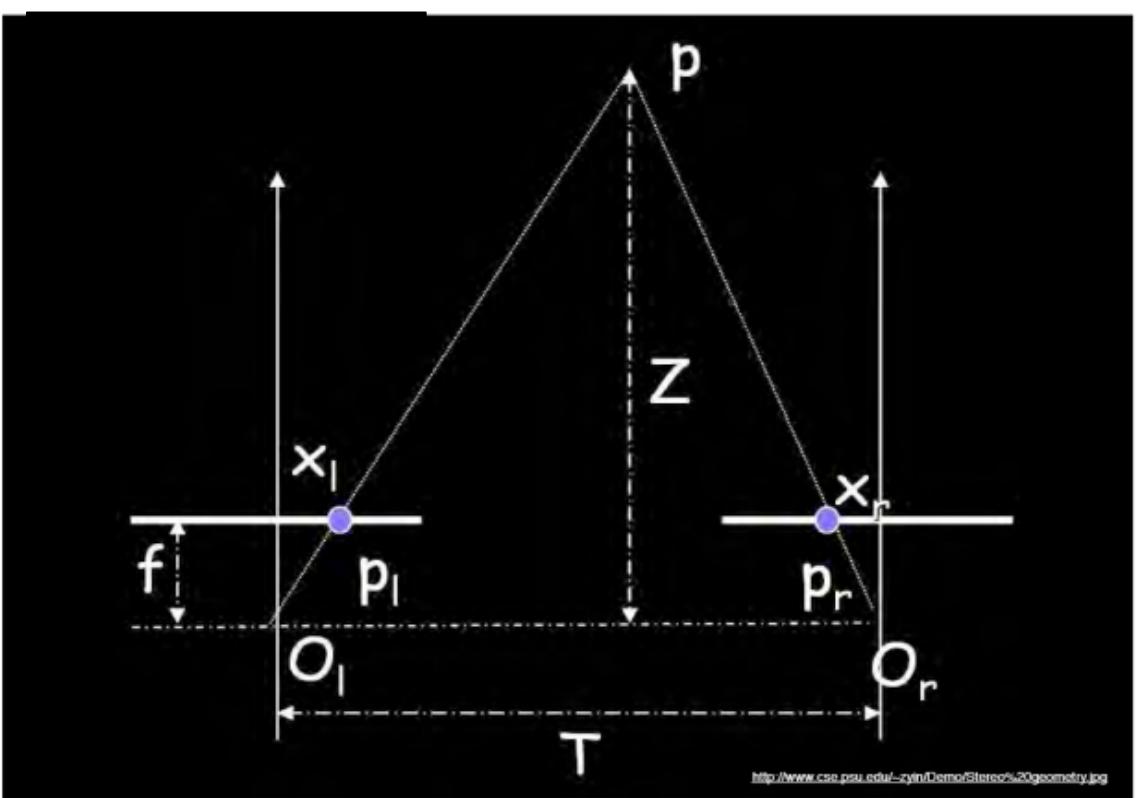
Essential matrix: properties

- Relates image of corresponding points in both cameras, given rotation and translation
- Assuming intrinsic parameters are known

$$\mathbf{E} = \mathbf{T}_x \mathbf{R}$$

- $E x'$ is the epipolar line associated with x' ($l = E x'$)
- $E^T x$ is the epipolar line associated with x ($l' = E^T x$)
- $E e' = 0$ and $E^T e = 0$
- E is singular (rank two)
- E has five degrees of freedom
 - (3 for R , 2 for t because it's up to a scale)

Essential matrix example: parallel cameras



$$\mathbf{R} =$$

$$\mathbf{T} =$$

$$\mathbf{E} = [\mathbf{T}_x] \mathbf{R} =$$

$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$

For the parallel cameras, image of any point must lie on same horizontal line in each image plane.

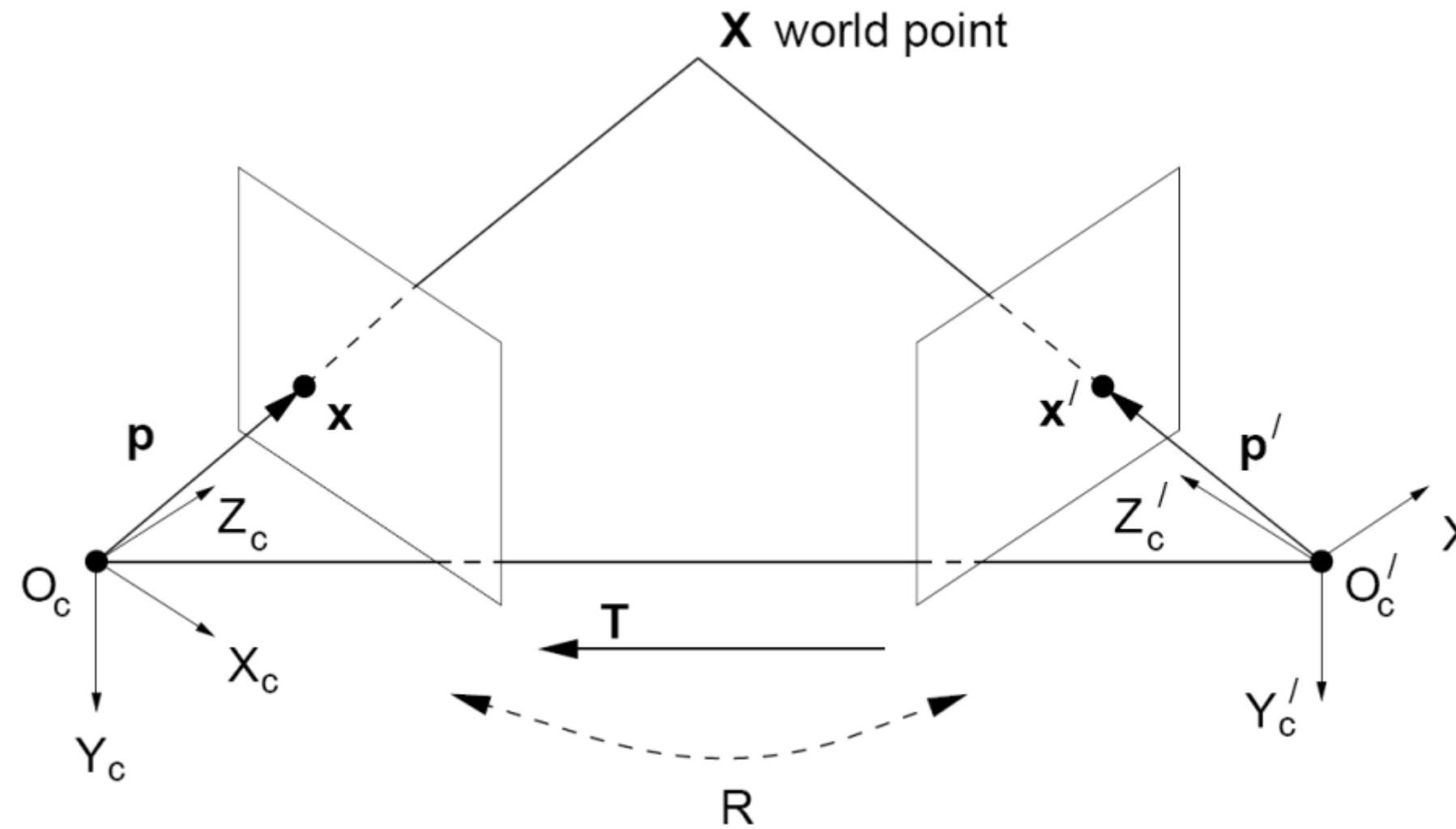
Weak calibration

- So far, we have assumed calibrated cameras and were able to perform dense stereo estimation
- What if we want to estimate world geometry without requiring calibrated cameras?
 - Archival videos
 - Photos from multiple unrelated users
 - Dynamic camera system

Uncalibrated cameras

$$\mathbf{E} = \mathbf{T}_x \mathbf{R}$$

$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$



- For an *uncalibrated* stereo rig, can we express the epipolar constraints algebraically via the **Essential Matrix**?
- No, we do not know \mathbf{T} or \mathbf{R}
- However we can use the **Fundamental Matrix**
 - Estimate epipolar geometry from a (redundant) set of point correspondences between two uncalibrated cameras

Uncalibrated case

For a given camera:

$$\bar{\mathbf{p}} = \mathbf{M}_{\text{int}} \mathbf{p}$$

Camera
coordinates

So, for two cameras (left and right):

$$\mathbf{p}_{(left)} = \mathbf{M}_{left,\text{int}}^{-1} \bar{\mathbf{p}}_{(left)}$$

Camera coordinates

Image pixel
coordinates

$$\mathbf{p}_{(right)} = \mathbf{M}_{right,\text{int}}^{-1} \bar{\mathbf{p}}_{(right)}$$

Internal calibration
matrices, one per camera

$$\mathbf{p}_{(left)} = \mathbf{M}_{left,int}^{-1} \bar{\mathbf{p}}_{(left)}$$

$$\mathbf{p}_{(right)} = \mathbf{M}_{right,int}^{-1} \bar{\mathbf{p}}_{(right)}$$

Uncalibrated case:

Fundamental matrix

$${}^c \mathbf{p}_{(right)}^T \mathbf{E} \mathbf{p}_{(left)} = 0$$

From before, the essential matrix \mathbf{E} .

$$\left(\mathbf{M}_{right,int}^{-1} \bar{\mathbf{p}}_{right} \right)^T \mathbf{E} \left(\mathbf{M}_{left,int}^{-1} \bar{\mathbf{p}}_{left} \right) = 0$$

$$\bar{\mathbf{p}}_{right}^T \underbrace{\left(\mathbf{M}_{right,int}^{-T} \mathbf{E} \mathbf{M}_{left,int}^{-1} \right)}_{\text{Fundamental matrix}} \bar{\mathbf{p}}_{left} = 0$$

$$\bar{\mathbf{p}}_{right}^T \boxed{\mathbf{F}} \bar{\mathbf{p}}_{left} = 0$$

Fundamental matrix

Grauman

Fundamental matrix

- Relates pixel coordinates in the two views
- More general form than essential matrix: we remove need to know intrinsic parameters
- If we estimate fundamental matrix from correspondences in pixel coordinates, can reconstruct epipolar geometry without intrinsic or extrinsic parameters

Computing F from correspondences

$$\mathbf{F} = \left(\mathbf{M}_{right,int}^{-T} \mathbf{E} \mathbf{M}_{left,int}^{-1} \right)$$

$$\bar{\mathbf{p}}_{right}^T \mathbf{F} \bar{\mathbf{p}}_{left} = 0$$

- Cameras are uncalibrated: we don't know \mathbf{E} or left or right \mathbf{M}_{int} matrices
- Estimate \mathbf{F} from 8+ point correspondences.

Computing F from correspondences

Each point correspondence generates one constraint on F

$$\bar{\mathbf{p}}_{right}^T \mathbf{F} \bar{\mathbf{p}}_{left} = 0$$

$$\begin{bmatrix} u' & v' & 1 \end{bmatrix} \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = 0$$

Collect n of these constraints

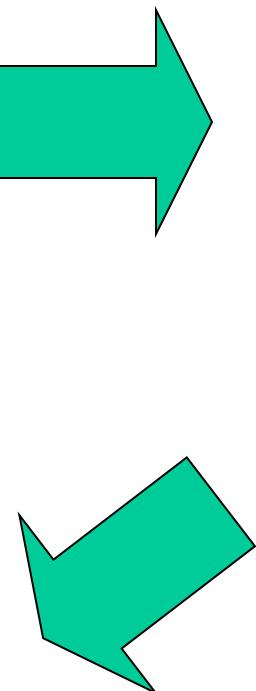
$$\begin{bmatrix} u'_1 u_1 & u'_1 v_1 & u'_1 & v'_1 u_1 & v'_1 v_1 & v'_1 & u_1 & v_1 & 1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = \mathbf{0}$$

Solve for f , vector of parameters.

Rank constraint

$$\mathbf{x} = (u, v, 1)^T, \quad \mathbf{x}' = (u', v', 1)$$

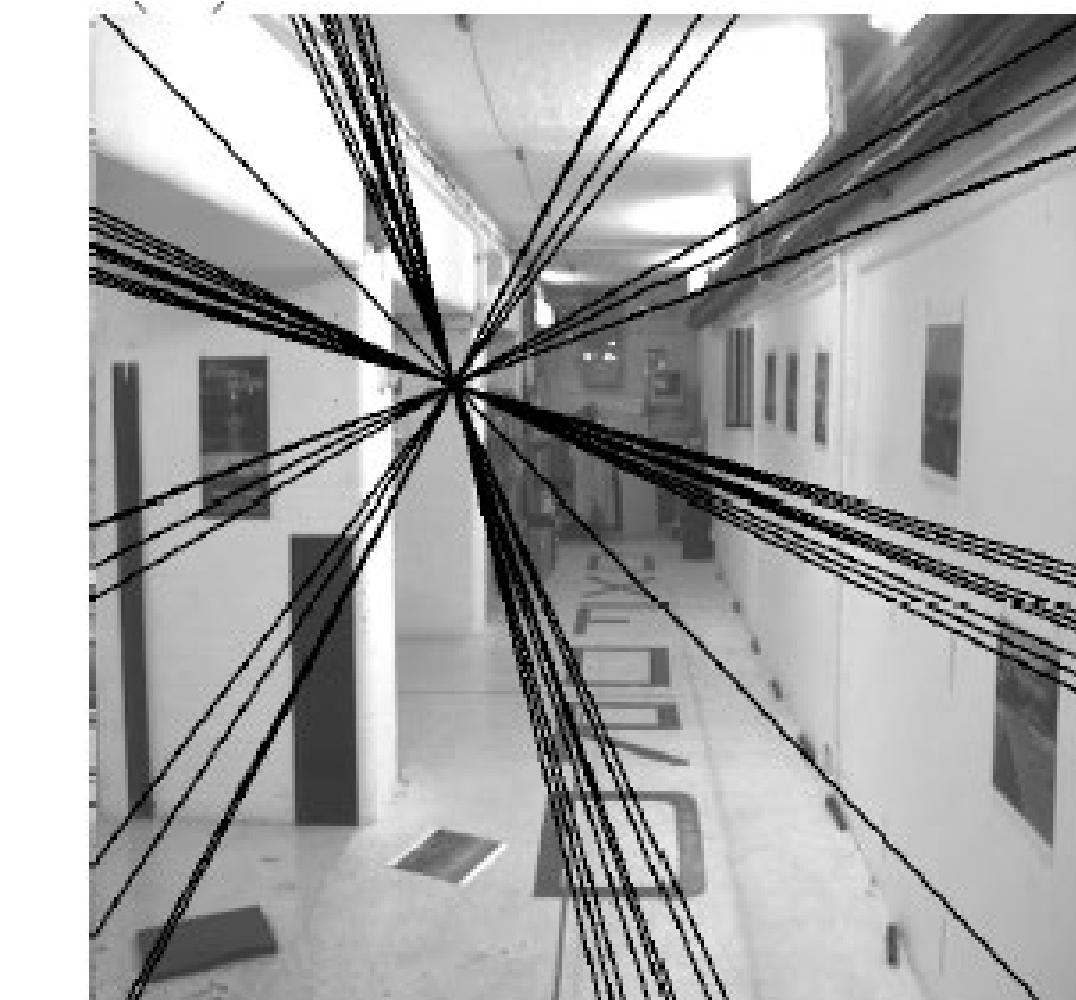
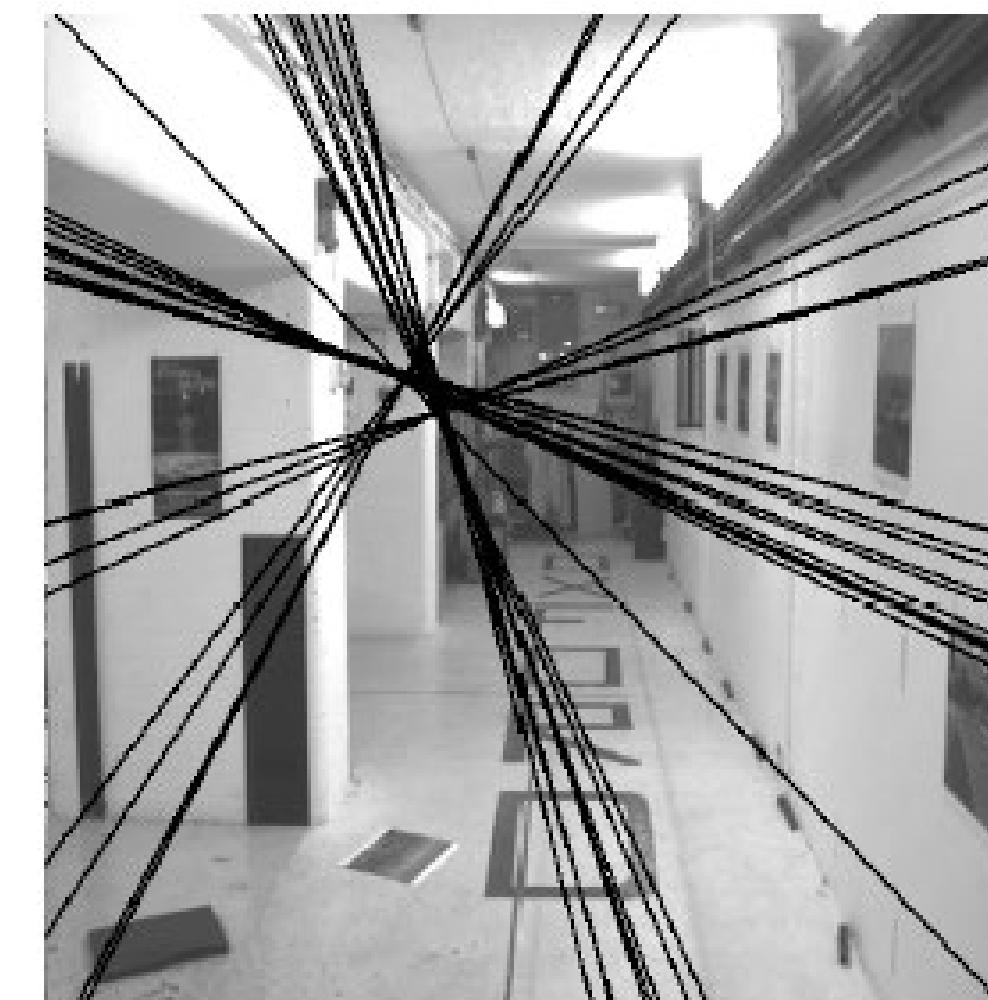
$$[u' \quad v' \quad 1] \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = 0$$



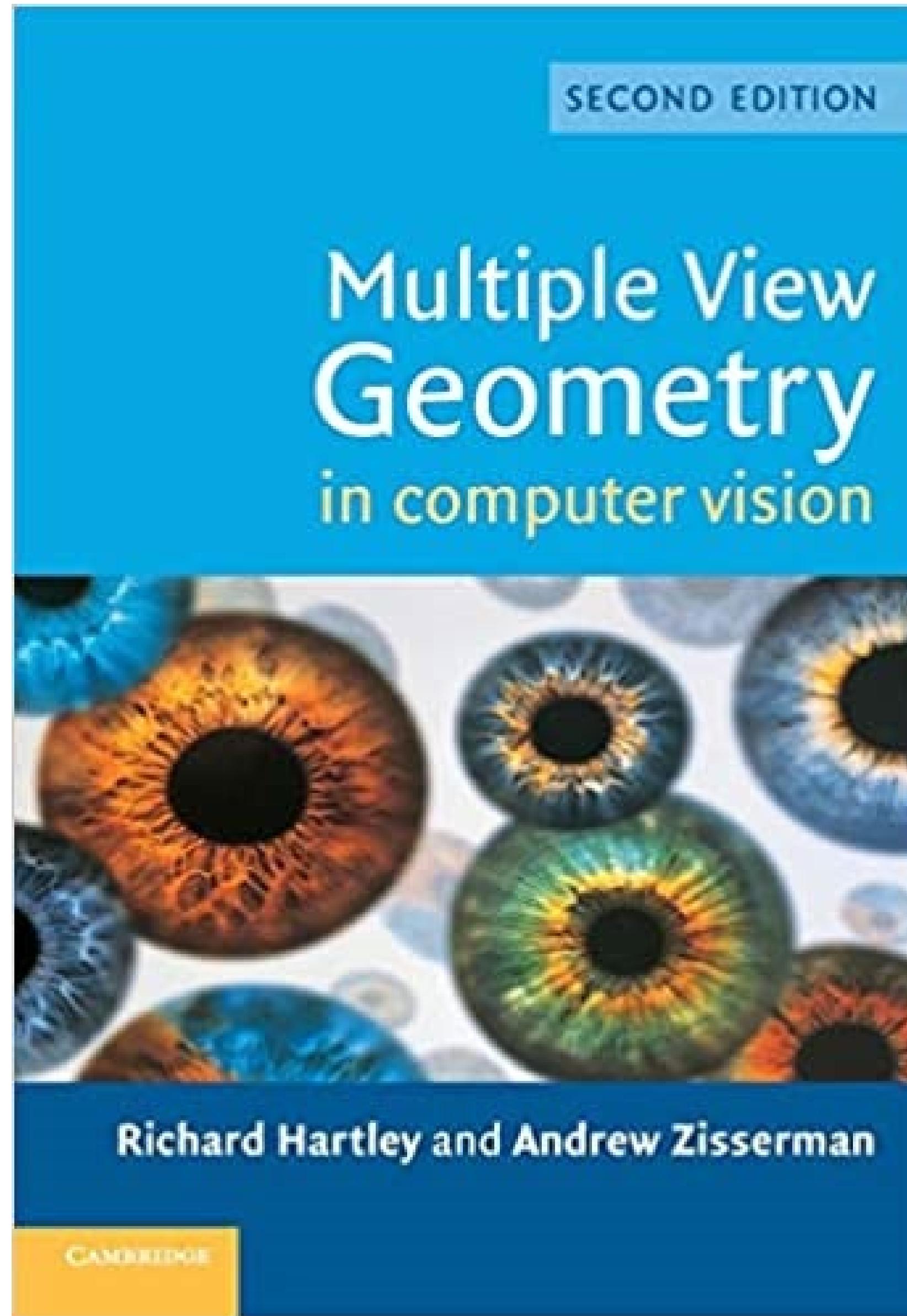
$$[u'u \quad u'v \quad u' \quad v'u \quad v'v \quad v' \quad u \quad v \quad 1] \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = 0$$

Solve homogeneous
linear system using
eight or more matches

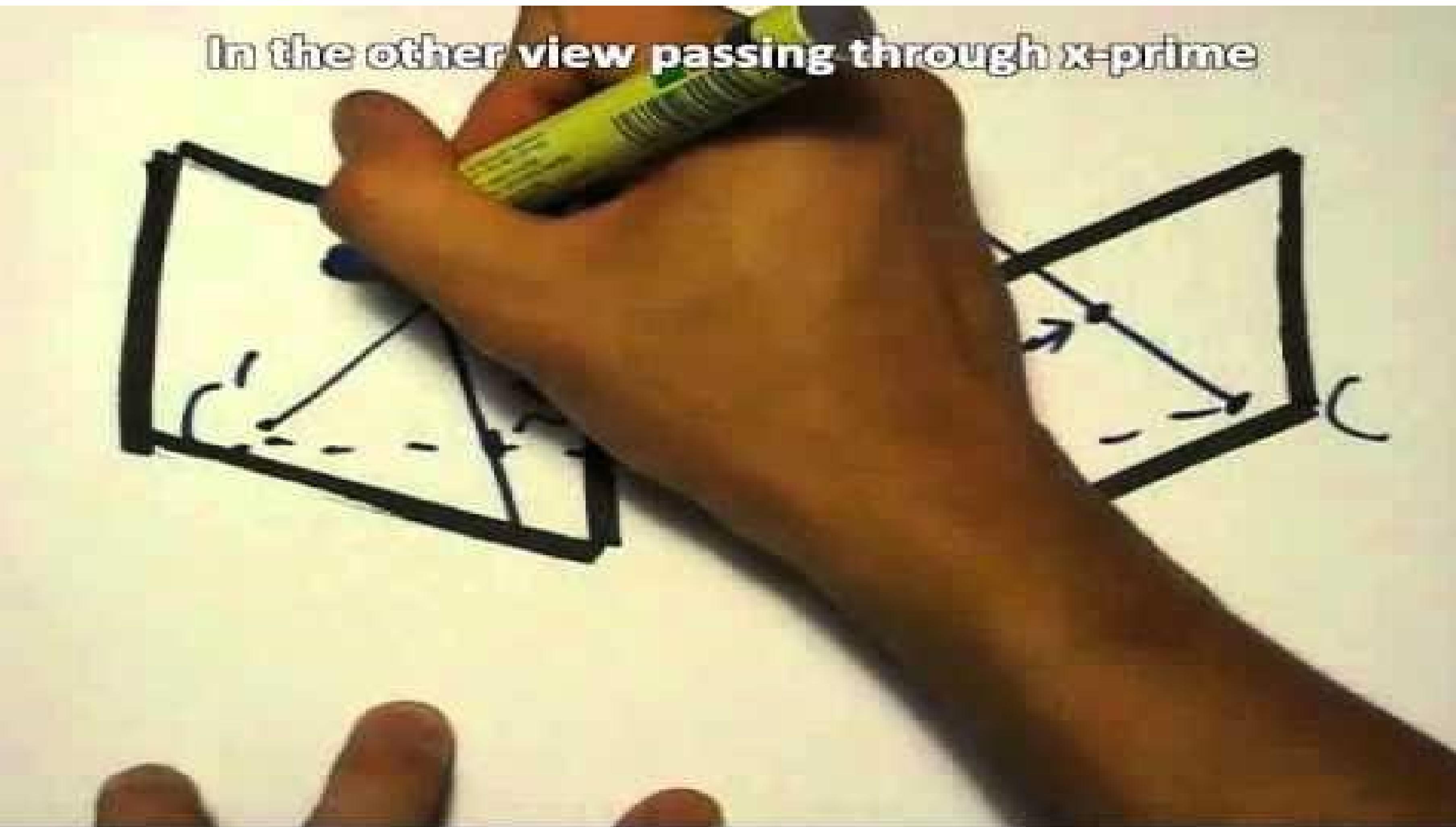
Enforce rank-2 constraint
(take SVD
of \mathbf{F} and throw out the
smallest singular value)



The Bible by Hartley & Zisserman



The Fundamental Matrix Song



<http://danielwedge.com/fmatrix/>

https://www.youtube.com/watch?time_continue=8&v=DgGV3I82NTk&feature=emb_title