

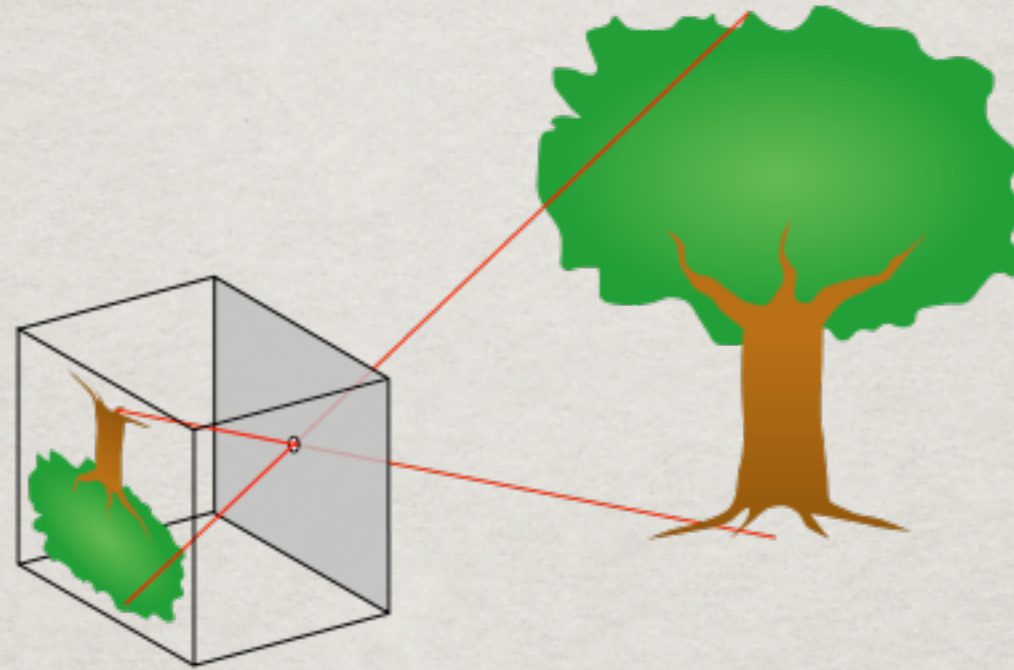
VISUAL OBJECT RECOGNITION

STATE-OF-THE-ART
TECHNIQUES AND
PERFORMANCE EVALUATION

LECTURE 2: IMAGE FORMATION

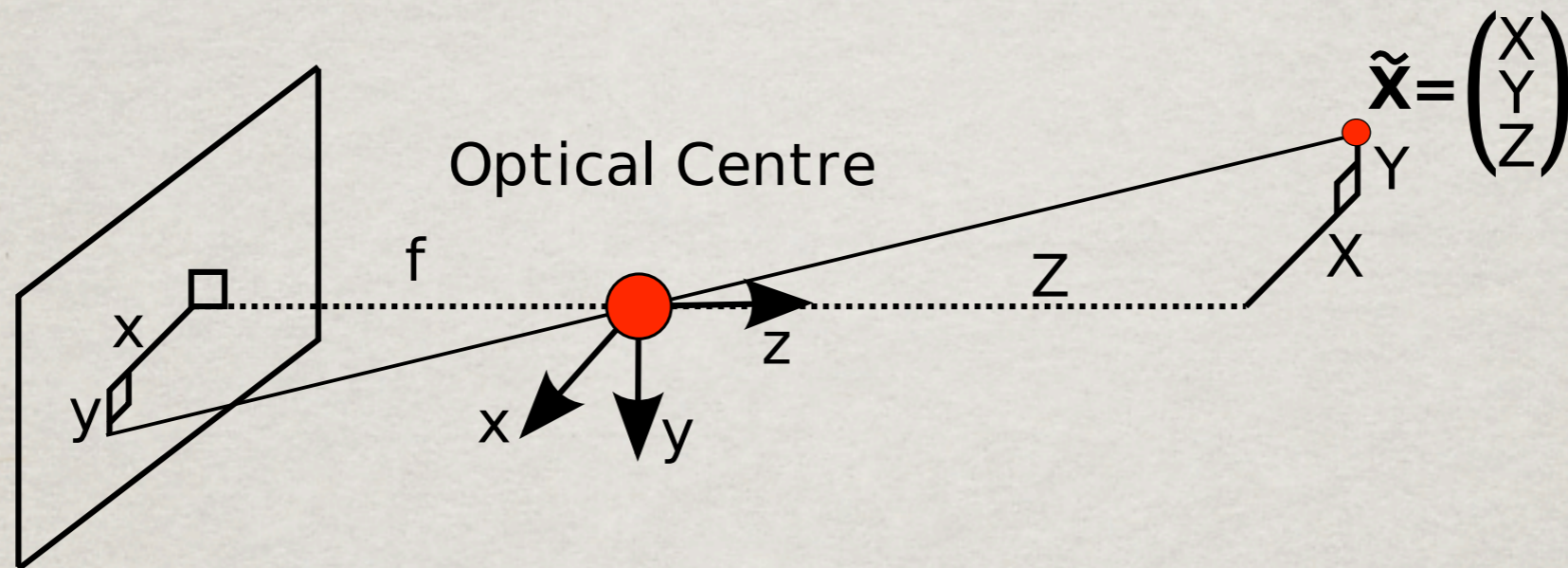
- ✻ Pin-hole, and thin lens cameras
- ✻ Illumination
- ✻ Homographies
- ✻ Epipolar Geometry
- ✻ Canonical Frames

THE PIN-HOLE CAMERA



- ✿ A brightly illuminated scene will be projected onto a wall opposite of the pin-hole.
- ✿ The image is rotated 180° .

THE PIN-HOLE CAMERA



✿ From similar triangles we get:

$$x = f \frac{X}{Z} \quad y = f \frac{Y}{Z}$$

$$\gamma \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

THE PIN-HOLE CAMERA

$$\gamma \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

✱ More generally, we write:

$$\gamma \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & s & c_x \\ 0 & fa & c_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

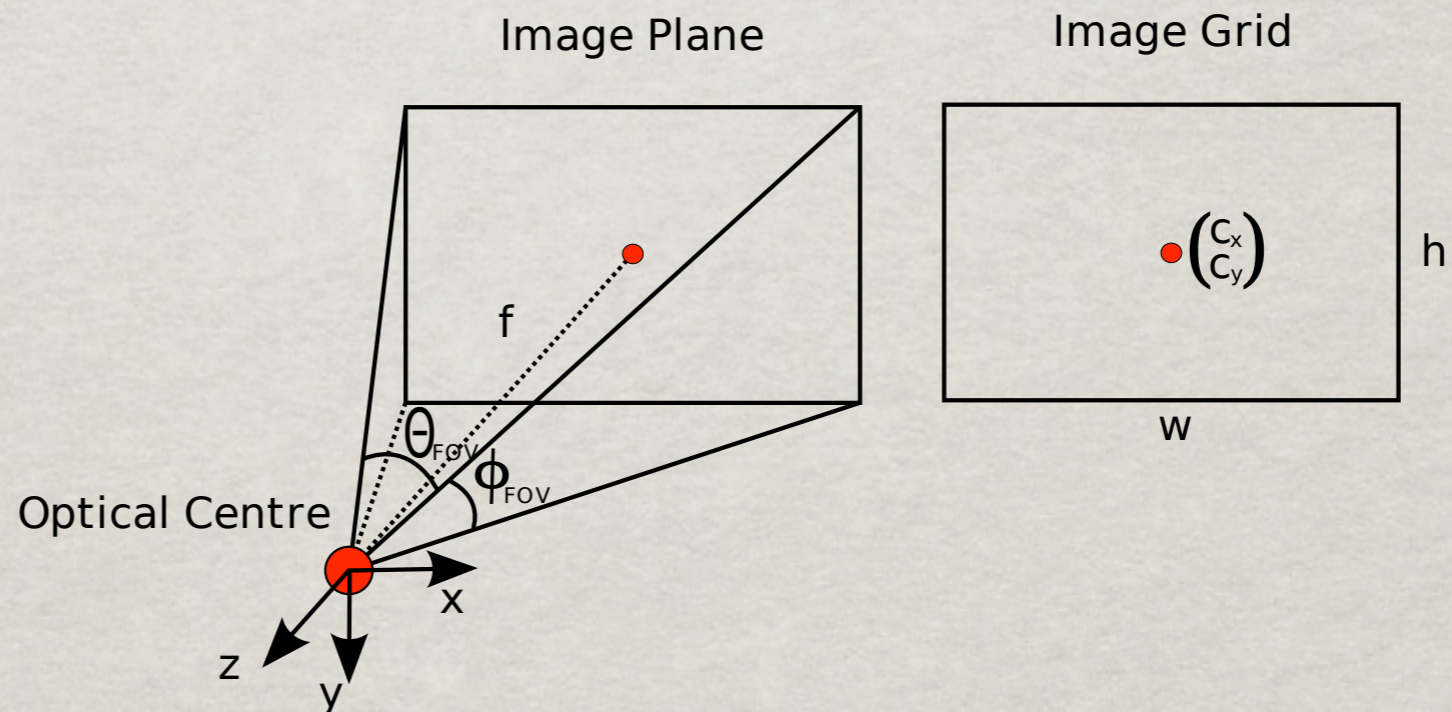
f-focal length, s-skew, a-aspect ratio,
c-projection of optical centre

THE PIN-HOLE CAMERA

$$\gamma \underbrace{\begin{bmatrix} x \\ y \\ 1 \end{bmatrix}}_{\mathbf{x}} = \underbrace{\begin{bmatrix} f & s & c_x \\ 0 & fa & c_y \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{K}} \underbrace{\begin{bmatrix} X \\ Y \\ Z \end{bmatrix}}_{\tilde{\mathbf{X}}}$$

$$\mathbf{x} \sim \mathbf{K}\tilde{\mathbf{X}}$$

☀ Motivation:



f -focal length, s -skew, a -aspect ratio,
 c -projection of optical centre

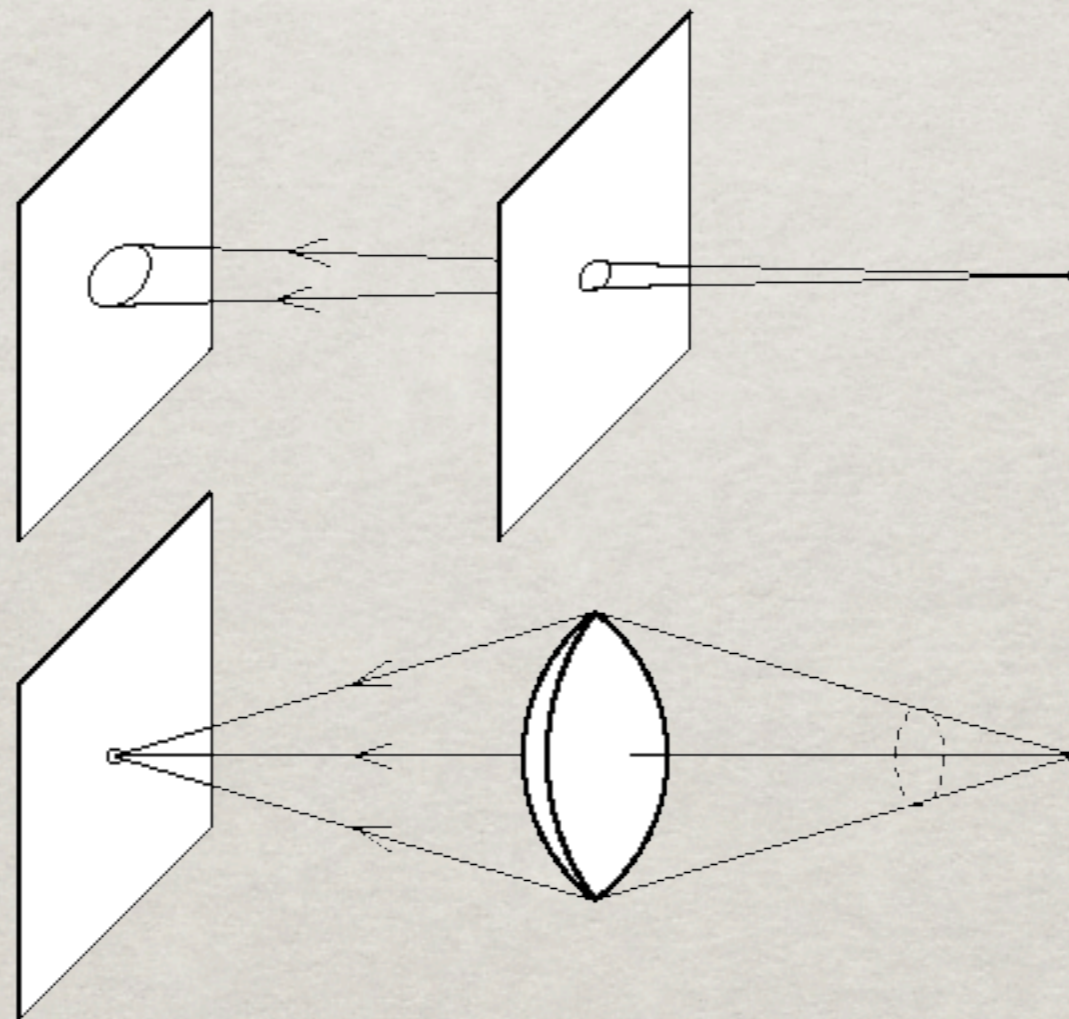
THE PIN-HOLE CAMERA

- ✻ For a general position of the world coordinate system (WCS) we have:

$$\mathbf{x} \sim \mathbf{K} \underbrace{\begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix}}_{[\mathbf{R}|\mathbf{t}]} \underbrace{\begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}}_{\mathbf{X}}$$

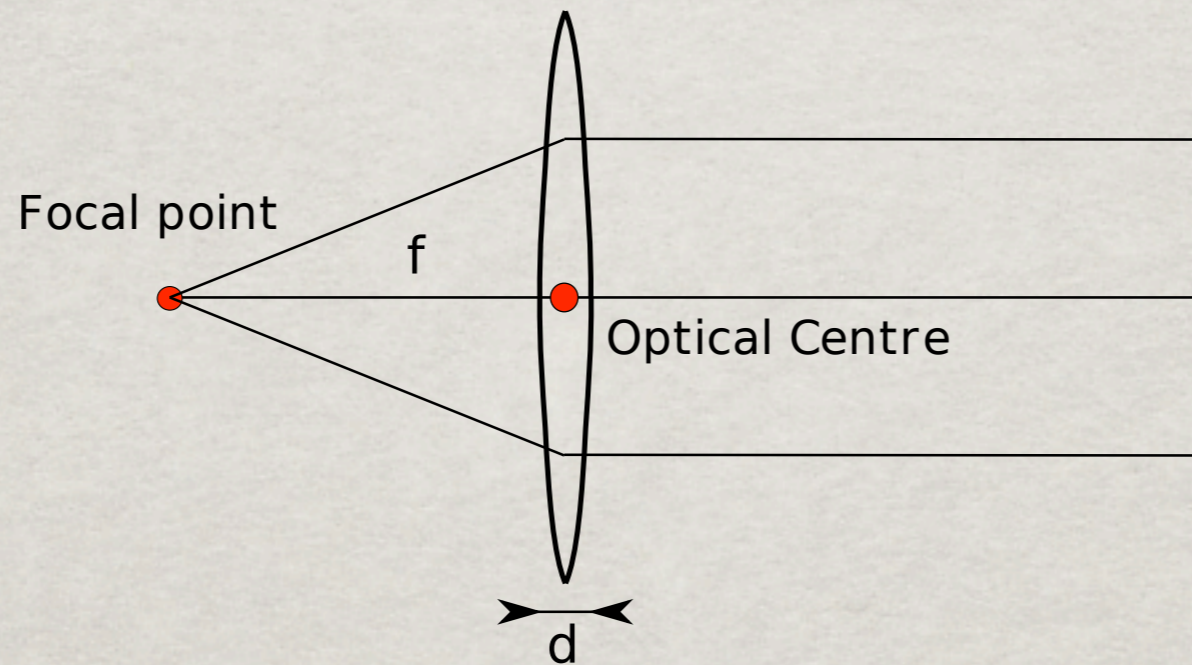
THIN LENS CAMERA

✻ But we use lenses, not pin-hole cameras!



THIN LENS CAMERA

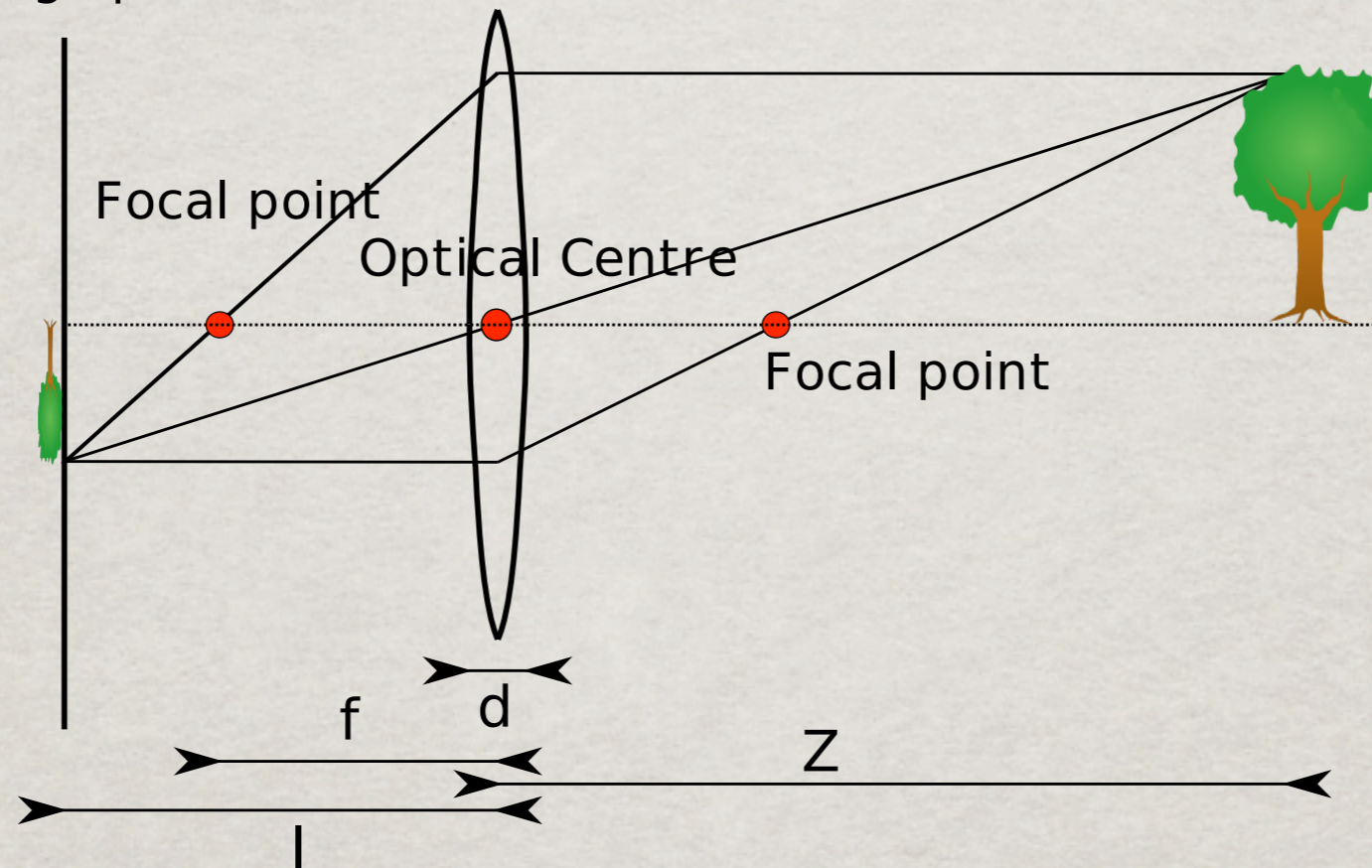
- ✱ A thin lens is a (positive) lens with $d \ll f$



- ✱ Parallel rays converge at the focal points
- ✱ Rays through the optical centre are not refracted

THIN LENS CAMERA

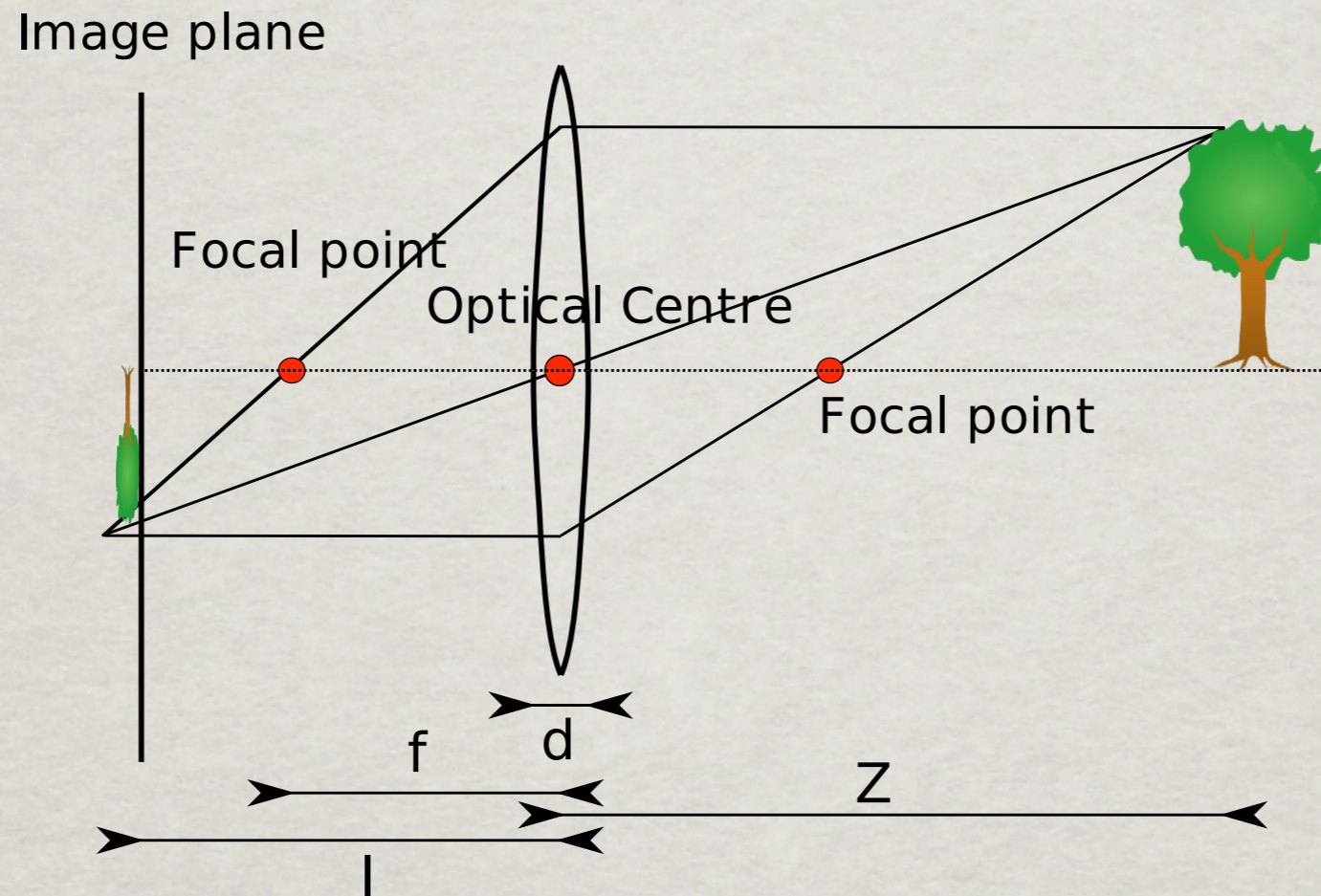
Image plane



✱ Thin lens relation (from similar triangles):

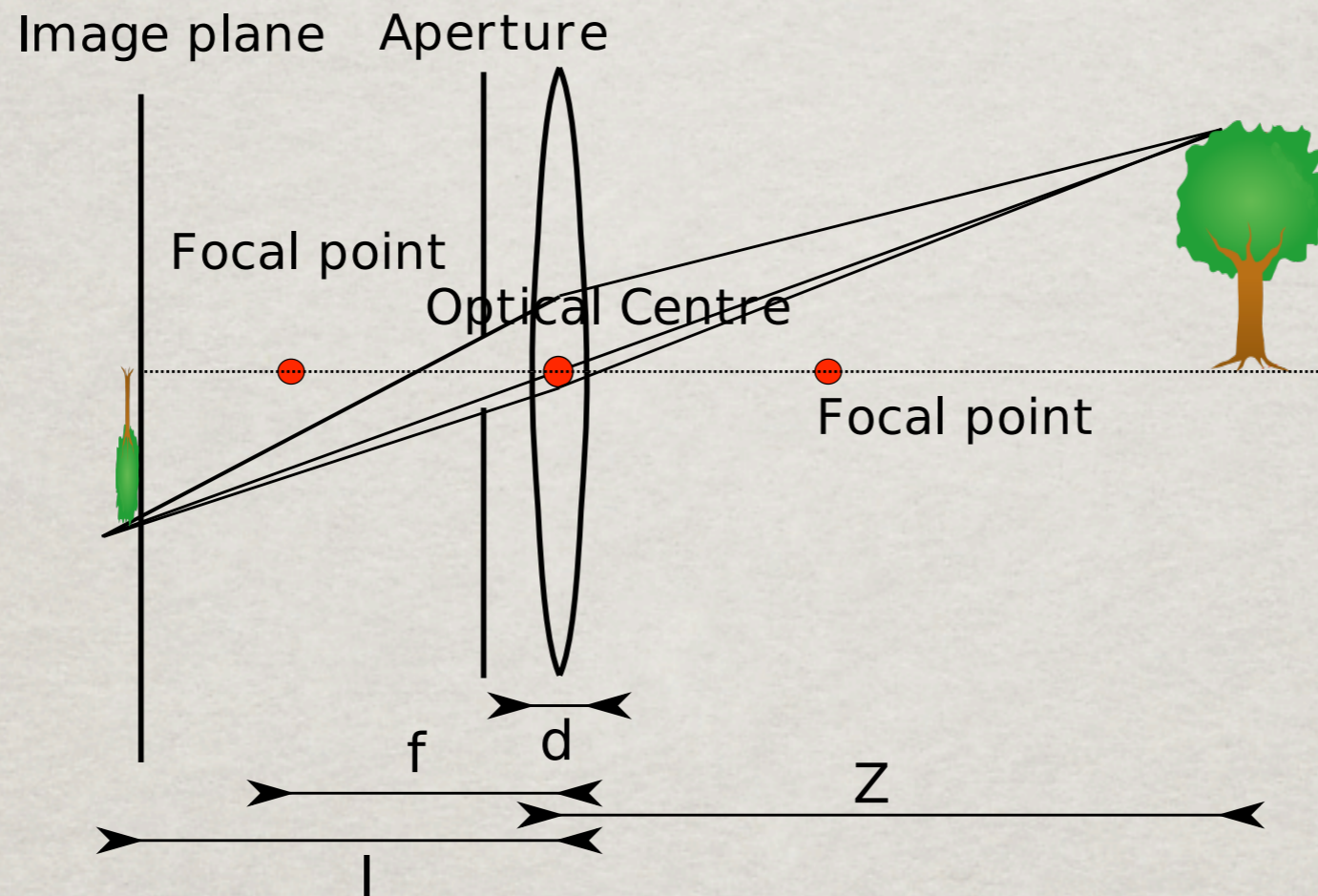
$$\frac{1}{f} = \frac{1}{Z} + \frac{1}{l}$$

THIN LENS CAMERA



- ✱ Focus at one depth only.
- ✱ Objects at other depths are blurred.

THIN LENS CAMERA



- ✿ Adding an aperture increases the *depth-of-field*, the range which is sharp in the image.
- ✿ A compromise between pinhole and thin lens.

THIN LENS EFFECTS



Correct



Barrel distortion



Pin-cushion distortion

☼ Radial distortion

☼ For zoom lenses: Barrel at wide FoV
pin-cushion at narrow FoV

THIN LENS EFFECTS



Correct

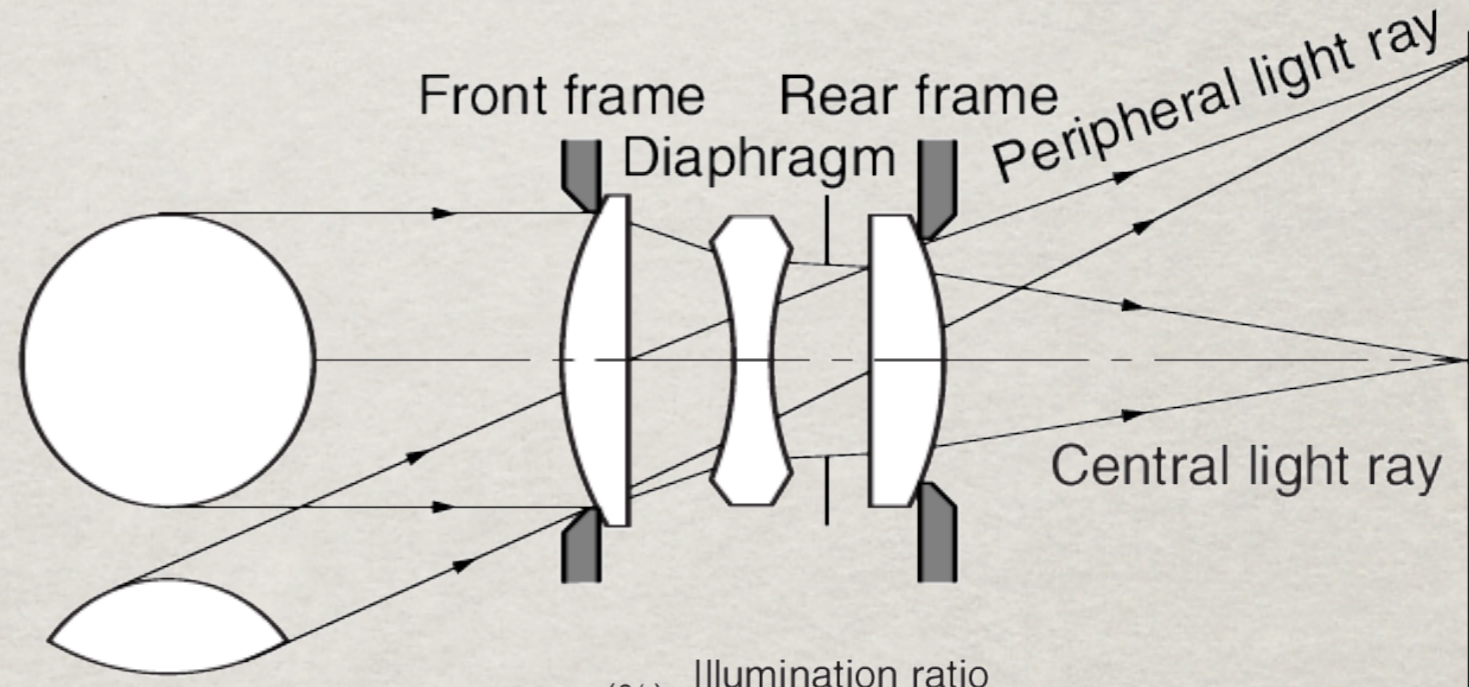


Darkened periphery

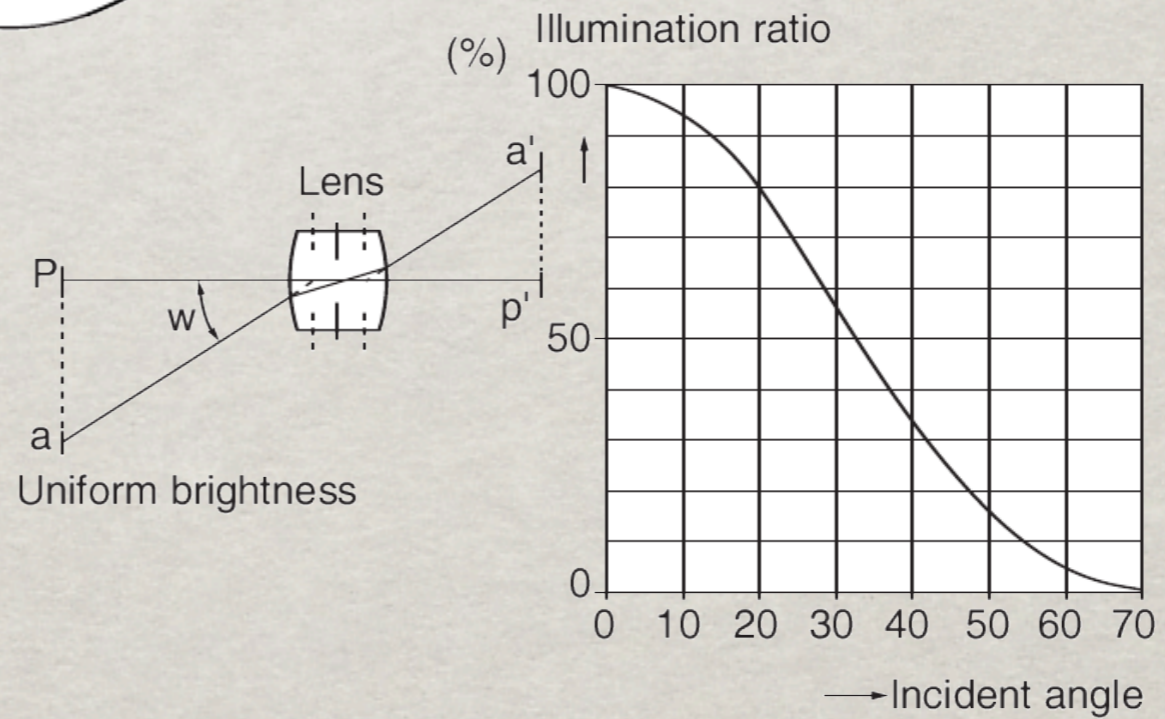
☀ Vignetting and \cos^4 -law

THIN LENS EFFECTS

☀ Vignetting



☀ \cos^4 -law dampening with $\cos^4(w)$



http://software.canon-europe.com/files/documents/EF_Lens_Work_Book_10_EN.pdf

ILLUMINATION

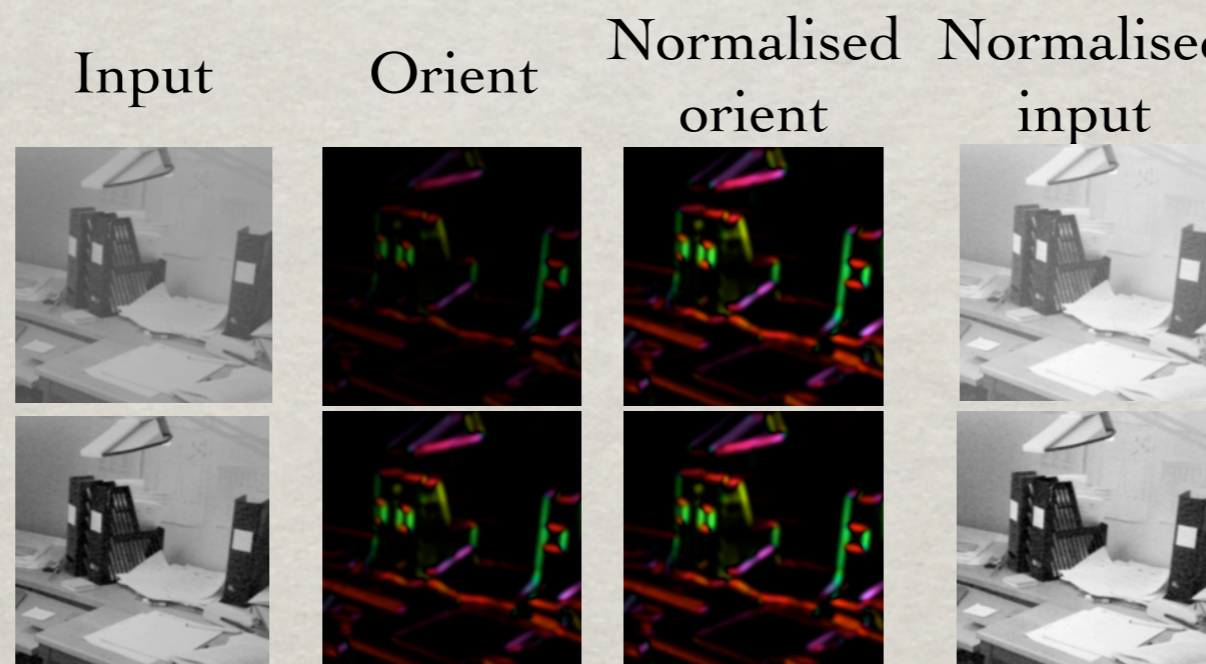
- ✱ Image intensity is linear in radiance (at least before gamma correction)
- ✱ E.g. adding a second, identical light source will double the sensor activation.

$$a(\mathbf{x}) = \int s(\lambda)r(\lambda, \mathbf{x})e(\lambda)d\lambda$$

- ✱ s-sensor absorption spectrum, r-reflectance spectrum of object, e-emission spectrum of light source (attenuated by the atmosphere)

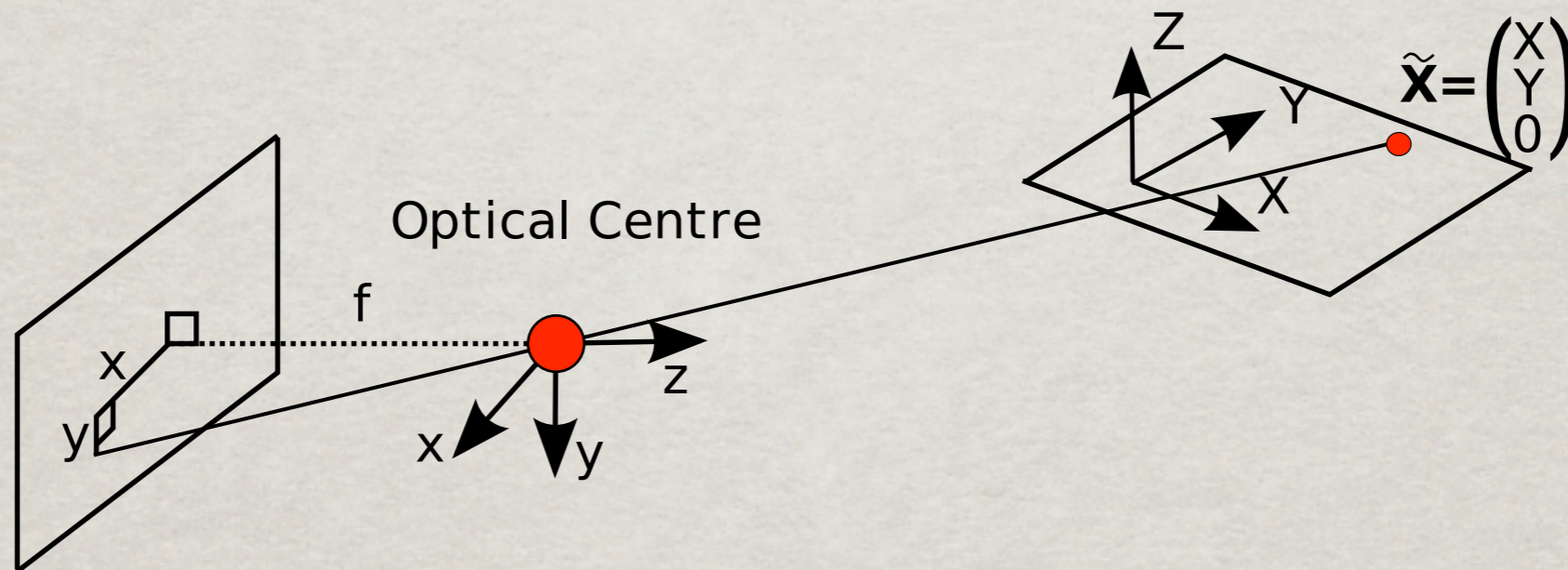
ILLUMINATION

- ☼ Mean subtraction, derivatives, and other DC free linear filters remove a *constant offset* in intensity
- ☼ Normalising a patch by e.g. the l^2 -norm removes *scalings* of the intensity.
- ☼ Affine invariance by combining both.



HOMOGRAPHIES

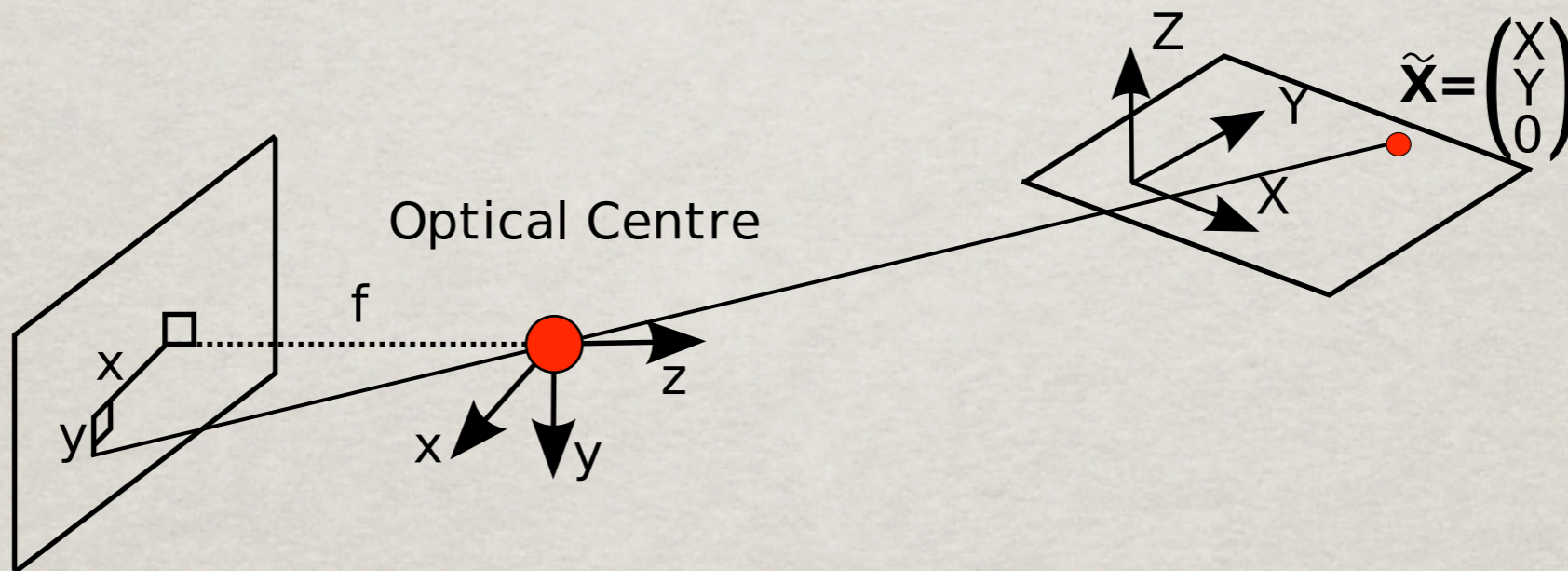
- ✪ For a planar object, we can imagine a world coordinate system fixed to the object



$$\gamma \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{K} \begin{bmatrix} r_{11} & r_{12} & r_{13} & t_1 \\ r_{21} & r_{22} & r_{23} & t_2 \\ r_{31} & r_{32} & r_{33} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

HOMOGRAPHIES

- ✪ For a planar object, we can imagine a world coordinate system fixed to the object



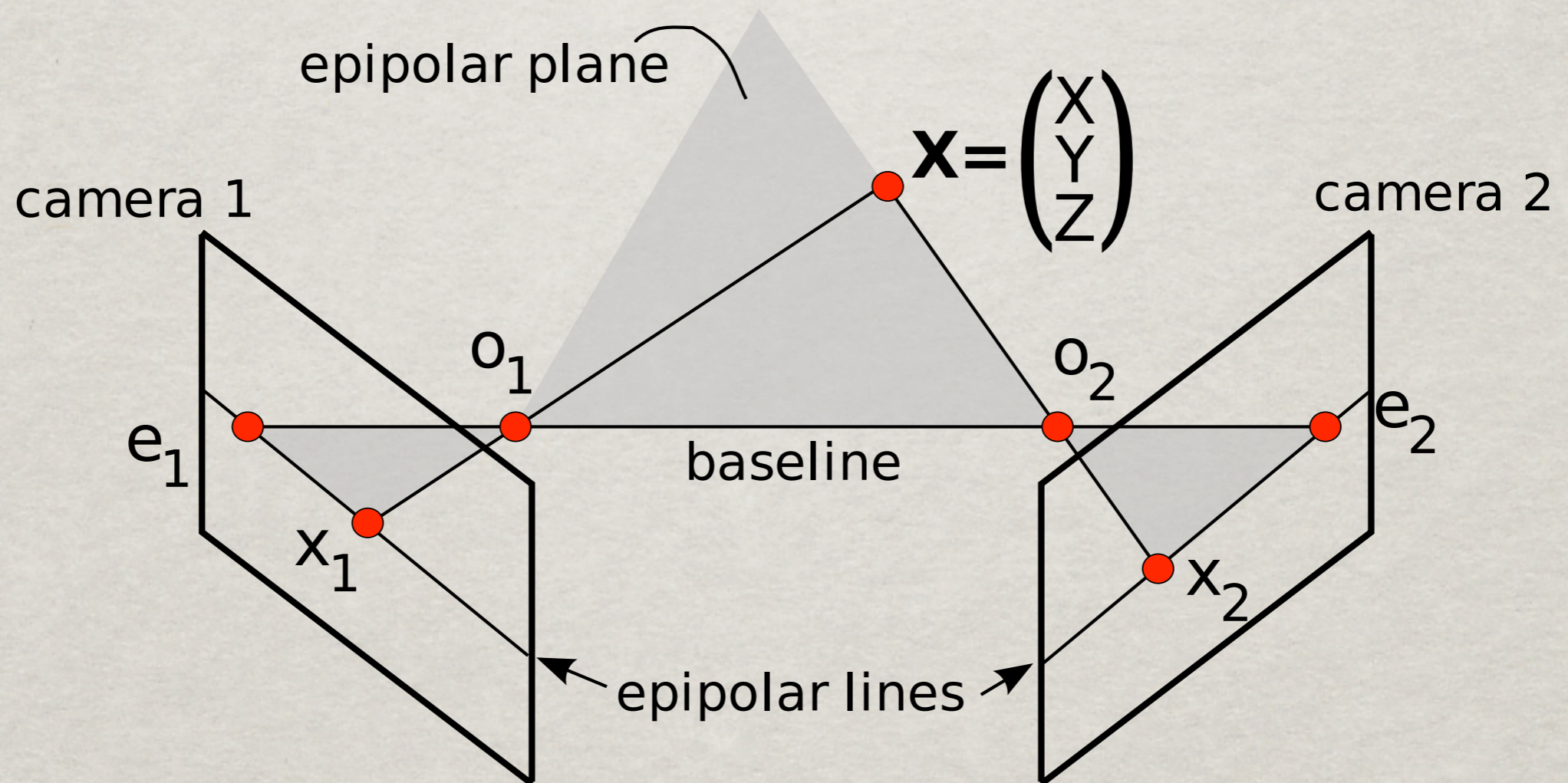
$$\gamma \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \mathbf{K} \begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix} = \underbrace{\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}}_{\mathbf{H}} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}$$

HOMOGRAPHIES

- ✻ In general, we can use homographies to describe the transformation between any two planes in 3D.
- ✻ Since the matrix \mathbf{H} is only unique up to scale, it has only 8 degrees of freedom.
- ✻ It can be estimated from 4 or more corresponding points on the two planes.
- ✻ See e.g. R. Hartley and A. Zisserman, *Multiple View Geometry for Computer Vision*

EPIPOLAR GEOMETRY

- ✿ The geometry of two cameras:



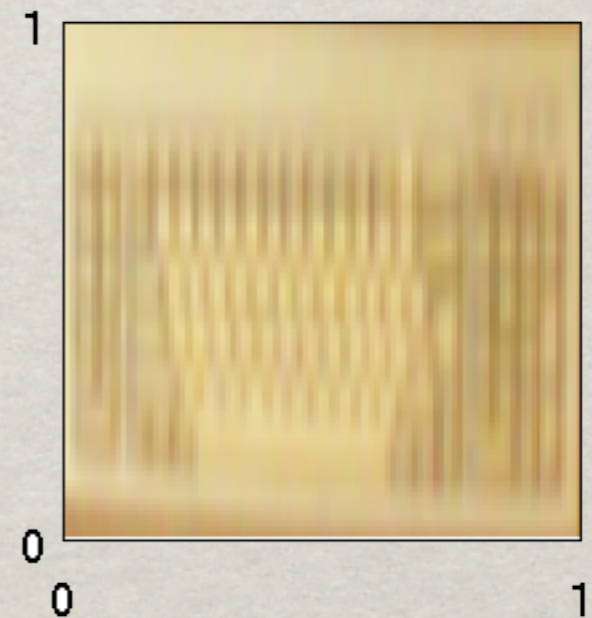
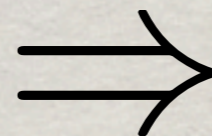
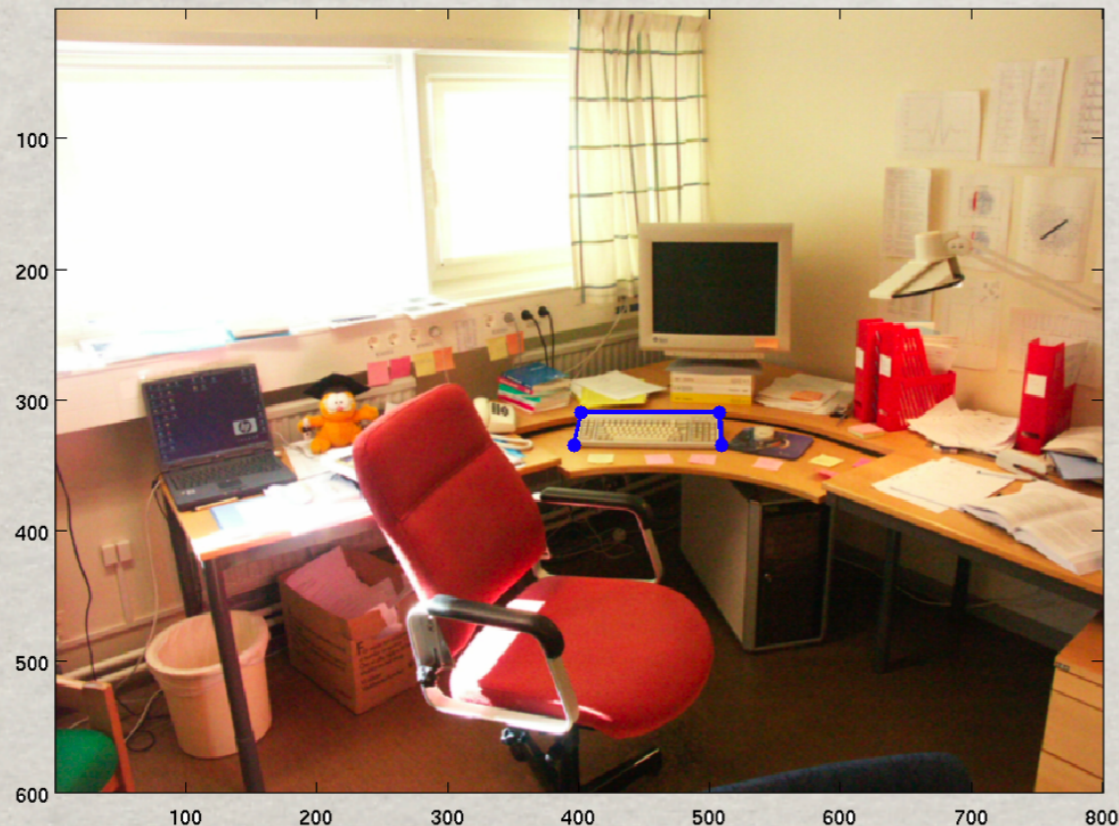
- ✿ e_1, e_2 are called epipoles. O_1, O_2 are the optical centres.

EPIPOLAR GEOMETRY

- ✱ So in general, two view geometry only tells us that a corresponding point lies somewhere along a line.
- ✱ In practice, we often know more, as objects often have planar, or near planar surfaces. i.e., we are close to the homography case.
- ✱ Also: If the views have a **short relative baseline**, we can use even more simple models.

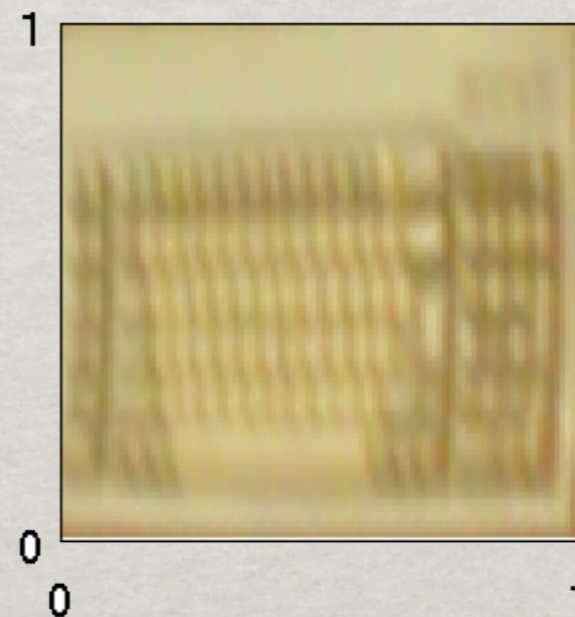
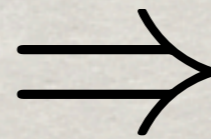
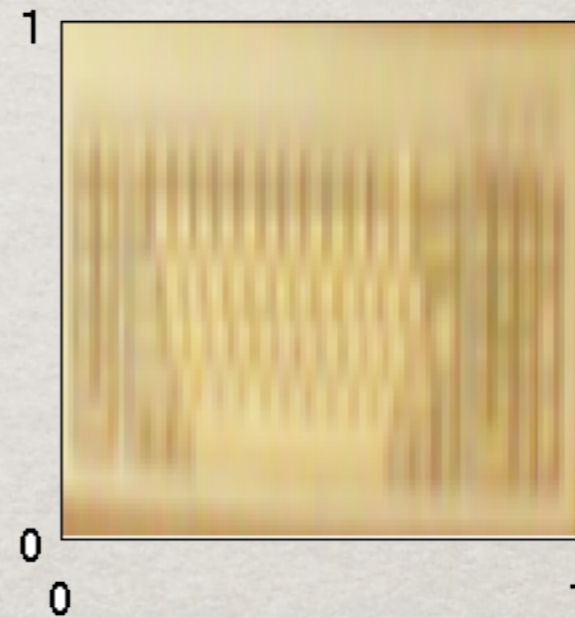
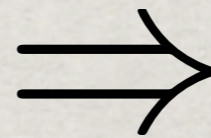
CANONICAL FRAMES

- ✿ Aka. covariant frames, and invariant frames.
- ✿ Resample patches to canonical frame.
- ✿ Points from e.g. Harris detector, or SIFT.



CANONICAL FRAMES

✿ After resampling matching is much easier.



CANONICAL FRAMES

☀ A hierarchy of transformations:

$$\begin{bmatrix} s & 0 & t_1 \\ 0 & s & t_2 \\ 0 & 0 & 1 \end{bmatrix}$$

☀ scale+translation

$$\begin{bmatrix} s_1 & s_2 & t_1 \\ -s_2 & s_1 & t_2 \\ 0 & 0 & 1 \end{bmatrix}$$

☀ similarity (scale+translation+rotation)

$$\begin{bmatrix} a_{11} & a_{12} & t_1 \\ a_{21} & a_{22} & t_2 \\ 0 & 0 & 1 \end{bmatrix}$$

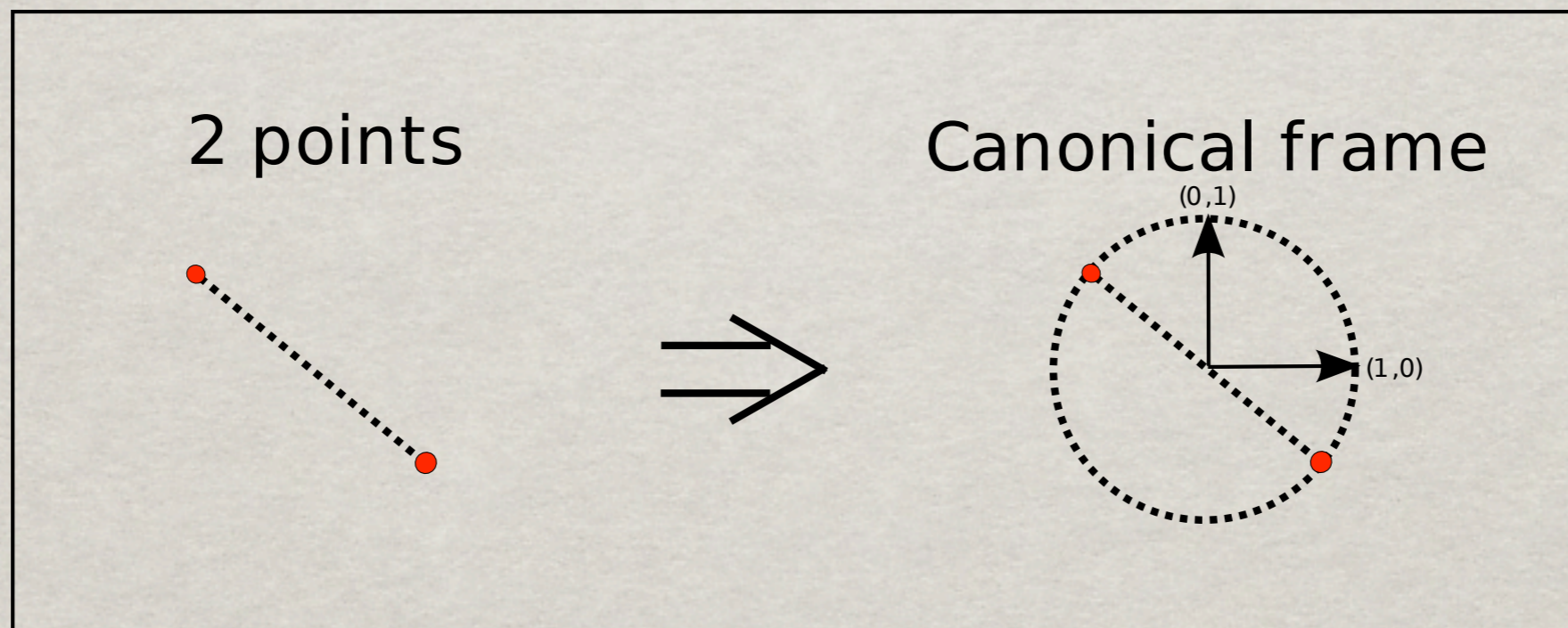
☀ affine (similarity+skew)

$$\begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix}$$

☀ plane projective (affine+foreshortening)

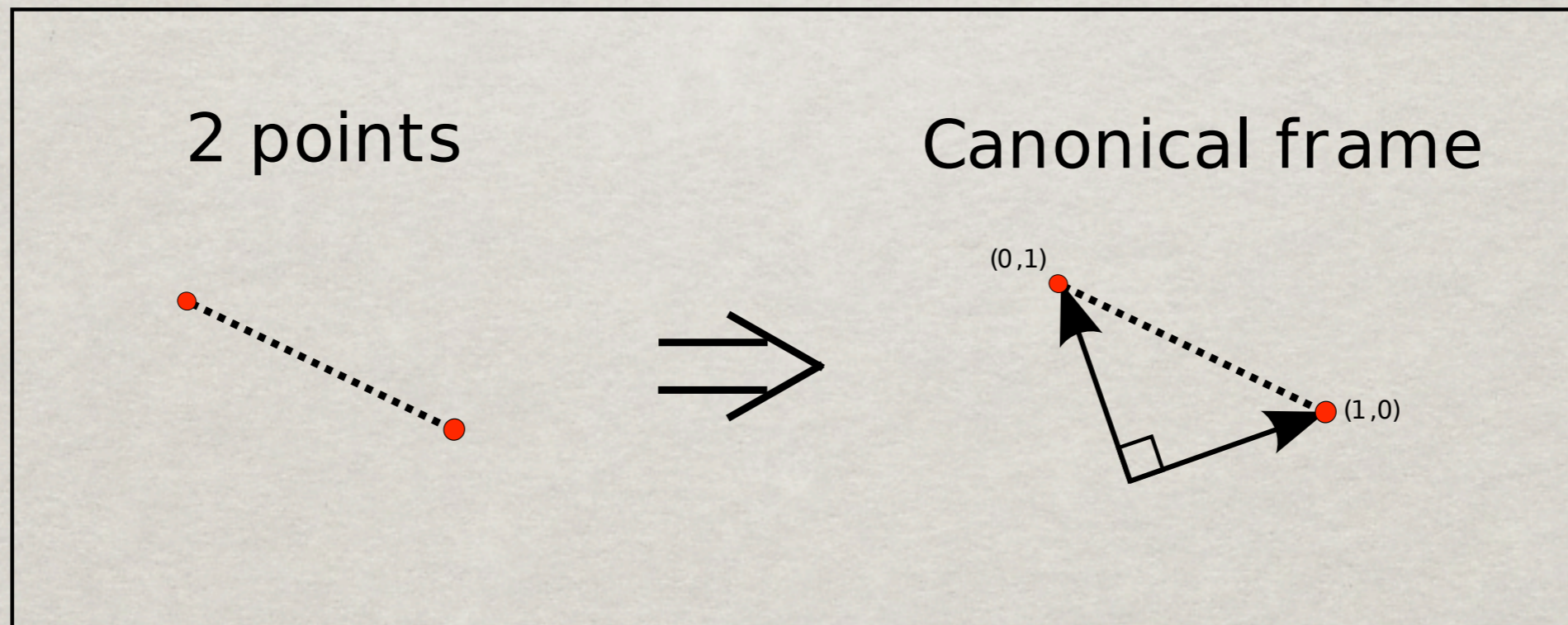
CANONICAL FRAMES

- ✪ **Scale+translation:** Useful if we know that there is no rotation.
E.g. for a camera mounted in a car, looking at upright pedestrians.



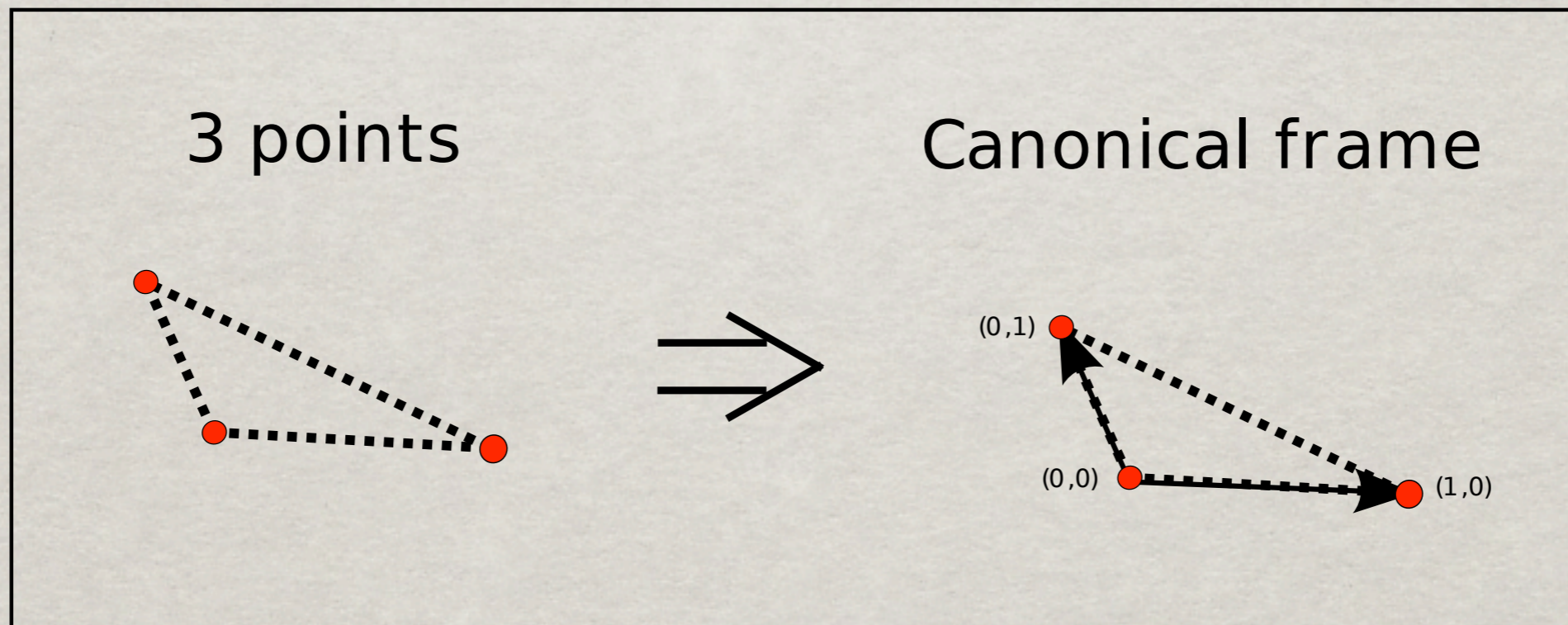
CANONICAL FRAMES

- ☼ **Similarity:** Full invariance in image plane, none outside image plane.
Useful e.g. for pose estimation.



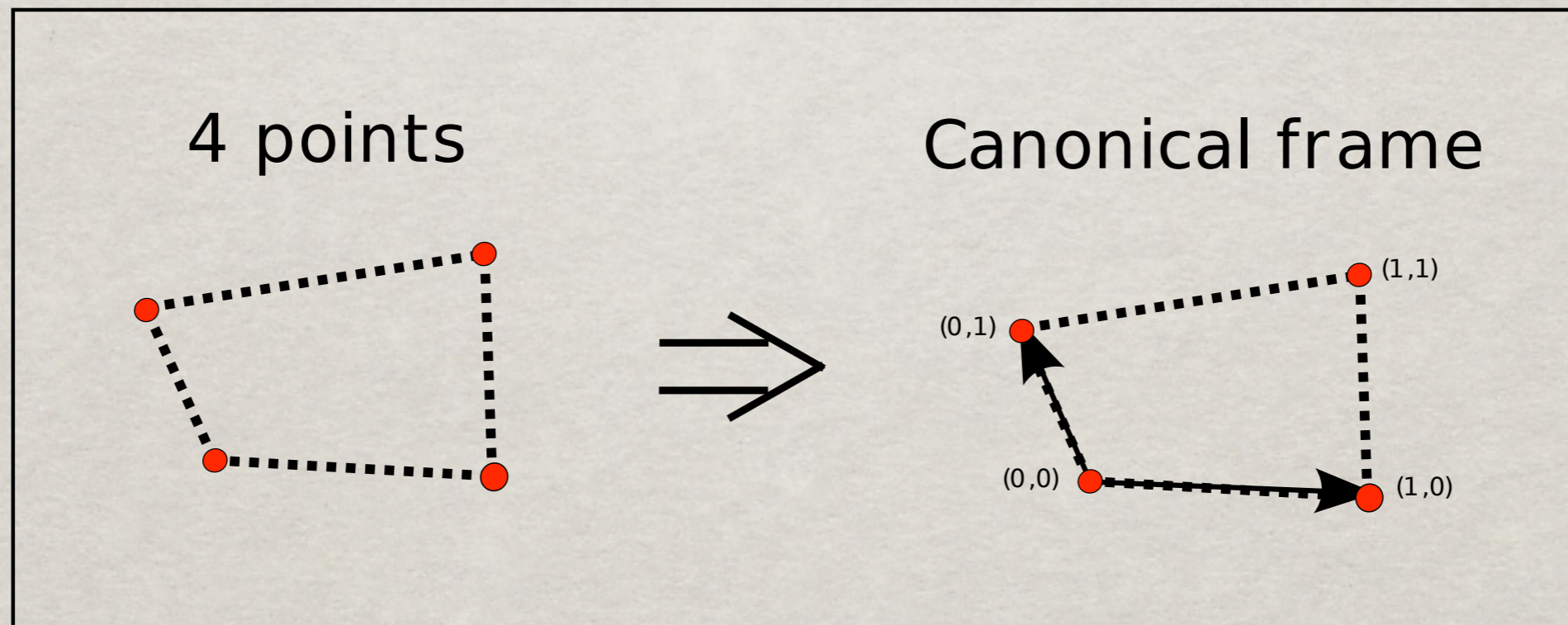
CANONICAL FRAMES

- ☀ **Affine:** Deals with most common projective distortions. Good if patch size is small relative to distance to patch.



CANONICAL FRAMES

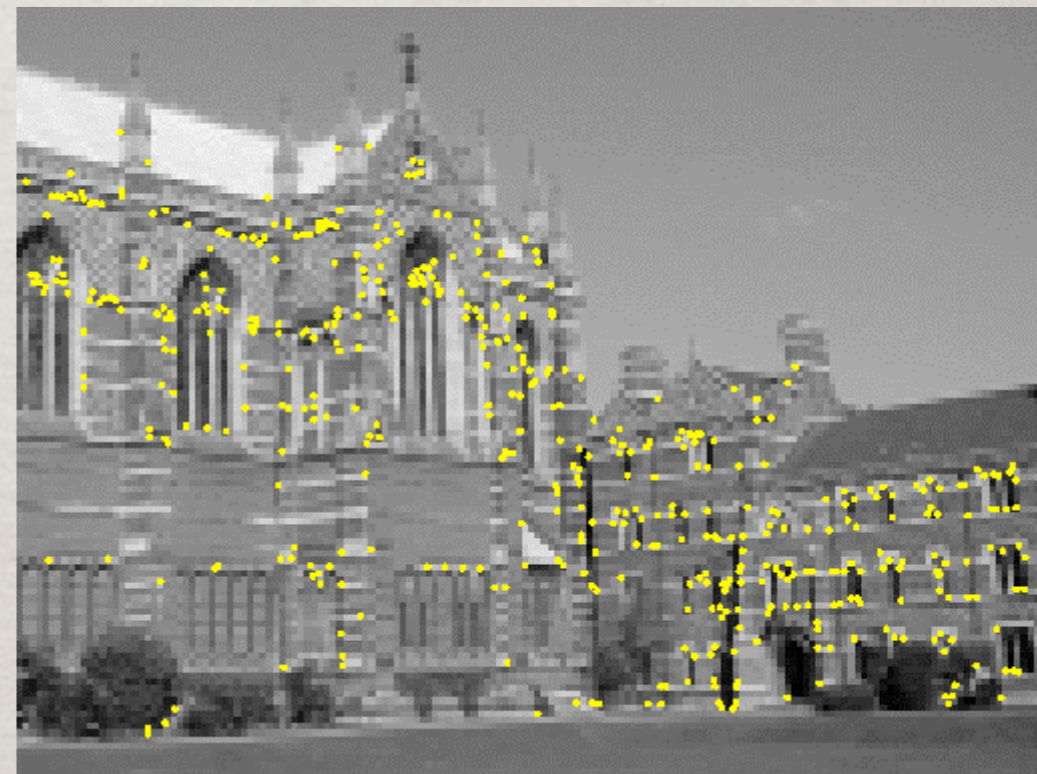
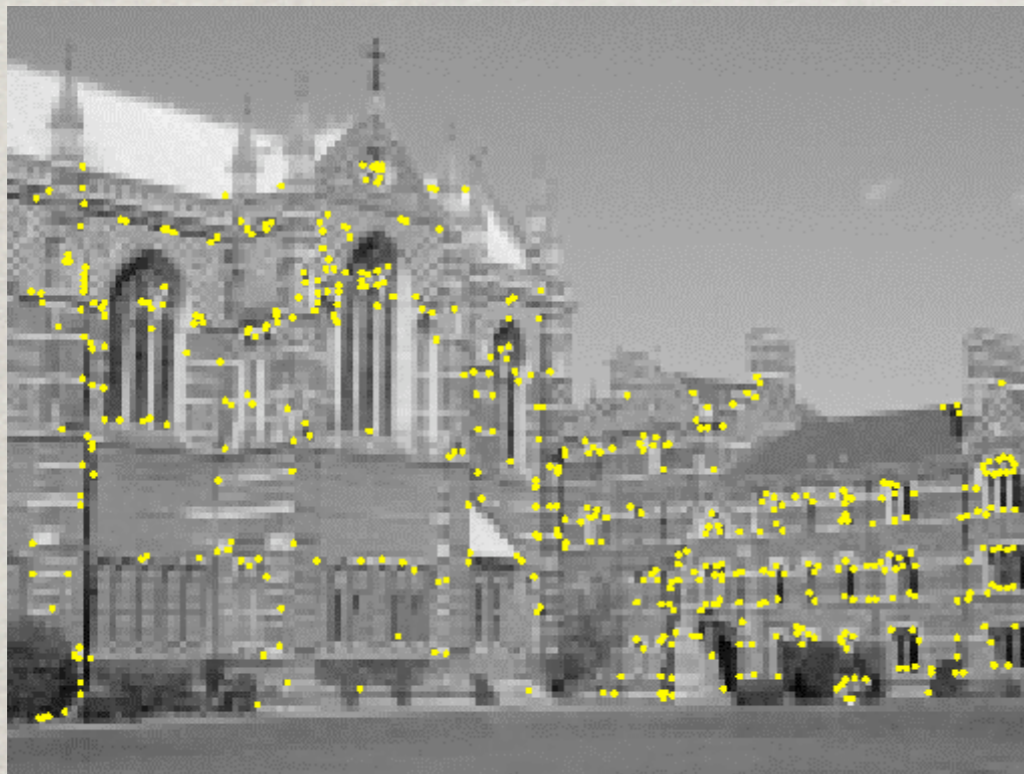
- ✱ **Plane projective:** Full modelling of a plane in 3D. Requires more image measurements, but is better for extreme view angles.



CANONICAL FRAMES

- ✱ **Combinatorial issues**

- ✱ From Harris or SIFT we get images full of keypoints.



CANONICAL FRAMES

✱ Combinatorial issues

✱ From Harris or SIFT we get images full of keypoints.

✱ Using the points, we want to generate frames in both reference and query view and match them.

✱ We don't want to miss a combination in one of the images, but we don't want to generate too many combinations either.

CANONICAL FRAMES

✱ Solutions:

- ✱ Use each point as a reference point.
- ✱ Restrict frame construction to k-nearest neighbours in scale space (or image plane).
- ✱ Remove duplicate groupings, and reflections.

DISCUSSION

- ✻ Questions/comments on paper and lecture
- ✻ E.g. Why k -nearest neighbours in scale-space? Are there other useful canonical frames?...