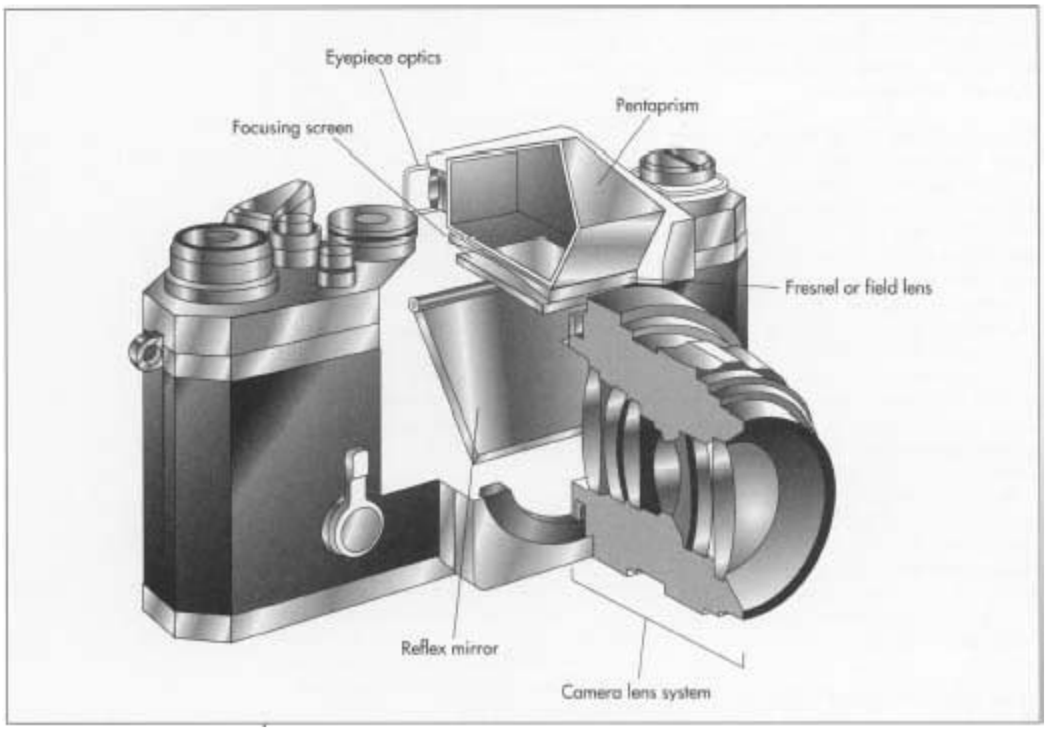
Week 4 – Stereo Reconstruction

Slides from A. Zisserman & S. Lazebnik

Overview

- Single camera geometry
  - Recap of Homogenous coordinates
  - Perspective projection model
  - Camera calibration
- Stereo Reconstruction
  - Epipolar geometry
  - Stereo correspondence
  - Triangulation

Single camera geometry



Projection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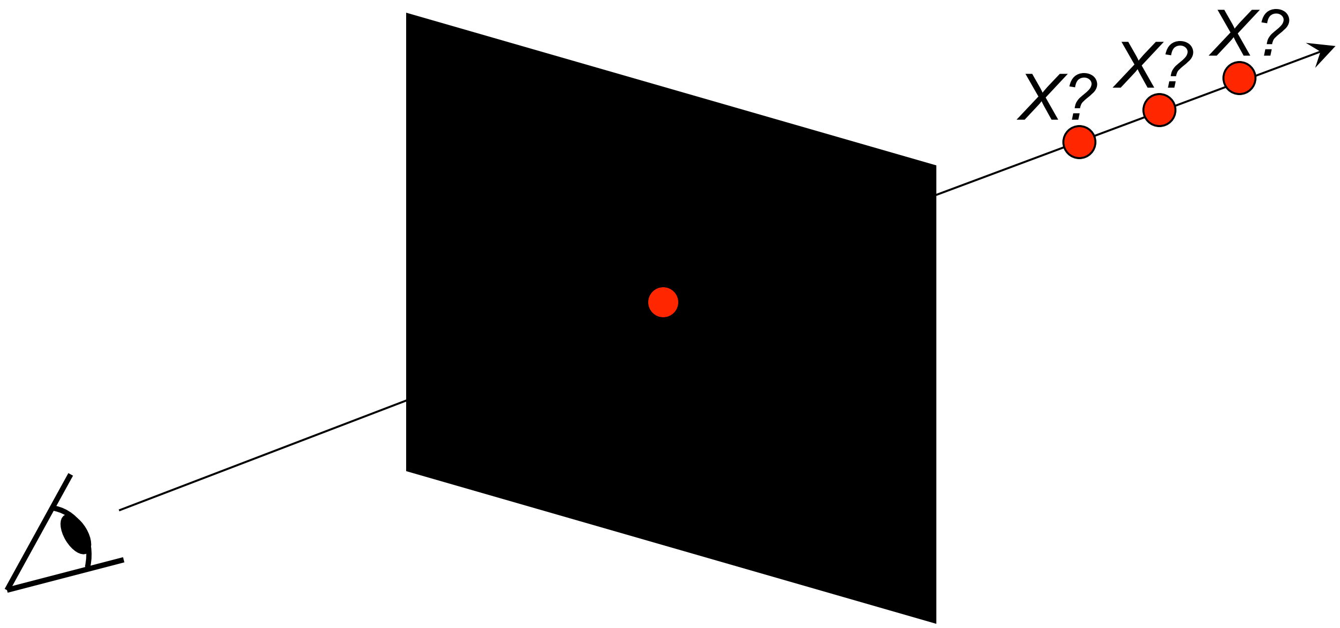
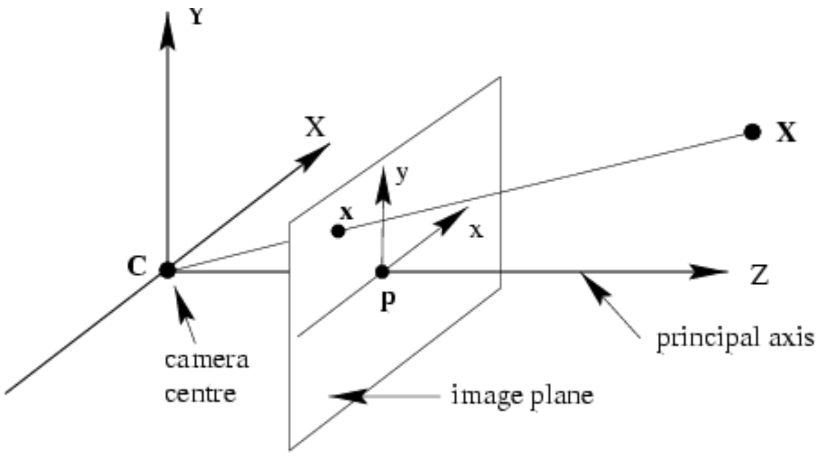
Projection

Projective Geometry

- Recovery of structure from one image is inherently ambiguous
- Today focus on geometry that maps world to camera image

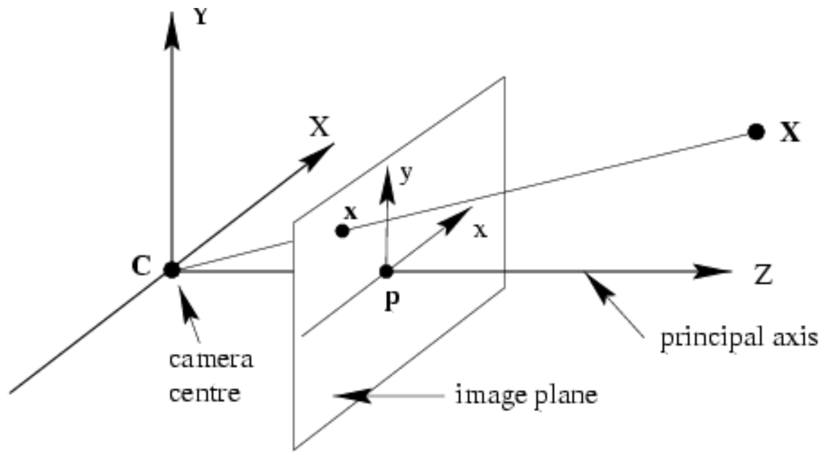


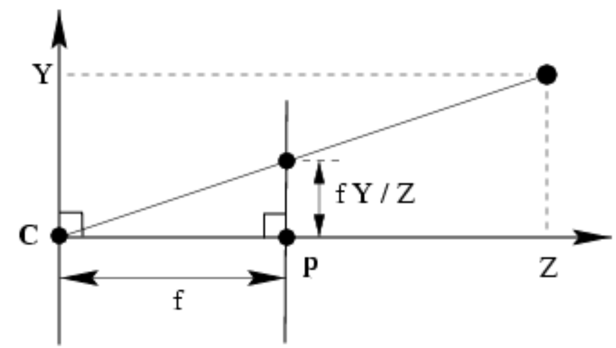
Recall: Pinhole camera model



- **Principal axis:** line from the camera center perpendicular to the image plane
- **Normalized (camera) coordinate system:** camera center is at the origin and the principal axis is the z-axis

Recall: Pinhole camera model





$$(X, Y, Z) \mapsto (fX/Z, fY/Z)$$

$$\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \mapsto \begin{pmatrix} fX \\ fY \\ Z \end{pmatrix} = \begin{bmatrix} f & & & 0 \\ & f & & 0 \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

$$\mathbf{x} = \mathrm{P}\mathbf{X}$$

Recap: Homogeneous coordinates

- Is this a linear transformation? $(x, y, z) \rightarrow (f\frac{x}{z}, f\frac{y}{z})$
  - no—division by z is nonlinear

Trick: add one more coordinate:

$$(x, y) \Rightarrow \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

homogeneous image coordinates

$$(x, y, z) \Rightarrow \begin{bmatrix} x \\ y \\ z \\ 1 \end{bmatrix}$$

homogeneous scene coordinates

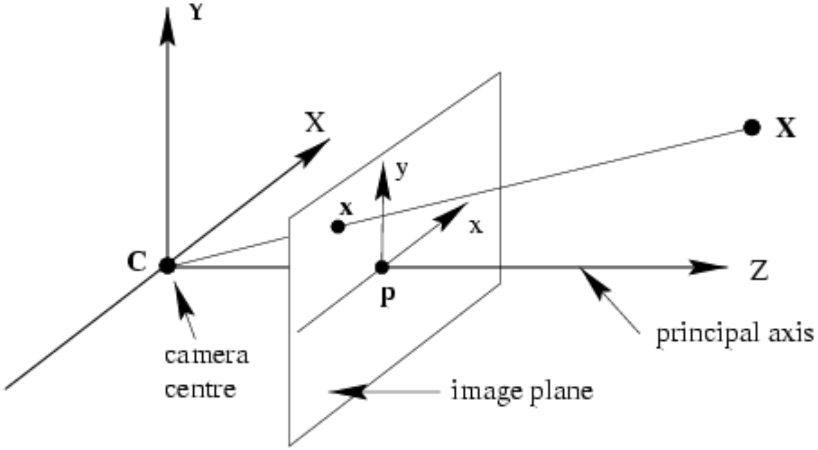
Converting *from* homogeneous coordinates

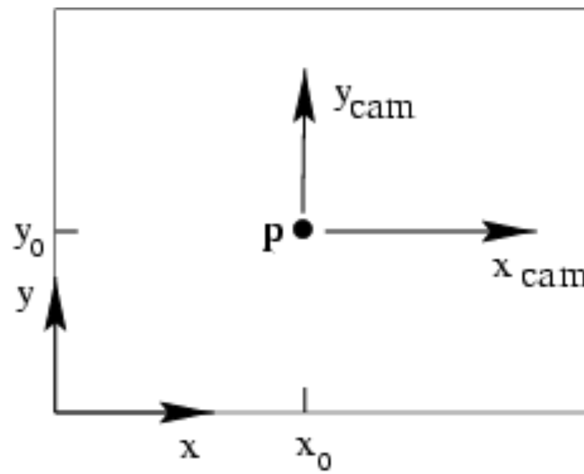
$$\begin{bmatrix} x \\ y \\ w \end{bmatrix} \Rightarrow (x/w, y/w)$$

$$\begin{bmatrix} x \\ y \\ z \\ w \end{bmatrix} \Rightarrow (x/w, y/w, z/w)$$

Slide by Steve Seitz

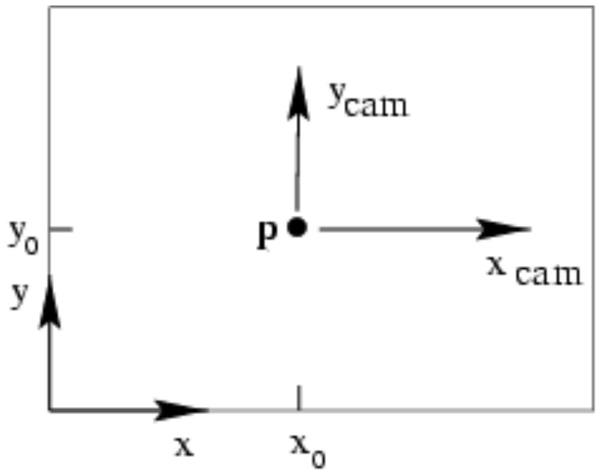
Principal point





- **Principal point (p):** point where principal axis intersects the image plane (origin of normalized coordinate system)
- Normalized coordinate system: origin is at the principal point
- Image coordinate system: origin is in the corner
- How to go from normalized coordinate system to image coordinate system?

Principal point offset

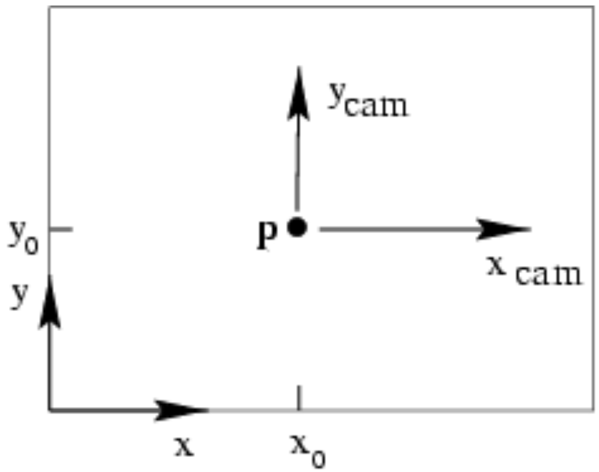


principal point: (p_x, p_y)

$$(X, Y, Z) \mapsto (f\,X/Z + p_x, f\,Y/Z + p_y)$$

$$\begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \mapsto \begin{pmatrix} f\,X + Z\,p_x \\ f\,Y + Z\,p_y \\ Z \end{pmatrix} = \begin{bmatrix} f & & p_x & 0 \\ & f & p_y & 0 \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

Principal point offset



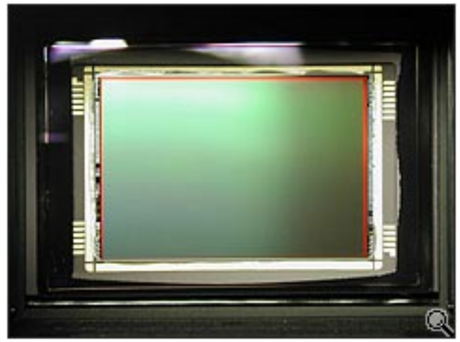
principal point: (p_x, p_y)

$$\begin{pmatrix} fX + Zp_x \\ fY + Zp_y \\ Z \end{pmatrix} = \begin{bmatrix} f & & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} \begin{bmatrix} 1 & & & 0 \\ & 1 & & 0 \\ & & 1 & 0 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix}$$

$$K = \begin{bmatrix} f & & p_x \\ & f & p_y \\ & & 1 \end{bmatrix}$$ calibration matrix

$$\mathrm{P} = \mathrm{K}[\mathrm{I} \mid 0]$$

Pixel coordinates



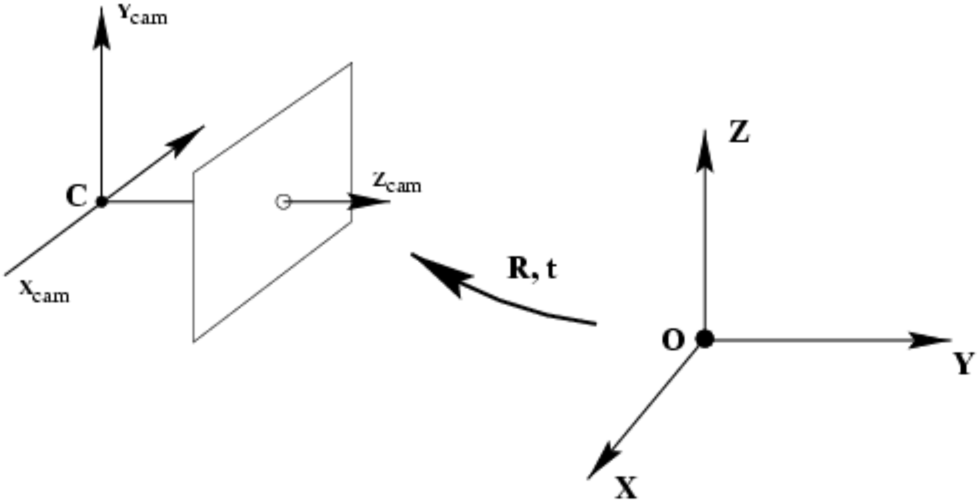
Pixel size: $\frac{1}{m_x} \times \frac{1}{m_y}$

- m_x pixels per meter in horizontal direction, m_y pixels per meter in vertical direction

$$K = \begin{bmatrix} m_x & & \\ & m_y & \\ & & 1 \end{bmatrix} \begin{bmatrix} f & & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & & \beta_x \\ & \alpha_y & \beta_y \\ & & 1 \end{bmatrix}$$

pixels/m m pixels

Camera rotation and translation



- In general, the camera coordinate frame will be related to the world coordinate frame by a rotation and a translation

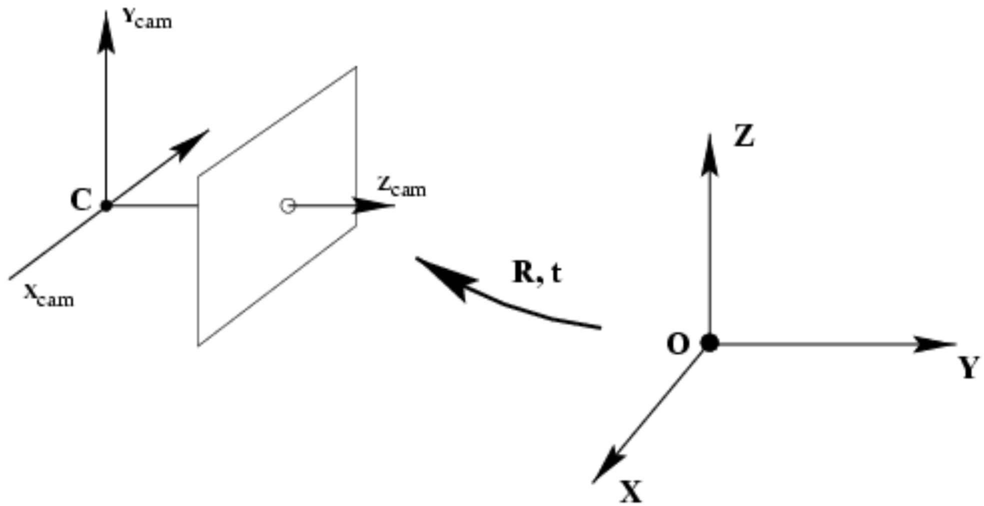
$$\tilde{X}_{cam} = R\left(\tilde{X} - \tilde{C}\right)$$

coords. of point in camera frame

coords. of a point in world frame (nonhomogeneous)

coords. of camera center in world frame

Camera rotation and translation



In non-homogeneous coordinates:

$$\tilde{X}_{cam} = R\left(\tilde{X} - \tilde{C}\right)$$

$$X_{cam} = \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} \begin{pmatrix} \tilde{X} \\ 1 \end{pmatrix} = \begin{bmatrix} R & -R\tilde{C} \\ 0 & 1 \end{bmatrix} X$$

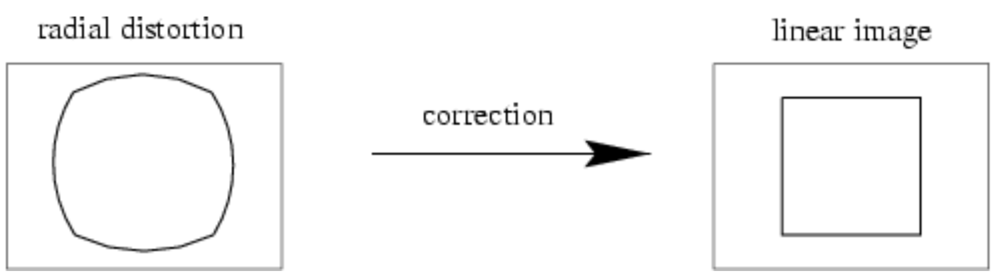
$$x = K[I \mid 0] X_{cam} = K\left[R \mid -R\tilde{C}\right] X \qquad P = K[R \mid t], \qquad t = -R\tilde{C}$$

Note: C is the null space of the camera projection matrix (PC=0)

Camera parameters

- Intrinsic parameters
  - Principal point coordinates
  - Focal length
  - Pixel magnification factors
  - *Skew (non-rectangular pixels)*
  - *Radial distortion*

$$K = \begin{bmatrix} m_x & & \\ & m_y & \\ & & 1 \end{bmatrix} \begin{bmatrix} f & & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} = \begin{bmatrix} \alpha_x & & \beta_x \\ & \alpha_y & \beta_y \\ & & 1 \end{bmatrix}$$

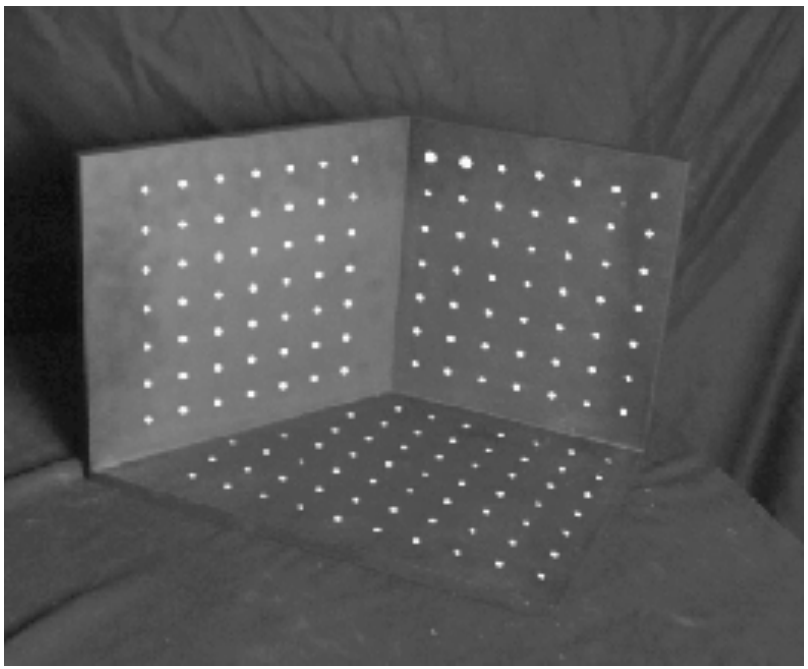


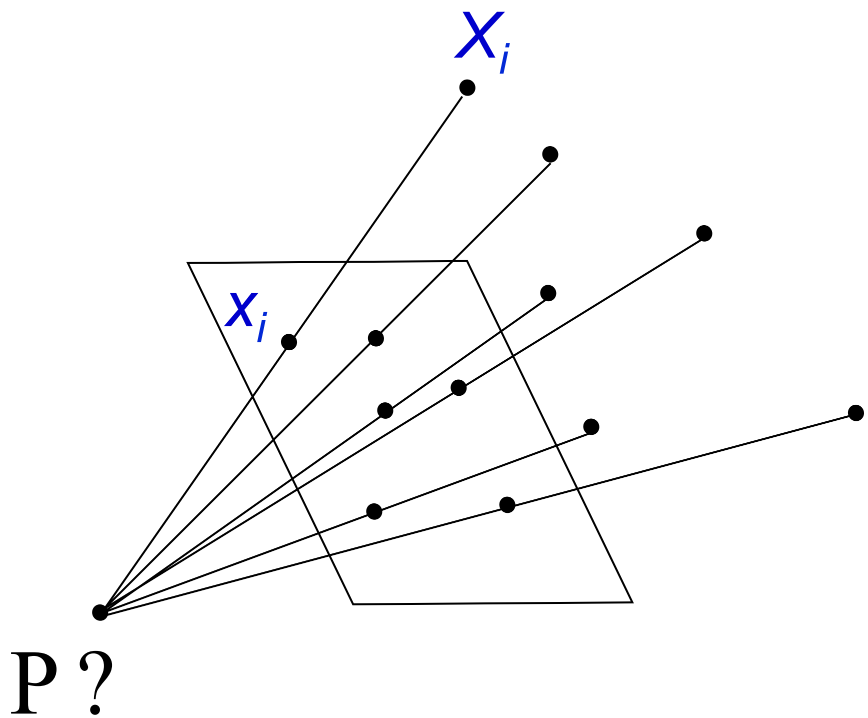
Camera parameters

- Intrinsic parameters
  - Principal point coordinates
  - Focal length
  - Pixel magnification factors
  - *Skew (non-rectangular pixels)*
  - *Radial distortion*
- Extrinsic parameters
  - Rotation and translation relative to world coordinate system

Camera calibration

- Given n points with known 3D coordinates X_i and known image projections x_i, estimate the camera parameters





Camera calibration

$$\lambda \mathrm{x}_i = \mathrm{P}\mathrm{X}_i \qquad \mathrm{x}_i \times \mathrm{P}\mathrm{X}_i = 0 \qquad \begin{bmatrix} x_i \\ y_i \\ 1 \end{bmatrix} \times \begin{bmatrix} \mathrm{P}_1^T \mathrm{X}_i \\ \mathrm{P}_2^T \mathrm{X}_i \\ \mathrm{P}_3^T \mathrm{X}_i \end{bmatrix} = 0$$

$$\begin{bmatrix} 0 & -\mathrm{X}_i^T & y_i \mathrm{X}_i^T \\ \mathrm{X}_i^T & 0 & -x_i \mathrm{X}_i^T \\ -y_i \mathrm{X}_i^T & x_i \mathrm{X}_i^T & 0 \end{bmatrix} \begin{pmatrix} \mathrm{P}_1 \\ \mathrm{P}_2 \\ \mathrm{P}_3 \end{pmatrix} = 0$$

Two linearly independent equations

Camera calibration

$$\begin{bmatrix} 0^T & X_1^T & -y_1 X_1^T \\ X_1^T & 0^T & -x_1 X_1^T \\ \cdots & \cdots & \cdots \\ 0^T & X_n^T & -y_n X_n^T \\ X_n^T & 0^T & -x_n X_n^T \end{bmatrix} \begin{pmatrix} P_1 \\ P_2 \\ P_3 \end{pmatrix} = 0 \qquad \mathbf{A}\mathbf{p} = 0$$

- P has 11 degrees of freedom (12 parameters, but scale is arbitrary)
- One 2D/3D correspondence gives us two linearly independent equations
- Homogeneous least squares
- 6 correspondences needed for a minimal solution

Camera calibration

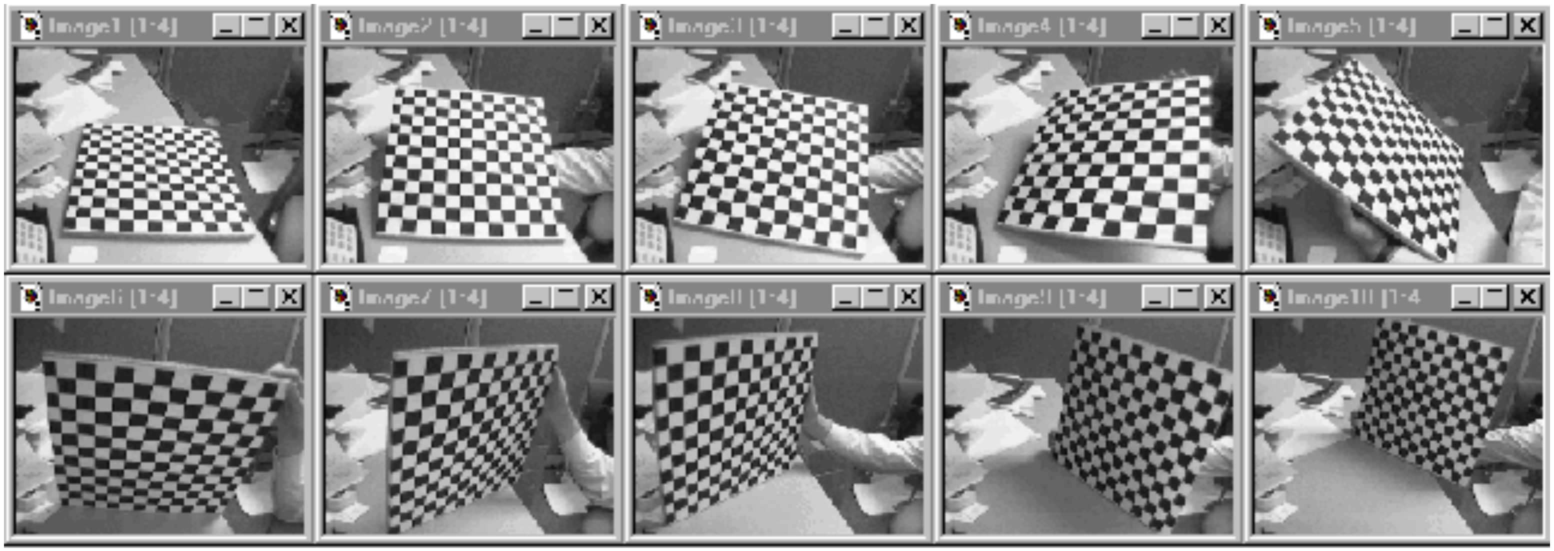
$$\begin{bmatrix} 0^T & X_1^T & -y_1 X_1^T \\ X_1^T & 0^T & -x_1 X_1^T \\ \cdots & \cdots & \cdots \\ 0^T & X_n^T & -y_n X_n^T \\ X_n^T & 0^T & -x_n X_n^T \end{bmatrix} \begin{pmatrix} P_1 \\ P_2 \\ P_3 \end{pmatrix} = 0 \qquad Ap = 0$$

- Note: for coplanar points that satisfy $\Pi^T X = 0$, we will get degenerate solutions $(\Pi,0,0)$, $(0,\Pi,0)$, or $(0,0,\Pi)$

Camera calibration

- Once we've recovered the numerical form of the camera matrix, we still have to figure out the intrinsic and extrinsic parameters
- This is a matrix decomposition problem, not an estimation problem (see F&P sec. 3.2, 3.3)

Alternative: multi-plane calibration



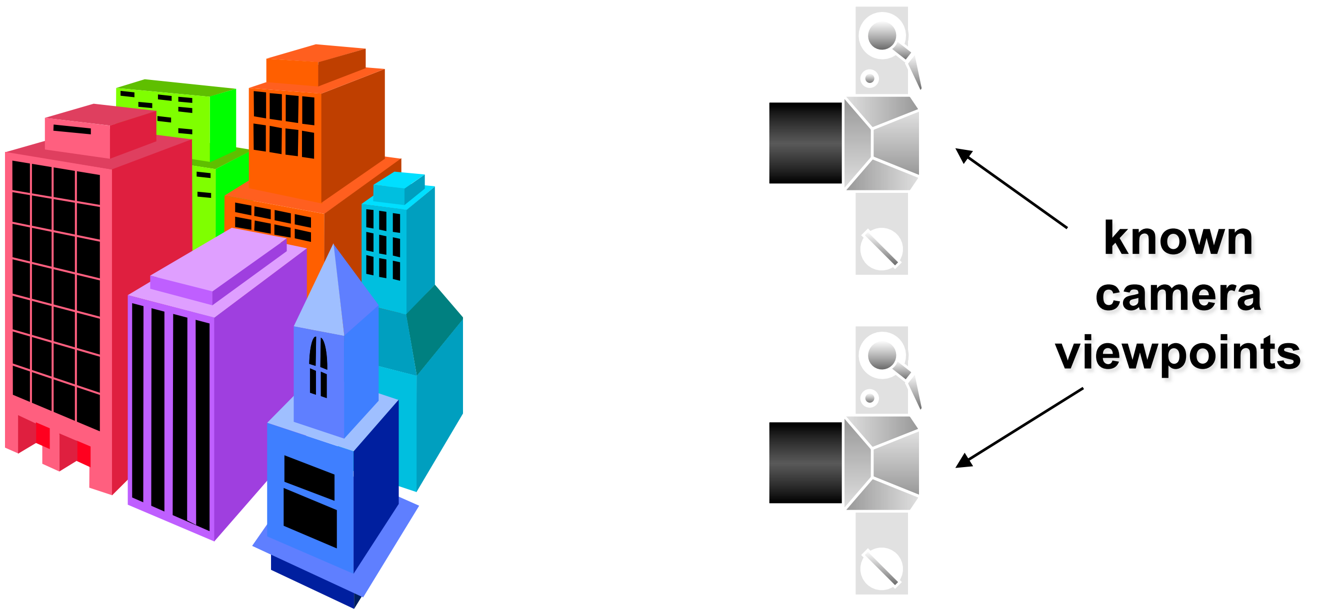
Images courtesy Jean-Yves Bouguet, Intel Corp.

Advantage

- Only requires a plane
- Don't have to know positions/orientations
- Good code available online!
  - Intel's OpenCV library: http://www.intel.com/research/mrl/research/opencv/
  - Matlab version by Jean-Yves Bouget: http://www.vision.caltech.edu/bouguetj/calib_doc/index.html
  - Zhengyou Zhang's web site: http://research.microsoft.com/~zhang/Calib/

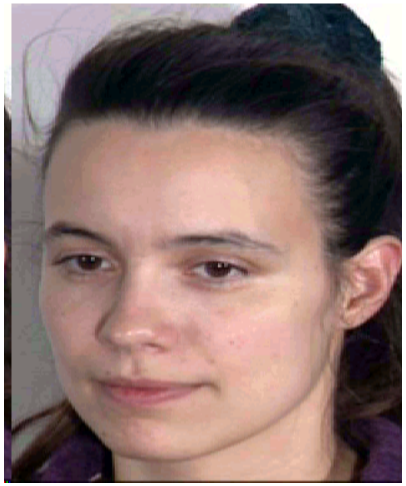
Stereo Reconstruction

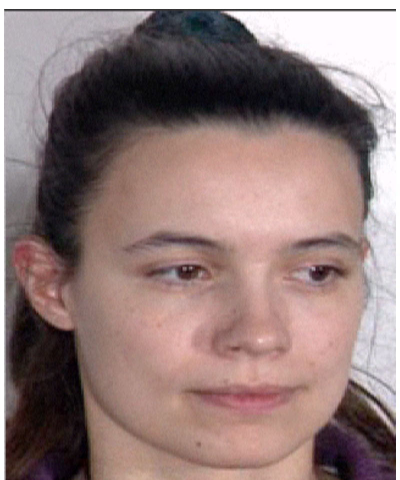
Shape (3D) from two (or more) images

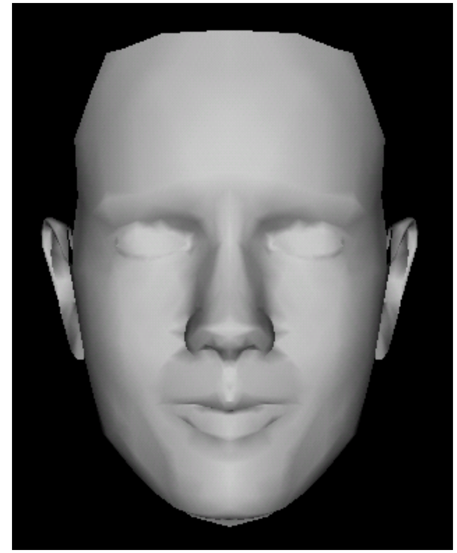


Example

images







shape

surface reflectance

Scenarios

The two images can arise from

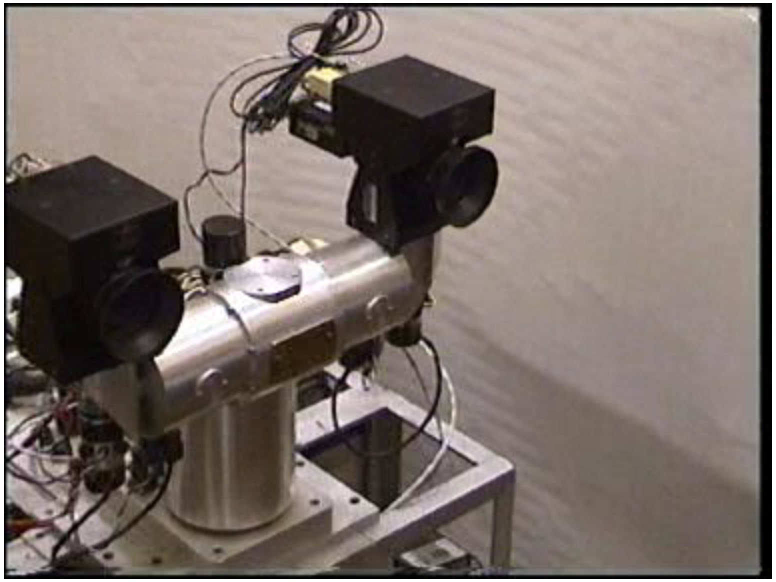
- A stereo rig consisting of two cameras
  - the two images are acquired simultaneously

or

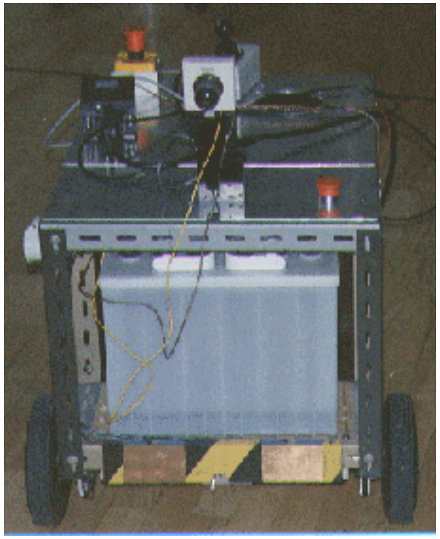
- A single moving camera (static scene)
  - the two images are acquired sequentially

The two scenarios are geometrically equivalent

Stereo head



Camera on a mobile vehicle



The objective

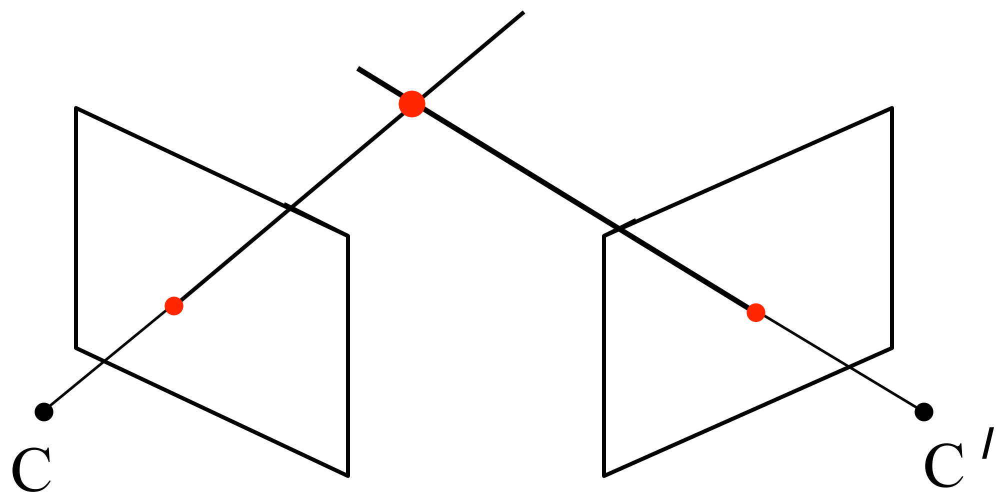
Given two images of a scene acquired by known cameras compute the 3D position of the scene (structure recovery)

Basic principle: triangulate from corresponding image points

- Determine 3D point at intersection of two back-projected rays

Corresponding points are images of the same scene point

Triangulation



The back-projected points generate rays which intersect at the 3D scene point

An algorithm for stereo reconstruction

1. For each point in the first image determine the corresponding point in the second image

   (this is a search problem)

2. For each pair of matched points determine the 3D point by triangulation

   (this is an estimation problem)

The correspondence problem

Given a point x in one image find the corresponding point in the other image

This appears to be a 2D search problem, but it is reduced to a 1D search by the epipolar constraint

Outline

1. Epipolar geometry

   - the geometry of two cameras
   - reduces the correspondence problem to a line search

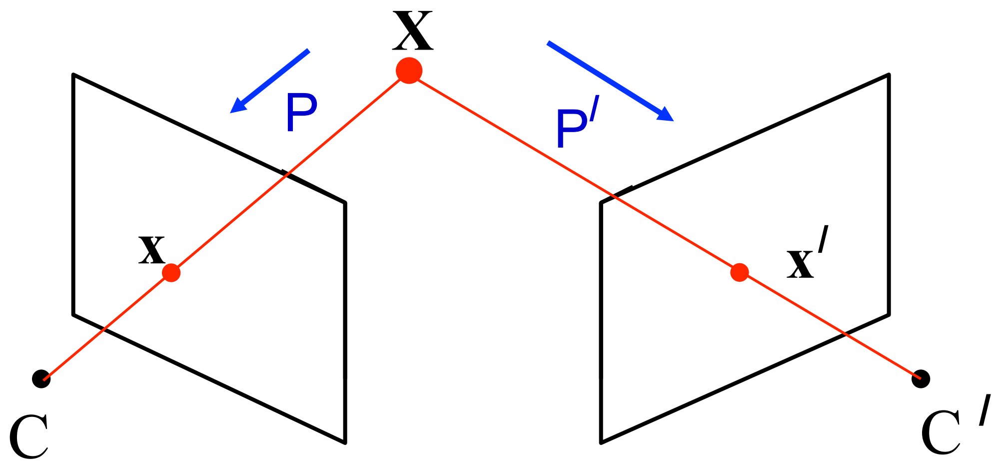
2. Stereo correspondence algorithms

3. Triangulation

Notation

The two cameras are P and P′, and a 3D point **X** is imaged as

$$\mathbf{x} = \mathtt{P}\mathbf{X} \qquad \mathbf{x}' = \mathtt{P}'\mathbf{X}$$



$\mathtt{P}$: 3×4 matrix

$\mathbf{X}$: 4-vector

$\mathbf{x}$: 3-vector

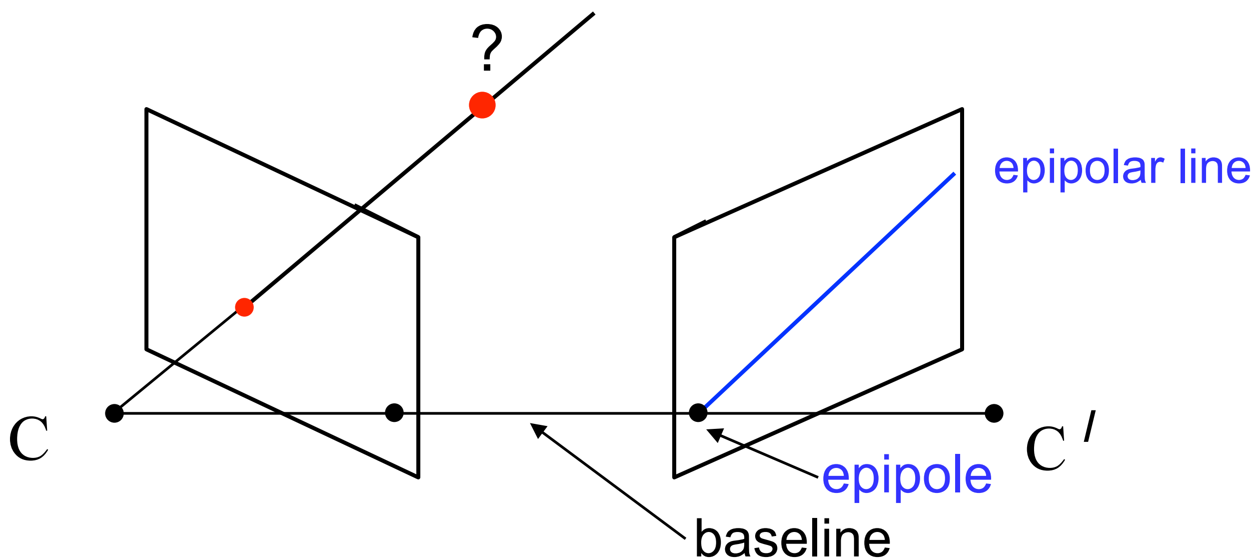
Warning

for equations involving homogeneous quantities '=' means 'equal up to scale'

Epipolar geometry

Epipolar geometry

Given an image point in one view, where is the corresponding point in the other view?



- A point in one view “generates” an epipolar line in the other view
- The corresponding point lies on this line

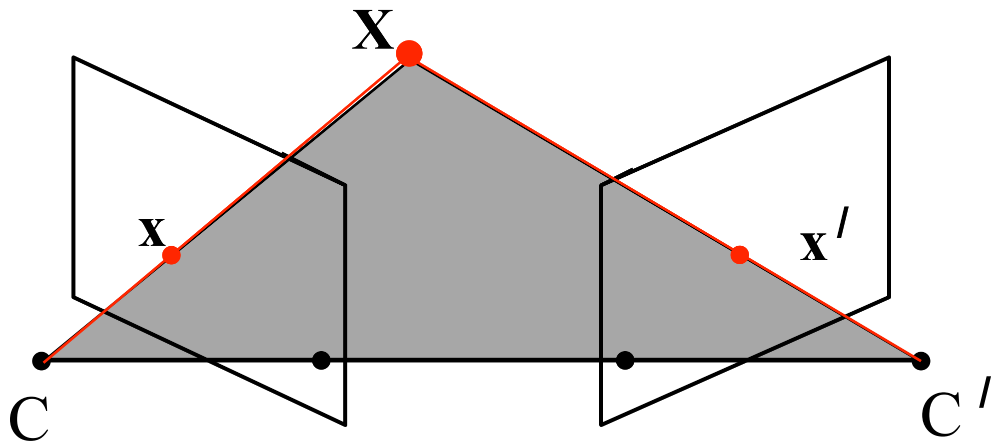
Epipolar line

Epipolar constraint

- Reduces correspondence problem to 1D search along an epipolar line

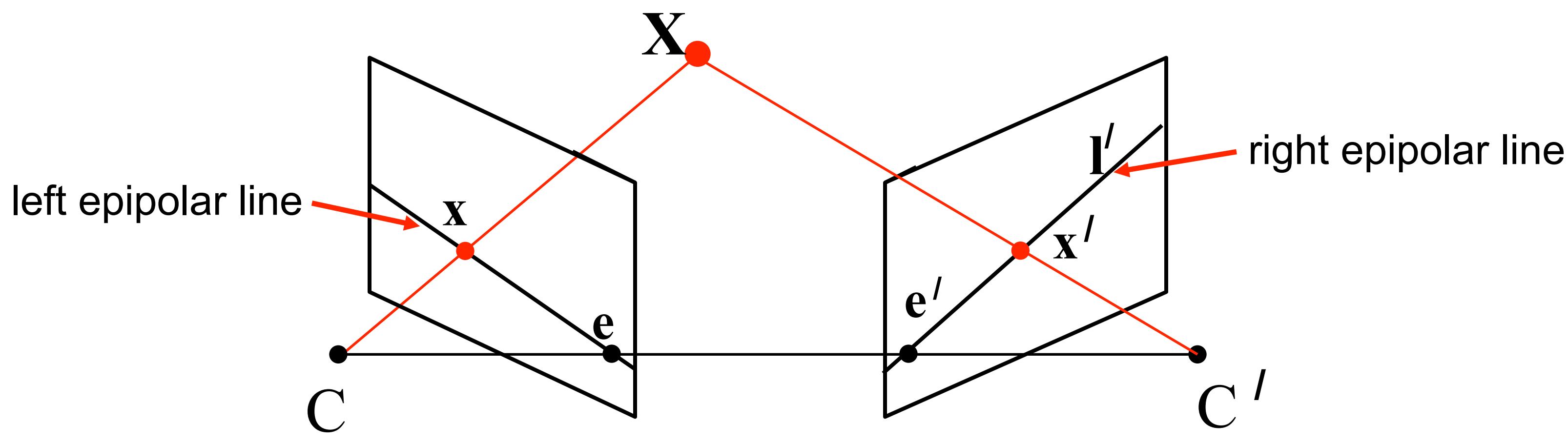
Epipolar geometry continued

Epipolar geometry is a consequence of the coplanarity of the camera centres and scene point



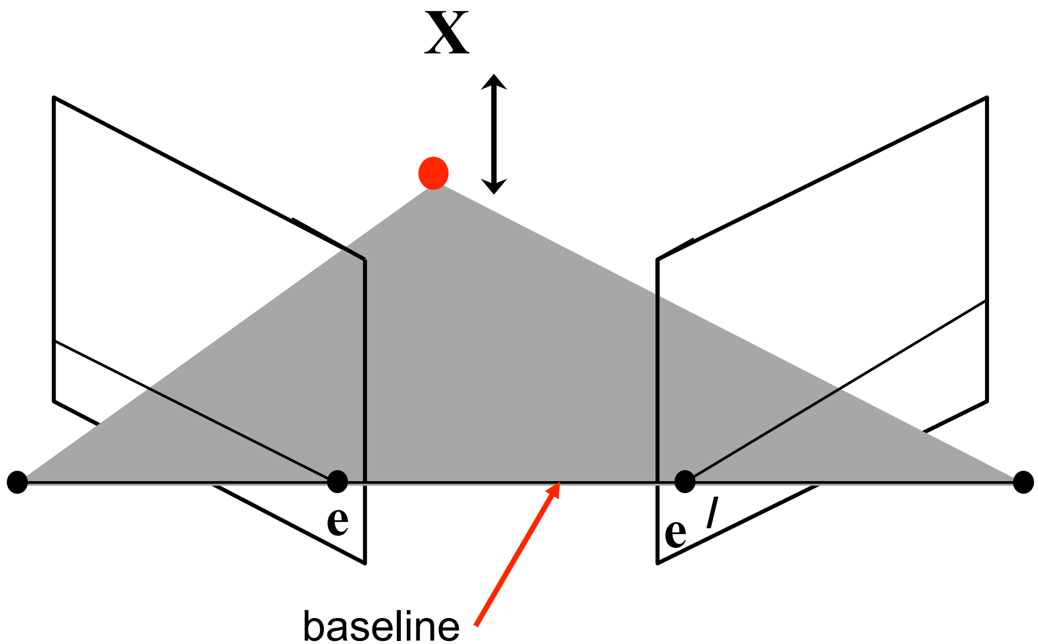
The camera centres, corresponding points and scene point lie in a single plane, known as the epipolar plane

Nomenclature



- The epipolar line $\mathbf{l}'$ is the image of the ray through $\mathbf{x}$
- The epipole $\mathbf{e}$ is the point of intersection of the line joining the camera centres with the image plane
  - this line is the baseline for a stereo rig, and
  - the translation vector for a moving camera
- The epipole is the image of the centre of the other camera: $\mathbf{e} = \mathrm{P}\mathbf{C}'$, $\mathbf{e}' = \mathrm{P}'\mathbf{C}$

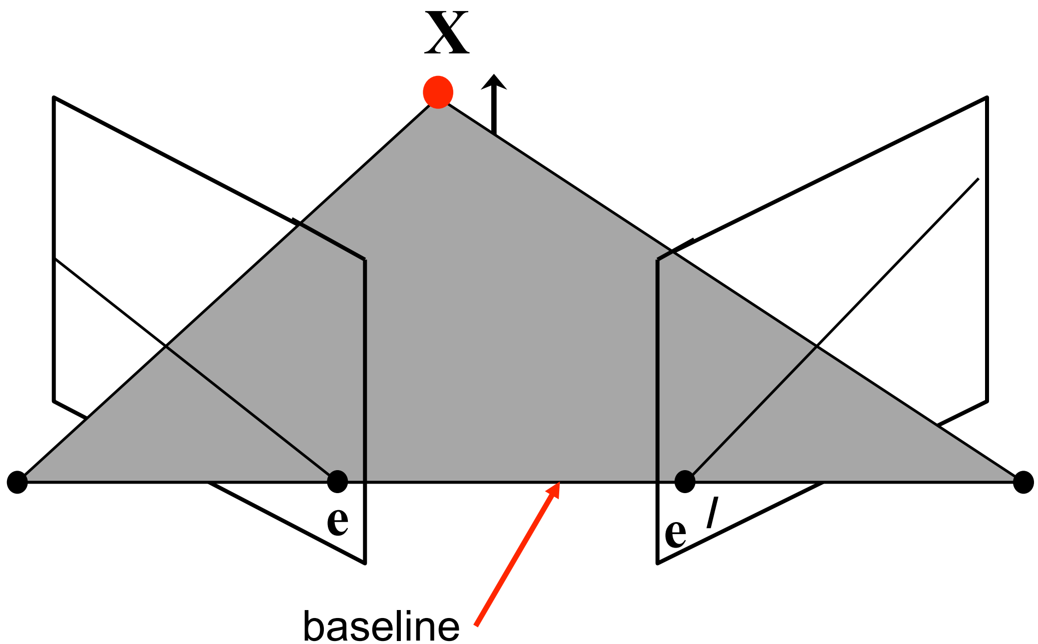
The epipolar pencil



As the position of the 3D point **X** varies, the epipolar planes “rotate” about the baseline. This family of planes is known as an epipolar pencil. All epipolar lines intersect at the epipole.

(a pencil is a one parameter family)

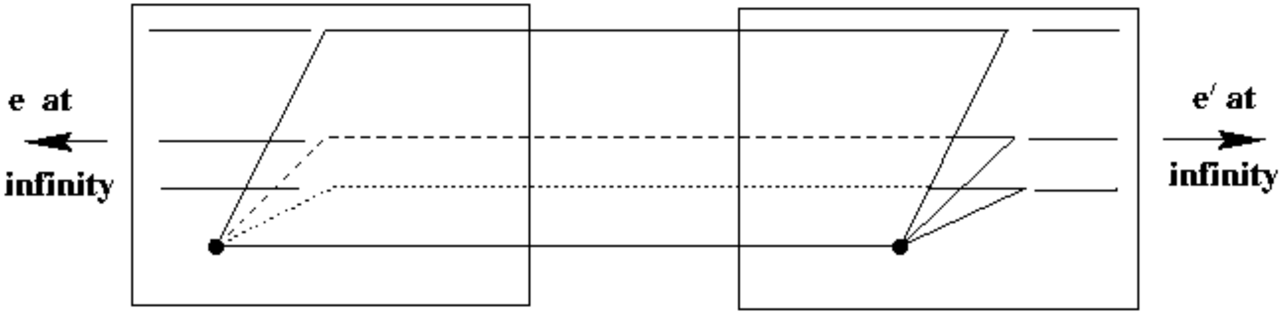
The epipolar pencil

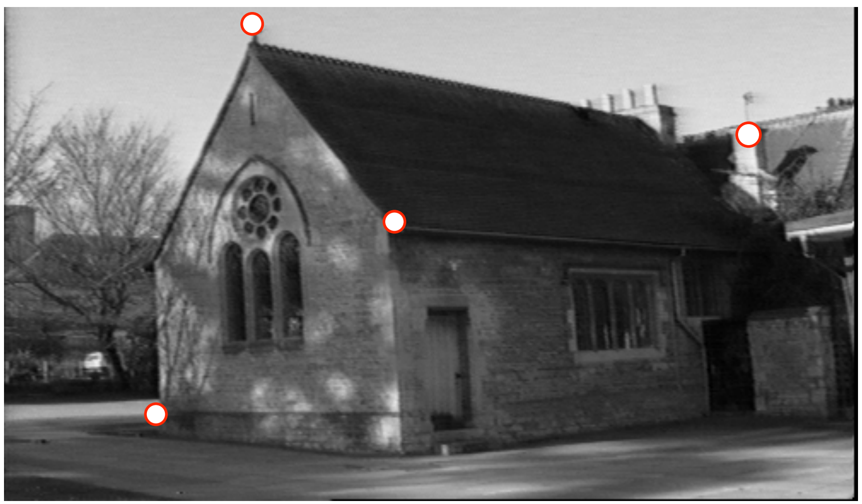


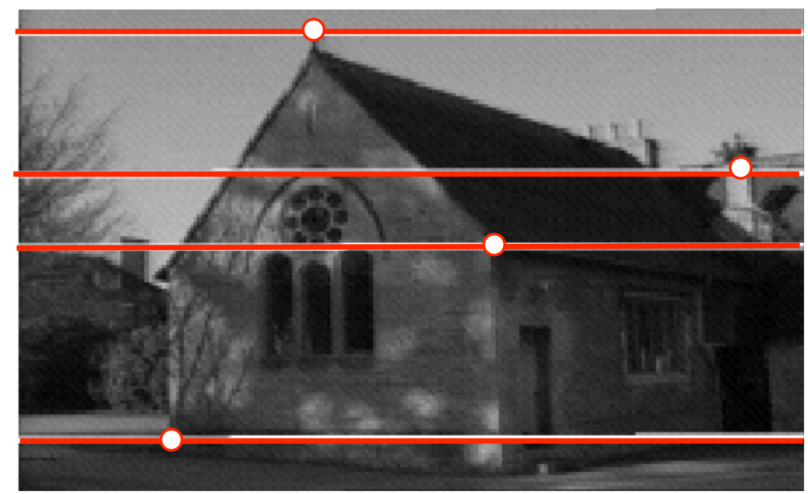
As the position of the 3D point $\mathbf{X}$ varies, the epipolar planes “rotate” about the baseline. This family of planes is known as an epipolar pencil. All epipolar lines intersect at the epipole.

(a pencil is a one parameter family)

Epipolar geometry example I: parallel cameras

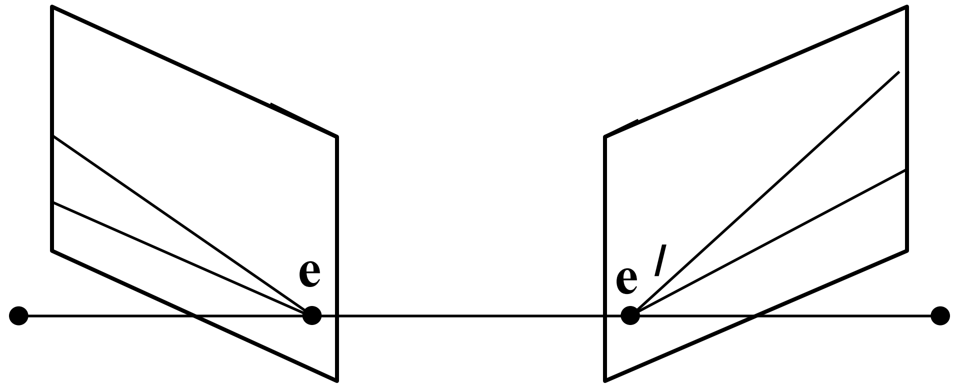


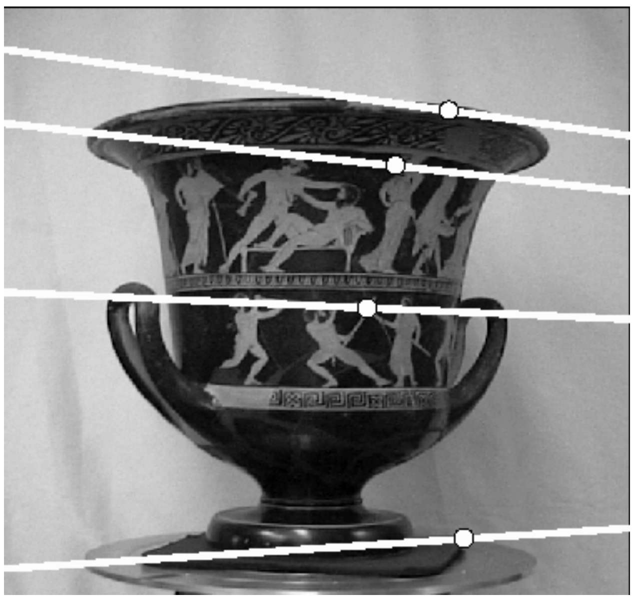


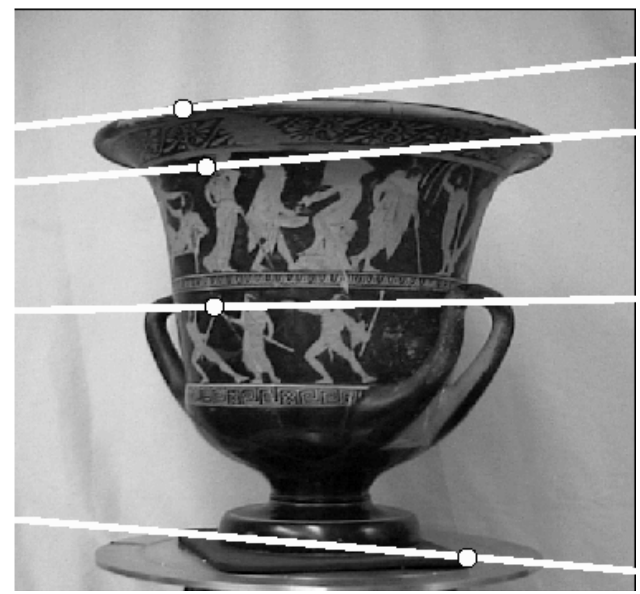


Epipolar geometry depends only on the relative pose (position and orientation) and internal parameters of the two cameras, i.e. the position of the camera centres and image planes. It does not depend on the scene structure (3D points external to the camera).

Epipolar geometry example II: converging cameras







Note, epipolar lines are in general not parallel

Homogeneous notation for lines

Recall that a point (x, y) in 2D is represented by the homogeneous 3-vector $\mathbf{x} = (x_1, x_2, x_3)^\top$, where $x = x_1/x_3, y = x_2/x_3$

A line in 2D is represented by the homogeneous 3-vector

$$\mathbf{l} = \begin{pmatrix} l_1 \\ l_2 \\ l_3 \end{pmatrix}$$

which is the line $l_1 x + l_2 y + l_3 = 0$.

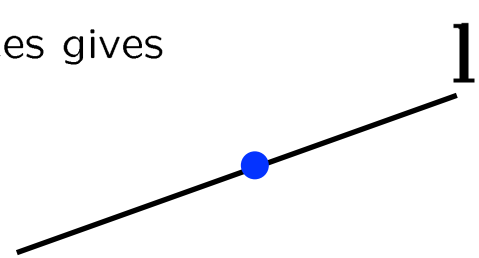
Example represent the line $y = 1$ as a homogeneous vector.

Write the line as $-y + 1 = 0$ then $l_1 = 0, l_2 = -1, l_3 = 1$, and $\mathbf{l} = (0, -1, 1)^\top$.

Note that $\mu(l_1 x + l_2 y + l_3) = 0$ represents the same line (only the ratio of the homogeneous line coordinates is significant).

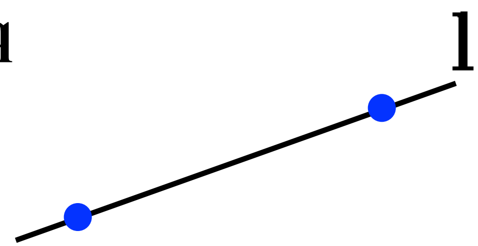
Writing both the point and line in homogeneous coordinates gives

$$l_1 x_1 + l_2 x_2 + l_3 x_3 = 0$$



- point on line $\mathbf{l}.\mathbf{x} = 0$ or $\mathbf{l}^\top \mathbf{x} = 0$ or $\mathbf{x}^\top \mathbf{l} = 0$

- The line $\mathbf{l}$ through the two points $\mathbf{p}$ and $\mathbf{q}$ is $\mathbf{l} = \mathbf{p} \times \mathbf{q}$



Proof

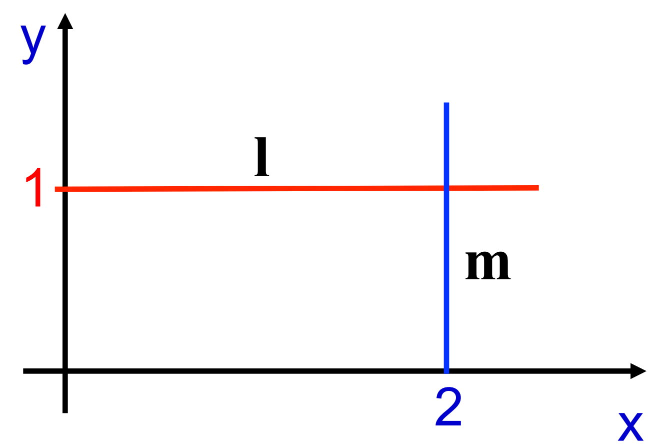
$$\mathbf{l}.\mathbf{p} = (\mathbf{p} \times \mathbf{q}).\mathbf{p} = 0 \qquad \mathbf{l}.\mathbf{q} = (\mathbf{p} \times \mathbf{q}).\mathbf{q} = 0$$

- The intersection of two lines $\mathbf{l}$ and $\mathbf{m}$ is the point $\mathbf{x} = \mathbf{l} \times \mathbf{m}$

Example: compute the point of intersection of the two lines $\mathbf{l}$ and $\mathbf{m}$ in the figure below

$$\mathbf{l} = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} \qquad \mathbf{m} = \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix}$$

$$\mathbf{x} = \mathbf{l} \times \mathbf{m} = \begin{vmatrix} \mathbf{i} & \mathbf{j} & \mathbf{k} \\ 0 & -1 & 1 \\ -1 & 0 & 2 \end{vmatrix} = \begin{pmatrix} -2 \\ -1 \\ -1 \end{pmatrix}$$



which is the point (2,1)

Matrix representation of the vector cross product

The vector product $\mathbf{v} \times \mathbf{x}$ can be represented as a matrix multiplication

$$\mathbf{v} \times \mathbf{x} = \begin{pmatrix} v_2 x_3 - v_3 x_2 \\ v_3 x_1 - v_1 x_3 \\ v_1 x_2 - v_2 x_1 \end{pmatrix} = [\mathbf{v}]_\times \mathbf{x}$$

where

$$[\mathbf{v}]_\times = \begin{bmatrix} 0 & -v_3 & v_2 \\ v_3 & 0 & -v_1 \\ -v_2 & v_1 & 0 \end{bmatrix}$$

- $[\mathbf{v}]_\times$ is a 3×3 skew-symmetric matrix of rank 2.
- $\mathbf{v}$ is the null-vector of $[\mathbf{v}]_\times$, since $\mathbf{v} \times \mathbf{v} = [\mathbf{v}]_\times \mathbf{v} = \mathbf{0}$.

Example: compute the cross product of **l** and **m**

$$\mathbf{l} = \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} \qquad \mathbf{m} = \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix} \qquad [\mathbf{v}]_\times = \begin{bmatrix} 0 & -v_3 & v_2 \\ v_3 & 0 & -v_1 \\ -v_2 & v_1 & 0 \end{bmatrix}$$

$$\mathbf{x} = \mathbf{l} \times \mathbf{m} = [\mathbf{l}]_\times \mathbf{m} = \begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{pmatrix} -1 \\ 0 \\ 2 \end{pmatrix} = \begin{pmatrix} -2 \\ -1 \\ -1 \end{pmatrix}$$

Note

$$\begin{bmatrix} 0 & -1 & -1 \\ 1 & 0 & 0 \\ 1 & 0 & 0 \end{bmatrix} \begin{pmatrix} 0 \\ -1 \\ 1 \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}$$

Algebraic representation of epipolar geometry

We know that the epipolar geometry defines a mapping

$$\mathbf{x} \quad \rightarrow \quad \mathbf{l}'$$

point in first image

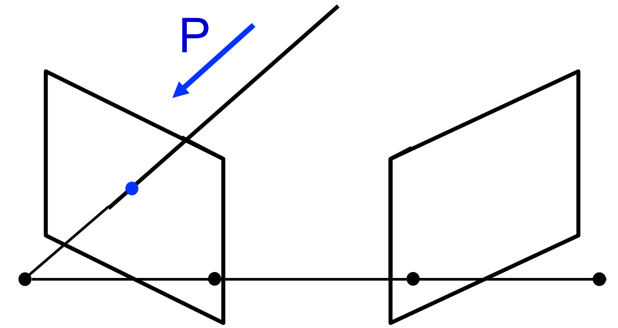
epipolar line in second image

- the map ony depends on the cameras $\mathtt{P}, \mathtt{P}'$ (not on structure)
- it will be shown that the map is linear and can be written as $\mathbf{l}' = \mathtt{F}\mathbf{x}$, where $\mathtt{F}$ is a 3×3 matrix called the fundamental matrix

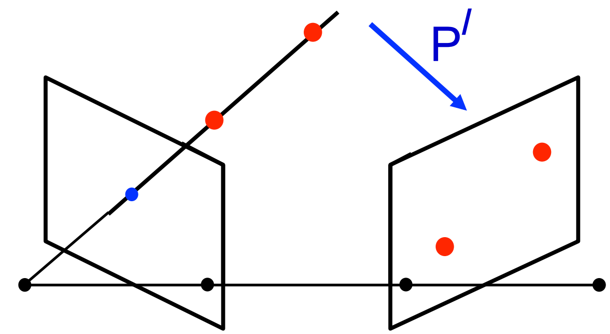
Derivation of the algebraic expression $\mathbf{l}' = \mathtt{F}\mathbf{x}$

Outline

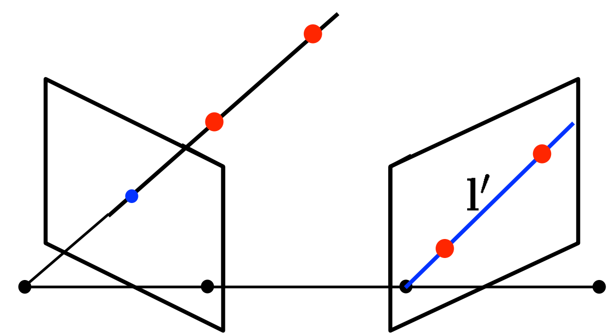
Step 1: for a point x in the first image back project a ray with camera P



Step 2: choose two points on the ray and project into the second image with camera P$'$



Step 3: compute the line through the two image points using the relation $\mathbf{l}' = \mathbf{p} \times \mathbf{q}$

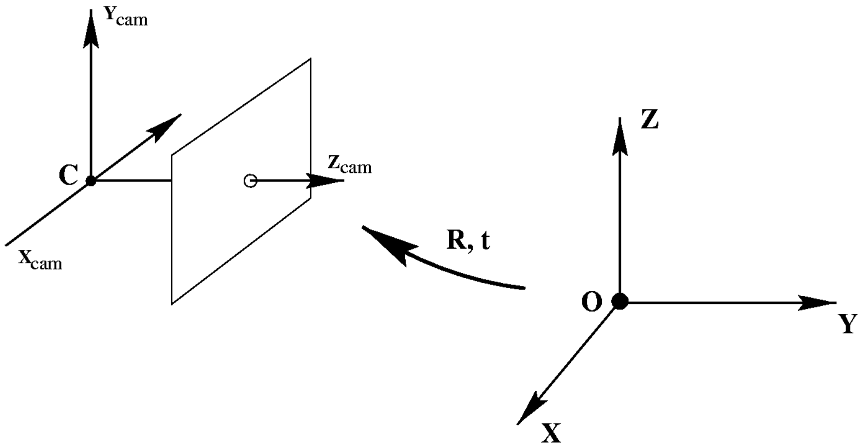


- choose camera matrices

$$P = K[R \mid t]$$

internal calibration (K) — rotation (R) — translation (t)

from world to camera coordinate frame



- first camera

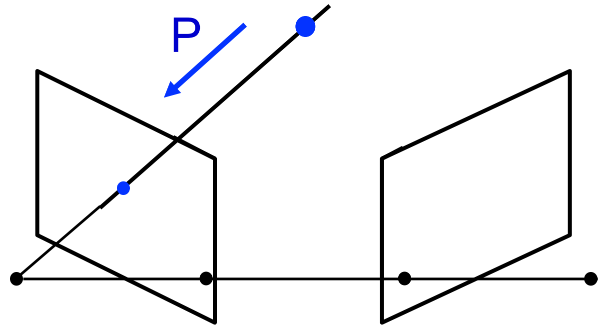
$$P = K[I \mid 0]$$

world coordinate frame aligned with first camera

- second camera

$$P' = K'[R \mid t]$$

Step 1: for a point x in the first image
back project a ray with camera $\mathtt{P} = \mathtt{K}[\,\mathtt{I} \mid \mathbf{0}\,]$



A point $\mathbf{x}$ back projects to a ray

$$\begin{pmatrix} \mathsf{x} \\ \mathsf{y} \\ \mathsf{z} \end{pmatrix} = \mathsf{z}\mathtt{K}^{-1} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \mathsf{z}\mathtt{K}^{-1}\mathbf{x}$$

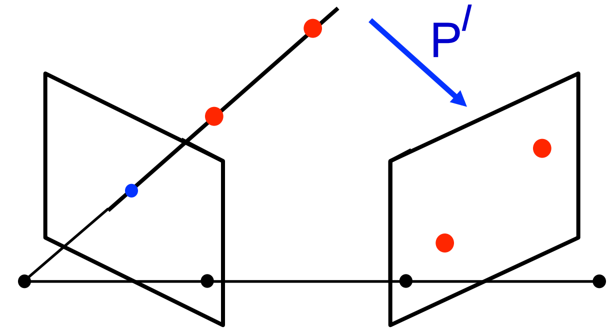
where $\mathbf{Z}$ is the point's depth, since

$$\mathtt{X}(\mathsf{z}) = \begin{pmatrix} \mathsf{z}\mathtt{K}^{-1}\mathbf{x} \\ 1 \end{pmatrix}$$

satisfies

$$\mathtt{P}\mathtt{X}(\mathsf{z}) = \mathtt{K}[\mathtt{I} \mid \mathbf{0}]\mathtt{X}(\mathsf{z}) = \mathbf{x}$$

Step 2: choose two points on the ray and project into the second image with camera P'



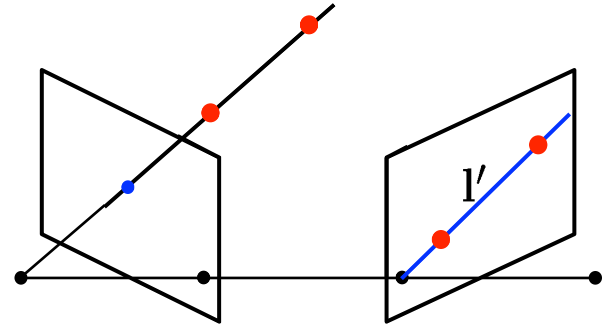
Consider two points on the ray $X(z) = \begin{pmatrix} zK^{-1}\mathbf{x} \\ 1 \end{pmatrix}$

- $z = 0$ is the camera centre $\begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix}$
- $z = \infty$ is the point at infinity $\begin{pmatrix} K^{-1}\mathbf{x} \\ 0 \end{pmatrix}$

Project these two points into the second view

$$P' \begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix} = K'[R \mid \mathbf{t}] \begin{pmatrix} \mathbf{0} \\ 1 \end{pmatrix} = K'\mathbf{t} \qquad P' \begin{pmatrix} K^{-1}\mathbf{x} \\ 0 \end{pmatrix} = K'[R \mid \mathbf{t}] \begin{pmatrix} K^{-1}\mathbf{x} \\ 0 \end{pmatrix} = K'RK^{-1}\mathbf{x}$$

Step 3: compute the line through the two image points using the relation $\mathbf{l}' = \mathbf{p} \times \mathbf{q}$



Compute the line through the points $\mathbf{l}' = (\mathtt{K}'\mathbf{t}) \times (\mathtt{K}'\mathtt{R}\mathtt{K}^{-1}\mathbf{x})$

Using the identity $(\mathtt{M}\mathbf{a}) \times (\mathtt{M}\mathbf{b}) = \mathtt{M}^{-\top}(\mathbf{a} \times \mathbf{b})$ where $\mathtt{M}^{-\top} = (\mathtt{M}^{-1})^\top = (\mathtt{M}^\top)^{-1}$

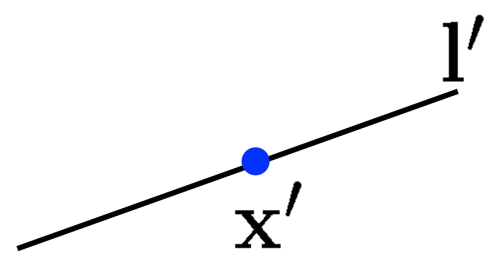
$$\mathbf{l}' = \mathtt{K}'^{-\top}\left(\mathbf{t} \times (\mathtt{R}\mathtt{K}^{-1}\mathbf{x})\right) = \underbrace{\mathtt{K}'^{-\top}[\mathbf{t}]_\times \mathtt{R}\mathtt{K}^{-1}}_{F}\mathbf{x}$$

F is the fundamental matrix

$$\mathbf{l}' = \mathtt{F}\mathbf{x} \qquad \mathtt{F} = \mathtt{K}'^{-\top}[\mathbf{t}]_\times \mathtt{R}\mathtt{K}^{-1}$$

Points $\mathbf{x}$ and $\mathbf{x}'$ correspond $(\mathbf{x} \leftrightarrow \mathbf{x}')$ then $\mathbf{x}'^\top \mathbf{l}' = 0$

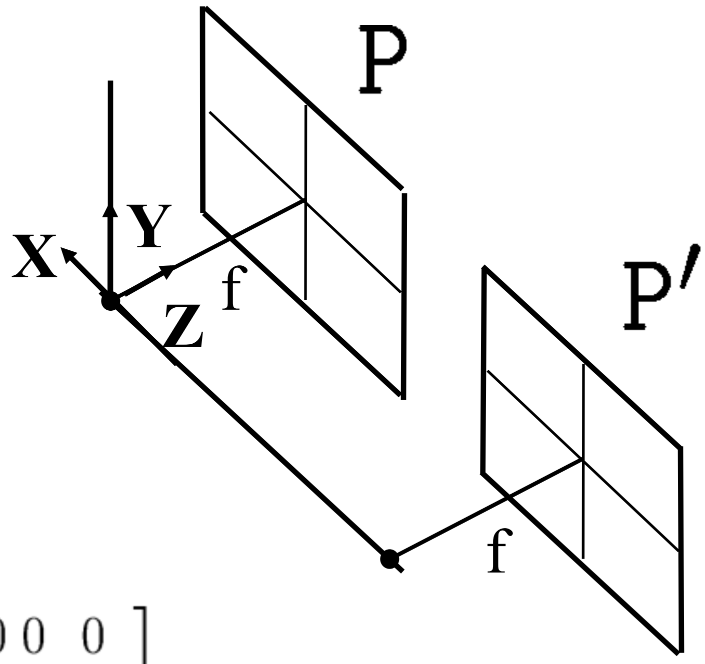
$$\mathbf{x}'^\top \mathtt{F}\mathbf{x} = 0$$



Example I: compute the fundamental matrix for a parallel camera stereo rig

$$\mathtt{P} = \mathtt{K}[\mathtt{I} \mid \mathbf{0}] \qquad \mathtt{P}' = \mathtt{K}'[\mathtt{R} \mid \mathbf{t}]$$

$$\mathtt{K} = \mathtt{K}' = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad \mathtt{R} = \mathtt{I} \quad \mathbf{t} = \begin{pmatrix} t_x \\ 0 \\ 0 \end{pmatrix}$$



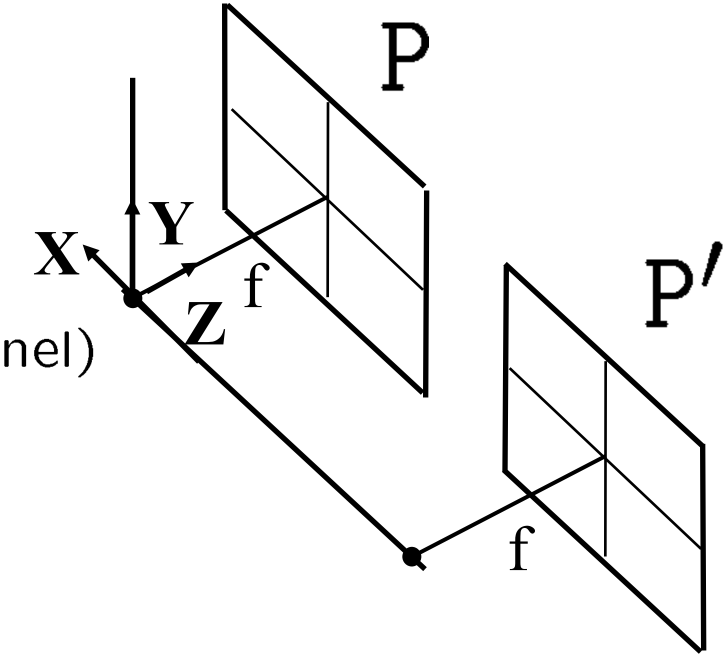
$$\mathtt{F} = \mathtt{K}'^{-\top}[\mathbf{t}]_\times \mathtt{R}\mathtt{K}^{-1}$$

$$= \begin{bmatrix} 1/f & 0 & 0 \\ 0 & 1/f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -t_x \\ 0 & t_x & 0 \end{bmatrix} \begin{bmatrix} 1/f & 0 & 0 \\ 0 & 1/f & 0 \\ 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

$$\mathbf{x}'^\top \mathbf{F} \mathbf{x} = \begin{pmatrix} x' & y' & 1 \end{pmatrix} \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = 0$$

- reduces to $y = y'$, i.e. raster correspondence (horizontal scan-lines)

$\mathtt{F}$ is a rank 2 matrix



The epipole $\mathbf{e}$ is the null-space vector (kernel) of $\mathtt{F}$ (exercise), i.e. $\mathtt{F}\mathbf{e} = \mathbf{0}$

In this case

$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix} = \mathbf{0}$$

so that

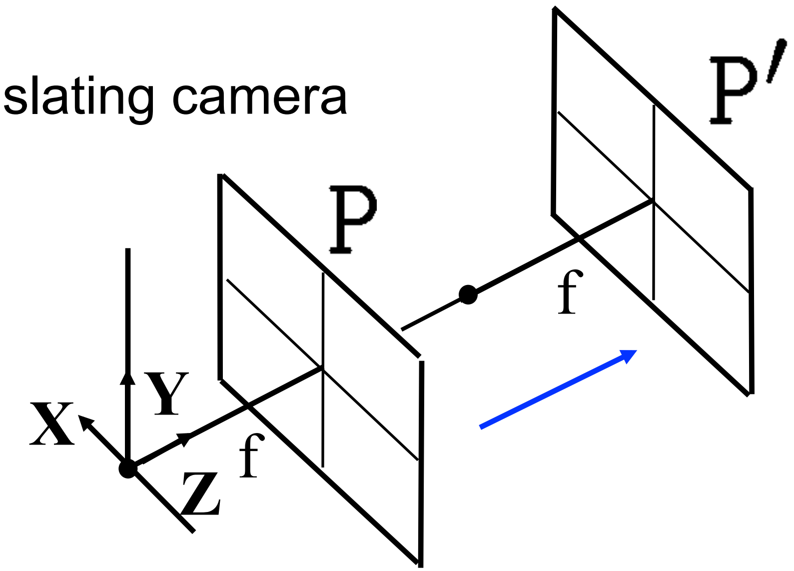
$$\mathbf{e} = \begin{pmatrix} 1 \\ 0 \\ 0 \end{pmatrix}$$

Geometric interpretation ?

Example II: compute F for a forward translating camera

$$P = K[I \mid \mathbf{0}] \qquad P' = K'[R \mid \mathbf{t}]$$

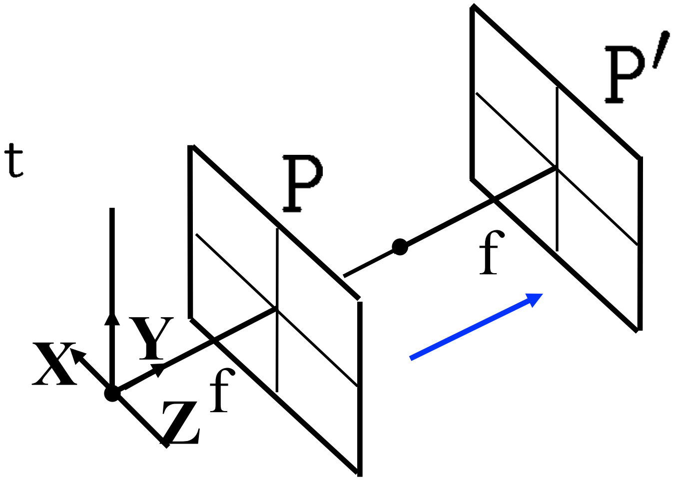
$$K = K' = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad R = I \quad \mathbf{t} = \begin{pmatrix} 0 \\ 0 \\ t_z \end{pmatrix}$$



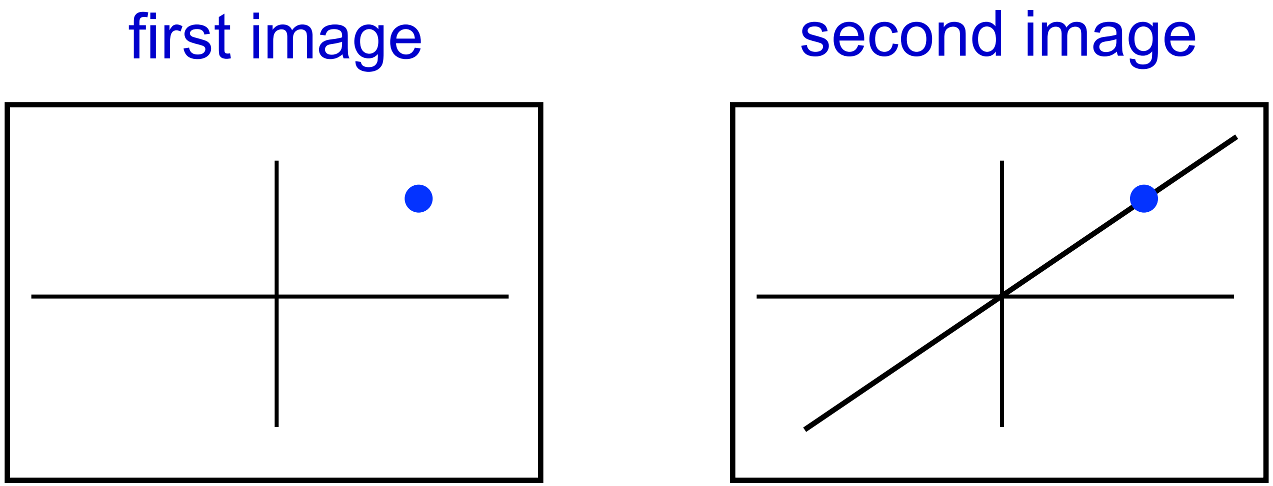
$$\begin{aligned} F &= K'^{-\top}[\mathbf{t}]_\times R K^{-1} \\ &= \begin{bmatrix} 1/f & 0 & 0 \\ 0 & 1/f & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 0 & -t_z & 0 \\ t_z & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} 1/f & 0 & 0 \\ 0 & 1/f & 0 \\ 0 & 0 & 1 \end{bmatrix} \\ &= \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \end{aligned}$$

From $\mathbf{l}' = \mathtt{F}\mathbf{x}$ the epipolar line for the point $\mathbf{x} = (x, y, 1)^\top$ is

$$\mathbf{l}' = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{pmatrix} x \\ y \\ 1 \end{pmatrix} = \begin{pmatrix} -y \\ x \\ 0 \end{pmatrix}$$



The points $(x, y, 1)^\top$ and $(0, 0, 1)^\top$ lie on this line




OXFORD


OXFORD

Summary: Properties of the Fundamental matrix

- $\mathtt{F}$ is a rank 2 homogeneous matrix with 7 degrees of freedom.

- Point correspondence:

  if $\mathbf{x}$ and $\mathbf{x}'$ are corresponding image points, then $\mathbf{x}'^{\top}\mathtt{F}\mathbf{x} = 0$.

- Epipolar lines:

  ◇ $\mathbf{l}' = \mathtt{F}\mathbf{x}$ is the epipolar line corresponding to $\mathbf{x}$.

  ◇ $\mathbf{l} = \mathtt{F}^{\top}\mathbf{x}'$ is the epipolar line corresponding to $\mathbf{x}'$.

- Epipoles:

  ◇ $\mathtt{F}\mathbf{e} = \mathbf{0}$.

  ◇ $\mathtt{F}^{\top}\mathbf{e}' = \mathbf{0}$.

- Computation from camera matrices $\mathtt{P}, \mathtt{P}'$:

  $\mathtt{P} = \mathtt{K}[\mathtt{I} \mid \mathbf{0}],\ \mathtt{P}' = \mathtt{K}'[\mathtt{R} \mid \mathbf{t}],\ \mathtt{F} = \mathtt{K}'^{-\top}[\mathbf{t}]_{\times}\mathtt{R}\mathtt{K}^{-1}$

Admin Interlude

- Assignment 1 due Sunday Oct 16th
- Class tutor: Anirudhan Rajagopalan
  - Email: anirudhan.rajagopalan@nyu.edu

Stereo correspondence algorithms

Problem statement

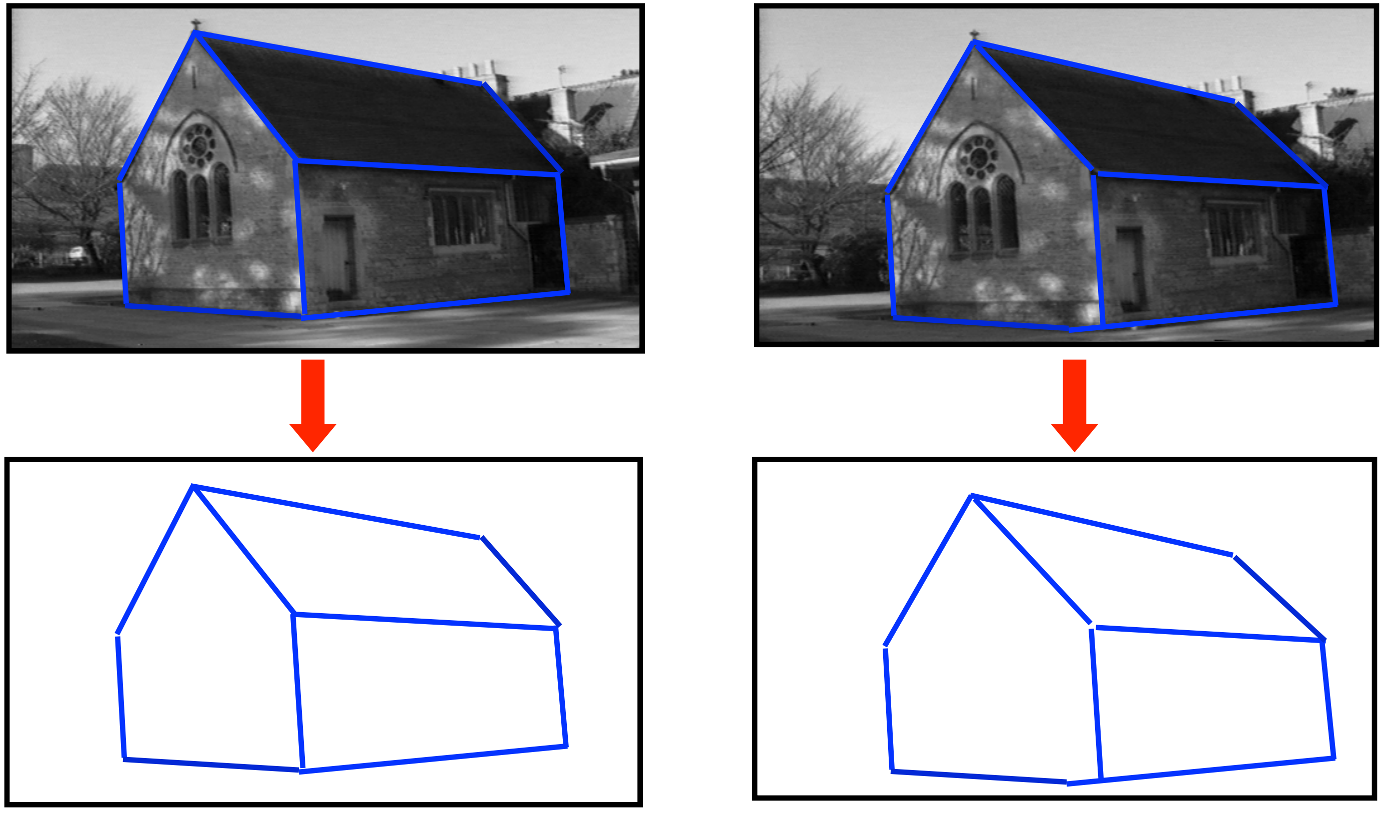
Given: two images and their associated cameras compute corresponding image points.

Algorithms may be classified into two types:

1. Dense: compute a correspondence at every pixel
2. Sparse: compute correspondences only for features

The methods may be top down or bottom up

Top down matching

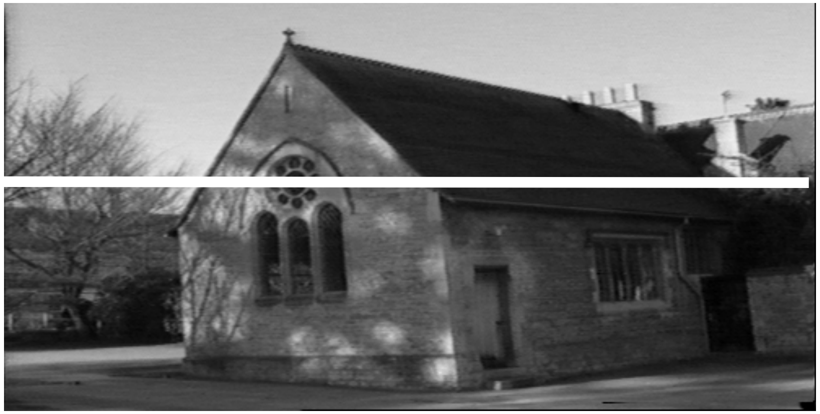


1. Group model (house, windows, etc) independently in each image

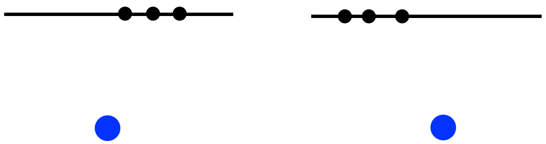
2. Match points (vertices) between images

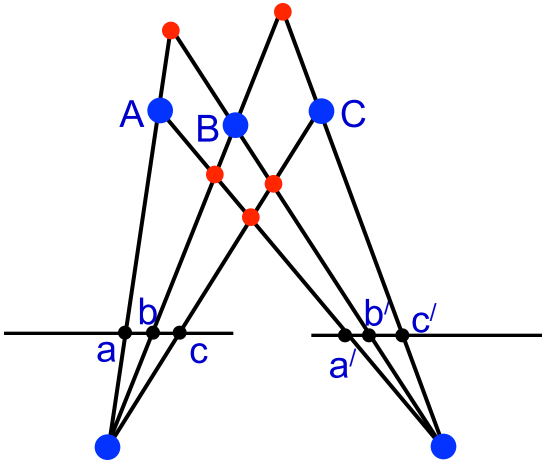
Bottom up matching

- epipolar geometry reduces the correspondence search from 2D to a 1D search on corresponding epipolar lines



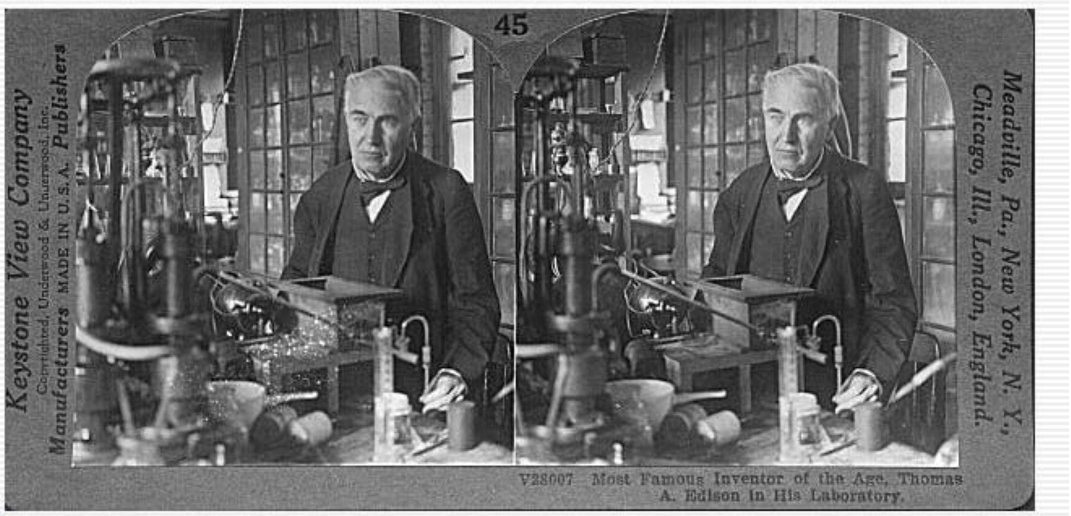
- 1D correspondence problem



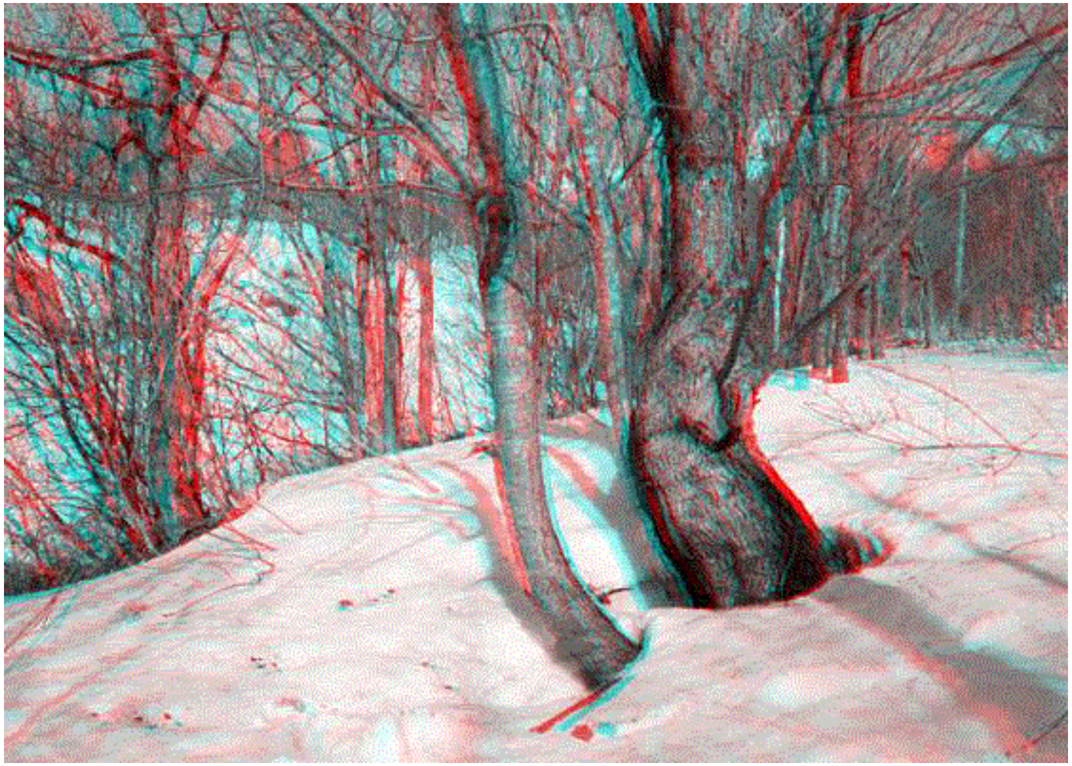



Stereograms

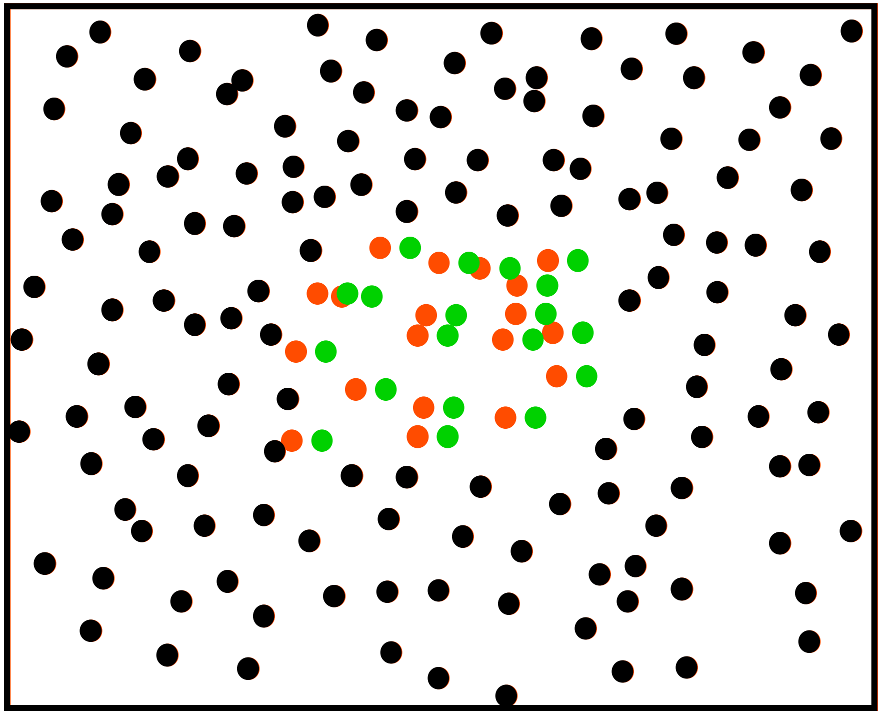
- Invented by Sir Charles Wheatstone, 1838

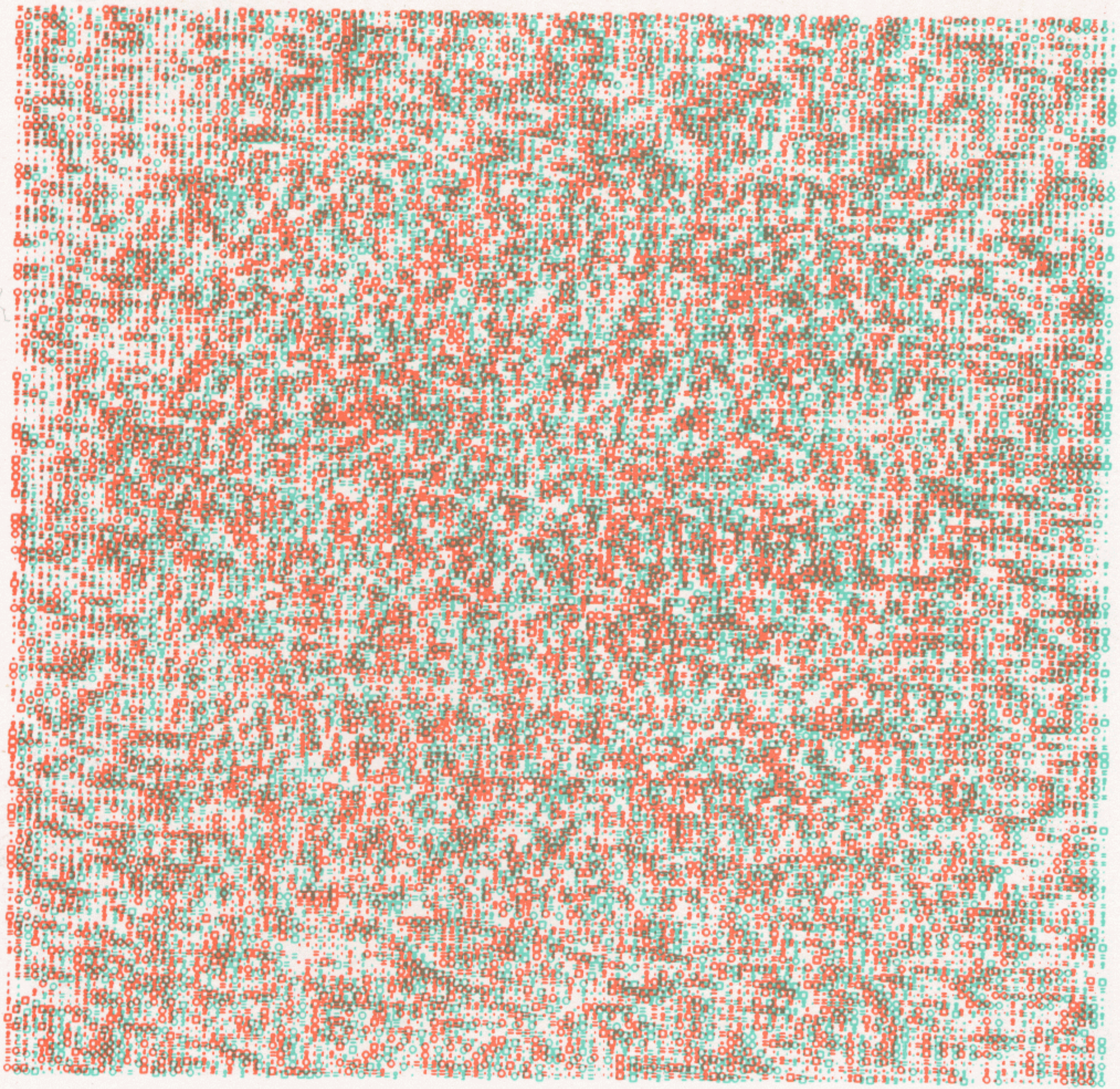


Red/green stereograms



Random dot stereograms





Autostereograms

Autostereograms: www.magiceye.com

Autostereograms

Autostereograms: www.magiceye.com

Correspondence algorithms

Algorithms may be top down or bottom up – random dot stereograms are an existence proof that bottom up algorithms are possible

From here on only consider bottom up algorithms

Algorithms may be classified into two types:

1. Dense: compute a correspondence at every pixel
2. Sparse: compute correspondences only for features

Example image pair – parallel cameras

First image

Second image

Dense correspondence algorithm

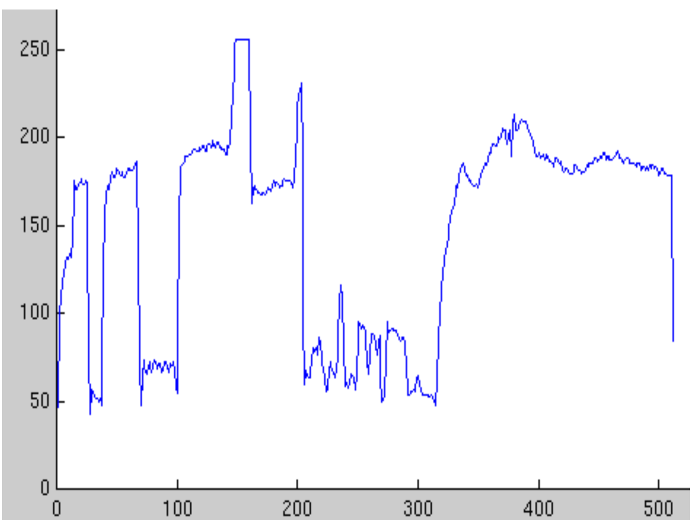
Parallel camera example – epipolar lines are corresponding rasters

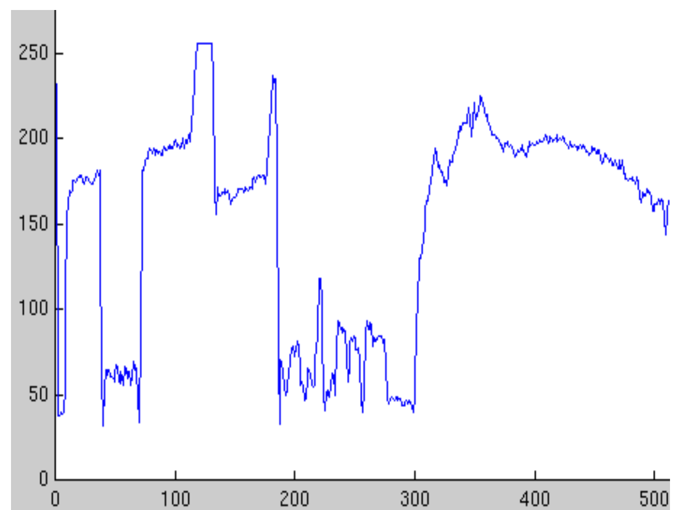
Search problem (geometric constraint): for each point in the left image, the corresponding point in the right image lies on the epipolar line (1D ambiguity)

Disambiguating assumption (photometric constraint): the intensity neighbourhood of corresponding points are similar across images

Measure similarity of neighbourhood intensity by cross-correlation

Intensity profiles





- Clear correspondence between intensities, but also noise and ambiguity

Normalized Cross Correlation

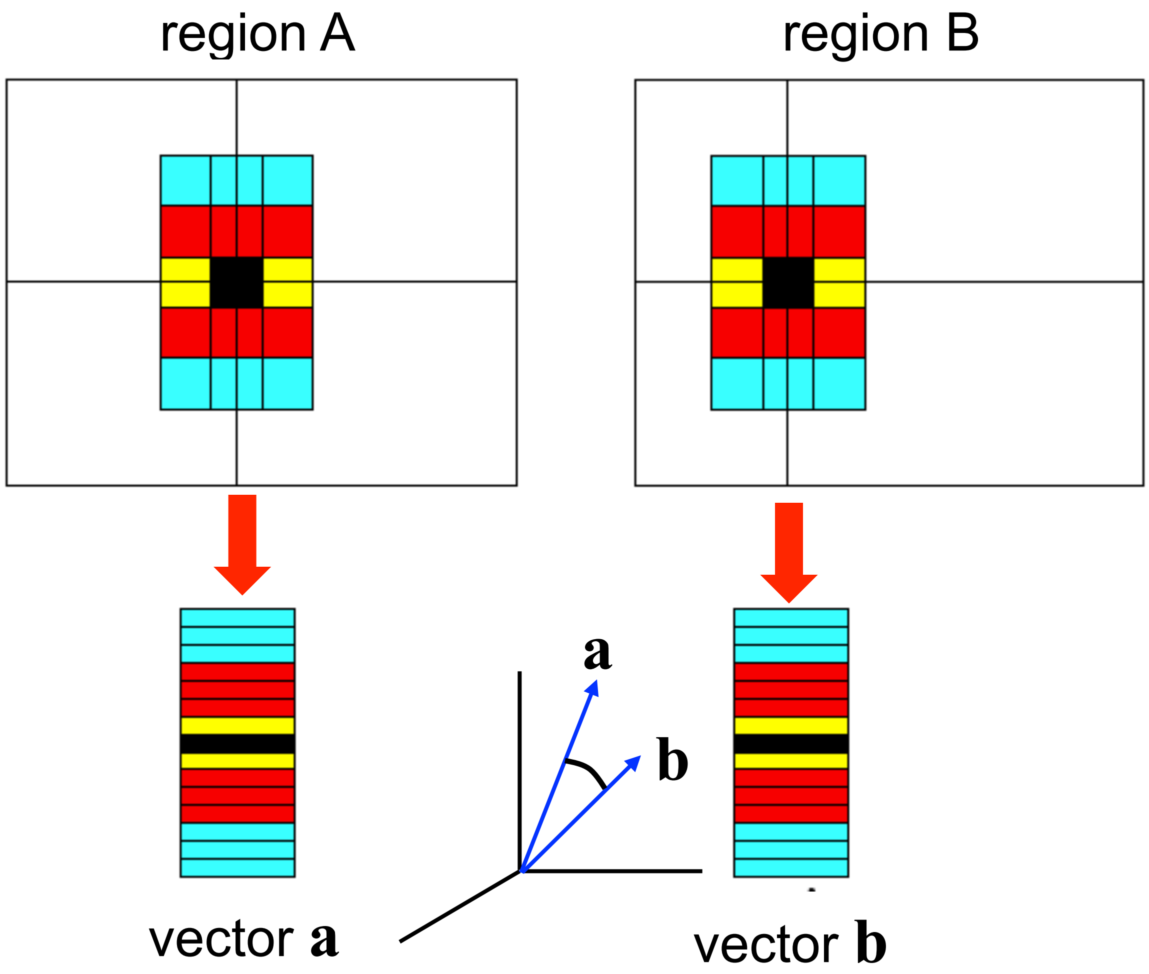
$$\text{NCC} = \frac{\sum_i \sum_j A(i,j)B(i,j)}{\sqrt{\sum_i \sum_j A(i,j)^2}\sqrt{\sum_i \sum_j B(i,j)^2}}$$

write regions as vectors

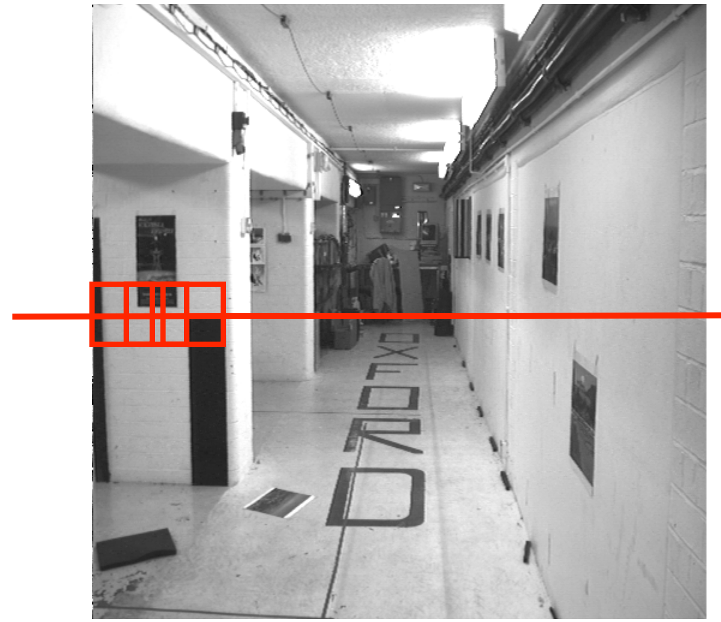
$$\mathtt{A} \rightarrow \mathbf{a}, \quad \mathtt{B} \rightarrow \mathbf{b}$$

$$\text{NCC} = \frac{\mathbf{a}.\mathbf{b}}{|\mathbf{a}||\mathbf{b}|}$$

$$-1 \leq \text{NCC} \leq 1$$



Cross-correlation of neighbourhood regions



regions A, B, write as vectors $\mathbf{a}, \mathbf{b}$

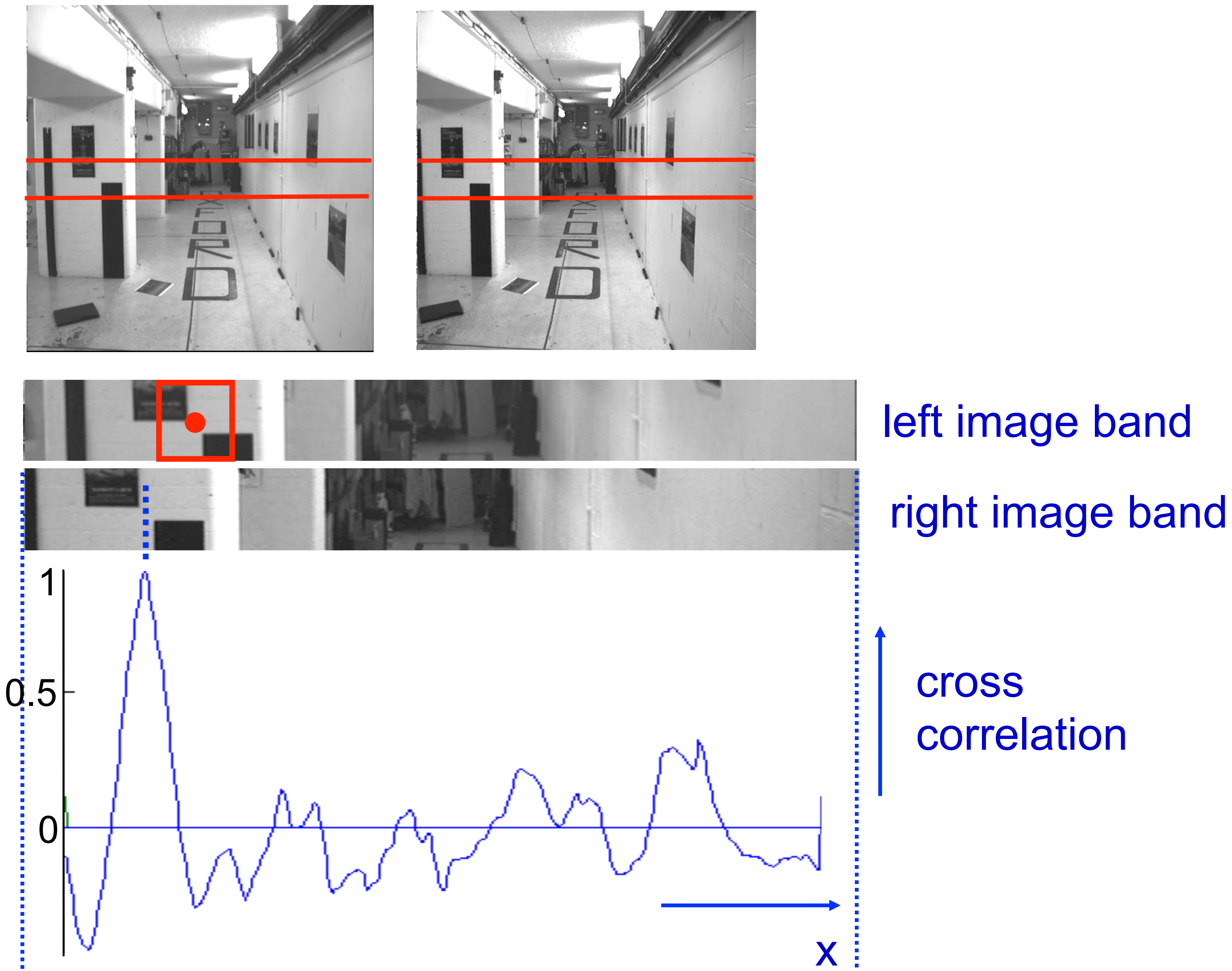
translate so that mean is zero

$$\mathtt{a} \rightarrow \mathtt{a} - \langle \mathbf{a} \rangle, \quad \mathtt{b} \rightarrow \mathtt{b} - \langle \mathbf{b} \rangle$$

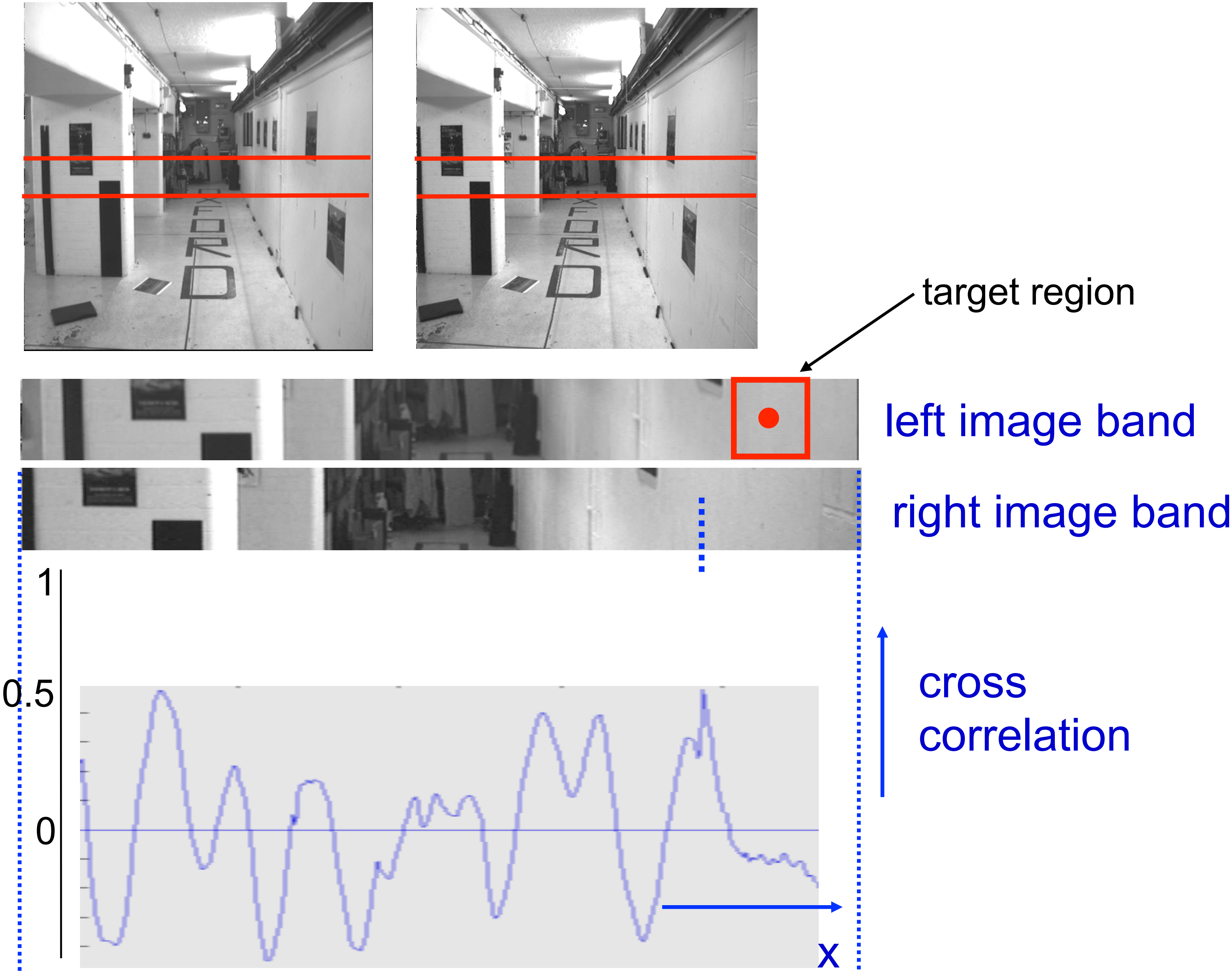
$$\text{cross correlation} = \frac{\mathbf{a}.\mathbf{b}}{|\mathbf{a}||\mathbf{b}|}$$

Invariant to $I \rightarrow \alpha I + \beta$

(exercise)



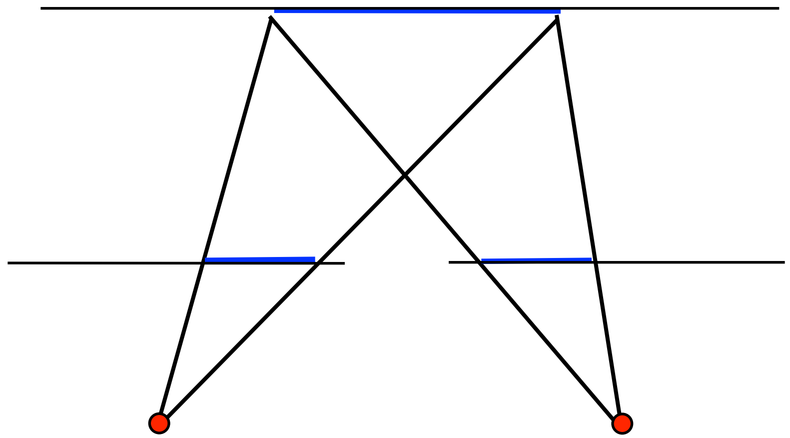
left image band
right image band
1
0.5
0
cross
correlation
x


target region
left image band
right image band
1
0.5
0
cross
correlation
x

Why is cross-correlation such a poor measure in the second case?

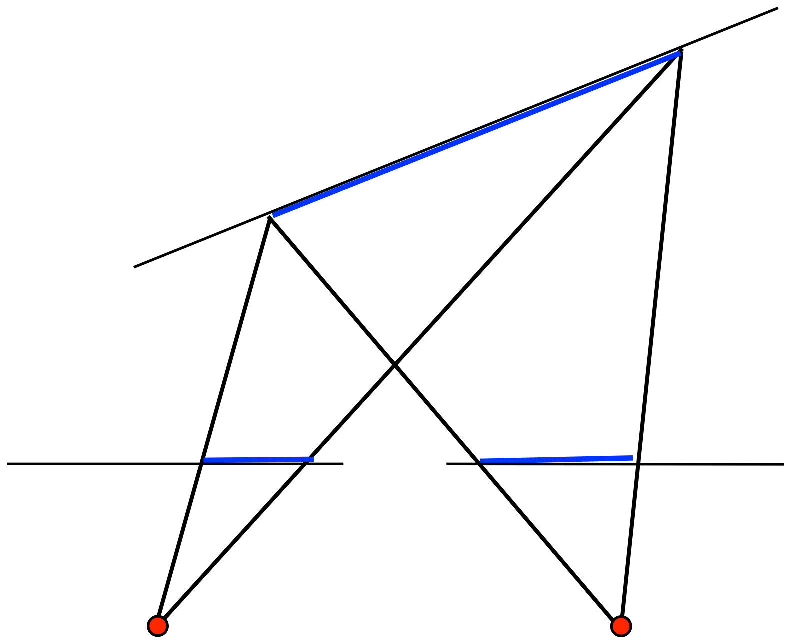
1. The neighbourhood region does not have a "distinctive" spatial intensity distribution

2. Foreshortening effects



fronto-parallel surface

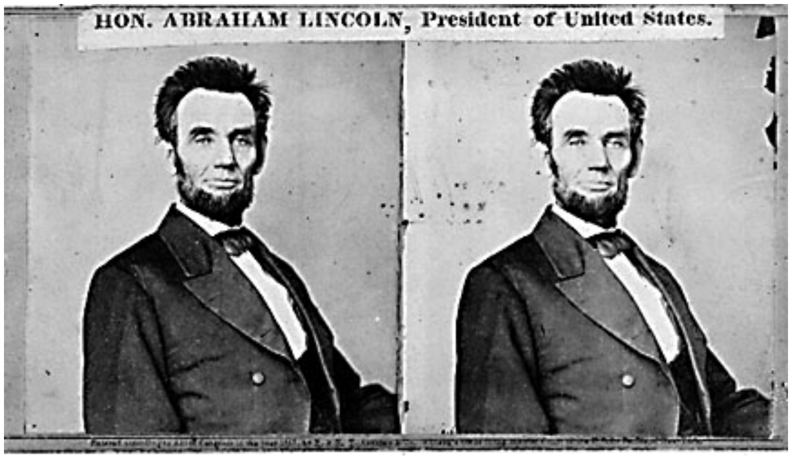
imaged length the same



slanting surface

imaged lengths differ

Limitations of similarity constraint



Textureless surfaces

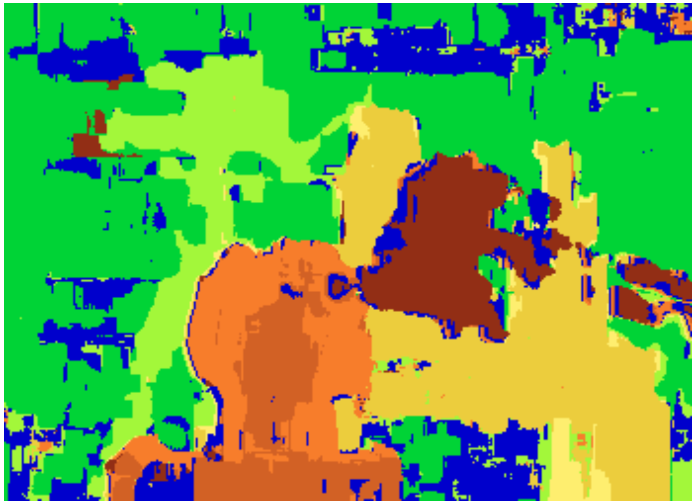
Occlusions, repetition

Non-Lambertian surfaces, specularities

Results with window search

Data

Window-based matching



Ground truth

Sketch of a dense correspondence algorithm

For each pixel in the left image

- compute the neighbourhood cross correlation along the corresponding epipolar line in the right image
- the corresponding pixel is the one with the highest cross correlation

Parameters

- size (scale) of neighbourhood
- search disparity

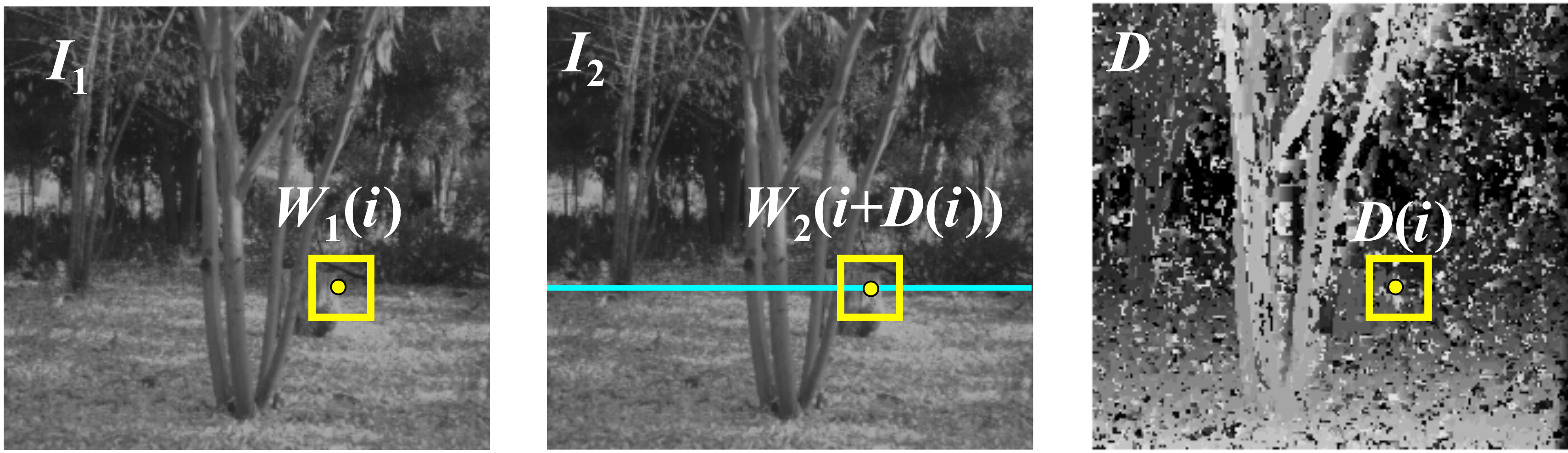
Other constraints

- uniqueness
- ordering
- smoothness of disparity field

Applicability

- textured scene, largely fronto-parallel

Stereo matching as energy minimization



MAP estimate of disparity image *D*: $P(D \mid I_1, I_2) \propto P(I_1, I_2 \mid D) P(D)$

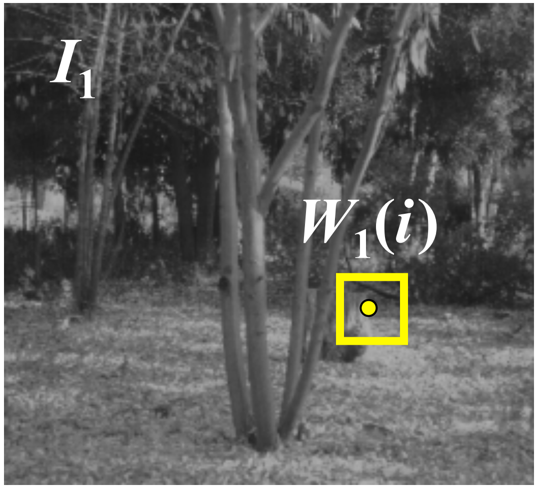
$$-\log P(D \mid I_1, I_2) \propto -\log P(I_1, I_2 \mid D) - \log P(D)$$

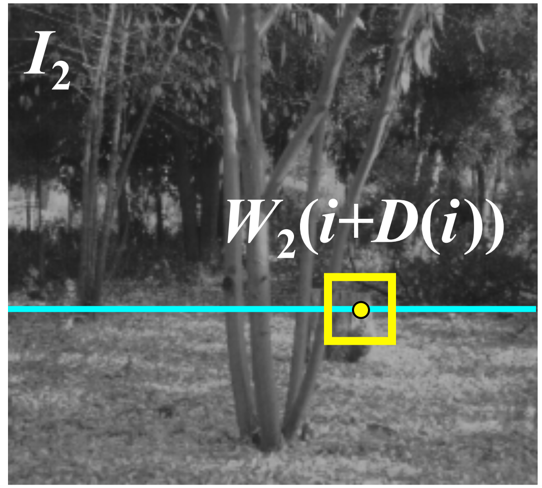
$$E = \alpha E_{\text{data}}(I_1, I_2, D) + \beta E_{\text{smooth}}(D)$$

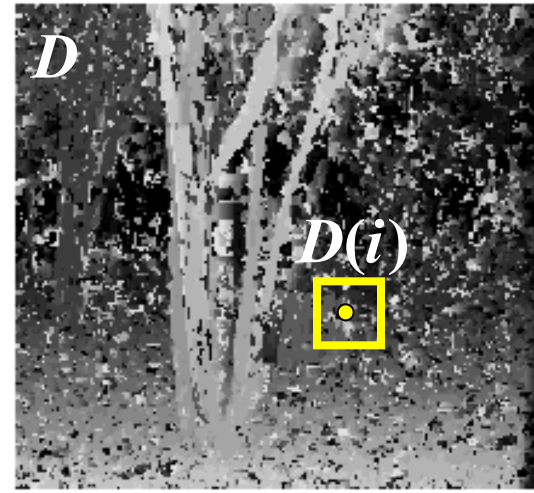
$$E_{\text{data}} = \sum_i \left(W_1(i) - W_2(i + D(i)) \right)^2$$

$$E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho\left(D(i) - D(j) \right)$$

Stereo matching as energy minimization







$$E = \alpha E_{\text{data}}(I_1, I_2, D) + \beta E_{\text{smooth}}(D)$$

$$E_{\text{data}} = \sum_i \left(W_1(i) - W_2(i + D(i))\right)^2$$

$$E_{\text{smooth}} = \sum_{\text{neighbors } i,j} \rho\left(D(i) - D(j)\right)$$

- Energy functions of this form can be minimized using *graph cuts*

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

Graph cuts solution

Graph cuts

Ground truth

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

For the latest and greatest: http://www.middlebury.edu/stereo/

Example dense correspondence algorithm

left image

right image

3D reconstruction

right image

depth map

intensity = depth

Texture mapped 3D triangulation

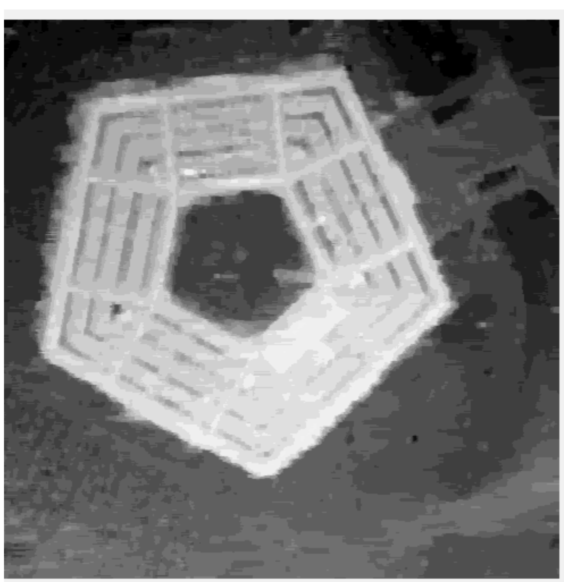
 

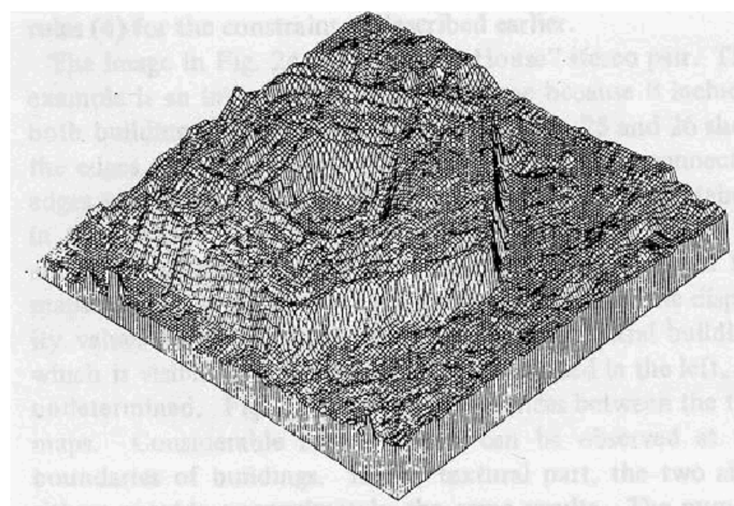
Pentagon example

left image

right image

range map

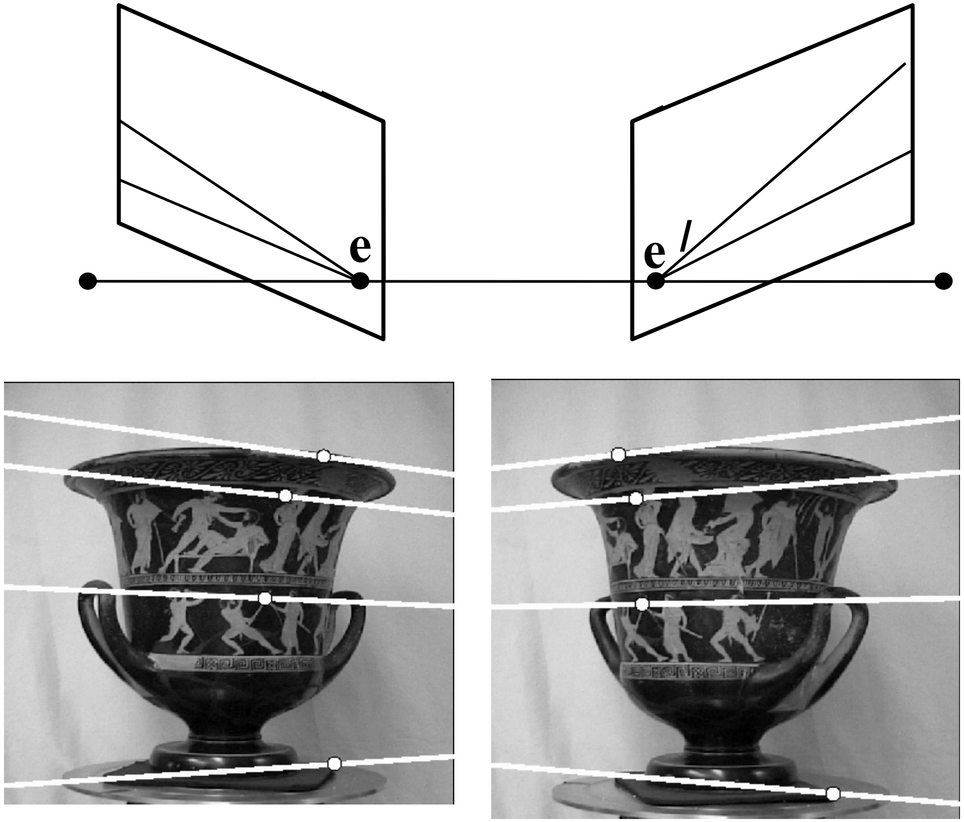




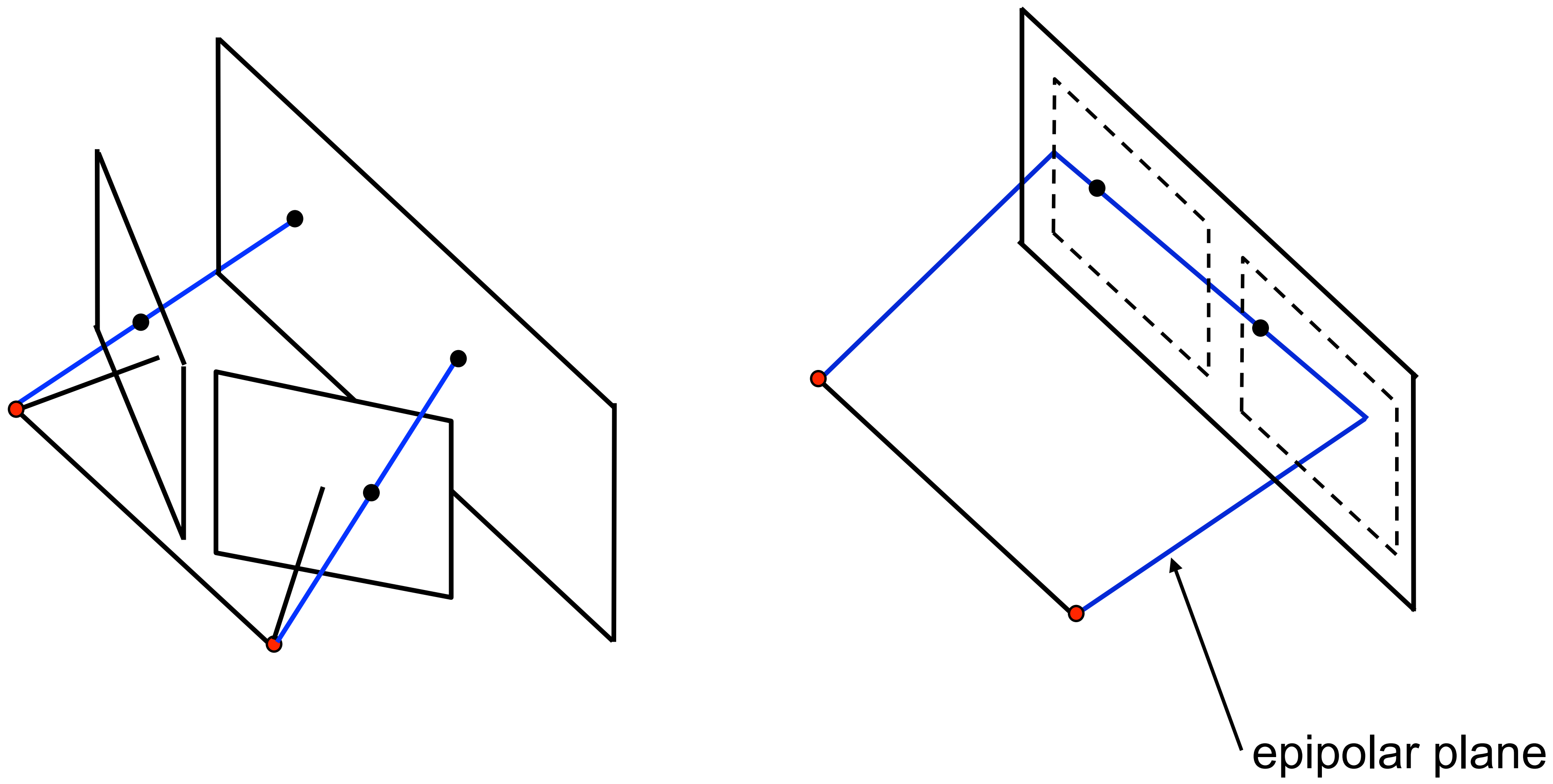
Rectification

For converging cameras

- epipolar lines are not parallel



Project images onto plane parallel to baseline



Rectification continued

Convert converging cameras to parallel camera geometry by an image mapping

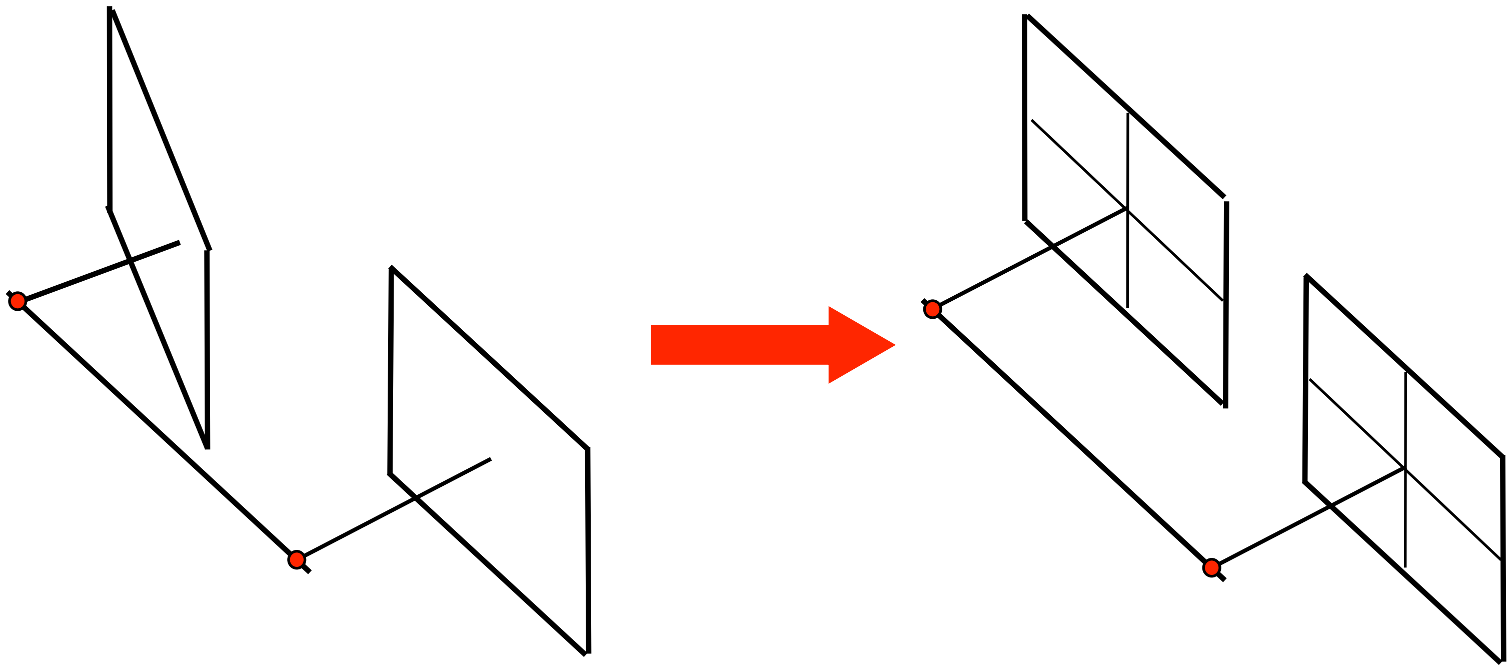


Image mapping is a 2D homography (projective transformation)

$$H = KRK^{-1}$$ (exercise)

Rectification continued

Convert converging cameras to parallel camera geometry by an image mapping

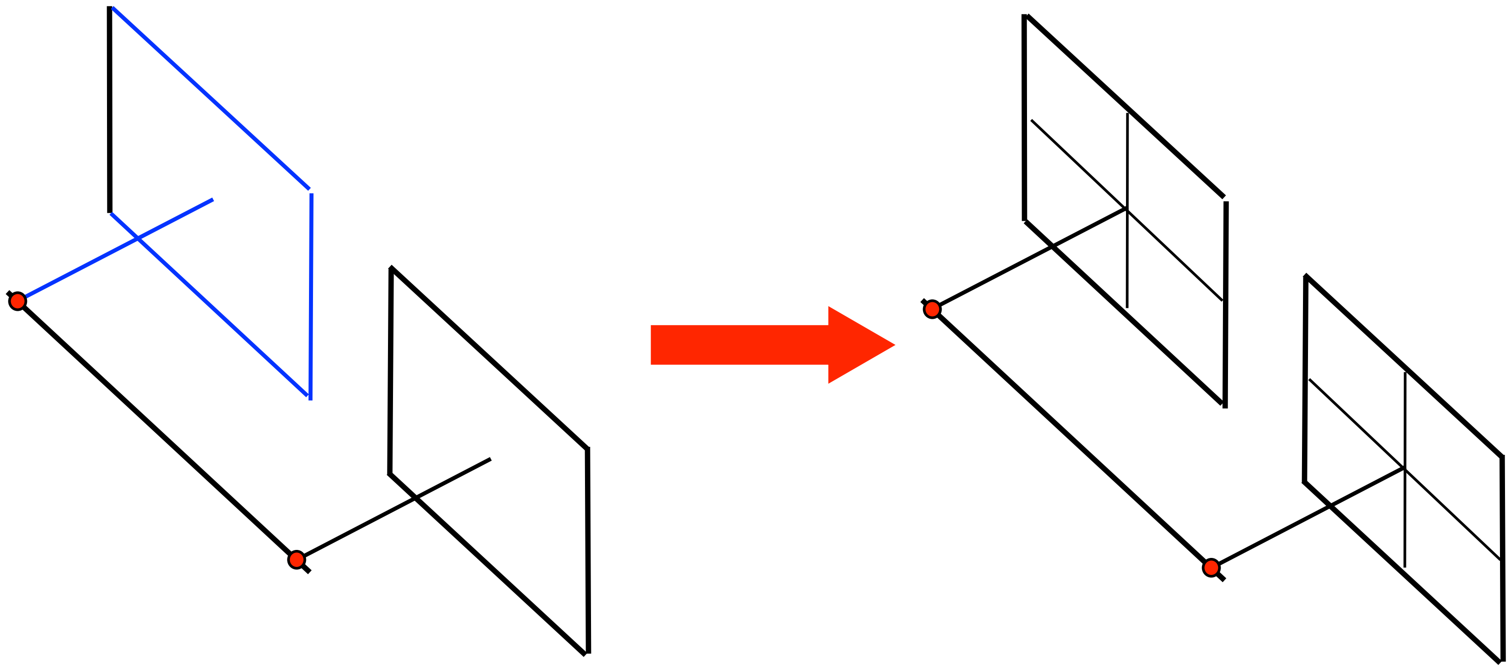
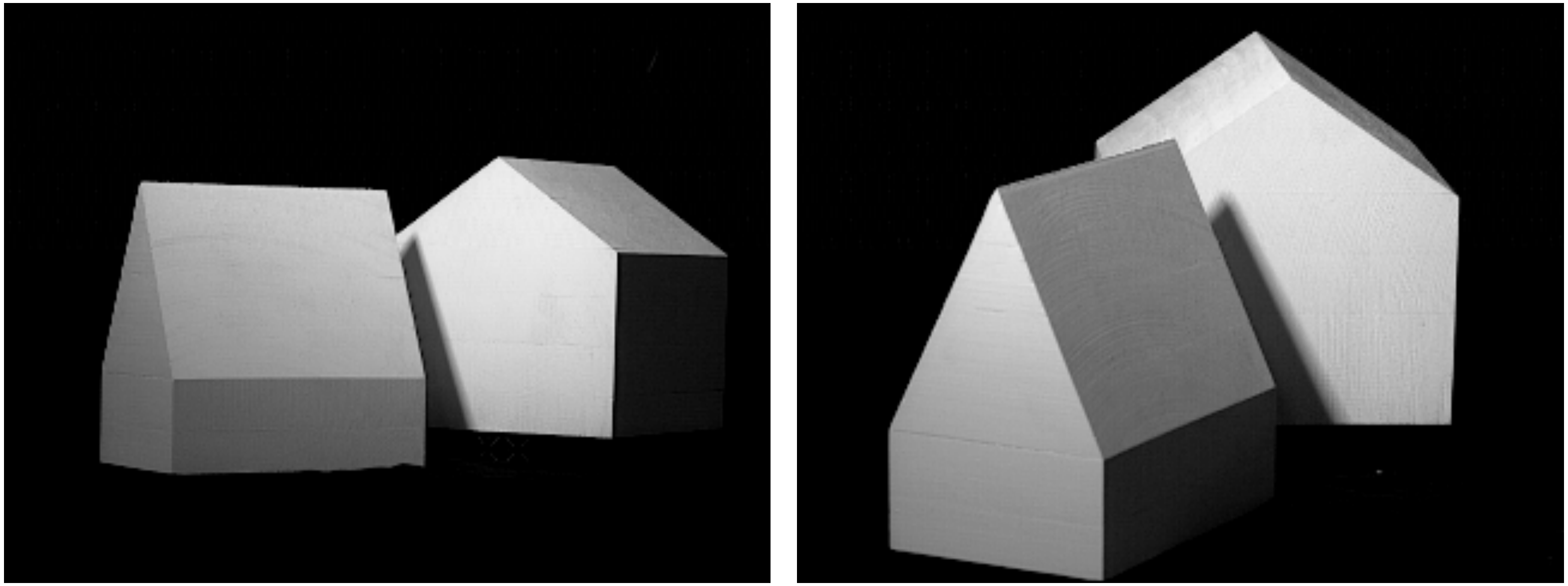


Image mapping is a 2D homography (projective transformation)

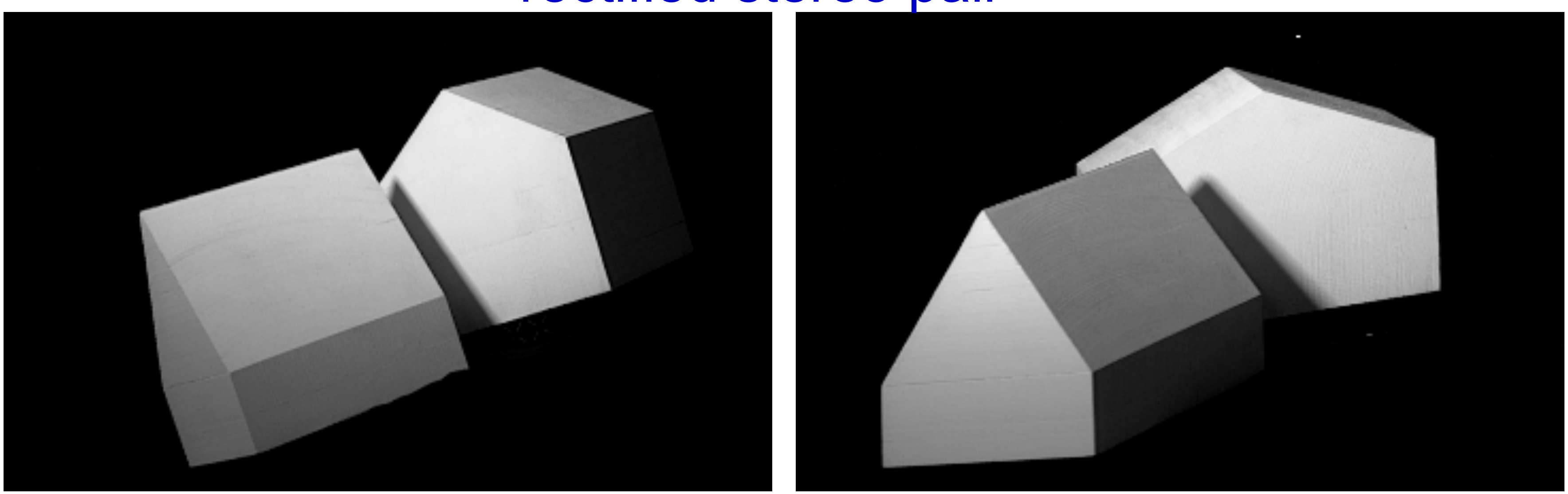
$$H = KRK^{-1}$$ (exercise)

Example

original stereo pair



rectified stereo pair



Example: depth and disparity for a parallel camera stereo rig

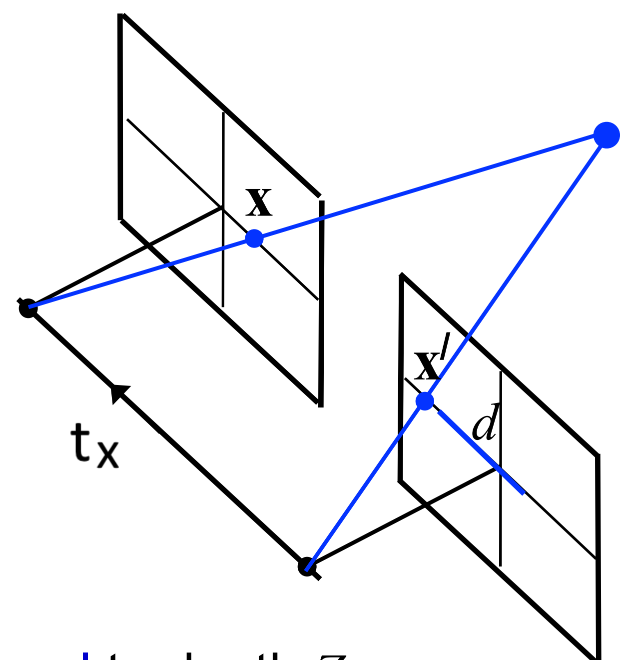
$$\mathtt{K} = \mathtt{K}' = \begin{bmatrix} f & 0 & 0 \\ 0 & f & 0 \\ 0 & 0 & 1 \end{bmatrix} \qquad \mathtt{R} = \mathtt{I} \quad \mathbf{t} = \begin{pmatrix} t_x \\ 0 \\ 0 \end{pmatrix}$$

Then, $y' = y$, and the disparity $d = x' - x = \frac{f t_x}{Z}$

Derivation

$$\frac{x}{f} = \frac{X}{Z} \qquad \frac{x'}{f} = \frac{X + t_x}{Z}$$

$$\frac{x'}{f} = \frac{x}{f} + \frac{t_x}{Z}$$



Note

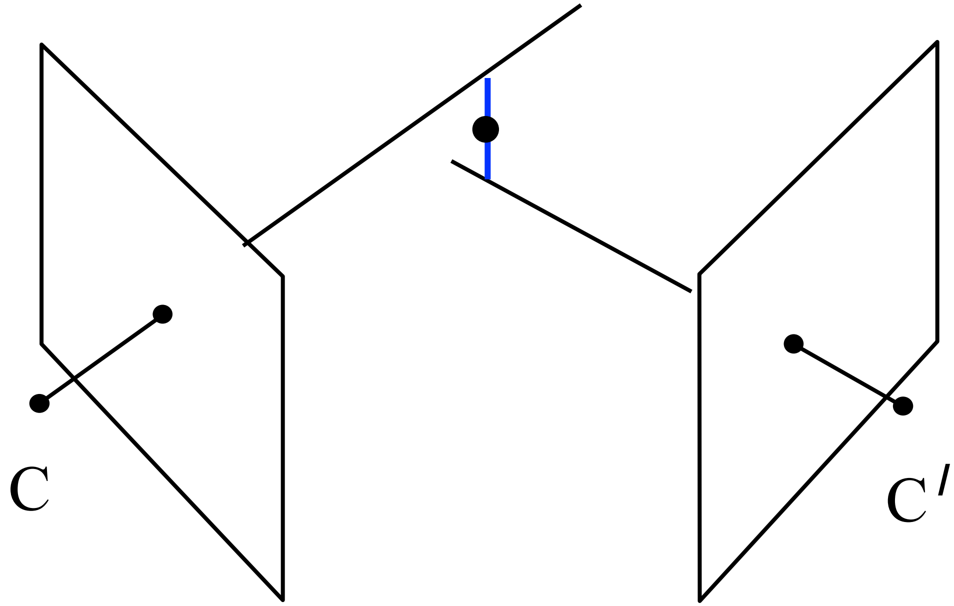
- image movement (disparity) is inversely proportional to depth Z

  as $z \to \infty,\ d \to 0$

- depth is inversely proportional to disparity

Triangulation

1. Vector solution



Compute the mid-point of the shortest line between the two rays

2. Linear triangulation (algebraic solution)

Use the equations $\mathbf{x} = \mathtt{P}\mathbf{X}$ and $\mathbf{x}' = \mathtt{P}'\mathbf{X}$ to solve for $\mathbf{X}$

For the first camera:

$$\mathtt{P} = \begin{bmatrix} p_{11} & p_{12} & p_{13} & p_{14} \\ p_{21} & p_{22} & p_{23} & p_{24} \\ p_{31} & p_{32} & p_{33} & p_{34} \end{bmatrix} = \begin{bmatrix} \mathbf{p}^{1\top} \\ \mathbf{p}^{2\top} \\ \mathbf{p}^{3\top} \end{bmatrix}$$

where $\mathbf{p}^{i\top}$ are the rows of $\mathtt{P}$

- eliminate unknown scale in $\lambda\mathbf{x} = \mathtt{P}\mathbf{X}$ by forming a cross product $\mathbf{x} \times (\mathtt{P}\mathbf{X}) = \mathbf{0}$

$$\begin{aligned} x(\mathbf{p}^{3\top}\mathbf{X}) - (\mathbf{p}^{1\top}\mathbf{X}) &= 0 \\ y(\mathbf{p}^{3\top}\mathbf{X}) - (\mathbf{p}^{2\top}\mathbf{X}) &= 0 \\ x(\mathbf{p}^{2\top}\mathbf{X}) - y(\mathbf{p}^{1\top}\mathbf{X}) &= 0 \end{aligned}$$

- rearrange as (first two equations only)

$$\begin{bmatrix} x\mathbf{p}^{3\top} - \mathbf{p}^{1\top} \\ y\mathbf{p}^{3\top} - \mathbf{p}^{2\top} \end{bmatrix} \mathbf{X} = \mathbf{0}$$

Similarly for the second camera:

$$\begin{bmatrix} x'\mathbf{p}'^{3\top} - \mathbf{p}'^{1\top} \\ y'\mathbf{p}'^{3\top} - \mathbf{p}'^{2\top} \end{bmatrix} \mathbf{X} = \mathbf{0}$$

Collecting together gives

$$\mathtt{A}\mathbf{X} = \mathbf{0}$$

where $\mathtt{A}$ is the 4×4 matrix

$$\mathtt{A} = \begin{bmatrix} x\mathbf{p}^{3\top} - \mathbf{p}^{1\top} \\ y\mathbf{p}^{3\top} - \mathbf{p}^{2\top} \\ x'\mathbf{p}'^{3\top} - \mathbf{p}'^{1\top} \\ y'\mathbf{p}'^{3\top} - \mathbf{p}'^{2\top} \end{bmatrix}$$

from which $\mathbf{X}$ can be solved up to scale.

Problem: does not minimize anything meaningful

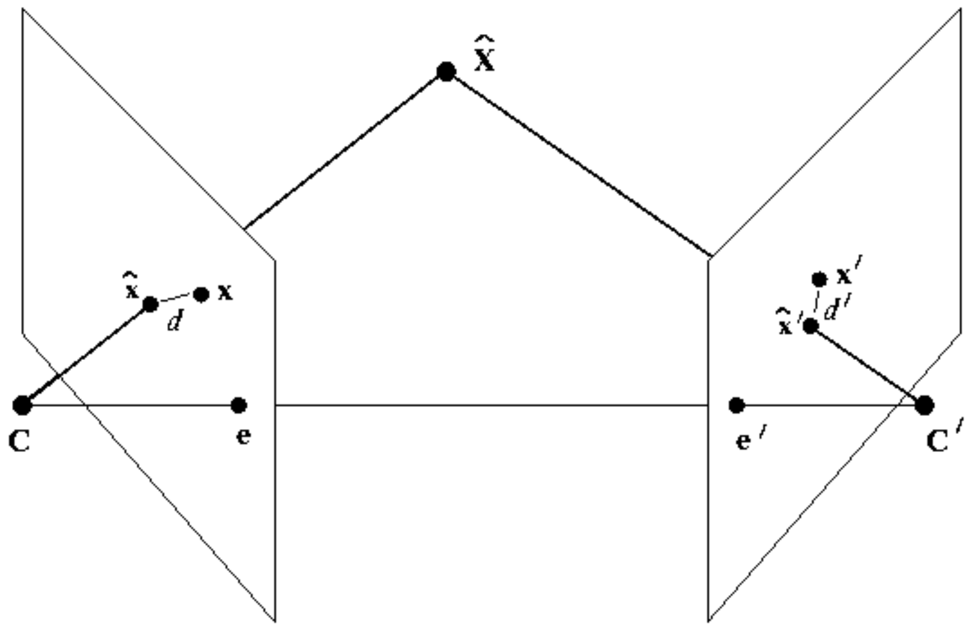
Advantage: extends to more than two views

3. Minimizing a geometric/statistical error

The idea is to estimate a 3D point $\widehat{\mathrm{X}}$ which exactly satisfies the supplied camera geometry, so it projects as

$$\hat{\mathrm{x}} = \mathrm{P}\widehat{\mathrm{X}} \qquad \hat{\mathrm{x}}' = \mathrm{P}'\widehat{\mathrm{X}}$$

and the aim is to estimate $\widehat{\mathrm{X}}$ from the image measurements x and x'.



$$\min_{\widehat{\mathrm{X}}} \quad \mathcal{C}(\mathbf{x}, \mathbf{x}') = d(\mathbf{x}, \hat{\mathbf{x}})^2 + d(\mathbf{x}', \hat{\mathbf{x}}')^2$$

where $d(*, *)$ is the Euclidean distance between the points.

- It can be shown that if the measurement noise is Gaussian mean zero, $\sim N(0, \sigma^2)$, then minimizing geometric error is the Maximum Likelihood Estimate of X

- The minimization appears to be over three parameters (the position X), but the problem can be reduced to a minimization over one parameter

Different formulation of the problem

The minimization problem may be formulated differently:

- Minimize

$$d(\mathbf{x}, \mathbf{l})^2 + d(\mathbf{x}', \mathbf{l}')^2$$

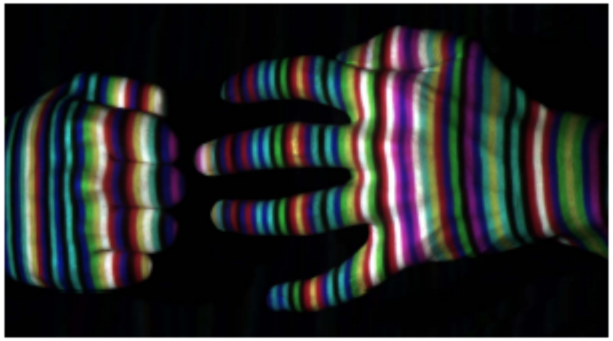
- $\mathbf{l}$ and $\mathbf{l}'$ range over all choices of corresponding epipolar lines.
- $\hat{\mathbf{x}}$ is the closest point on the line $\mathbf{l}$ to $\mathbf{x}$.
- Same for $\hat{\mathbf{x}}'$.

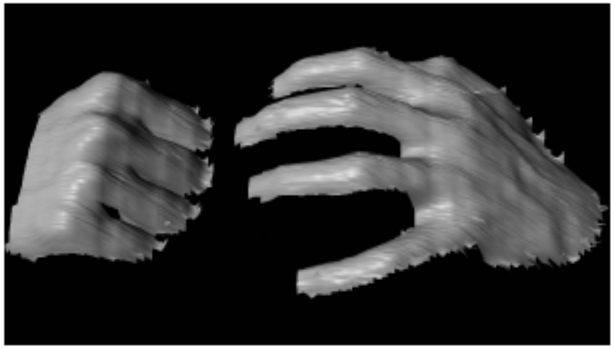
Minimization method

- Parametrize the pencil of epipolar lines in the first image by t, such that the epipolar line is $\mathbf{l}(t)$
- Using F compute the corresponding epipolar line in the second image $\mathbf{l}'(t)$
- Express the distance function $d(\mathbf{x}, \mathbf{l})^2 + d(\mathbf{x}', \mathbf{l}')^2$ explicitly as a function of t
- Find the value of t that minimizes the distance function
- Solution is a 6th degree polynomial in t

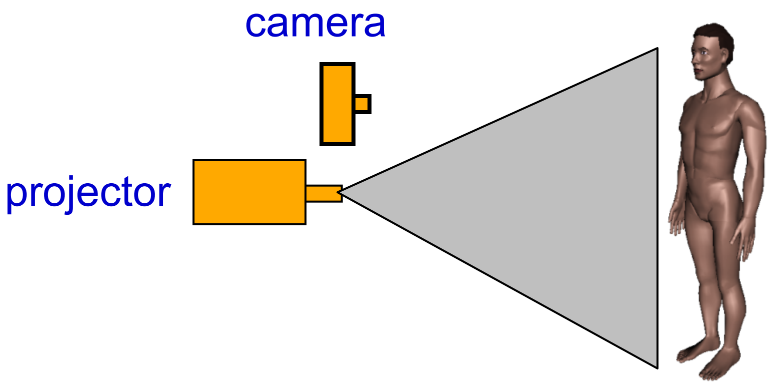
Other approaches to obtaining 3D structure

Active stereo with structured light



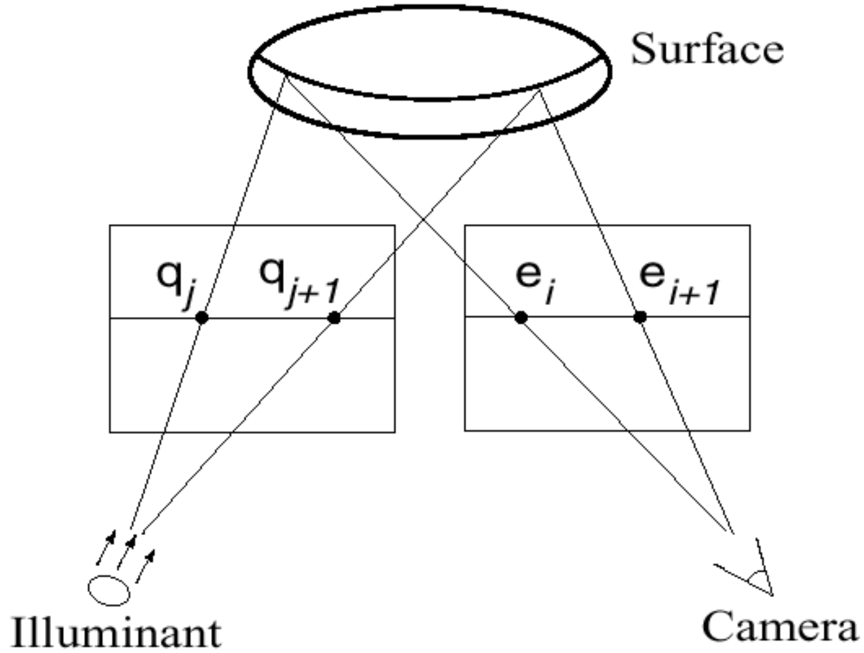


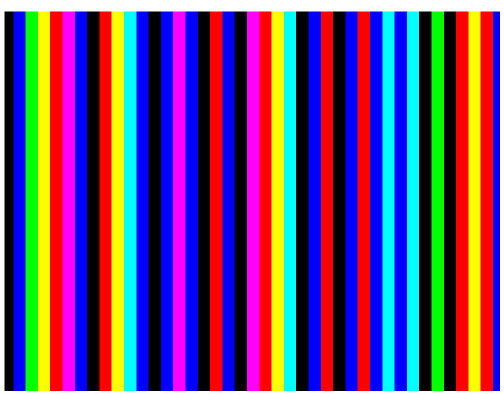
- Project "structured" light patterns onto the object
  - simplifies the correspondence problem
  - Allows us to use only one camera

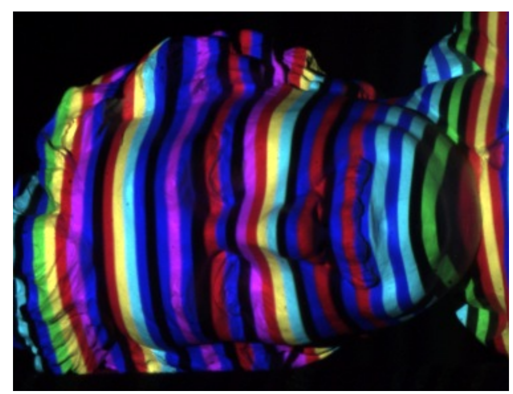


L. Zhang, B. Curless, and S. M. Seitz.
Rapid Shape Acquisition Using Color Structured Light and Multi-pass Dynamic Programming. *3DPVT* 2002

Active stereo with structured light

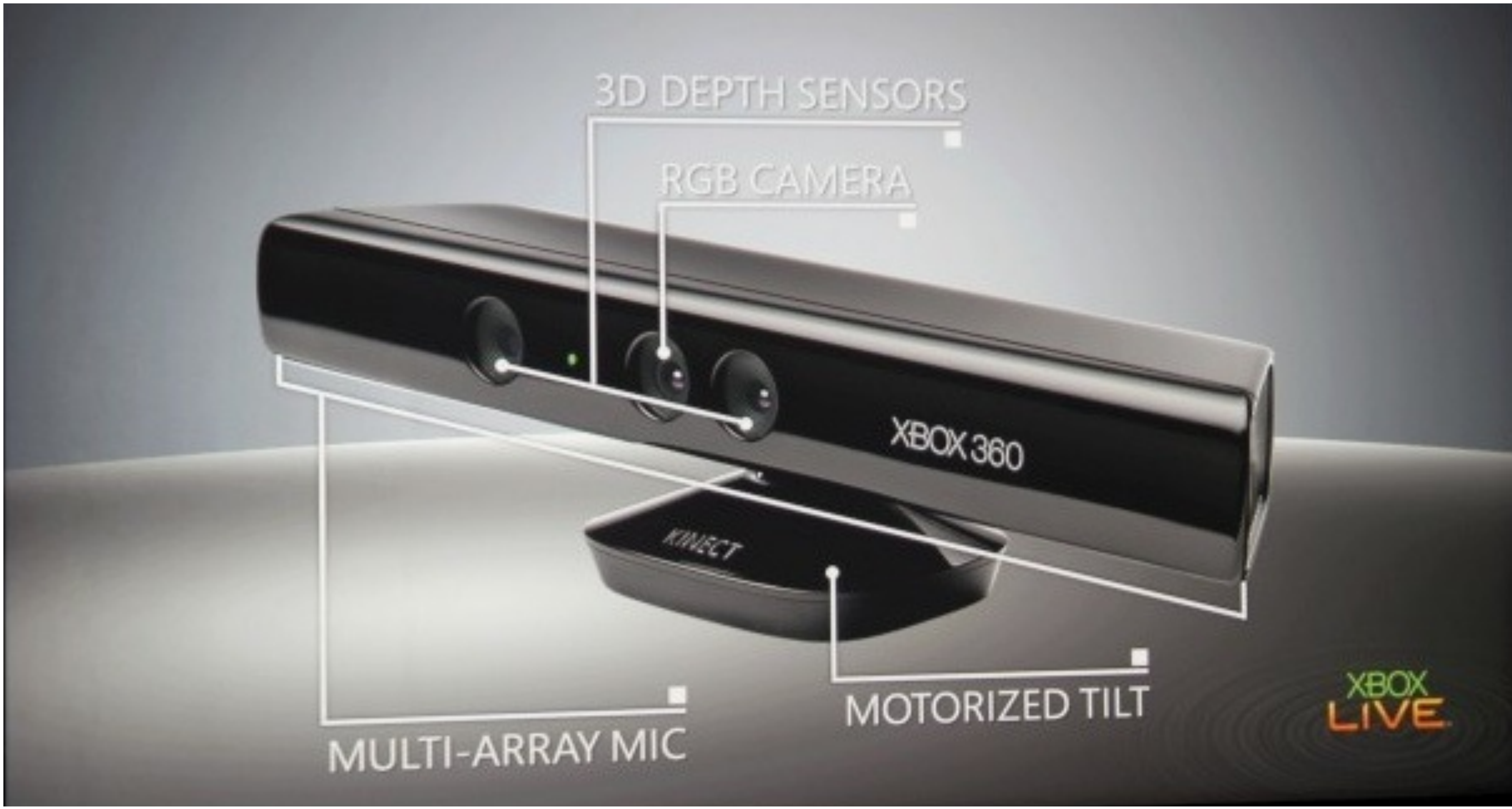




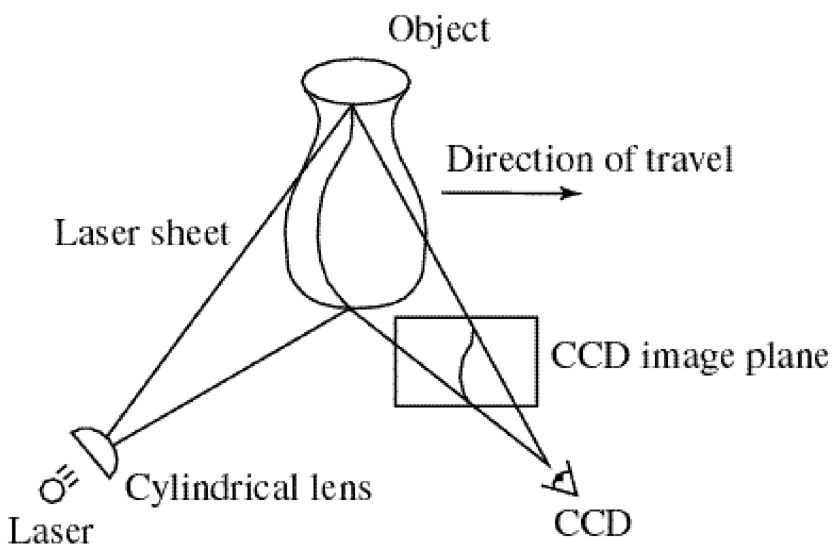


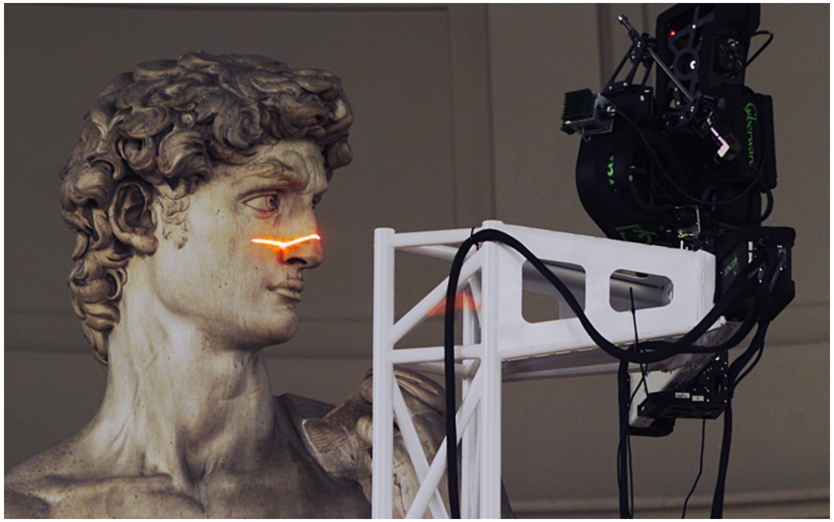
L. Zhang, B. Curless, and S. M. Seitz.
Rapid Shape Acquisition Using Color Structured Light and Multi-pass Dynamic Programming. *3DPVT* 2002

Microsoft Kinect



Laser scanning





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

Source: S. Seitz

Laser scanned models

The Digital Michelangelo Project, Levoy et al.

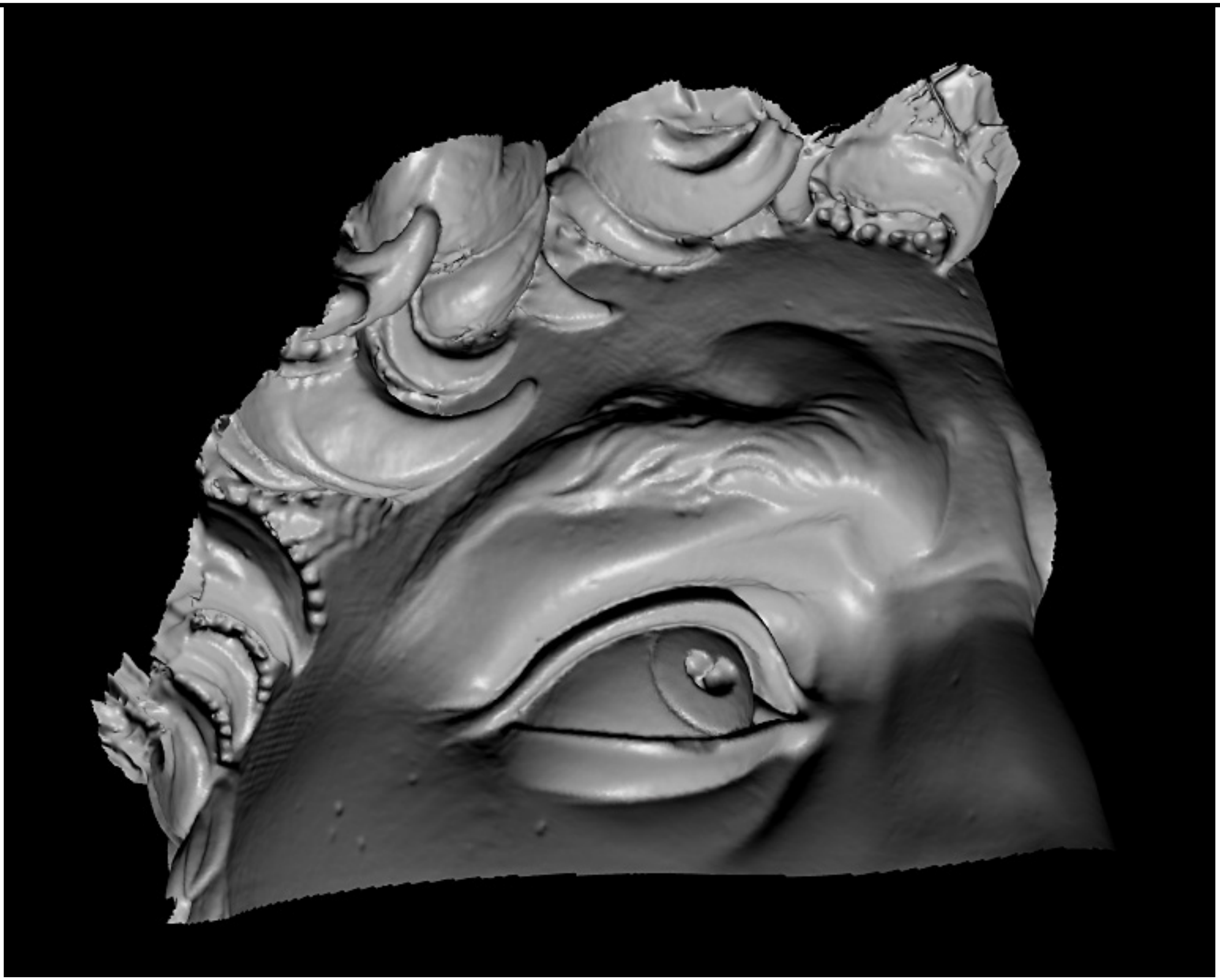
Source: S. Seitz

Laser scanned models

The Digital Michelangelo Project, Levoy et al.

Source: S. Seitz

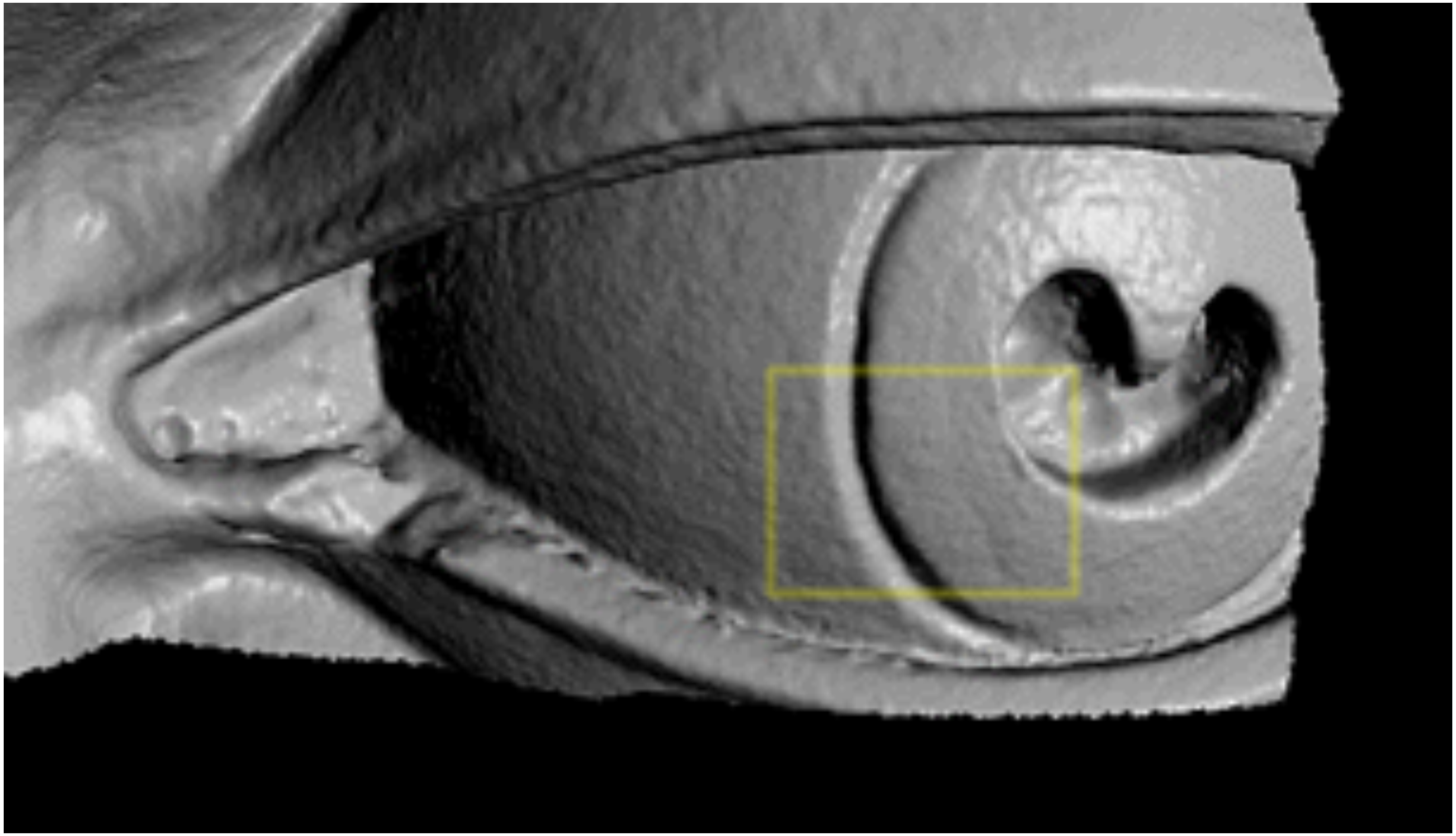
Laser scanned models



The Digital Michelangelo Project, Levoy et al.

Source: S. Seitz

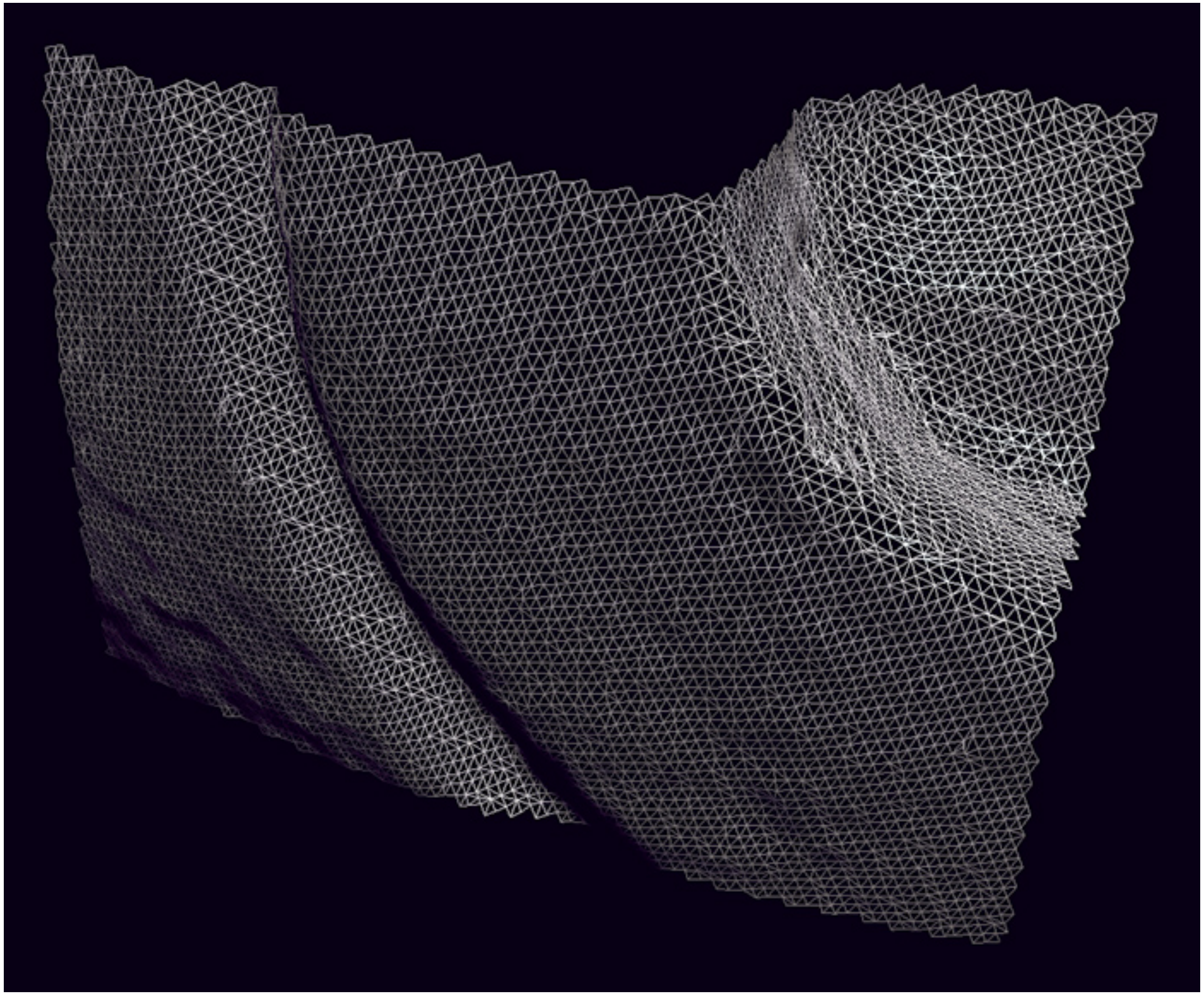
Laser scanned models



The Digital Michelangelo Project, Levoy et al.

Source: S. Seitz

Laser scanned models

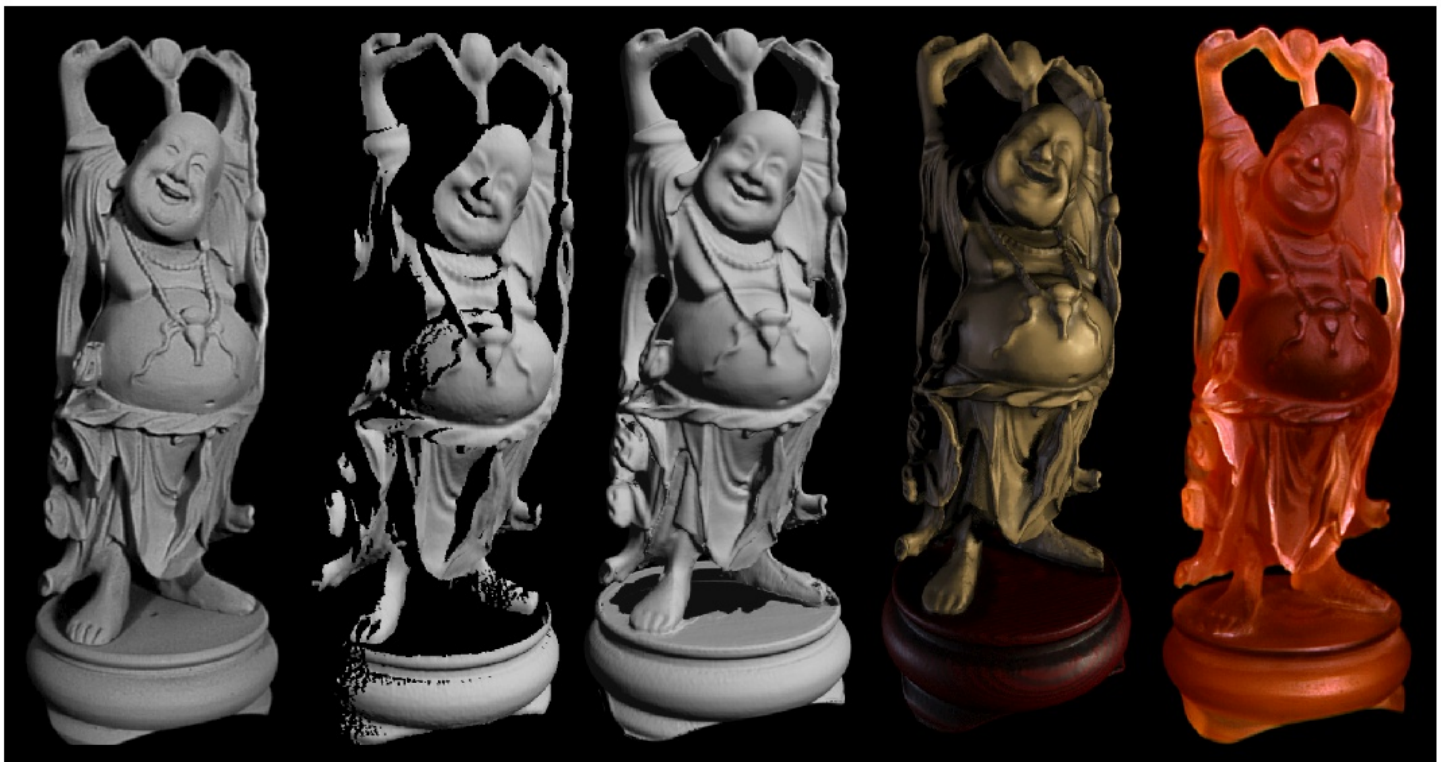


The Digital Michelangelo Project, Levoy et al.

Source: S. Seitz

Aligning range images

- A single range scan is not sufficient to describe a complex surface
- Need techniques to register multiple range images



B. Curless and M. Levoy,
A Volumetric Method for Building Complex Models from Range Images, SIGGRAPH 1996

Aligning range images

- A single range scan is not sufficient to describe a complex surface
- Need techniques to register multiple range images

  - … which brings us to *multi-view stereo*