Industrial Computer Vision

- Epipolar Geometry

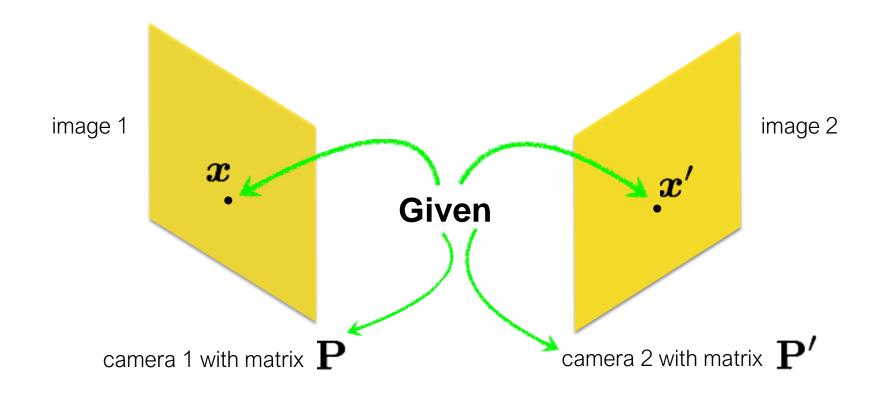


12th lecture, 2021.11.24 Lecturer: Youngbae Hwang

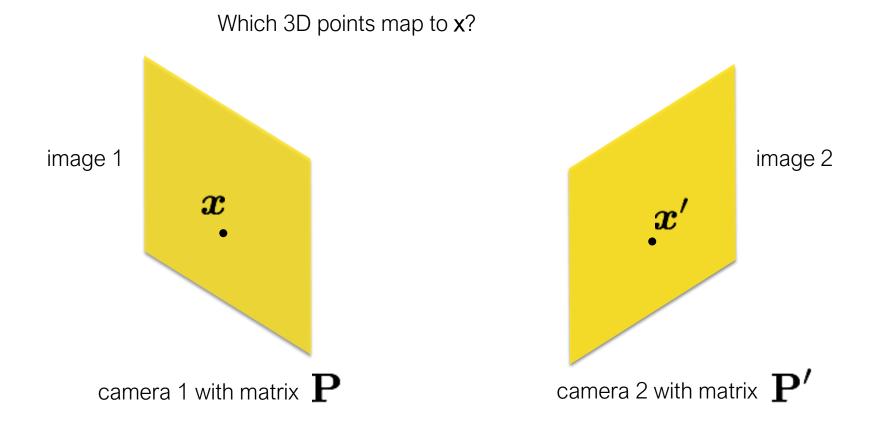


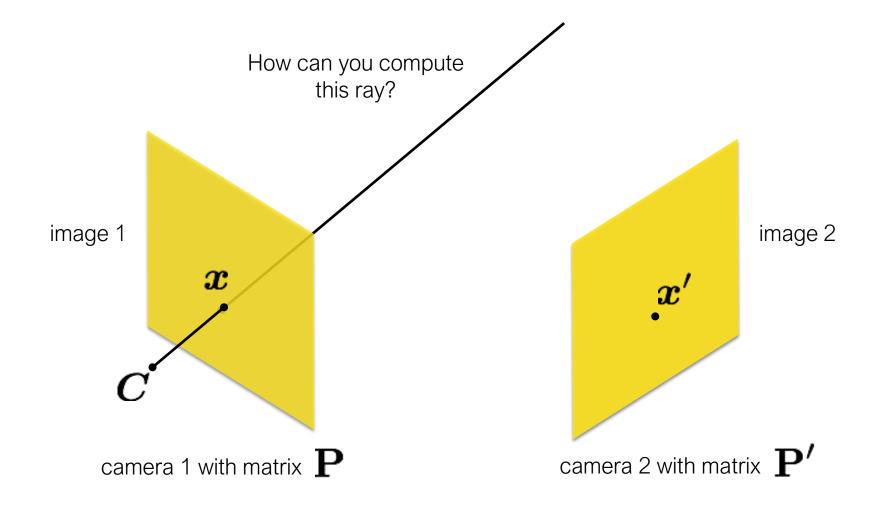
Contents

- Triangulation
- Epipolar Geometry
- Essential/Fundamental Matrix
- Stereo Rectification









Create two points on the ray:

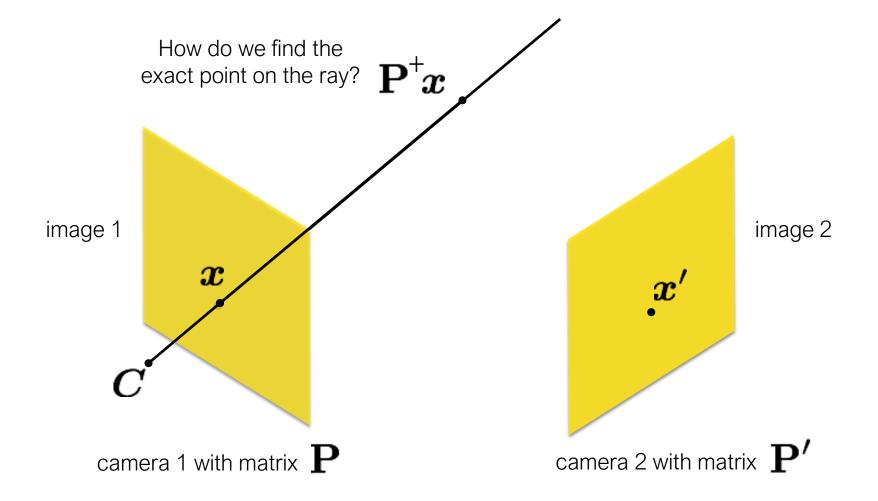
1) find the camera center; and

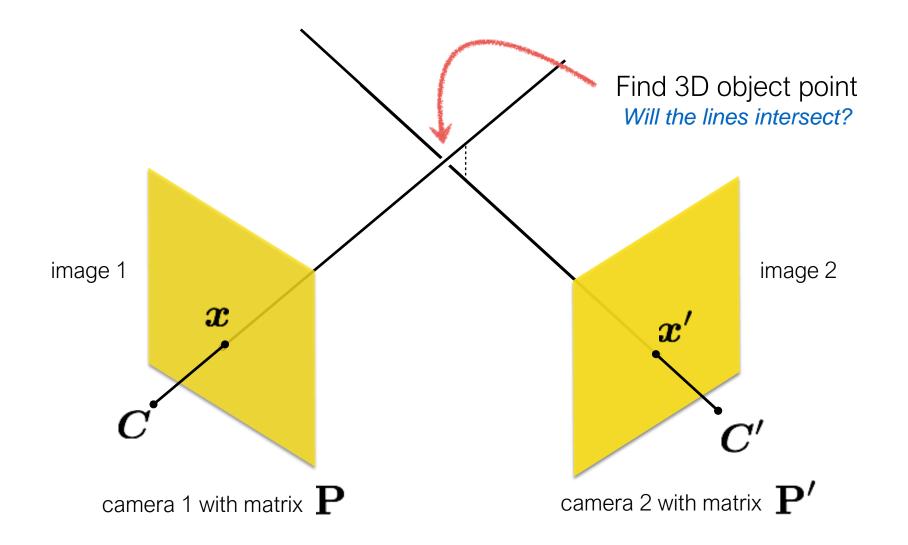
2) apply the pseudo-inverse of **P** on **x**. Then connect the two points. This procedure is called backprojection Why does this poin t map to x? image 2 image 1

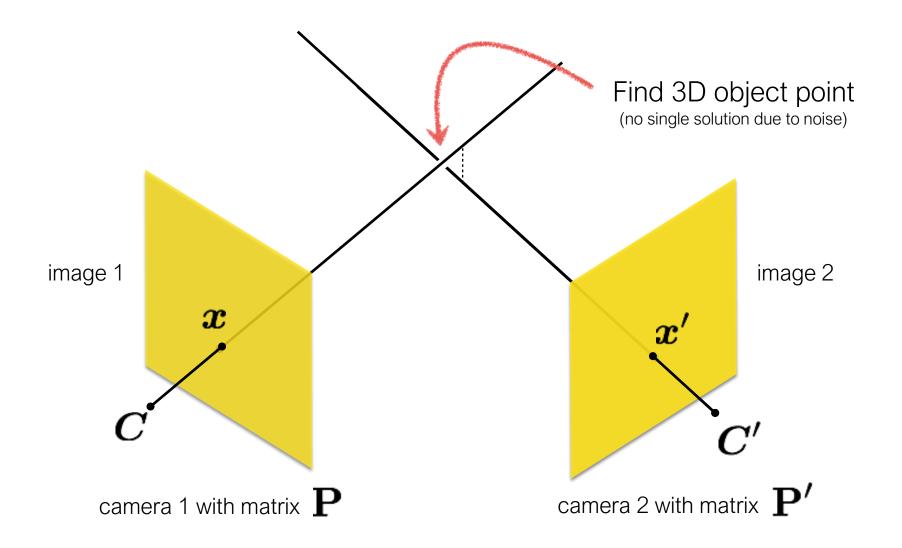
camera 1 with matrix ${f P}$



camera 2 with matrix $\mathbf{P'}$







Given a set of (noisy) matched points

$$\{oldsymbol{x}_i,oldsymbol{x}_i'\}$$

and camera matrices

$$\mathbf{P}, \mathbf{P}'$$

Estimate the 3D point

 ${f X}$



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

Can we compute **X** from a single correspondence **x**?



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

(homogeneous co ordinate)

This is a similarity relation because it involves homogeneous coordinates

$$\mathbf{x} = lpha \mathbf{P} X$$
(homorogeneous coordinate)

Same ray direction but differs by a scale factor

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we solve for unknowns in a similarity relation?



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

(homogeneous co ordinate)

Also, this is a similarity relation because it involves homogeneous coordinates

$$\mathbf{x} = lpha \mathbf{P} X$$
 (inhomogeneous coordinate)

Same ray direction but differs by a scale factor

$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

How do we solve for unknowns in a similarity relation?



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

Same direction but differs by a scale factor

$$\mathbf{x} \times \mathbf{P} X = \mathbf{0}$$

Cross product of two vectors of same direction is zero (this equality removes the scale factor)



$$\begin{bmatrix} x \\ y \\ z \end{bmatrix} = \alpha \begin{bmatrix} p_1 & p_2 & p_3 & p_4 \\ p_5 & p_6 & p_7 & p_8 \\ p_9 & p_{10} & p_{11} & p_{12} \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

rix and points

$$\left[egin{array}{c} x \ y \ z \end{array}
ight] = lpha \left[egin{array}{c} oldsymbol{p}_1^ op oldsymbol{X} \ oldsymbol{p}_2^ op oldsymbol{X} \ oldsymbol{p}_3^ op oldsymbol{X} \end{array}
ight]$$

$$\begin{bmatrix} x \\ y \\ 1 \end{bmatrix} \times \begin{bmatrix} \boldsymbol{p}_1^{\top} \boldsymbol{X} \\ \boldsymbol{p}_2^{\top} \boldsymbol{X} \\ \boldsymbol{p}_3^{\top} \boldsymbol{X} \end{bmatrix} = \begin{bmatrix} y \boldsymbol{p}_3^{\top} \boldsymbol{X} - \boldsymbol{p}_2^{\top} \boldsymbol{X} \\ \boldsymbol{p}_1^{\top} \boldsymbol{X} - x \boldsymbol{p}_3^{\top} \boldsymbol{X} \\ x \boldsymbol{p}_2^{\top} \boldsymbol{X} - y \boldsymbol{p}_1^{\top} \boldsymbol{X} \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \end{bmatrix}$$



Using the fact that the cross product should be zero

$$\mathbf{x} \times \mathbf{P} X = \mathbf{0}$$

$$\left[egin{array}{c} y oldsymbol{p}_3^ op oldsymbol{X} - oldsymbol{p}_2^ op oldsymbol{X} \ oldsymbol{p}_1^ op oldsymbol{X} - x oldsymbol{p}_3^ op oldsymbol{X} \ x oldsymbol{p}_2^ op oldsymbol{X} - y oldsymbol{p}_1^ op oldsymbol{X} \end{array}
ight] = \left[egin{array}{c} 0 \ 0 \ 0 \end{array}
ight]$$

Third line is a linear combination of the first and second lines. (x times the first line plus y times the second line)

One 2D to 3D point correspondence give you equations



Using the fact that the cross product should be zero

$$\mathbf{x} \times \mathbf{P} X = \mathbf{0}$$

$$\left[egin{array}{c} y oldsymbol{p}_3^ op oldsymbol{X} - oldsymbol{p}_2^ op oldsymbol{X} \ oldsymbol{p}_1^ op oldsymbol{X} - x oldsymbol{p}_3^ op oldsymbol{X} \ oldsymbol{p}_1^ op oldsymbol{X} - x oldsymbol{p}_3^ op oldsymbol{X} \ x oldsymbol{p}_2^ op oldsymbol{X} - y oldsymbol{p}_1^ op oldsymbol{X} \end{array}
ight] = \left[egin{array}{c} 0 \\ 0 \\ 0 \end{array}
ight]$$

Third line is a linear combination of the first and second lines. (x times the first line plus y times the second line)

One 2D to 3D point correspondence give you 2 equations



$$\left[egin{array}{c} y oldsymbol{p}_3^ op oldsymbol{X} - oldsymbol{p}_2^ op oldsymbol{X} \ oldsymbol{p}_1^ op oldsymbol{X} - x oldsymbol{p}_3^ op oldsymbol{X} \end{array}
ight] = \left[egin{array}{c} 0 \ 0 \end{array}
ight]$$

Remove third row, and rear range as system on unknowns

$$\left[egin{array}{c} y oldsymbol{p}_3^ op - oldsymbol{p}_2^ op \ oldsymbol{p}_1^ op - x oldsymbol{p}_3^ op \end{array}
ight] oldsymbol{X} = \left[egin{array}{c} 0 \ 0 \end{array}
ight]$$

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

Now we can make a system of linear equations (two lines for each 2D point correspondence)



Concatenate the 2D points from both images

Two rows from camera one

Two rows from camera two

$$\left[egin{array}{c} m{y} m{p}_3^ op - m{p}_2^ op \ m{p}_1^ op - x m{p}_3^ op \ y' m{p}_3'^ op - m{p}_2'^ op \ m{p}_1'^ op - x' m{p}_3'^ op \end{array}
ight] m{X} = \left[egin{array}{c} 0 \ 0 \ 0 \ 0 \end{array}
ight]$$

sanity check! dimensions?

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

How do we solve homogeneous linear system?



Concatenate the 2D points from both images

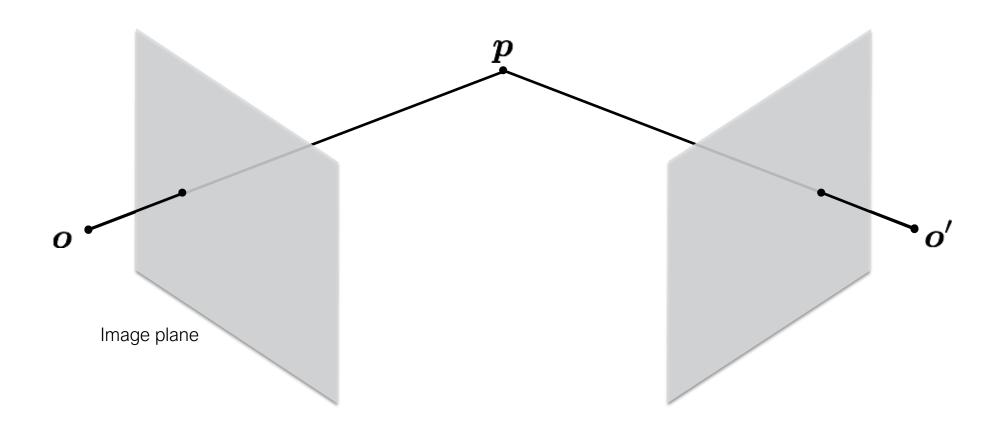
$$\left[egin{array}{c} yoldsymbol{p}_3^ op - oldsymbol{p}_2^ op \ oldsymbol{p}_1^ op - xoldsymbol{p}_3^ op \ y'oldsymbol{p}_3'^ op - oldsymbol{p}_2'^ op \ oldsymbol{p}_1'^ op - x'oldsymbol{p}_3'^ op \ oldsymbol{p}_1'^ op \end{array}
ight] oldsymbol{X} = \left[egin{array}{c} 0 \ 0 \ 0 \ 0 \end{array}
ight]$$

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

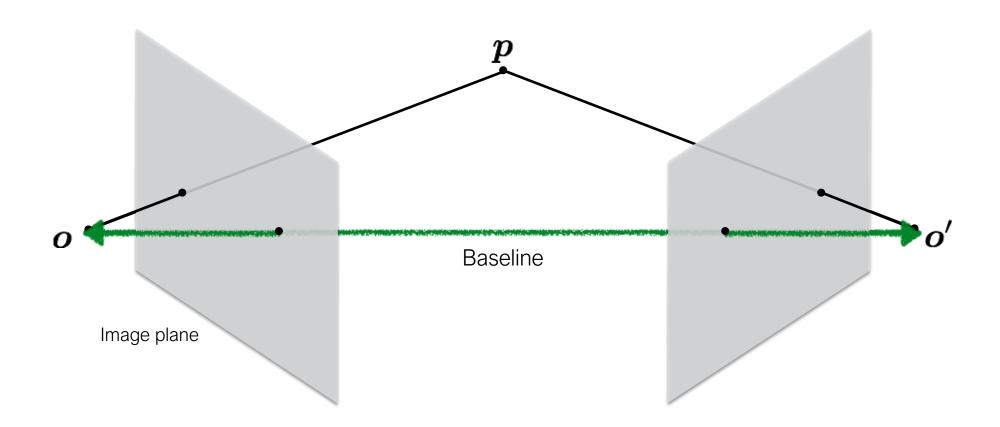
How do we solve homogeneous linear system?

S V D!

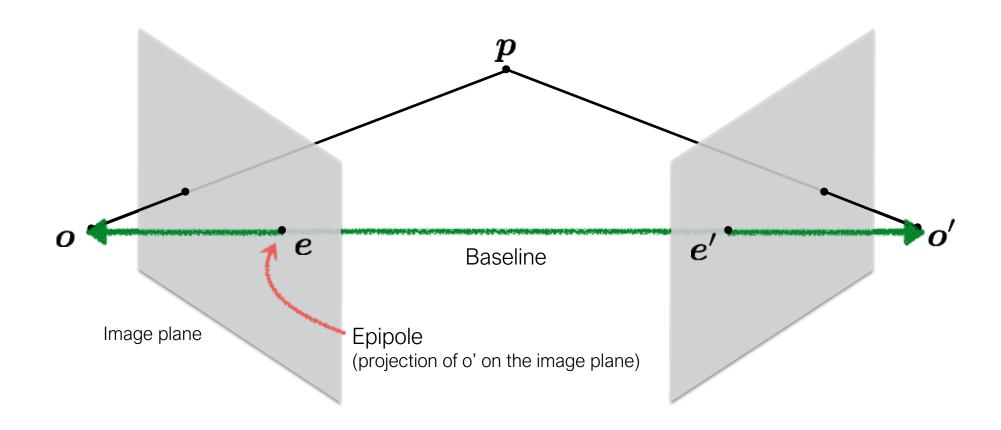




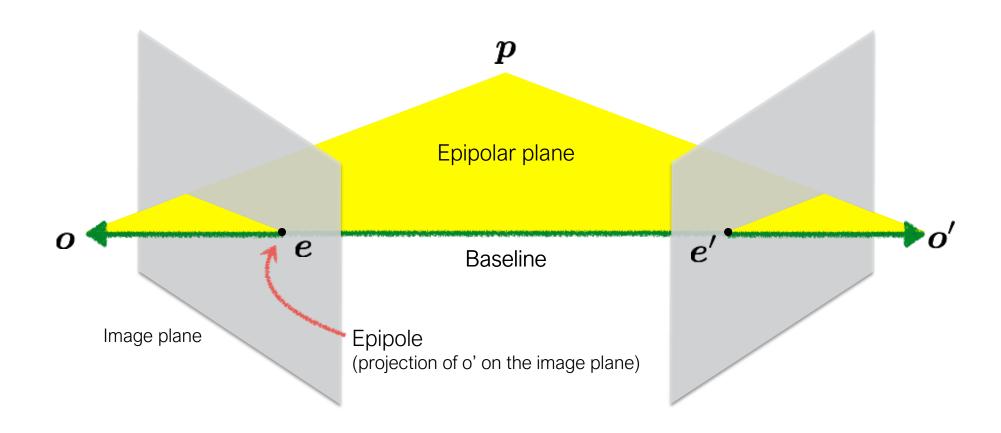




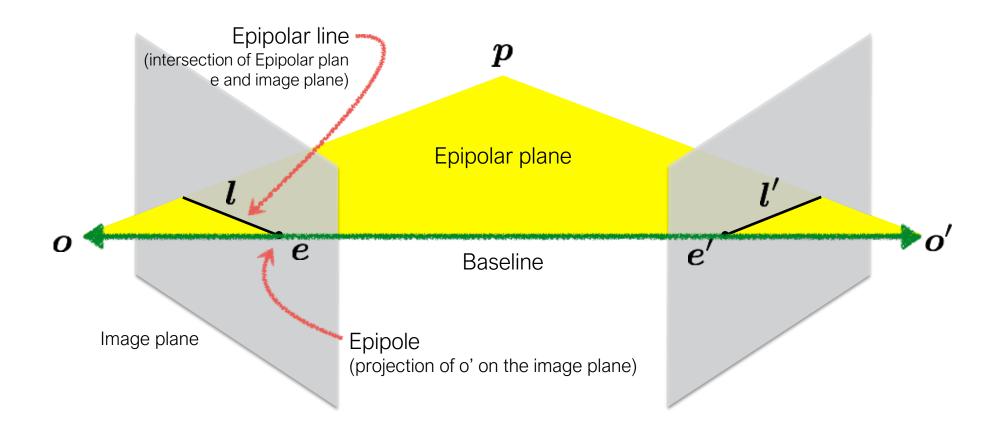


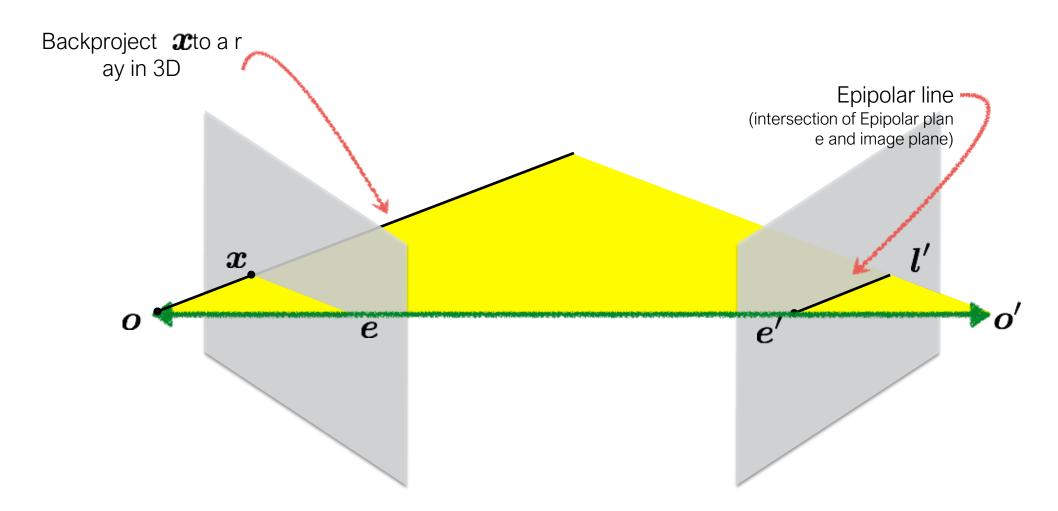






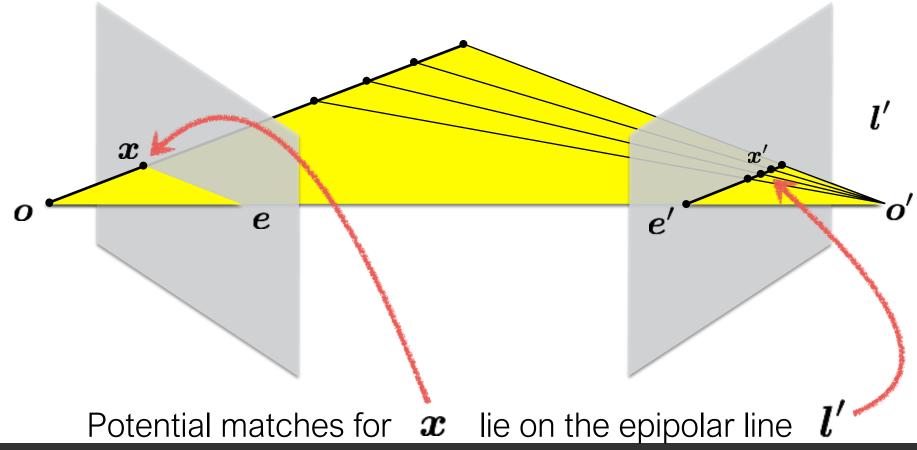


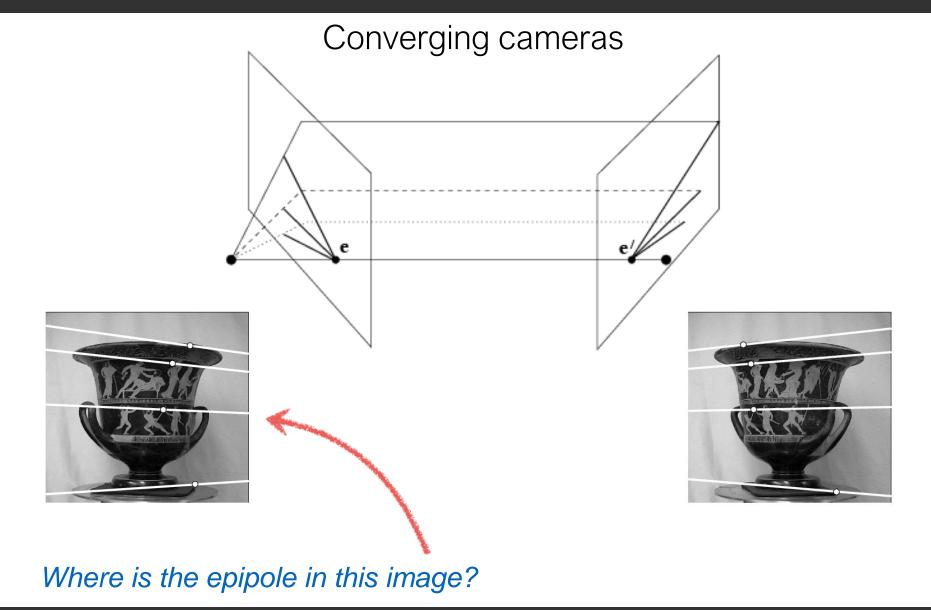


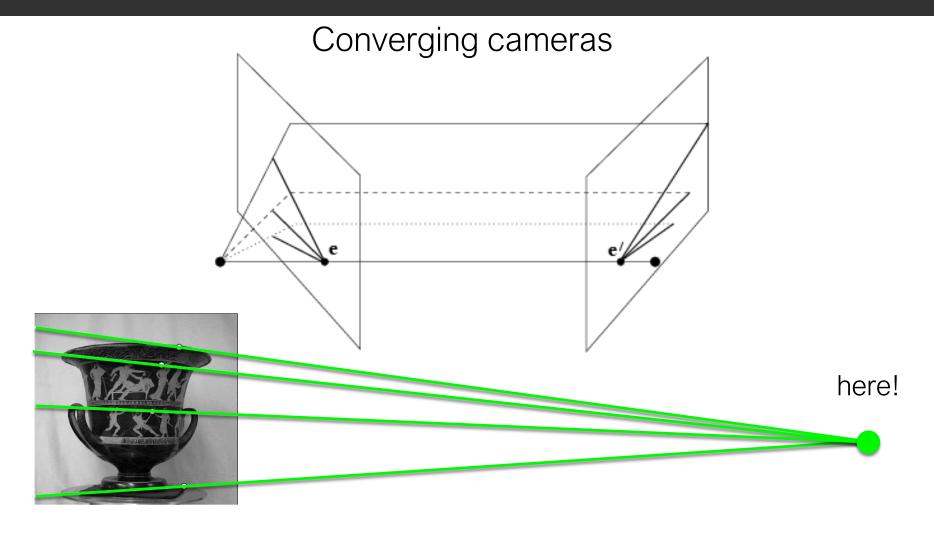


Another way to construct the epipolar plane, this time given $oldsymbol{x}$







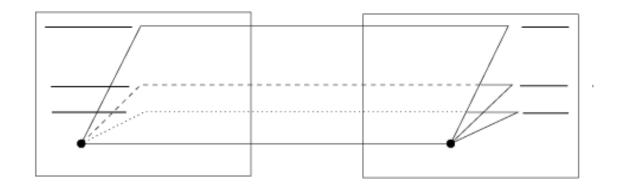


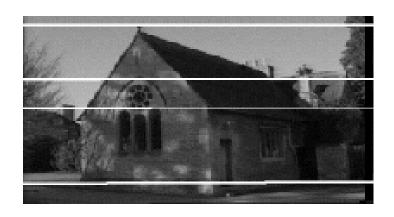
Where is the epipole in this image?

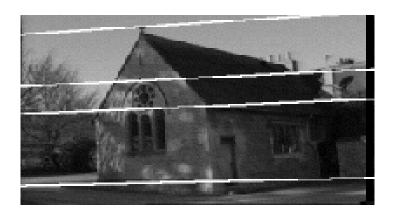
It's not always in the image



Parallel cameras



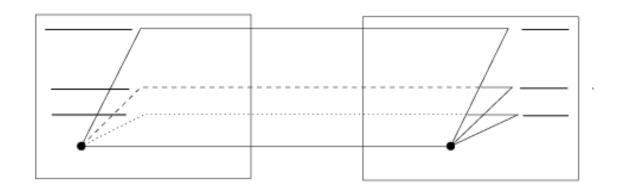


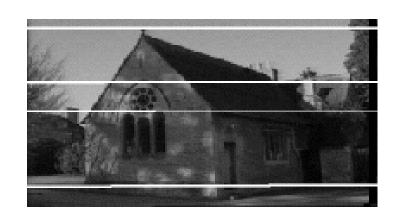


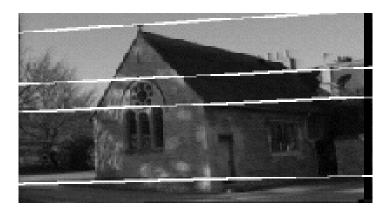
Where is the epipole?



Parallel cameras







epipole at infinity

The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image



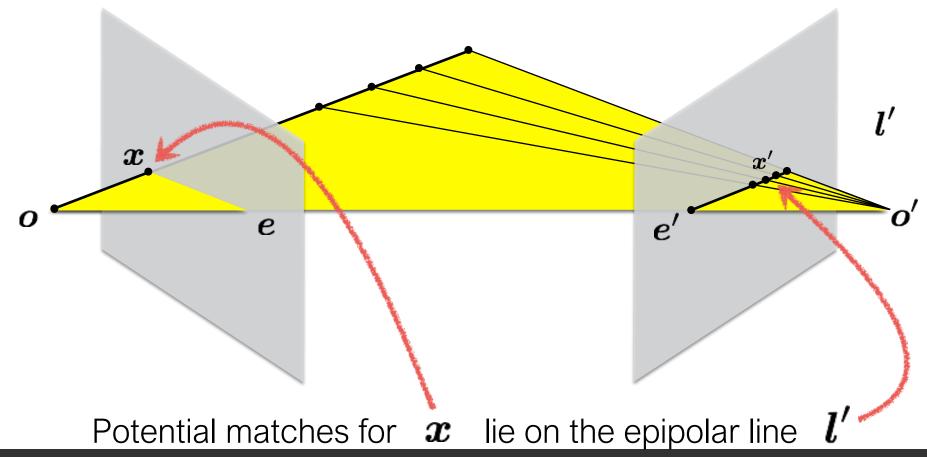
Left image



Right image

How would you do it?

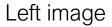




The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image







Right image

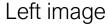
Want to avoid search over entire image Epipolar constraint reduces search to a single line

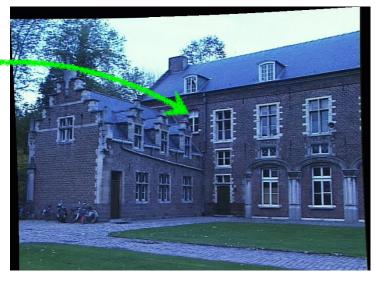


The epipolar constraint is an important concept for stereo vision

Task: Match point in left image to point in right image







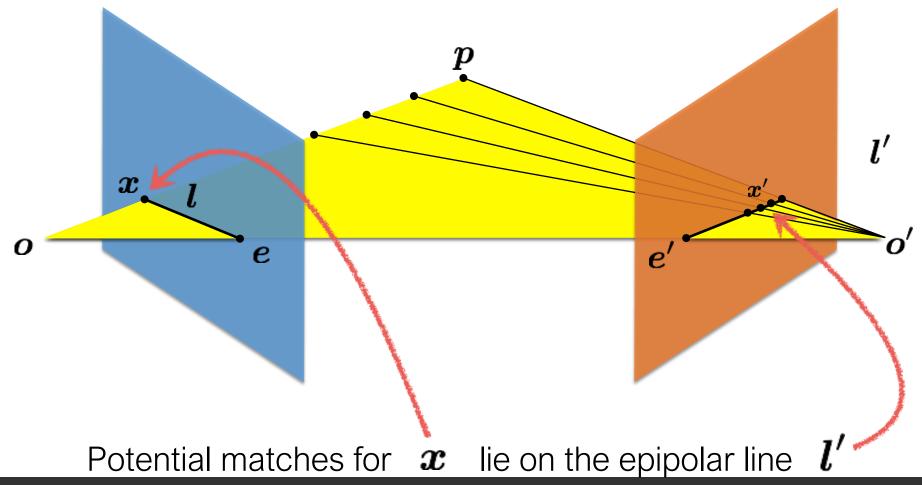
Right image

Want to avoid search over entire image Epipolar constraint reduces search to a single line

How do you compute the epipolar line?

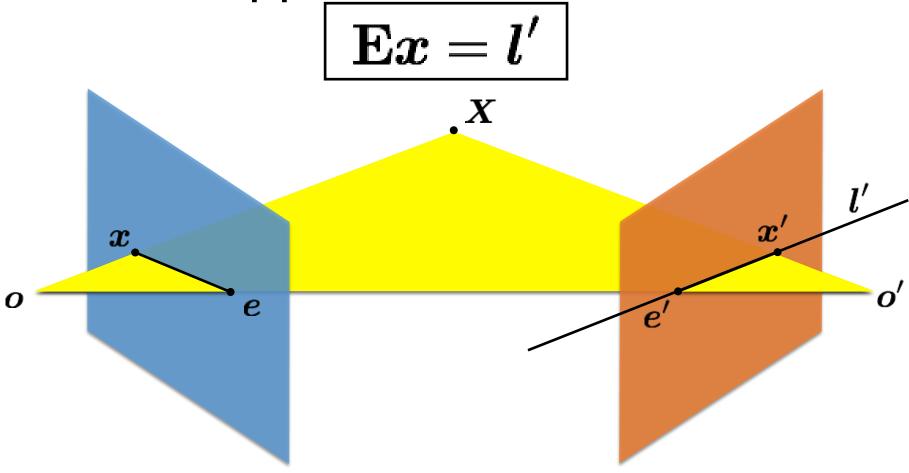


Recall:Epipolar constraint



Recall:Epipolar constraint

Given a point in one image, multiplying by the **essential matrix** will tell us the **epipolar line** in the second view.



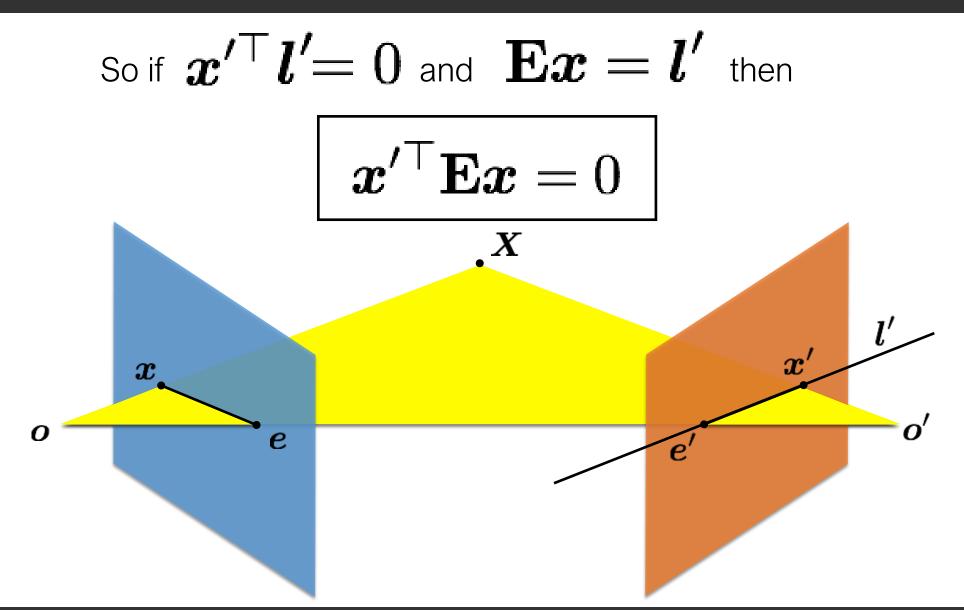
Motivation

The Essential Matrix is a 3 x 3 matrix that en codes **epipolar geometry**

Given a point in one image, multiplying by the **essential matrix** will tell us the **epipolar line** in the second image.



Epipolar Line



Essential Matrix vs Homography

What's the difference between the essential matrix and a homography?

They are both 3 x 3 matrices but ...

$$oldsymbol{l}' = \mathbf{E} oldsymbol{x}$$

Essential matrix maps a **point** to a **line**

$$x' = \mathbf{H}x$$

Homography maps a **point** to a **point**



properties of the E matrix

Longuet-Higgins equation

$$\boldsymbol{x}'^{\top} \mathbf{E} \boldsymbol{x} = 0$$

(2D points expressed in <u>camera</u> coordinate system)



properties of the E matrix

Longuet-Higgins equation

$$\boldsymbol{x}'^{\top} \mathbf{E} \boldsymbol{x} = 0$$

Epipolar lines

$$\boldsymbol{x}^{\mathsf{T}}\boldsymbol{l} = 0$$

$$oldsymbol{l}' = \mathbf{E} oldsymbol{x}$$

$$\boldsymbol{x}'^{\top} \boldsymbol{l}' = 0$$

$$oldsymbol{l} = oldsymbol{E}^T oldsymbol{x}'$$

(2D points expressed in <u>camera</u> coordinate system)



properties of the E matrix

Longuet-Higgins equation

$$\boldsymbol{x}'^{\top} \mathbf{E} \boldsymbol{x} = 0$$

Epipolar lines

$$\boldsymbol{x}^{\mathsf{T}}\boldsymbol{l} = 0$$

$$oldsymbol{l}' = \mathbf{E} oldsymbol{x}$$

$$\boldsymbol{x}'^{\top}\boldsymbol{l}' = 0$$

$$oldsymbol{l} = \mathbf{E}^T oldsymbol{x}'$$

Epipoles

$$e'^{\top}\mathbf{E} = \mathbf{0}$$

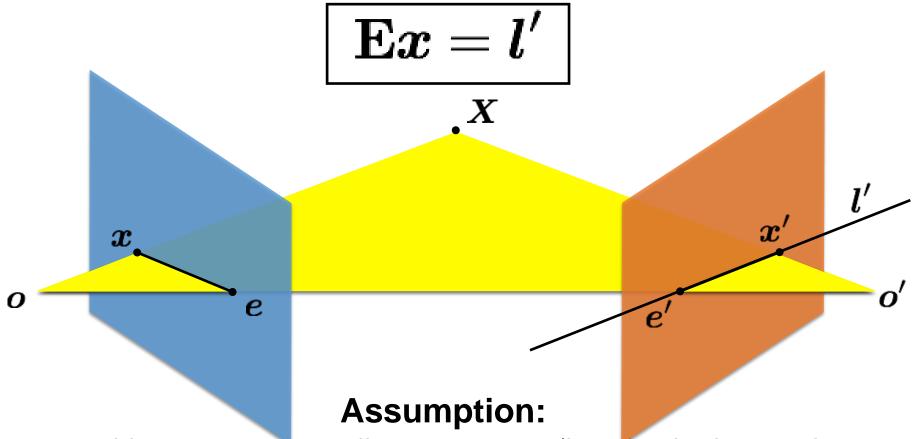
$$\mathbf{E}e = \mathbf{0}$$

(2D points expressed in <u>camera</u> coordinate system)



Essential Matrix

Given a point in one image, multiplying by the **essential matrix** will tell us the **epipolar line** in the second view.



2D points expressed in camera coordinate system (i.e., intrinsic matrices are identities)

How do you generalize to non-identity intrinsic matrices?



Fundamental matrix

The

fundamental matrix

is a

generalization

of the

essential matrix,

where the assumption of

Identity matrices

is removed



Fundamental matrix

$$\hat{\boldsymbol{x}}'^{\top}\mathbf{E}\hat{\boldsymbol{x}} = 0$$

The essential matrix operates on image points expressed in **2D coordinates** expressed in the camera coordinate system

$$\hat{m{x}}' = \mathbf{K}'^{-1} m{x}'$$
 $\hat{m{x}} = \mathbf{K}^{-1} m{x}$



$$\hat{\boldsymbol{x}}'^{\top}\mathbf{E}\hat{\boldsymbol{x}} = 0$$

The essential matrix operates on image points expressed in **2D coordinates** expressed in the camera coordinate system

$$\hat{m{x}'} = \mathbf{K'}^{-1} m{x}'$$
 $\hat{m{x}} = \mathbf{K}^{-1} m{x}$

Writing out the epipolar constraint in terms of image coordinates

$$\mathbf{x}'^{\top}\mathbf{E}\mathbf{K}^{-1}\mathbf{x} = 0$$

 $\mathbf{x}'^{\top}(\mathbf{K}'^{-\top}\mathbf{E}\mathbf{K}^{-1})\mathbf{x} = 0$
 $\mathbf{x}'^{\top}\mathbf{F}\mathbf{x} = 0$



Fundamental matrix

Same equation works in image coordinates!

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

it maps pixels to epipolar lines



properties of the Ematrix

Longuet-Higgins equation

$$\boldsymbol{x}'^{\top} \mathbf{E} \boldsymbol{x} = 0$$

Epipolar lines

$$\boldsymbol{x}^{\top}\boldsymbol{l} = 0$$

$$oldsymbol{l}' = oldsymbol{\mathbb{E}} oldsymbol{x}$$

$$\mathbf{x}'^{\top} \mathbf{l}' = 0$$

$$\boldsymbol{x}'^{\top} \boldsymbol{l}' = 0$$

 $\boldsymbol{l} = \mathbf{E}^T \boldsymbol{x}'$

Epipoles

$$e'^{\top}\mathbf{E} = \mathbf{0}$$

$$\mathbf{E}e=\mathbf{0}$$

(points in **image** coordinates)



Assume you have *M* matched *image* points

$$\{\boldsymbol{x_m}, \boldsymbol{x_m'}\}$$
 $m = 1, \dots, M$

Each correspondence should satisfy

$$\boldsymbol{x}_m^{\prime \top} \mathbf{F} \boldsymbol{x}_m = 0$$

How would you solve for the 3 x 3 **F** matrix?

Set up a homogeneous linear system with 9 unknowns



$$\boldsymbol{x}_m^{\prime \top} \mathbf{F} \boldsymbol{x}_m = 0$$

How many equation do you get from one correspondence?



ONE correspondence gives you ONE equation

$$x_m x'_m f_1 + x_m y'_m f_2 + x_m f_3 + y_m x'_m f_4 + y_m y'_m f_5 + y_m f_6 + x'_m f_7 + y'_m f_8 + f_9 = 0$$



Set up a homogeneous linear system with 9 unknowns

Set up a homogeneous linear system with 9 unknowns
$$\begin{bmatrix} x_1x'_1 & x_1y'_1 & x_1 & y_1x'_1 & y_1y'_1 & y_1 & x'_1 & y'_1 & 1 \\ \vdots & \vdots \\ x_Mx'_M & x_My'_M & x_M & y_Mx'_M & y_My'_M & y_M & x'_M & y'_M & 1 \end{bmatrix} \begin{bmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \\ f_8 \\ f_9 \end{bmatrix} = \mathbf{0}$$

How many equations do you need?



Each point pair (according to epipolar constraint) contributes only one <u>scalar</u> equation

$$\boldsymbol{x}_m^{\prime \top} \mathbf{F} \boldsymbol{x}_m = 0$$

Note: This is different from the Homography estimation where each point pair contributes 2 equations.

We need at least 8 points

Hence, the 8 point algorithm!

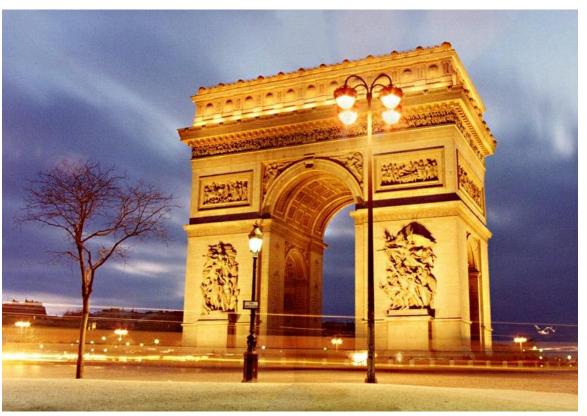


Eight-Point Algorithm

- 0. (Normalize points)
- 1. Construct the M x 9 matrix A
- 2. Find the SVD of A
- 3. Entries of **F** are the elements of column of **V** corresponding to the least singular value
- 4. (Enforce rank 2 constraint on F)
- 5. (Un-normalize F)



Example

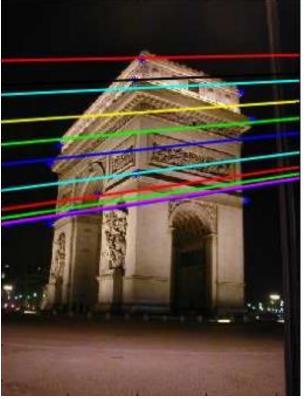






Epipolar lines







Computation

$$\mathbf{F} = \begin{bmatrix} -0.00310695 & -0.0025646 & 2.96584 \\ -0.028094 & -0.00771621 & 56.3813 \\ 13.1905 & -29.2007 & -9999.79 \end{bmatrix}$$



$$m{x} = \left[egin{array}{c} 343.53 \\ 221.70 \\ 1.0 \end{array}
ight]$$

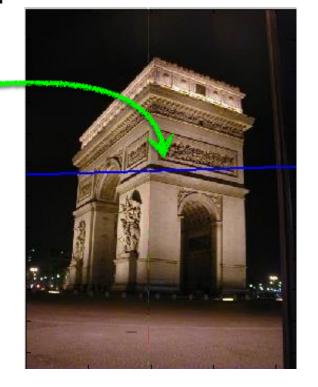
$$m{l}' = \mathbf{F} m{x}$$
 $= egin{bmatrix} 0.0295 \\ 0.9996 \\ -265.1531 \end{bmatrix}$



Computation

$$m{l}' = \mathbf{F} m{x} \ = egin{bmatrix} 0.0295 \ 0.9996 \ -265.1531 \end{bmatrix}$$





Where is the epipole?



How would you compute it?



Where is the epipole?



$$\mathbf{F}e = \mathbf{0}$$

The epipole is in the right null space of **F**

How would you solve for the epipole?



Where is the epipole?



$$\mathbf{F}e = \mathbf{0}$$

The epipole is in the right null space of **F**

How would you solve for the epipole?

SVD!





Left image



Right image





Left image

1. Select point in one image (how?)



Right image





Left image

Right image

- 1. Select point in one image (how?)
- 2. Form epipolar line for that point in second image (how?)





Left image

Right image

- 1. Select point in one image (how?)
- 2. Form epipolar line for that point in second image (how?)
- 3. Find matching point along line (how?)





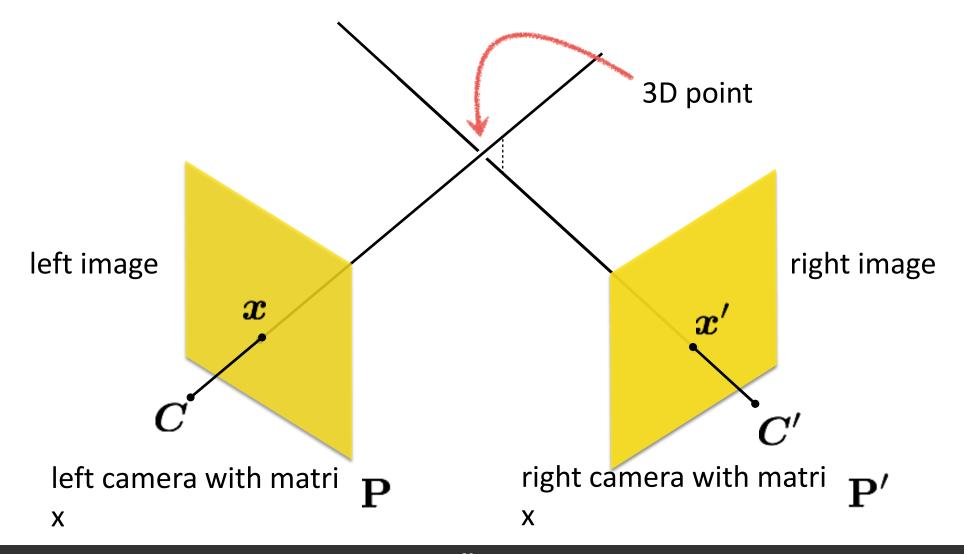
Left image

Right image

- 1. Select point in one image (how?)
- 2. Form epipolar line for that point in second image (how?)
- 3. Find matching point along line (how?)
- 4. Perform triangulation (how?)



Triangulation





Left image

Right image

- 1. Select point in one image (how?)
- 2. Form epipolar line for that point in second image (how?)
- 3. Find matching point along line (how?)
- 4. Perform triangulation (how?)

What are the disadvantages of this procedure?



Stereo rectification





What's different between these two images?











Objects that are close move more or less?



The amount of horizontal movement is inversely proportional to ...





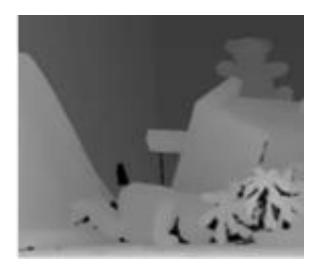




The amount of horizontal movement is inversely proportional to ...



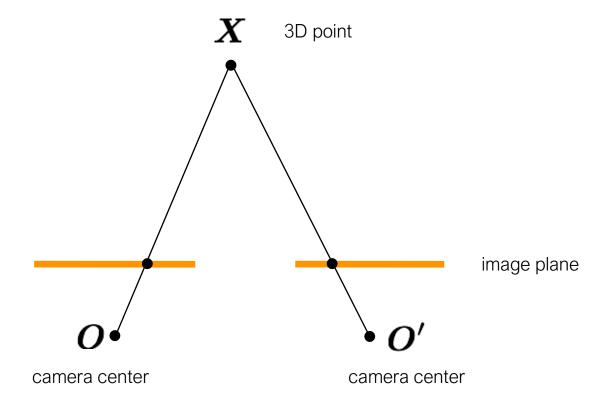




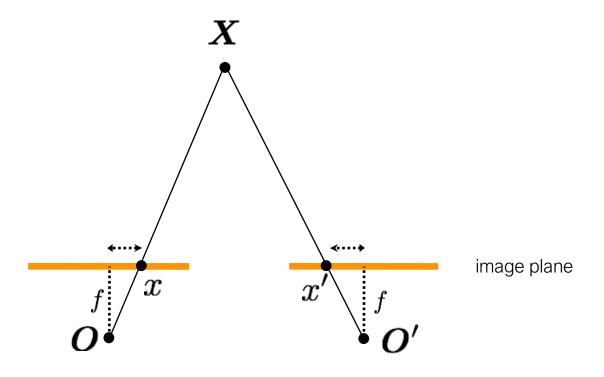
... the distance from the camera.

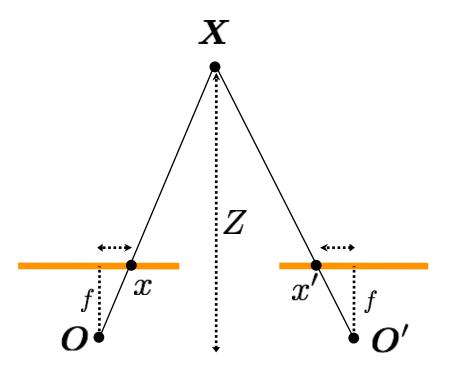
More formally...



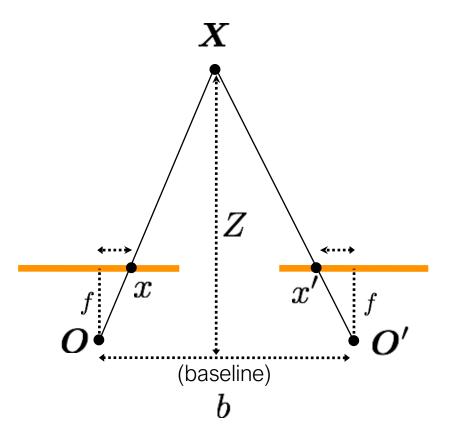




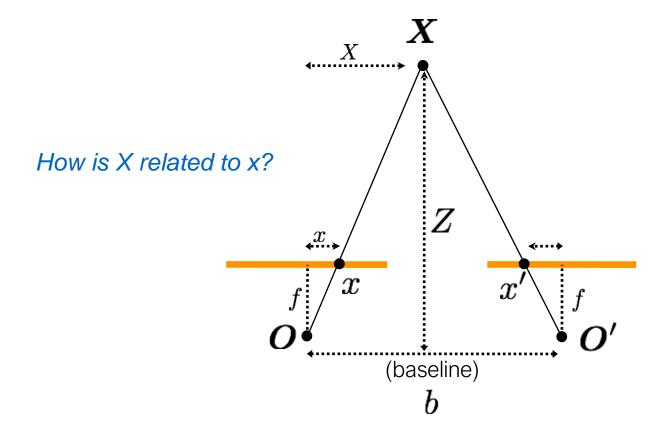




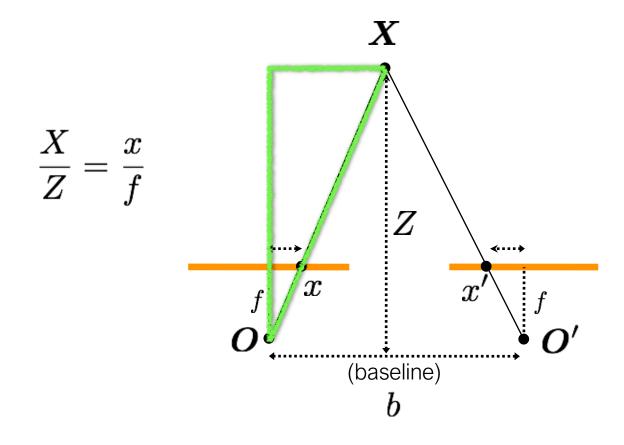




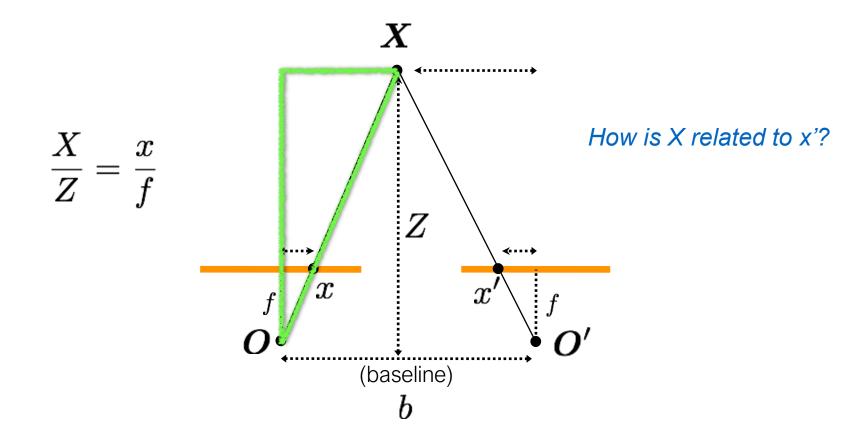


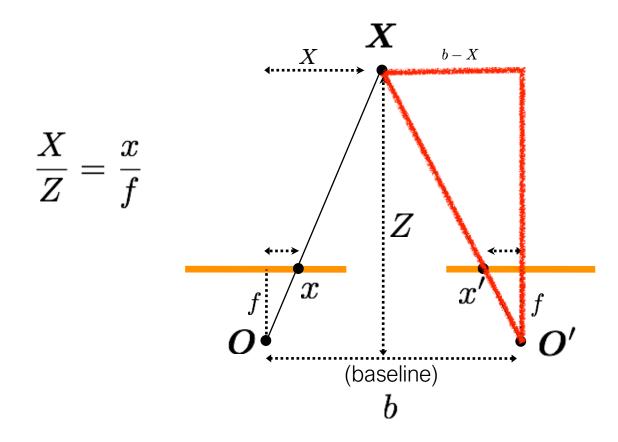




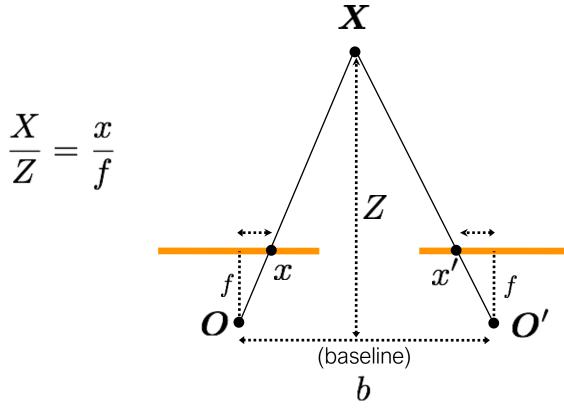








$$\frac{b-X}{Z} = \frac{x'}{f}$$

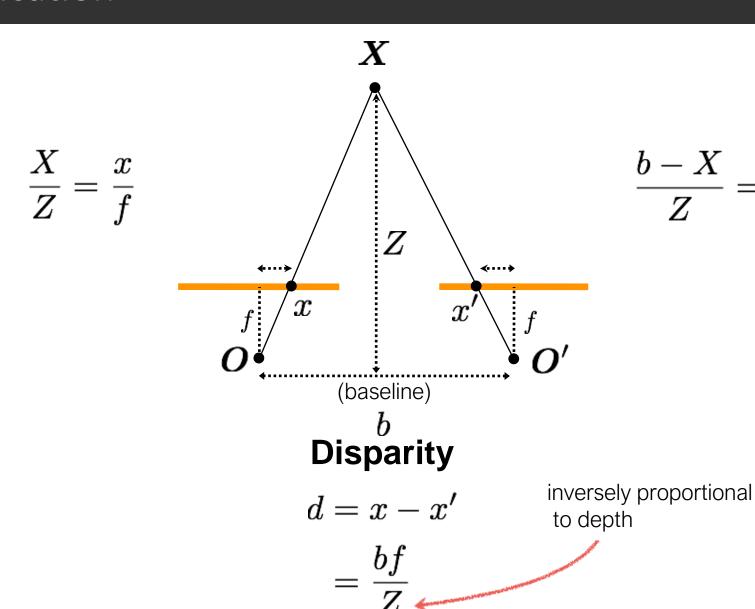


$$\frac{b-X}{Z} = \frac{x'}{f}$$

Disparity

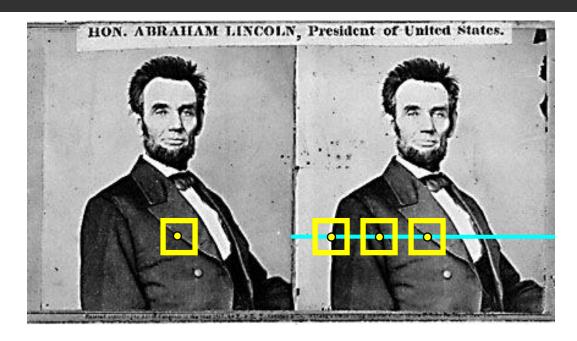
$$d=x-x'$$
 (wrt to camera origin of image plane) $=rac{bf}{7}$







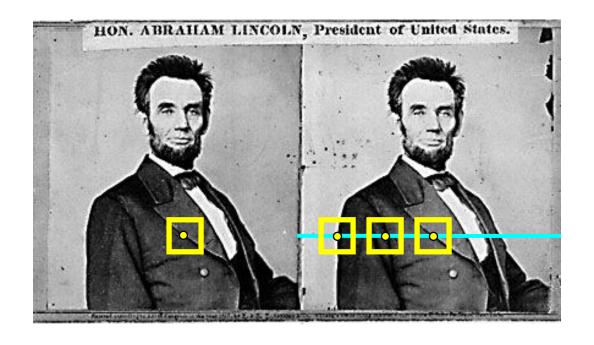
Stereo depth sensing



- 1. Rectify images (make epipolar lines horizontal)
- 2. For each pixel
 - a. Find epipolar line
 - b. Scan line for best match
 - b. Scan line for best match c. Compute depth from disparity $Z=rac{bf}{d}$

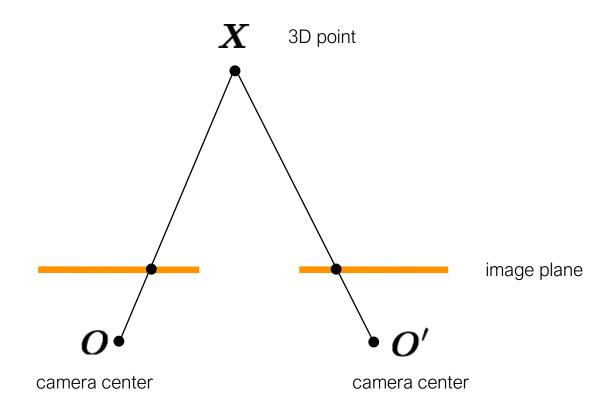


Stereo depth sensing



How can you make the epipolar lines horizontal?

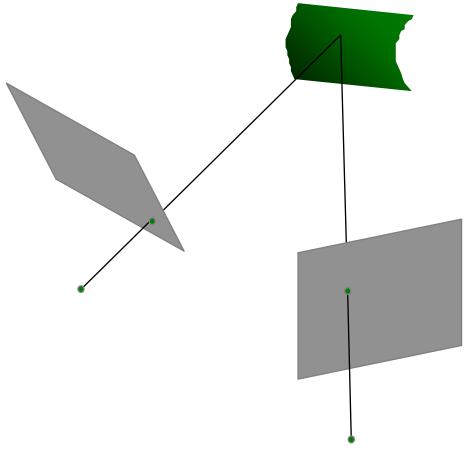
Stereo depth sensing



What's special about these two cameras?



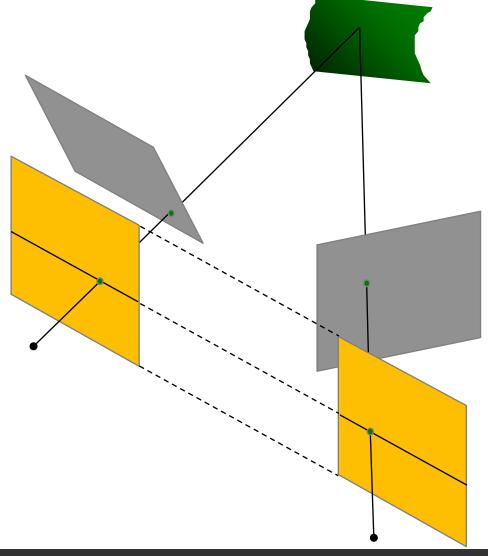
What is stereo rectification?



What is stereo rectification?

Reproject image planes onto a common plane parallel to the line between camera centers

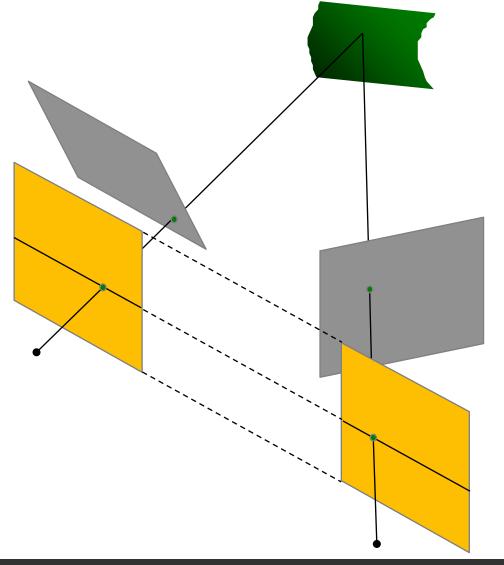
How can you do this?



What is stereo rectification?

Reproject image planes onto a common plane parallel to the line between camera centers

Need two homographies (3x3 transform), one for each input image reprojection





- Rotate the right camera by R
 (aligns camera coordinate system orientation only)
- 2. Rotate (**rectify**) the left camera so that the epipole is at infinity
- 3. Rotate (**rectify**) the right camera so that the epipole is at infinity
- 4. Adjust the **scale**

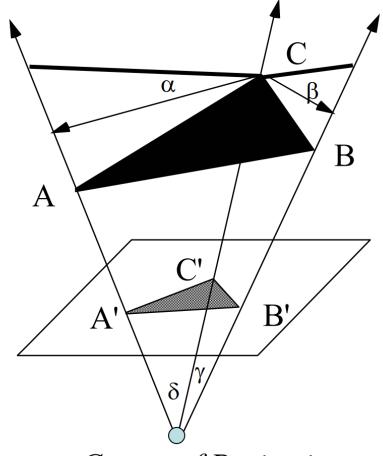


What can we do after rectification?





Perspective 3 Point Algorithm



Center of Projection

- If distance R_c to C is known, then possible locations of A (and B) can be computed
- they lie on the intersections of the line of sight through A' and the sphere of radius AC centered at C
- Once A and B are located, their distance can be computed and compared against the actual distance AB

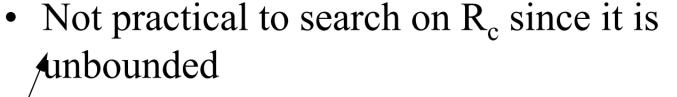


Perspective 3 Point Algorithm

 α

B'

H



Instead, search on one angular pose parameter, α .

$$-R_c = AC \cos \alpha / \sin \delta$$

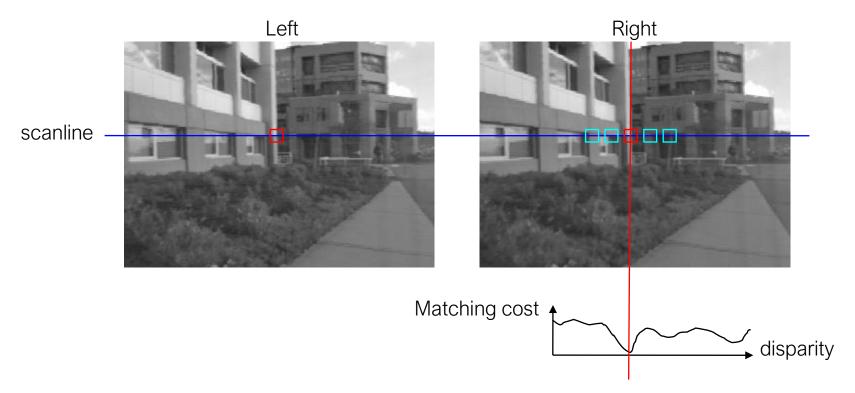
$$-R_a = R_c \cos \delta \pm AC \sin \alpha$$

$$- R_b = R_c \cos \gamma \pm [(BC^2 - (RC \sin \gamma)^2]^{1/2}]$$

This results in four possible lengths for side AB

Keep poses with the right AB length



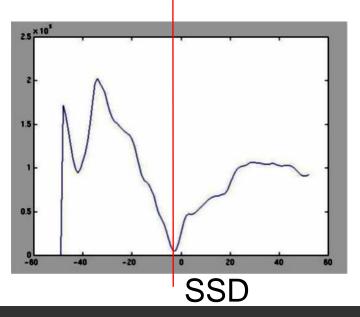


- Slide a window along the epipolar line and compare contents of th at window with the reference window in the left image
- Matching cost: SSD or normalized correlation

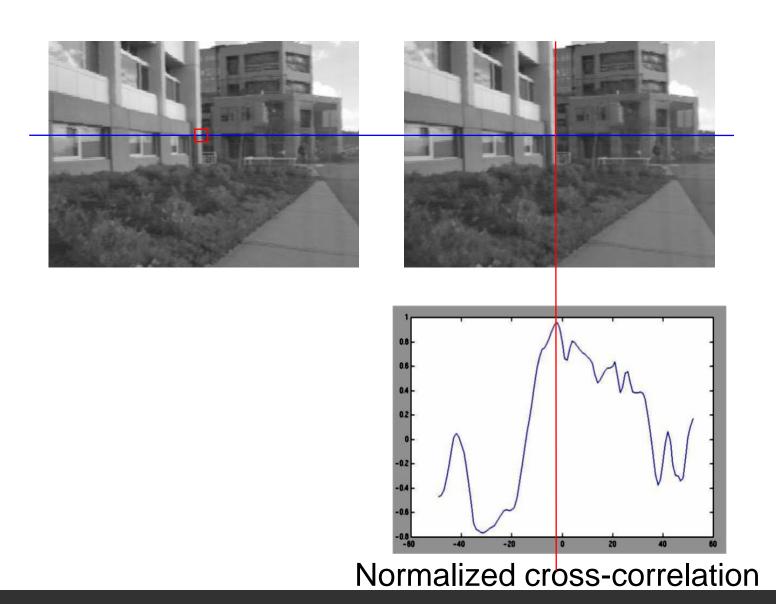






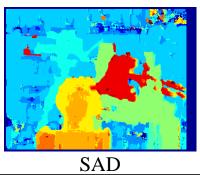


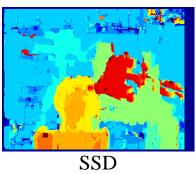


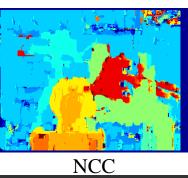




Similarity Measure	Formula
Sum of Absolute Differences (SAD)	$\sum_{(i,j) \in W} I_1(i,j) - I_2(x+i,y+j) $
Sum of Squared Differences (SSD)	$\sum_{(i,j)\in W} (I_1(i,j) - I_2(x+i,y+j))^2$
Zero-mean SAD	$\sum_{(i,j)\in W} I_1(i,j) - \bar{I}_1(i,j) - I_2(x+i,y+j) + \bar{I}_2(x+i,y+j) $
Locally scaled SAD	$\sum_{(i,j)\in W} I_1(i,j) - \frac{\bar{I}_1(i,j)}{\bar{I}_2(x+i,y+j)} I_2(x+i,y+j) $
Normalized Cross Correlation (NCC)	$\frac{\sum_{(i,j)\in W} I_1(i,j). I_2(x+i,y+j)}{\sqrt[2]{\sum_{(i,j)\in W} I_1^2(i,j). \sum_{(i,j)\in W} I_2^2(x+i,y+j)}}$









Ground truth

Effect of window size







$$W = 3$$

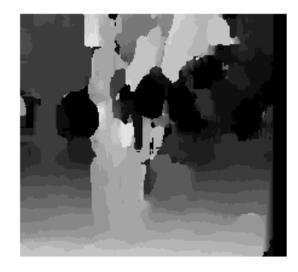
W = 20

Effect of window size









W = 20

Smaller window

- + More detail
- More noise

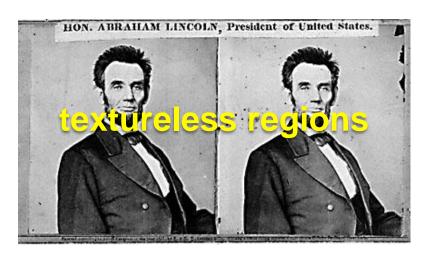
Larger window

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

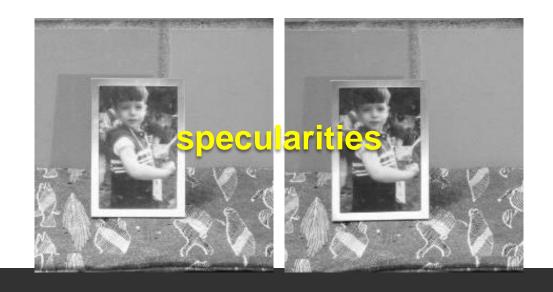


Stereo Matching

When will stereo block matching fail?

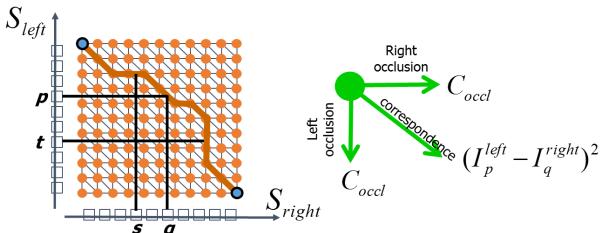




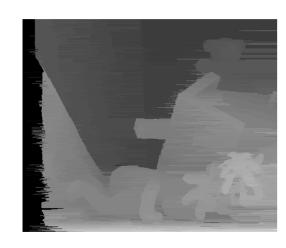




Semi-Global Matching

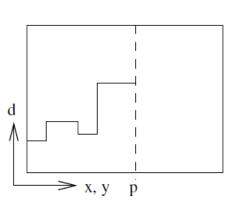






Dynamic programming based Stereo matching

(a) Minimum Cost Path L_r(p, d)



(b) 16 Paths from all Directions r

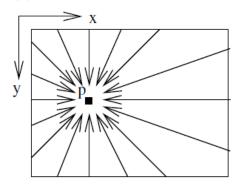






Figure 1. Aggregation of costs.



3D triangulation

```
import cv2
import numpy as np
P1 = np.eye(3, 4, dtype=np.float32)
P2 = np.eye(3, 4, dtype=np.float32)
P2[0, 3] = -1
N = 5
points3d = np.empty((4, N), np.float32)
points3d[:3, :] = np.random.randn(3, N)
points3d[3, :] = 1
points1 = P1 @ points3d
points1 = points1[:2, :] / points1[2, :]
points1[:2, :] += np.random.randn(2, N) * 1e-2
points2 = P2 @ points3d
points2 = points2[:2, :] / points2[2, :]
points2[:2, :] += np.random.randn(2, N) \star 1e-2
points3d_reconstr = cv2.triangulatePoints(P1, P2, points1, points2)
points3d_reconstr /= points3d_reconstr[3, :]
print('Original points')
print(points3d[:3].T)
print('Reconstructed points')
print(points3d_reconstr[:3].T)
```



Find relative camera-object pose using PnP algorithm

```
import cv2
import numpy as np
camera_matrix = np.load('../data/pinhole_calib/camera_mat.npy')
dist_coefs = np.load('../data/pinhole_calib/dist_coefs.npy')
img = cv2.imread('../data/pinhole_calib/img_00.png')
pattern_size = (10, 7)
res, corners = cv2.findChessboardCorners(imq, pattern_size)
criteria = (cv2.TERM_CRITERIA_EPS + cv2.TERM_CRITERIA_MAX_ITER, 30, 1e-3)
corners = cv2.cornerSubPix(cv2.cvtColor(img, cv2.COLOR_BGR2GRAY),
                           corners, (10, 10), (-1,-1), criteria)
pattern_points = np.zeros((np.prod(pattern_size), 3), np.float32)
pattern_points[:, :2] = np.indices(pattern_size).T.reshape(-1, 2)
ret, rvec, tvec = cv2.solvePnP(pattern_points, corners, camera_matrix, dist_coefs,
                               None, None, False, cv2.SOLVEPNP_ITERATIVE)
img_points, _ = cv2.projectPoints(pattern_points, rvec, tvec, camera_matrix, dist_coefs)
for c in img_points.squeeze():
    cv2.circle(img, tuple(c), 10, (0, 255, 0), 2)
cv2.imshow('points', img)
cv2.waitKey()
cv2.destroyAllWindows()
```

```
import cv2
import numpy as np
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 20})
np_load_old = np.load
np.load = lambda *a,**k: np_load_old(*a, allow_pickle=True, **k)
data = np.load('../data/stereo/case1/stereo.npy').item()
Kl, Dl, Kr, Dr, R, T, img_size = data['Kl'], data['Dl'], data['Kr'], data['Dr'], \
                                 data['R'], data['T'], data['img_size']
left_img = cv2.imread('../data/stereo/case1/left14.png')
right_img = cv2.imread('../data/stereo/case1/right14.png')
R1, R2, P1, P2, Q, validRoi1, validRoi2 = cv2.stereoRectify(Kl, Dl, Kr, Dr, img_size, R, T)
xmap1, ymap1 = cv2.initUndistortRectifyMap(Kl, Dl, R1, Kl, img_size, cv2.CV_32FC1)
xmap2, ymap2 = cv2.initUndistortRectifyMap(Kr, Dr, R2, Kr, img_size, cv2.CV_32FC1)
left_img_rectified = cv2.remap(left_img, xmap1, ymap1, cv2.INTER_LINEAR)
right_img_rectified = cv2.remap(right_img, xmap2, ymap2, cv2.INTER_LINEAR)
```

```
plt.figure(0, figsize=(12,10))
plt.subplot(221)
plt.title('left original')
plt.imshow(left_img, cmap='gray')
plt.subplot(222)
plt.title('right original')
plt.imshow(right_img, cmap='gray')
plt.subplot(223)
plt.title('left rectified')
plt.imshow(left_img_rectified, cmap='gray')
plt.subplot(224)
plt.title('right rectified')
plt.imshow(right_img_rectified, cmap='gray')
plt.tight_layout()
plt.show()
```



Fundamental matrix computation

```
import cv2
import numpy as np
np_load_old = np.load
np.load = lambda *a,**k: np_load_old(*a, allow_pickle=True, **k)
data = np.load('../data/stereo/case1/stereo.npy').item()
Kl, Kr, Dl, Dr, left_pts, right_pts, E_from_stereo, F_from_stereo = \
data['Kl'], data['Kr'], data['Dl'], data['Dr'], data['left_pts'], data['right_pts'], data['E'], data['F']
left_pts = np.vstack(left_pts)
right_pts = np.vstack(right_pts)
left_pts = cv2.undistortPoints(left_pts, Kl, Dl, P=Kl)
right_pts = cv2.undistortPoints(right_pts, Kr, Dr, P=Kr)
F, mask = cv2.findFundamentalMat(left_pts, right_pts, cv2.FM_LMEDS)
E = Kr.T @ F @ Kl
print('Fundamental matrix:')
print(F)
print('Essential matrix:')
print(E)
```

Essential decomposition into rotation and translation

```
import cv2
import numpy as np
np_load_old = np.load
np.load = lambda *a,**k: np_load_old(*a, allow_pickle=True, **k)
data = np.load('../data/stereo/case1/stereo.npy').item()
E = data['E']
R1, R2, T = cv2.decomposeEssentialMat(E)
print('Rotation 1:')
print(R1)
print('Rotation 2:')
print(R2)
print('Translation:')
print(T)
```



Estimating disparity map for stereo images

```
import cv2
import matplotlib.pyplot as plt
import matplotlib
matplotlib.rcParams.update({'font.size': 20})
left_img = cv2.imread('../data/stereo/left.png')
right_img = cv2.imread('../data/stereo/right.png')
stereo_bm = cv2.StereoBM_create(32)
dispmap_bm = stereo_bm.compute(cv2.cvtColor(left_img, cv2.COLOR_BGR2GRAY),
                                cv2.cvtColor(right_img, cv2.COLOR_BGR2GRAY))
stereo_sgbm = cv2.StereoSGBM_create(0, 32)
dispmap_sgbm = stereo_sgbm.compute(left_img, right_img)
plt.figure(figsize=(12,10))
plt.subplot(221)
plt.title('left')
plt.imshow(left_img[:_{\iota}:_{\iota}[2_{\iota}1_{\iota}0]])
plt.subplot(222)
plt.title('right')
plt.imshow(right_img[:,:,[2,1,0]])
plt.subplot(223)
plt.title('BM')
plt.imshow(dispmap_bm, cmap='gray')
plt.subplot(224)
plt.title('SGBM')
plt.imshow(dispmap_sgbm, cmap='gray')
plt.show()
```

