

Computer Vision



Epipolar Geometry and Stereo Vision

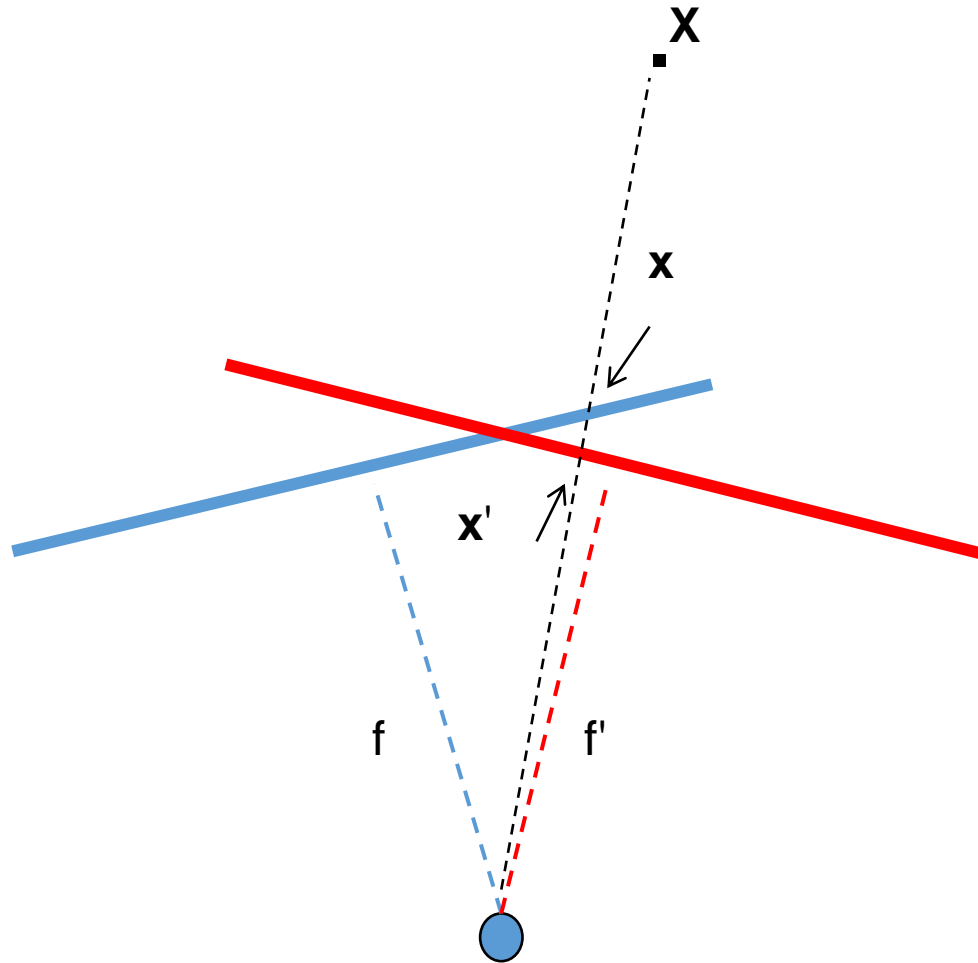
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**Indian Institute of Information Technology
Sri City, Chittoor**



Last class: Image Stitching

- Two images with rotation/zoom but no translation



Perspective and 3D Geometry

- **Camera models and Projective geometry**

- What's the **mapping between image and world** coordinates?

- **Projection Matrix and Camera calibration**

- What's the **projection matrix** between scene and image coordinates?
- How to **calibrate** the projection matrix?

- **Single view metrology and Camera properties**

- How can we measure the **size of 3D objects** in an image?
- What are the important **camera properties**?

- **Photo stitching**

- What's the **mapping from two images** taken **without camera translation**?

- **Epipolar Geometry and Stereo Vision**

- What's the **mapping from two images** taken **with camera translation**?

- **Structure from motion**

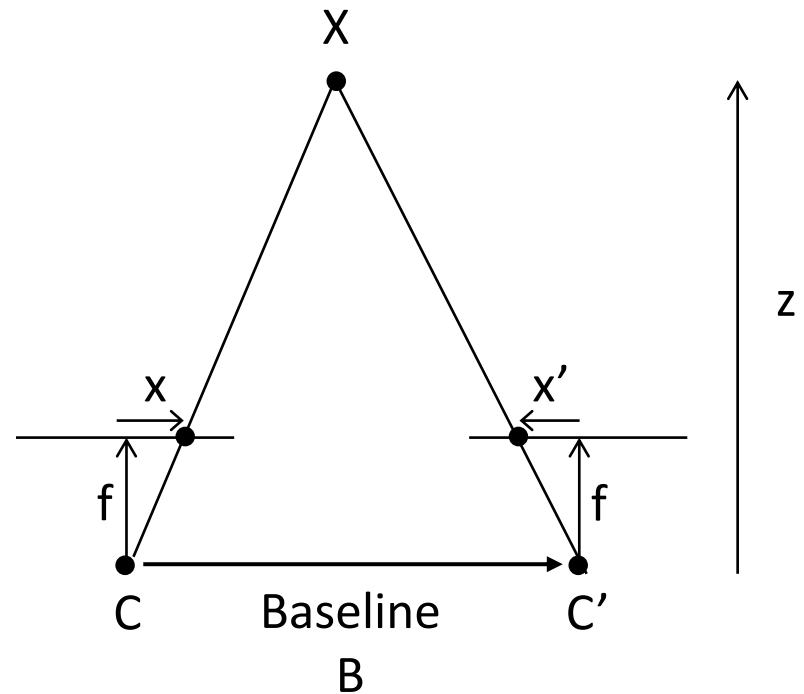
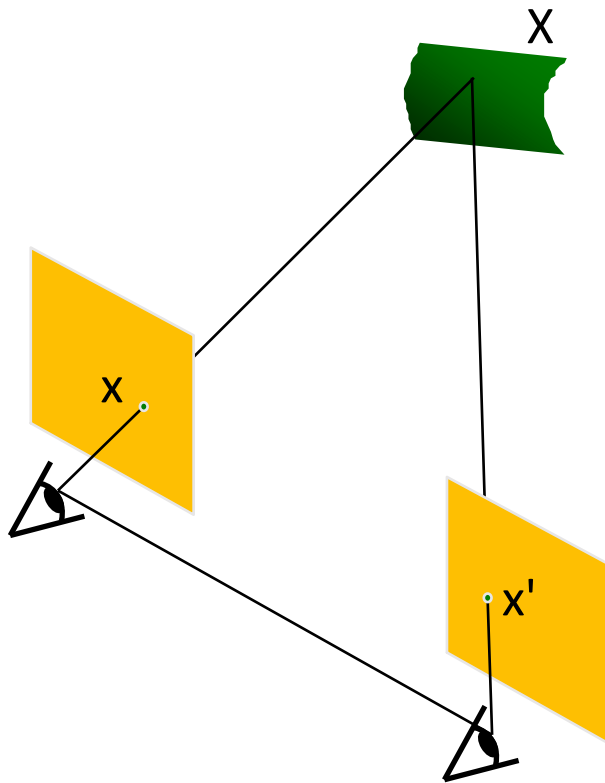
- How can we **recover 3D points from multiple images**?

This class: Two-View Geometry

- Epipolar geometry
 - Relates cameras from two positions
- Stereo depth estimation
 - Recover depth from two images

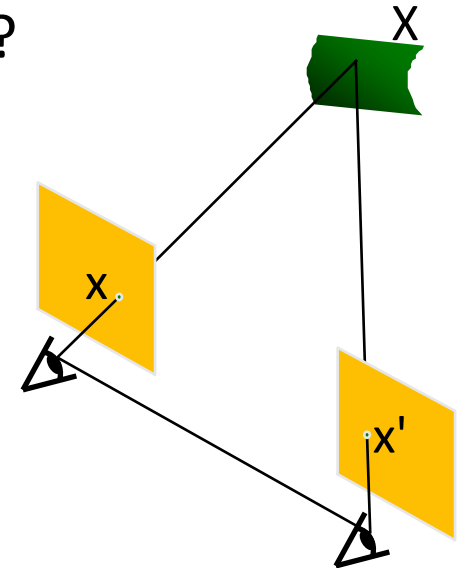
Depth from Stereo

- Goal: Recover depth by finding image coordinate x' that corresponds to x



Depth from Stereo

- Goal: Recover depth by finding image coordinate x' that corresponds to x
- Sub-Problems
 1. **Calibration:**
What's the relation of the two cameras?
 2. **Correspondence:**
Where is the matching point x' ?



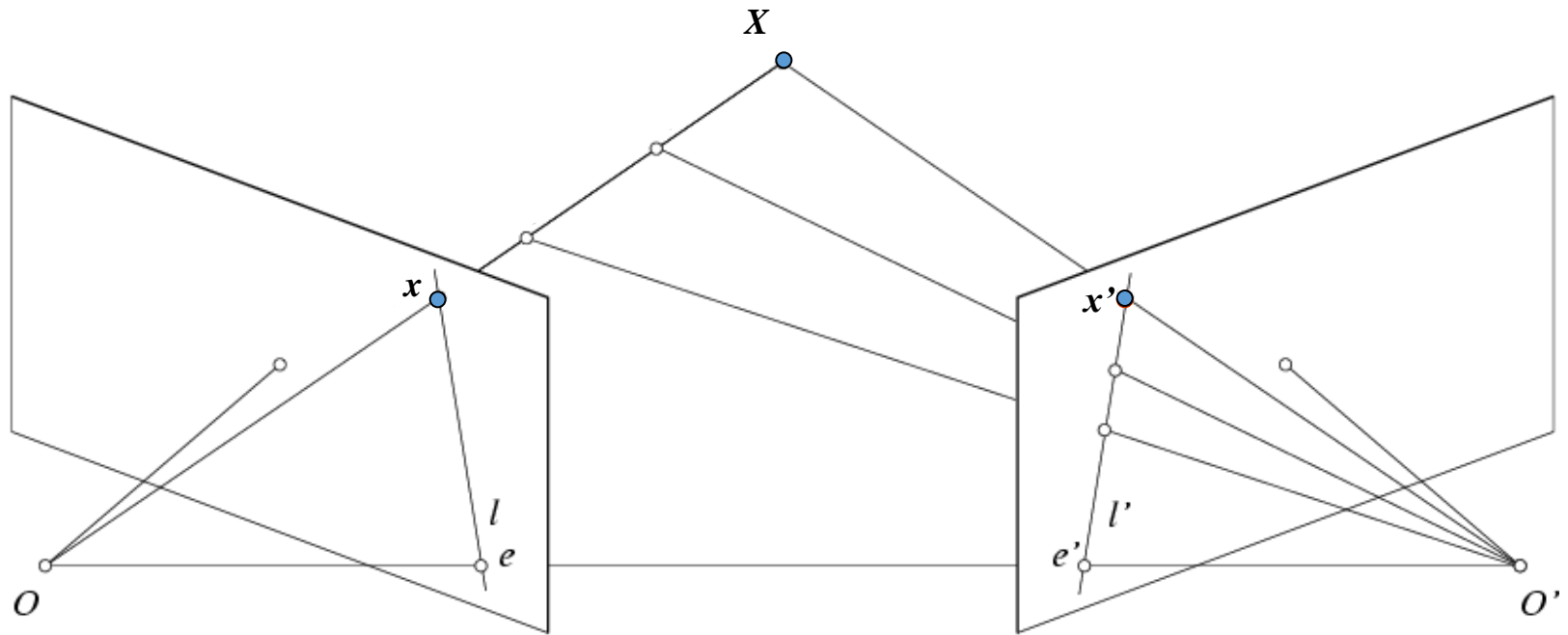
Correspondence Problem



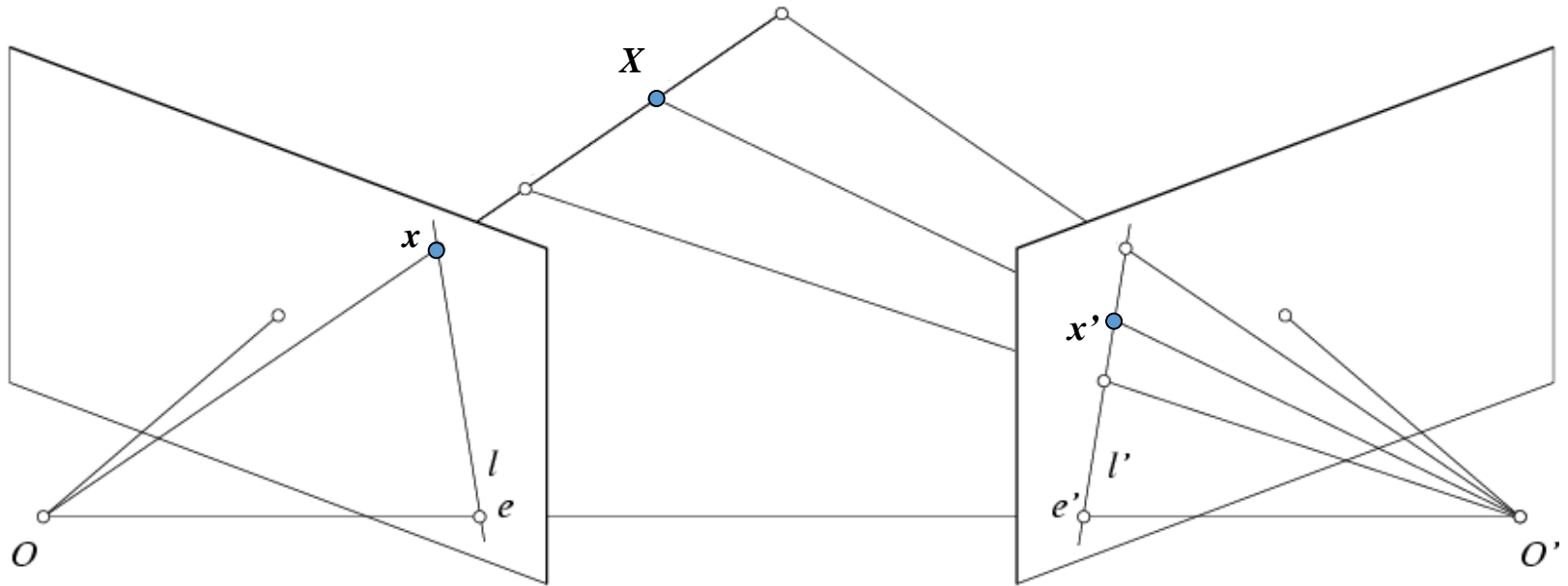
- Two images taken from cameras with different intrinsic and extrinsic parameters
- How do we match a point in the first image to a point in the second?
- How can we constrain our search?

Key idea: Epipolar constraint

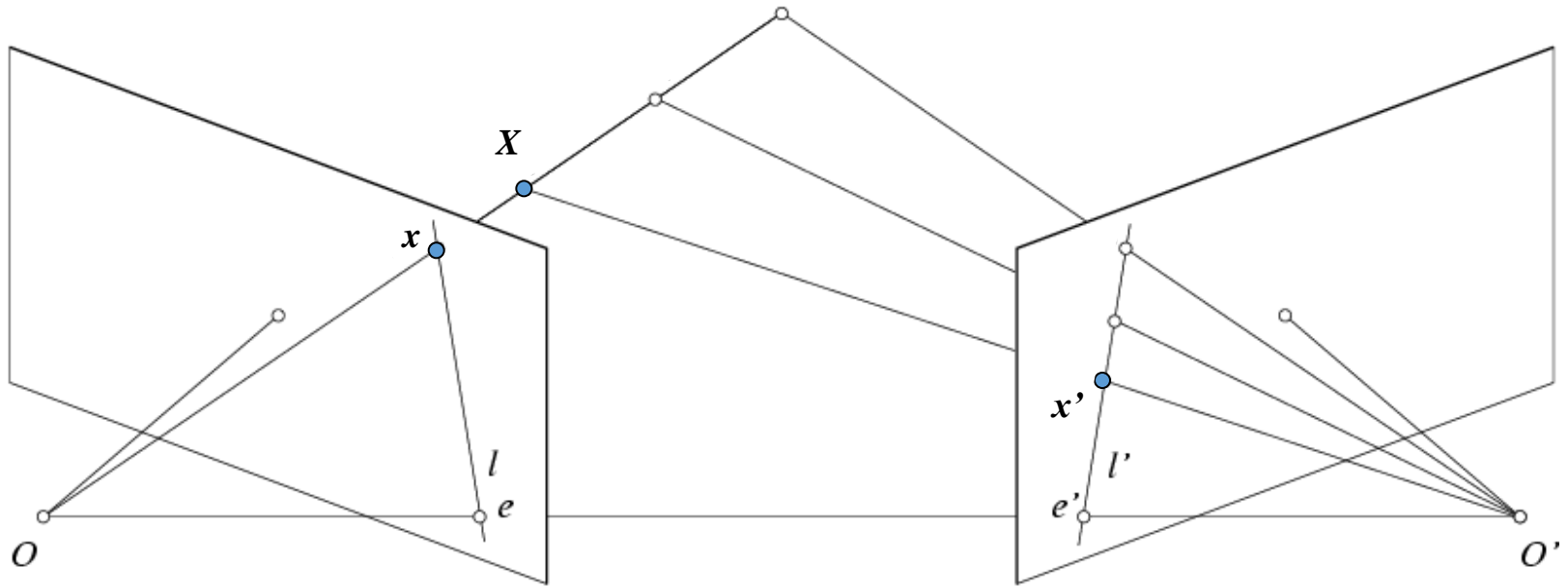
Key idea: Epipolar constraint



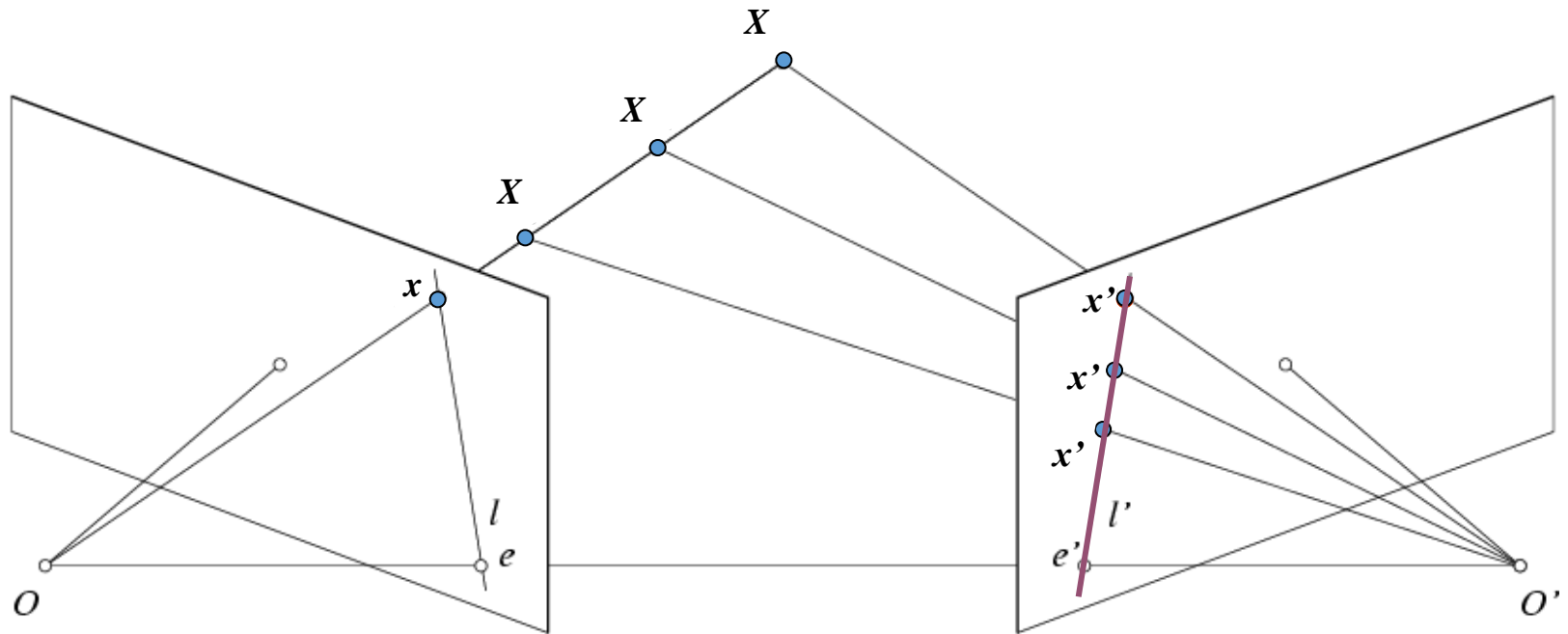
Key idea: Epipolar constraint



Key idea: Epipolar constraint

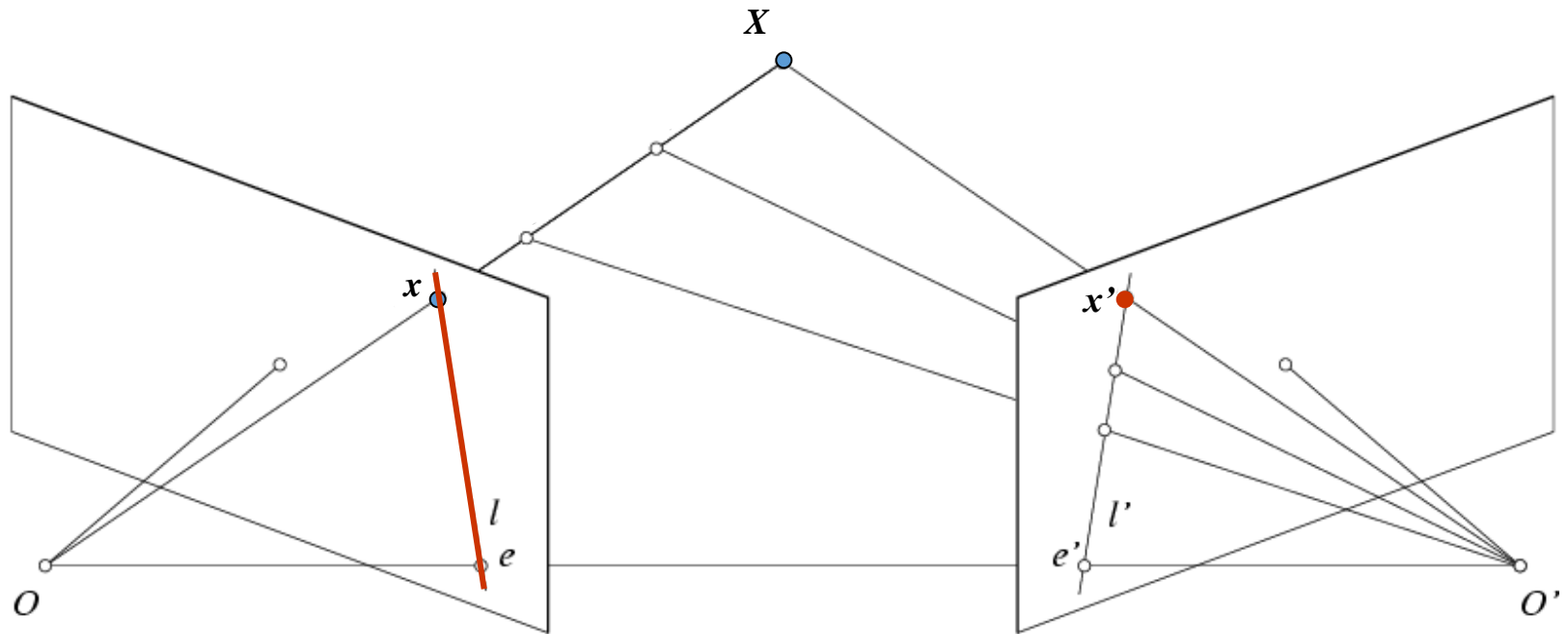


Key idea: Epipolar constraint



Potential matches for x have to lie on the corresponding line l' .

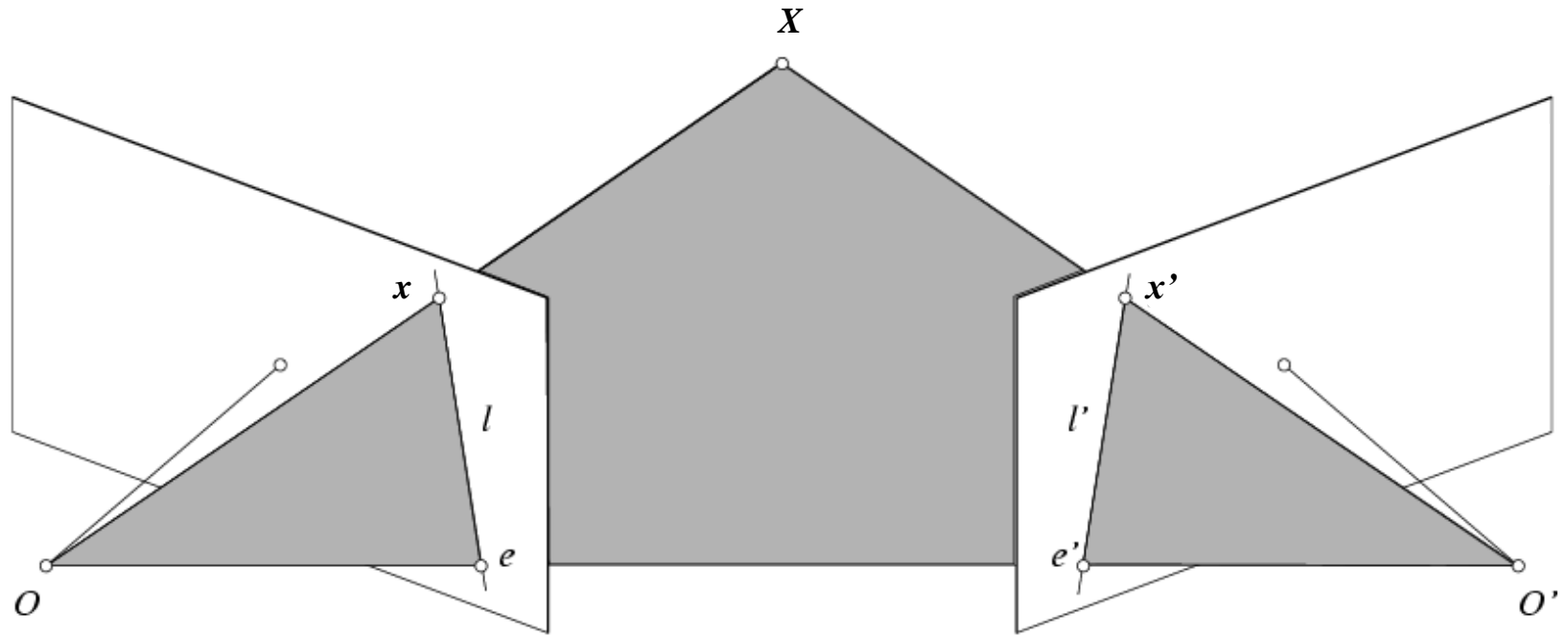
Key idea: Epipolar constraint



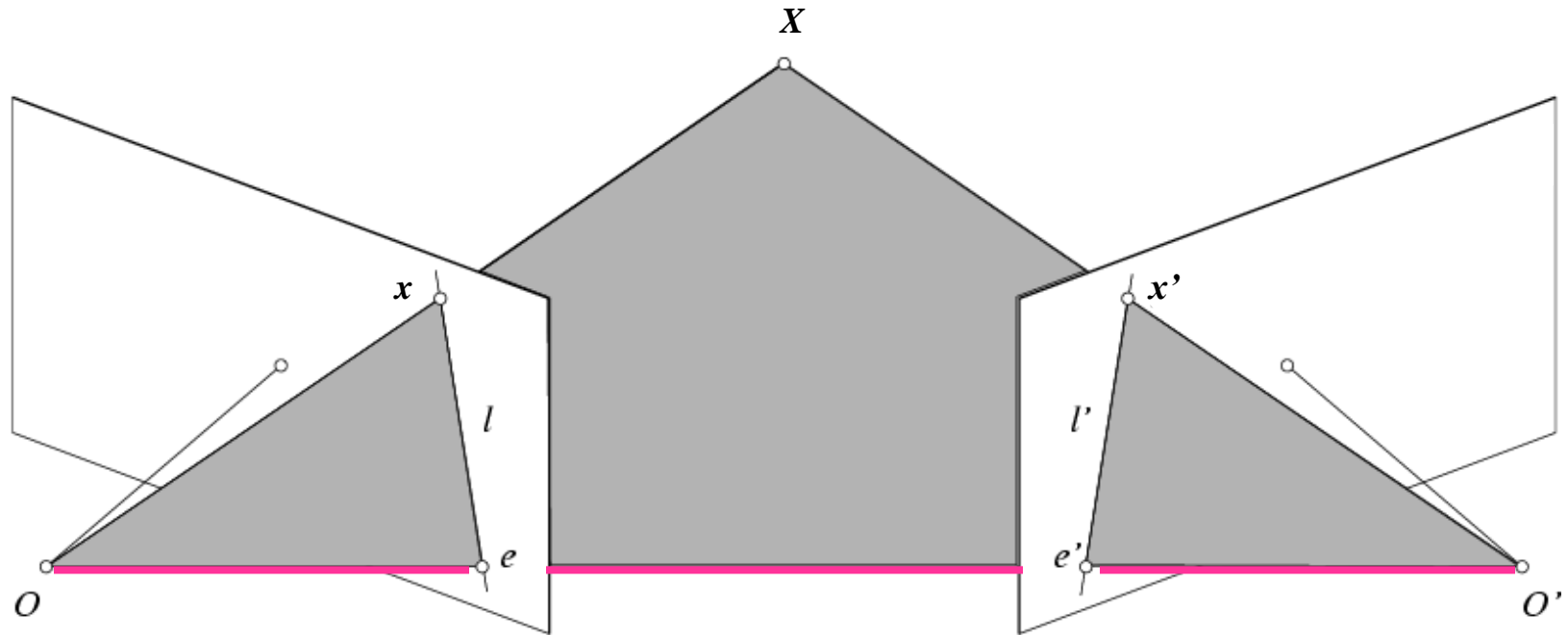
Potential matches for x have to lie on the corresponding line l' .

Potential matches for x' have to lie on the corresponding line l .

Epipolar geometry: notation

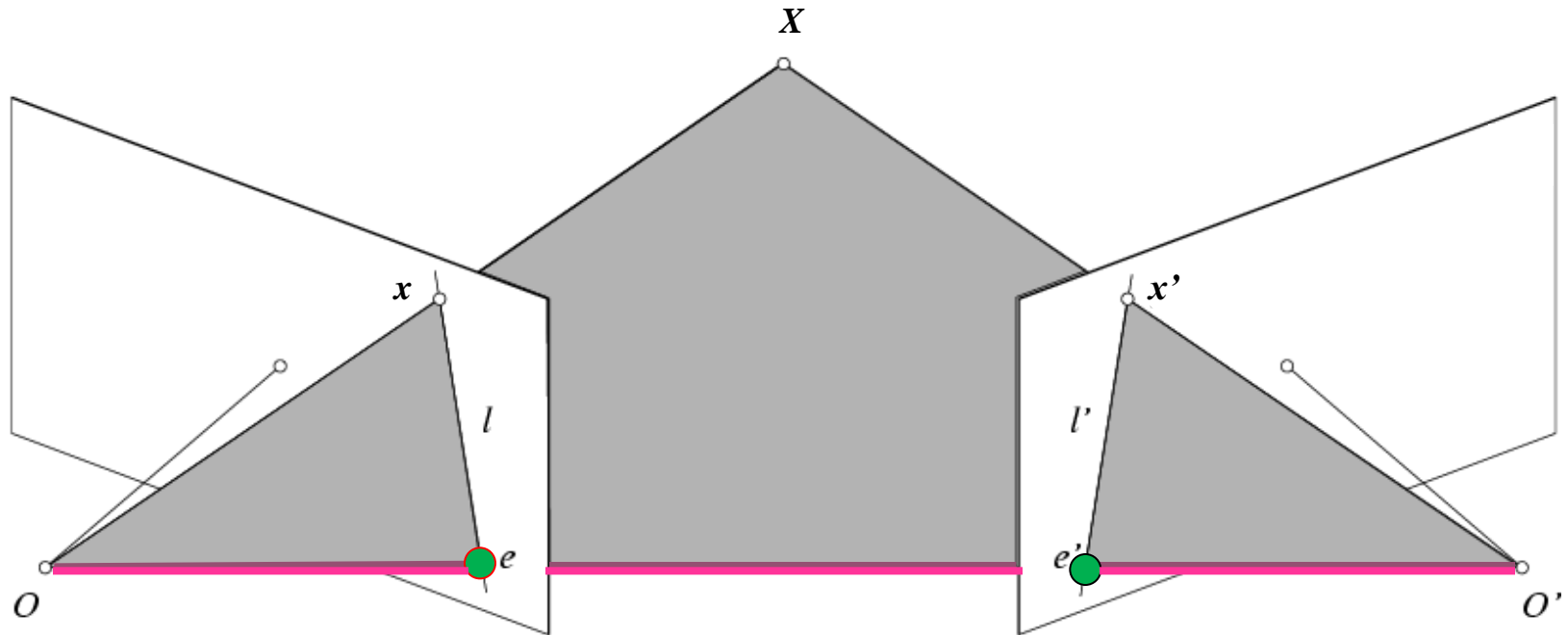


Epipolar geometry: notation



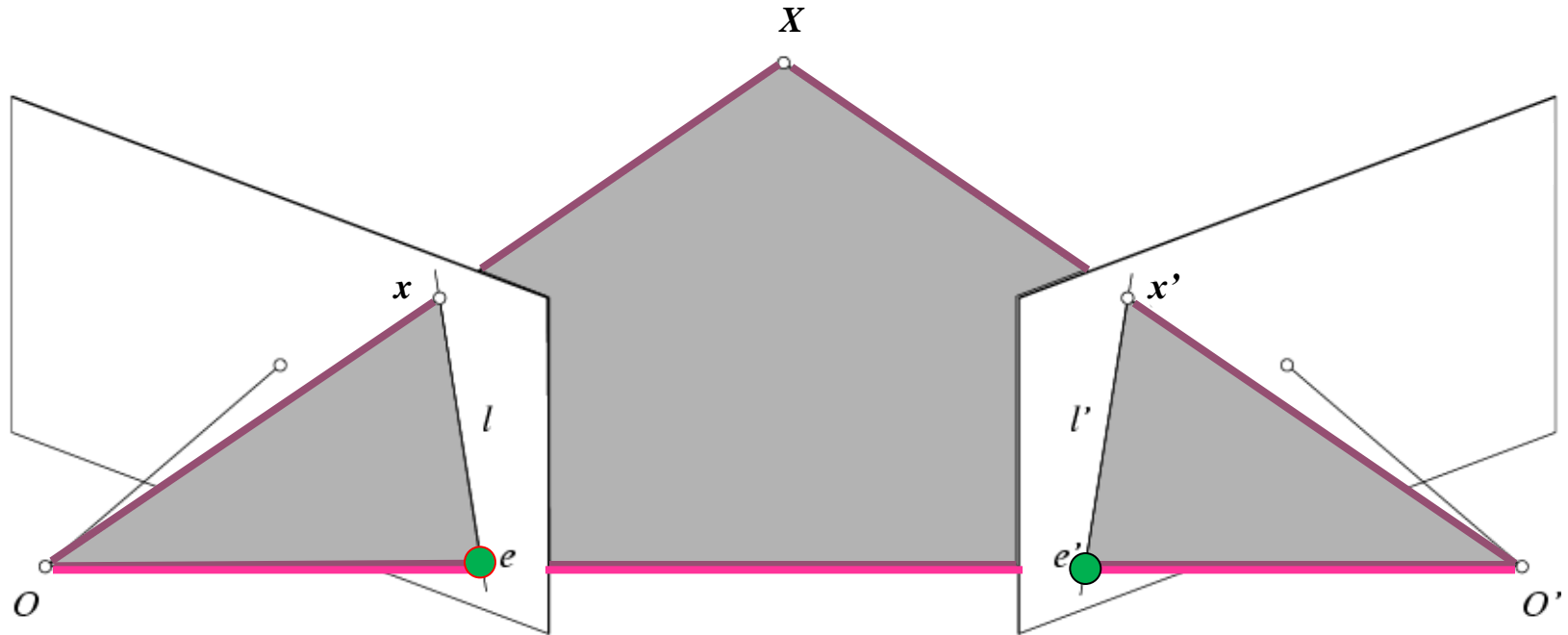
- **Baseline** – line connecting the two camera centers

Epipolar geometry: notation



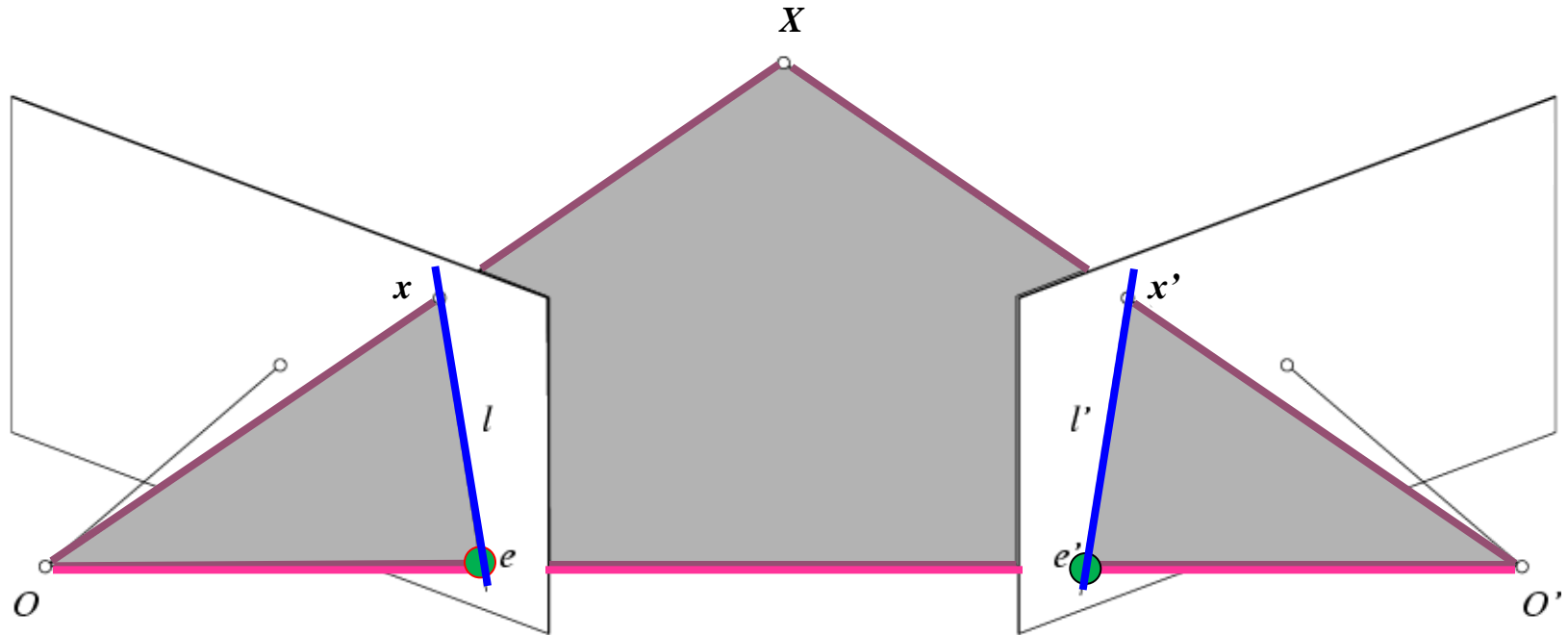
- **Baseline** – line connecting the two camera centers
- **Epipoles**
 - = intersections of baseline with image planes
 - = projections of the other camera center

Epipolar geometry: notation



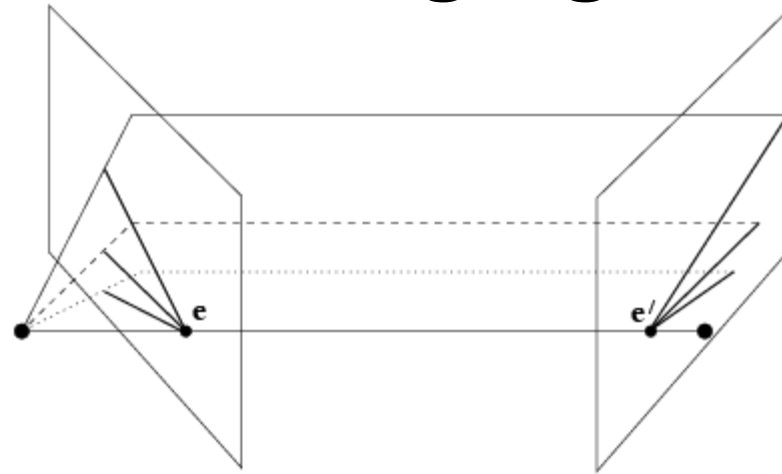
- **Baseline** – line connecting the two camera centers
- **Epipoles**
= intersections of baseline with image planes
= projections of the other camera center
- **Epipolar Plane** – plane containing baseline and 3d point

Epipolar geometry: notation

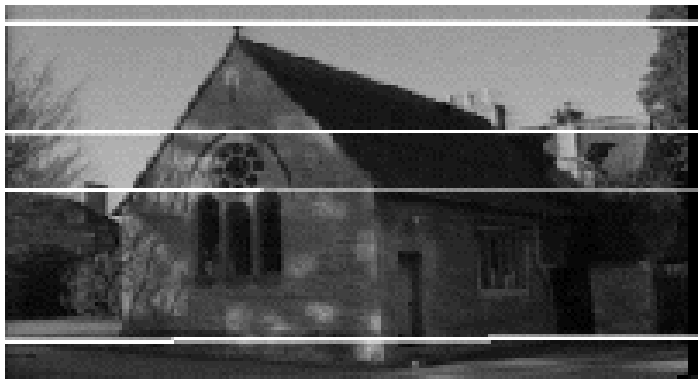
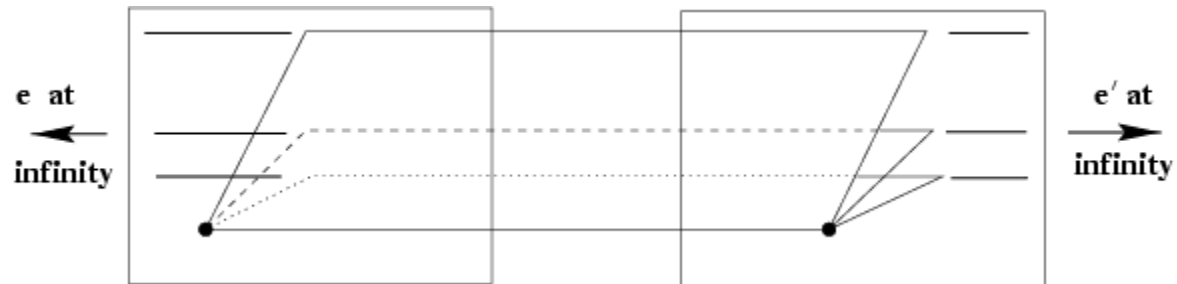


- **Baseline** – line connecting the two camera centers
- **Epipoles**
= intersections of baseline with image planes
= projections of the other camera center
- **Epipolar Plane** – plane containing baseline and 3d point
- **Epipolar Lines** - intersections of epipolar plane with image planes (always come in corresponding pairs)

Example: Converging cameras

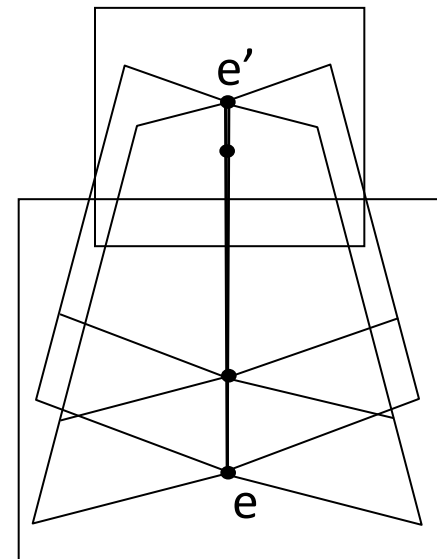
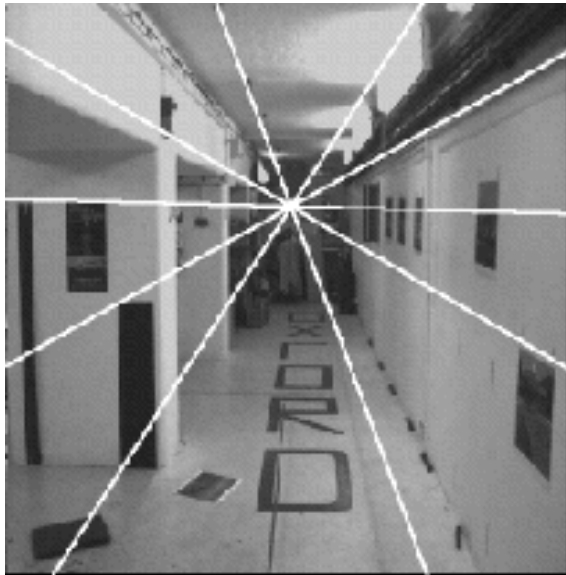


Example: Parallel cameras



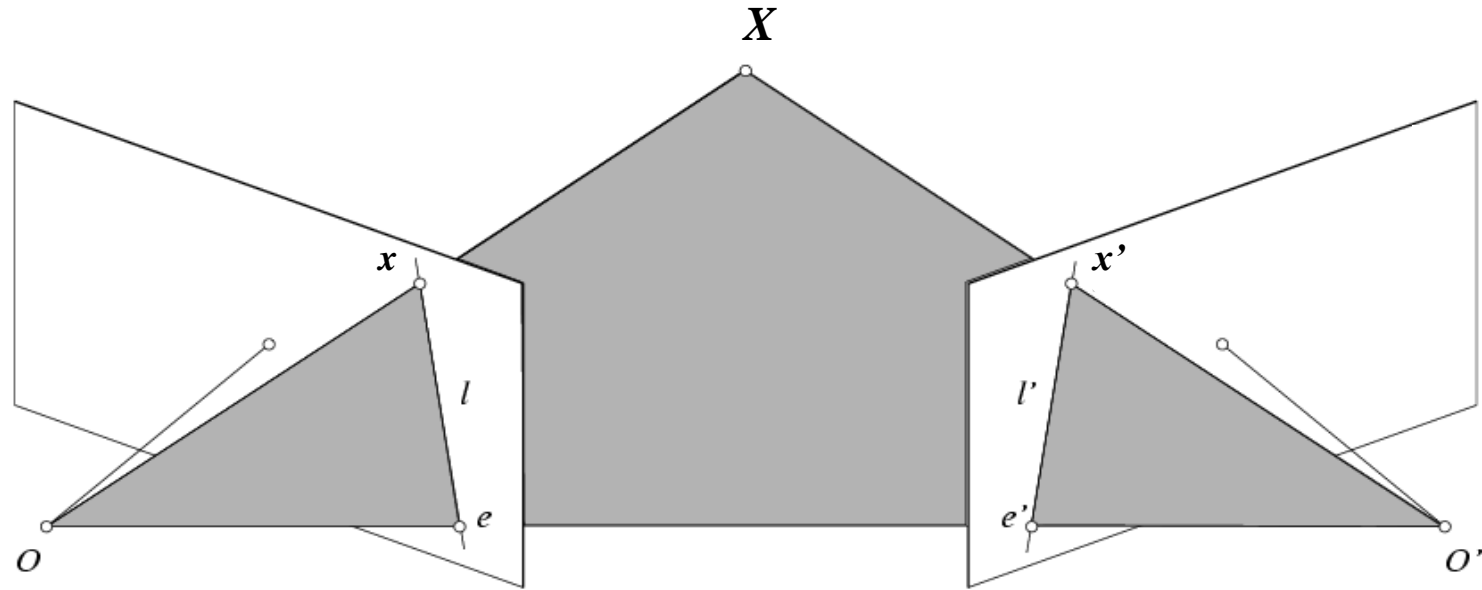
Example: Forward motion

The camera moves directly forward



Epipole has same coordinates in both images.
Points move along lines radiating from e:
“Focus of expansion”

Epipolar constraint: Calibrated case



Given the intrinsic parameters of the cameras:

1. Convert to normalized coordinates by pre-multiplying all points with the inverse of the calibration matrix; set first camera's coordinate system to world coordinates

$$\hat{x} = K^{-1} x = X$$

Homogeneous 2d point
(3D ray towards X)

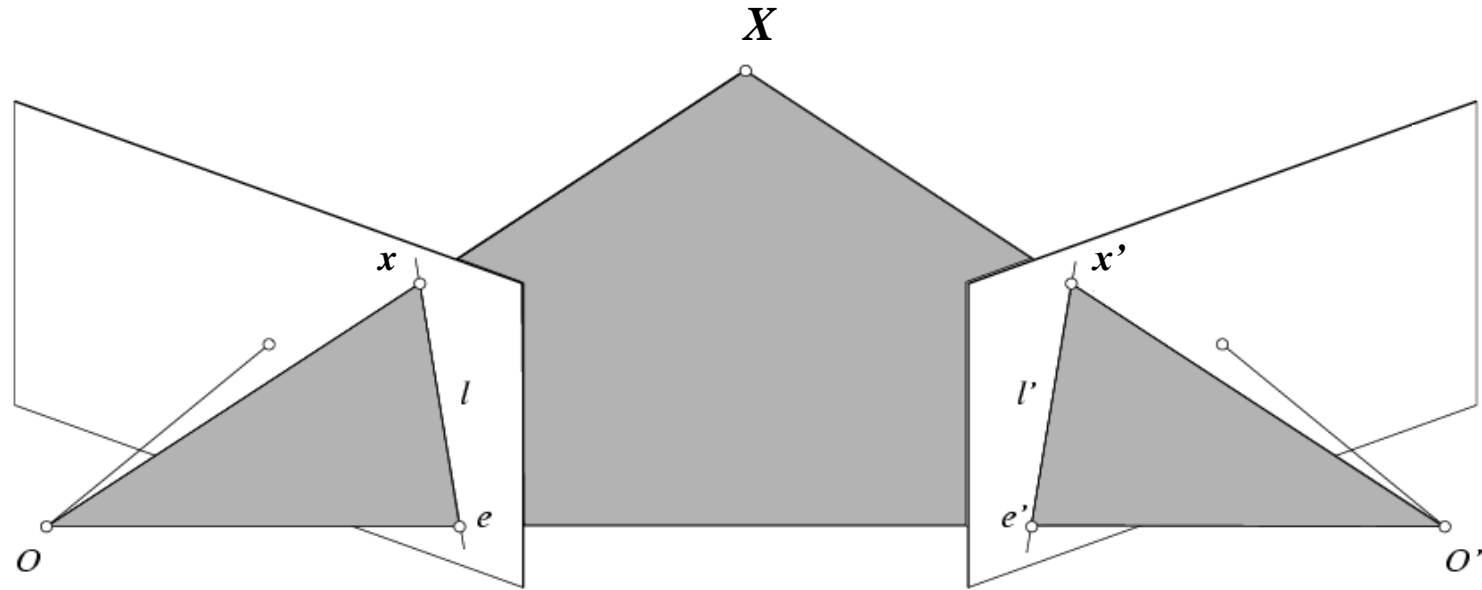
2D pixel coordinate
(homogeneous)

3D scene point

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

3D scene point in 2nd camera's
3D coordinates

Epipolar constraint: Calibrated case



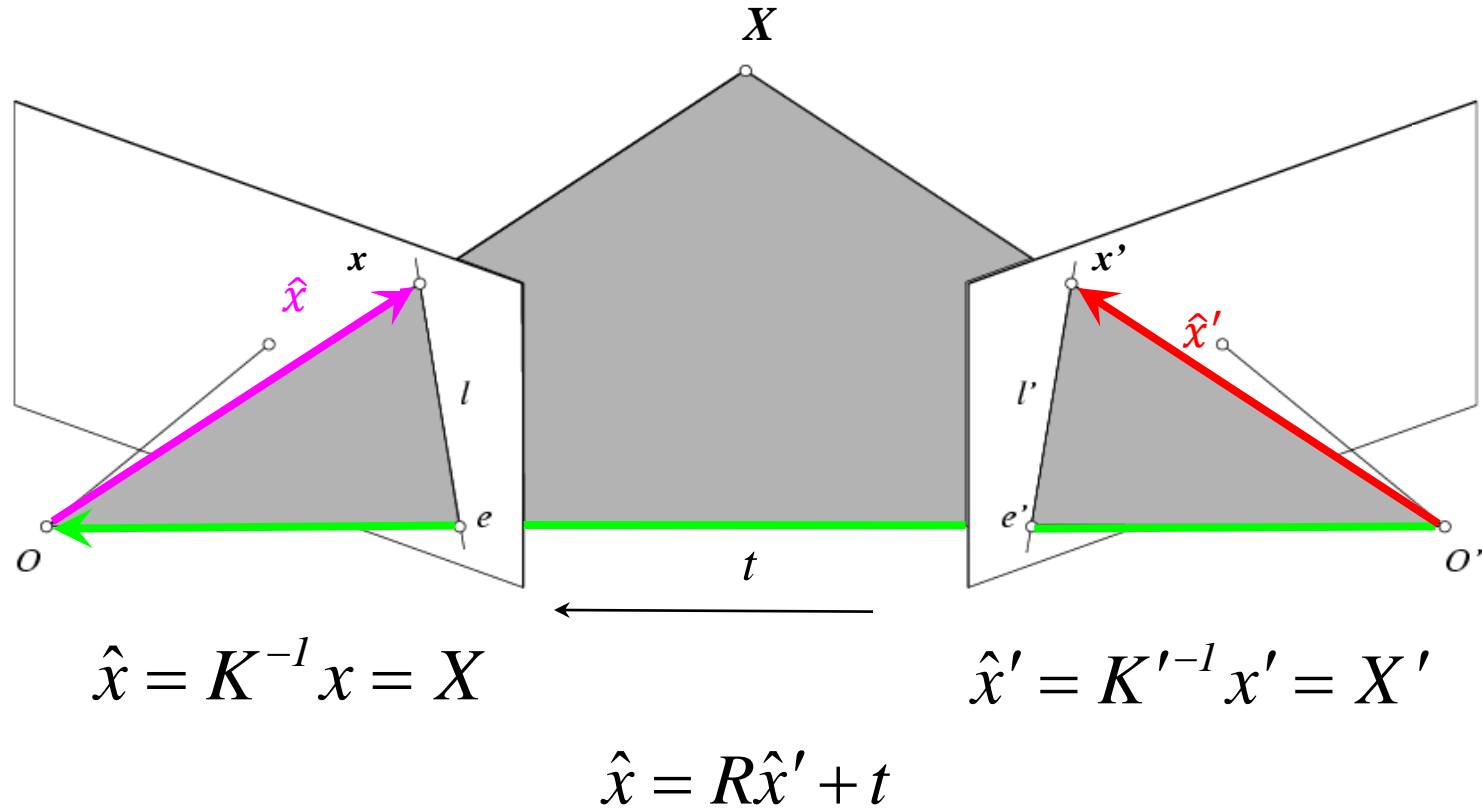
Given the intrinsic parameters of the cameras:

1. Convert to normalized coordinates by pre-multiplying all points with the inverse of the calibration matrix; set first camera's coordinate system to world coordinates
2. Define some R and t that relate X to X' as below

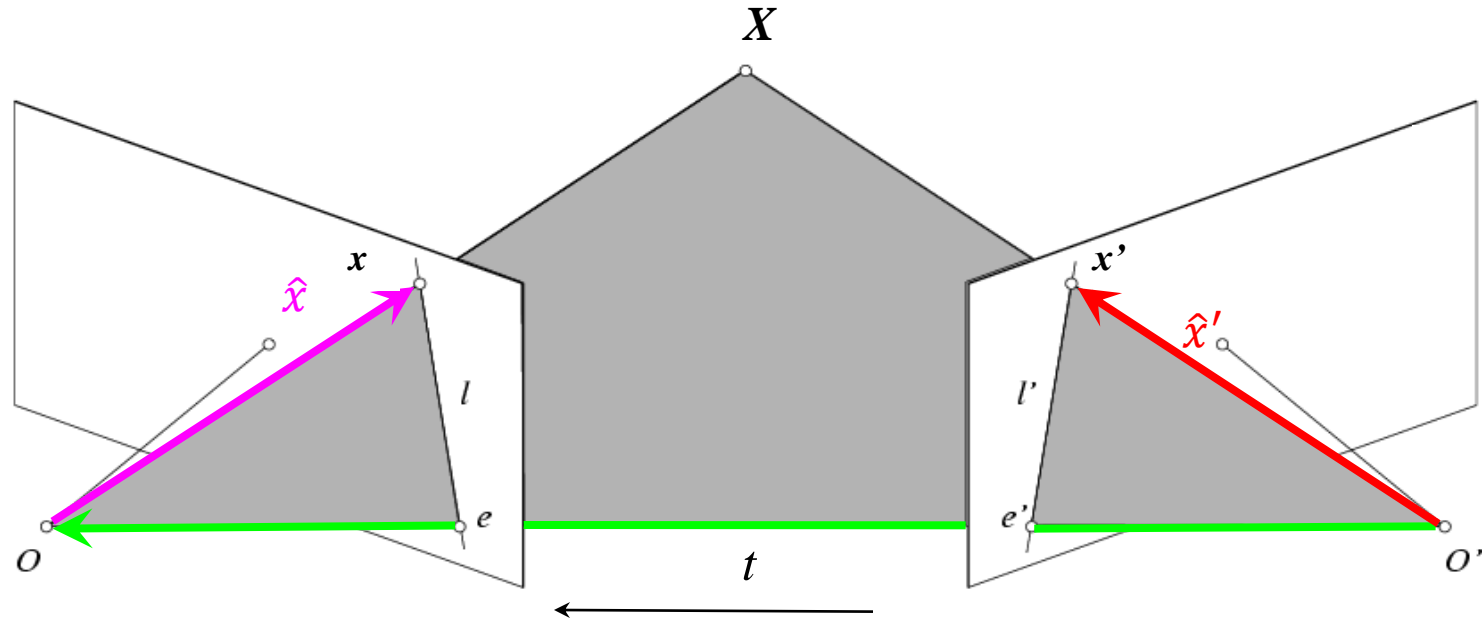
$$\hat{x} = K^{-1}x = X \quad \text{for some scale factor} \quad \hat{x}' = K'^{-1}x' = X'$$

$$\boxed{\hat{x} = R\hat{x}' + t}$$

Epipolar constraint: Calibrated case



Epipolar constraint: Calibrated case



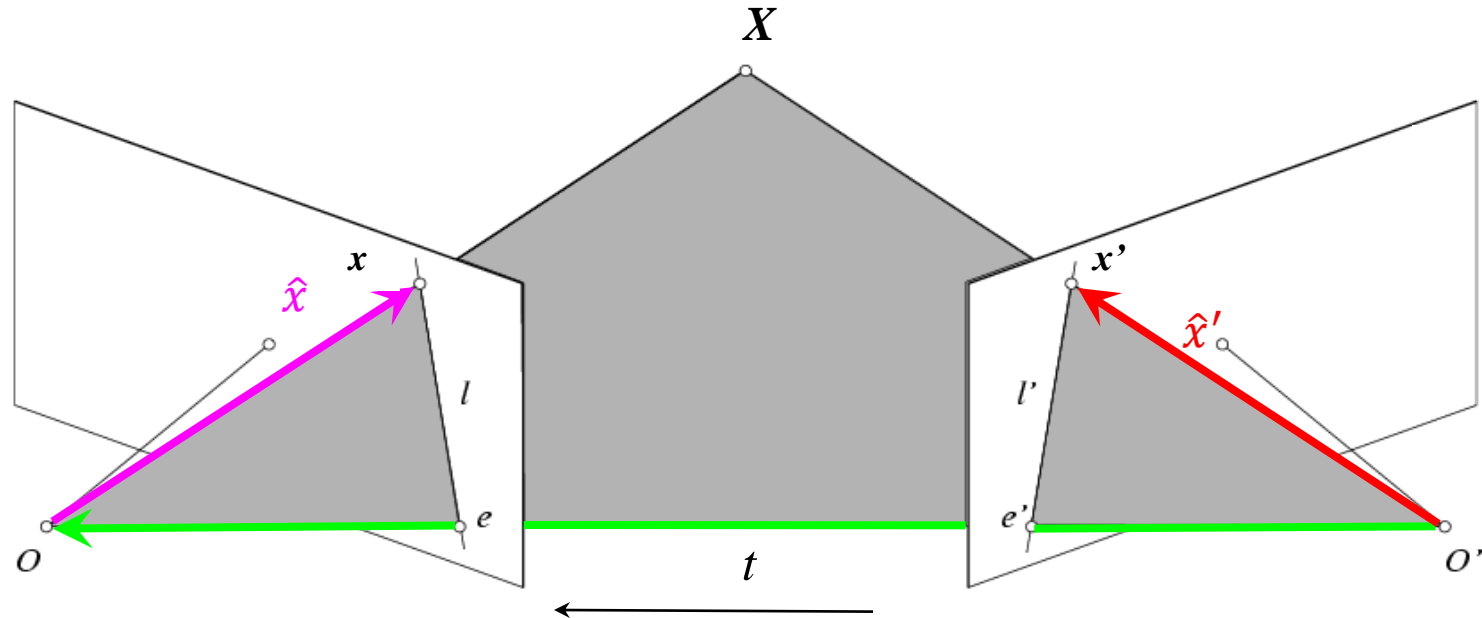
$$\hat{x} = K^{-1}x = X$$

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

$$\hat{x} = R\hat{x}' + t$$

$$\hat{x} \cdot [t \times \hat{x}] = 0$$

Epipolar constraint: Calibrated case



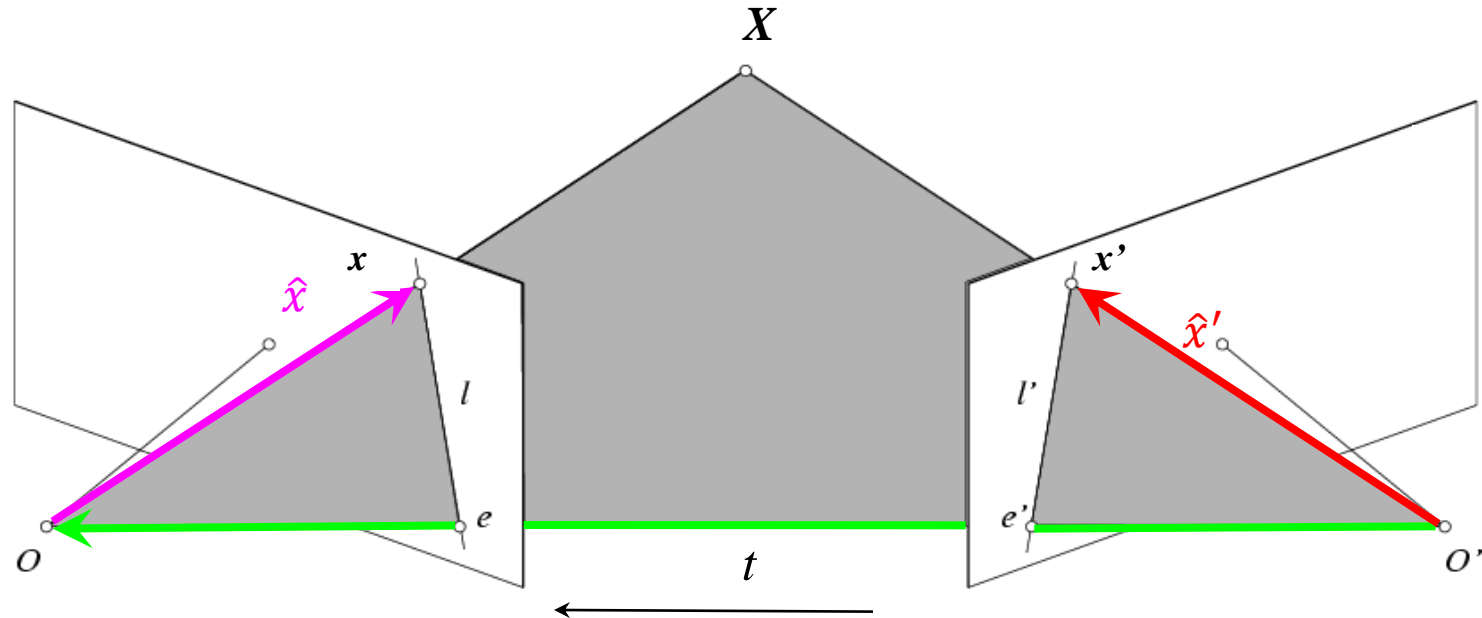
$$\hat{x} = K^{-1}x = X$$

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

$$\hat{x} = R\hat{x}' + t$$

$$\hat{x} \cdot [t \times \hat{x}] = 0 \quad \Rightarrow \quad \hat{x} \cdot [t \times (R\hat{x}' + t)] = 0$$

Epipolar constraint: Calibrated case



$$\hat{x} = K^{-1}x = X$$

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

$$\hat{x} = R\hat{x}' + t$$

$$\hat{x} \cdot [t \times \hat{x}] = 0 \quad \Rightarrow \quad \hat{x} \cdot [t \times (R\hat{x}' + t)] = 0$$

$$\Rightarrow \quad \hat{x} \cdot [t \times (R\hat{x}')] = 0$$

(because \hat{x} , $R\hat{x}'$, and t are co-planar)

Matrix representation of cross product

$$\mathbf{a} = (a_1 \ a_2 \ a_3)^T$$

$$\mathbf{b} = (b_1 \ b_2 \ b_3)^T$$

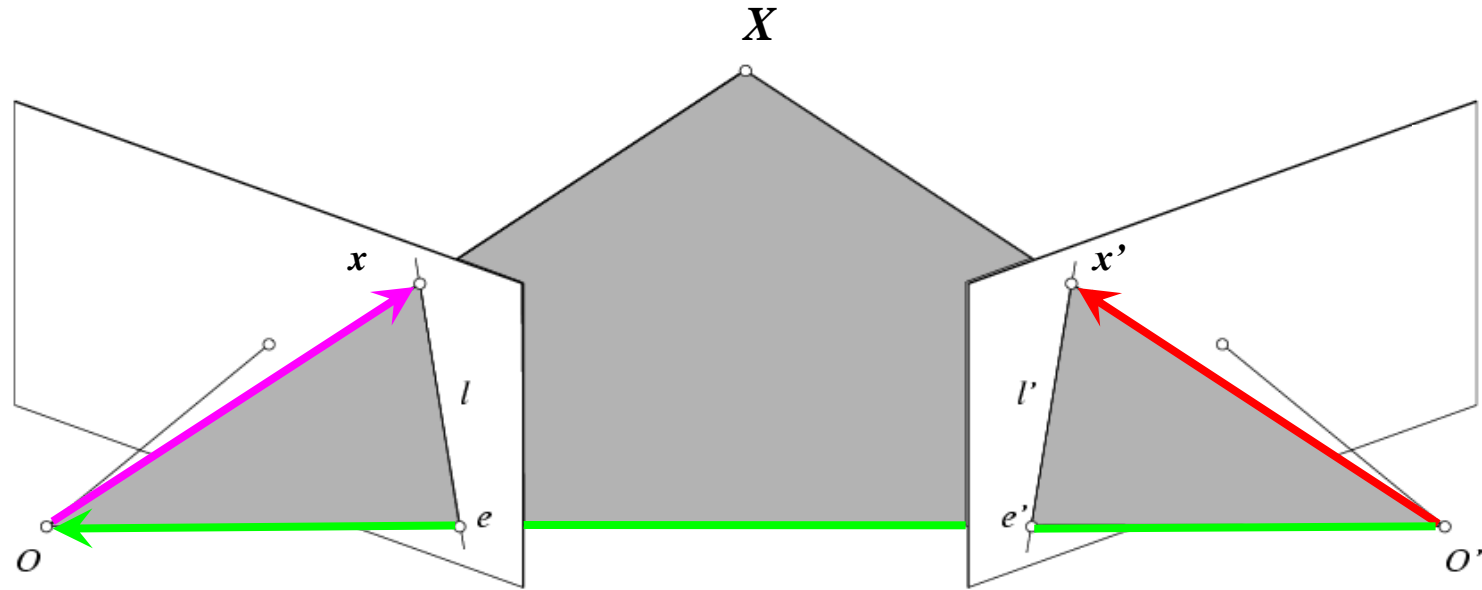
$$[\mathbf{a}]_{\times} = \begin{bmatrix} 0 & -a_3 & a_2 \\ a_3 & 0 & -a_1 \\ -a_2 & a_1 & 0 \end{bmatrix}$$

Skew-symmetric matrix
(Rank 2)

$$\mathbf{a} \times \mathbf{b} = [\mathbf{a}]_{\times} \mathbf{b}$$

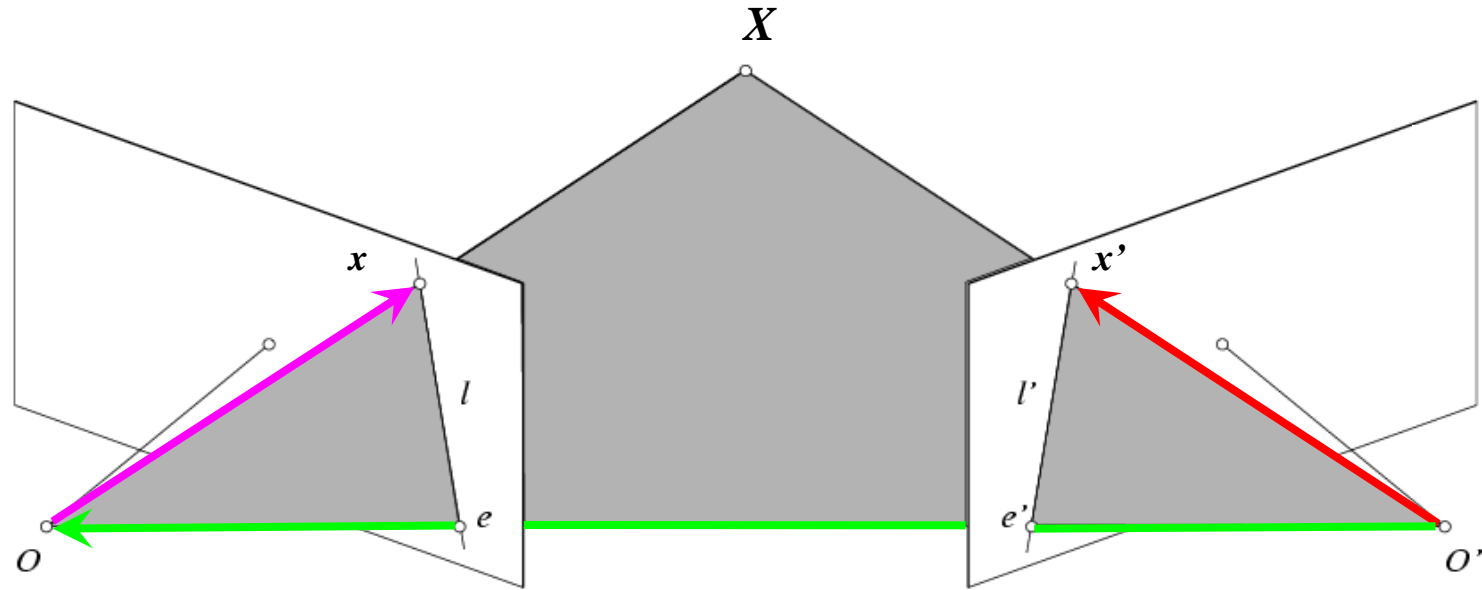
[Matrix representation of the cross product](#)

Essential matrix



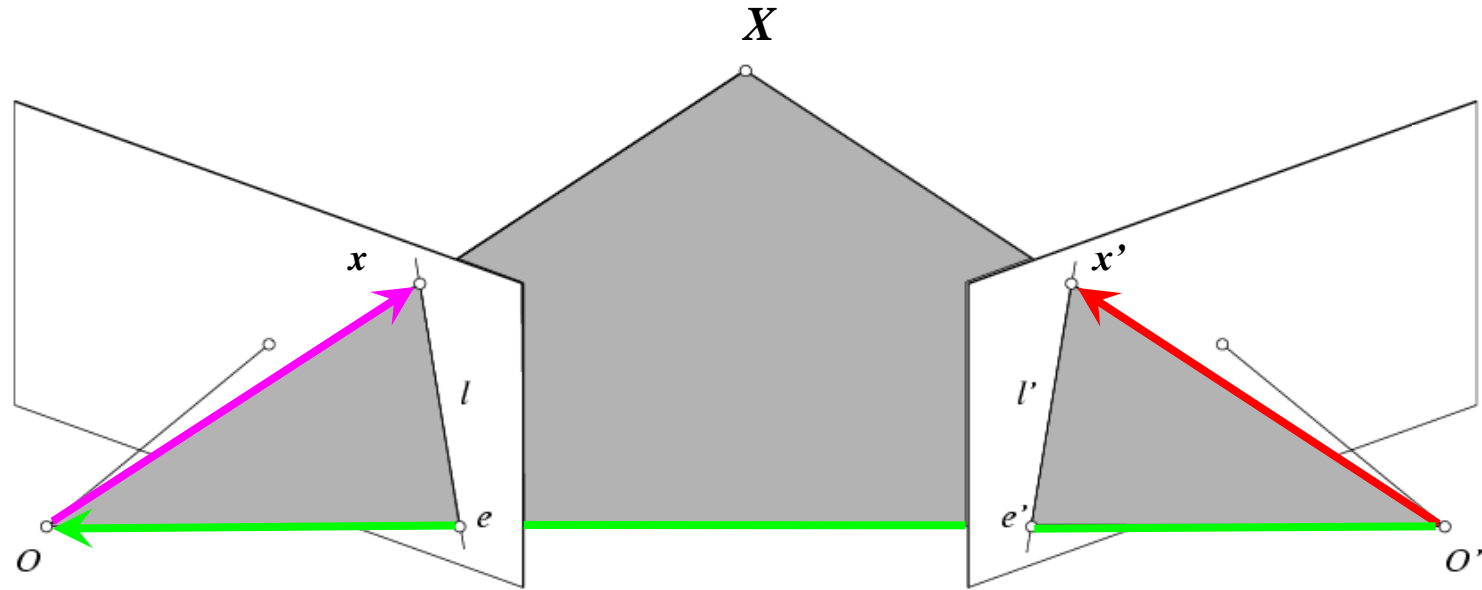
$$\hat{x} \cdot [t \times (R \hat{x}')] = \hat{x}^T [t]_{\times} R \hat{x}'$$

Essential matrix



$$\hat{x} \cdot [t \times (R \hat{x}')] = \hat{x}^T [t]_{\times} R \hat{x}' = \hat{x}^T E \hat{x}' = 0 \quad \text{with} \quad E = [t]_{\times} R$$

Essential matrix

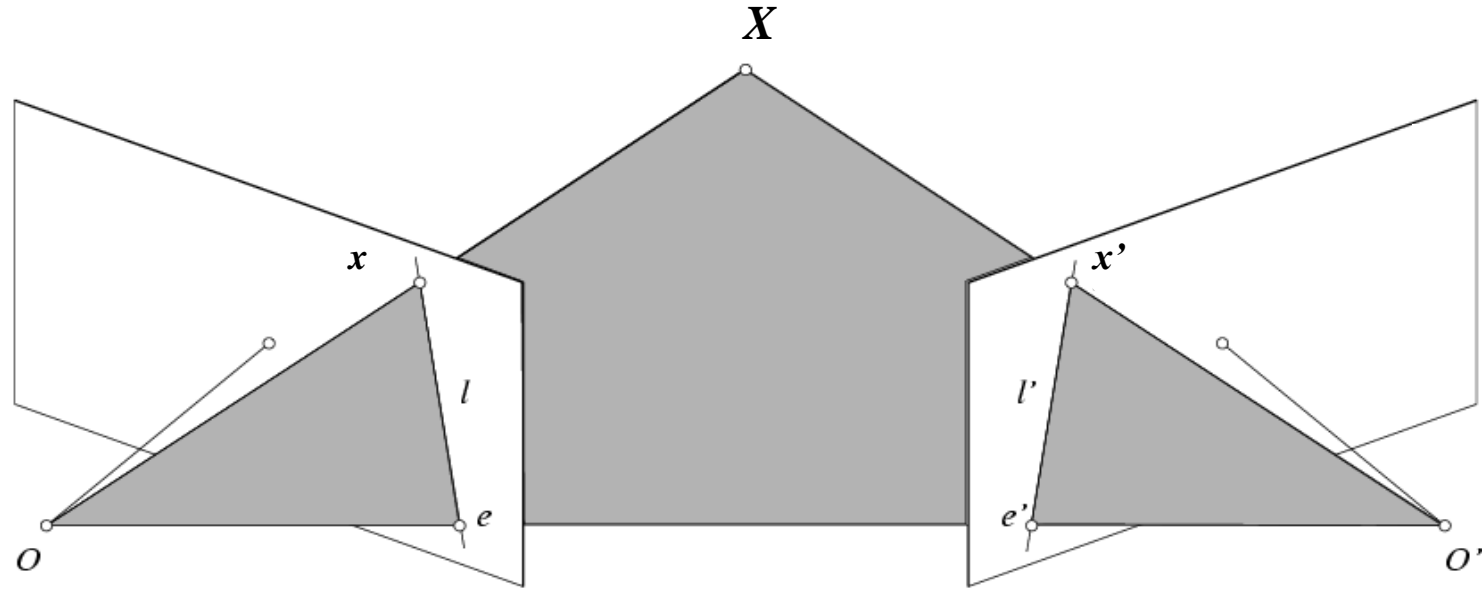


$$\hat{x} \cdot [t \times (R \hat{x}')] = \hat{x}^T [t]_{\times} R \hat{x}' = \hat{x}^T E \hat{x}' = 0 \quad \text{with} \quad E = [t]_{\times} R$$



Essential Matrix
(Longuet-Higgins, 1981)

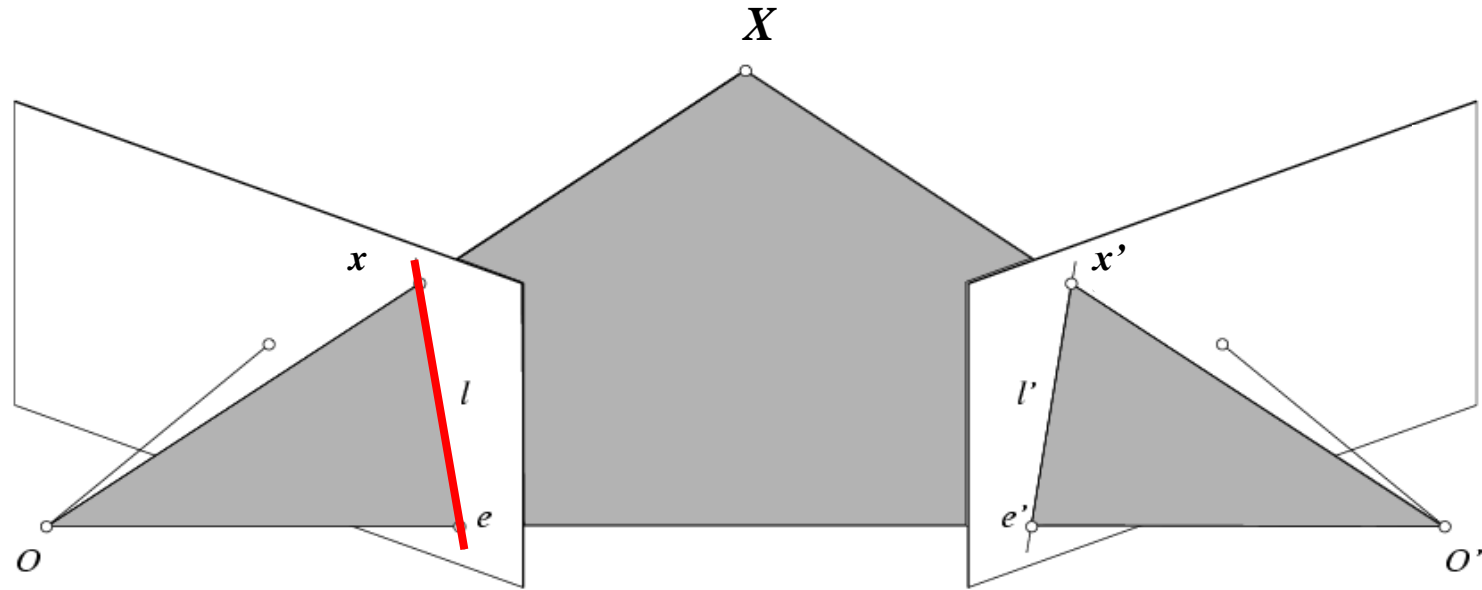
Properties of the Essential matrix



$$\hat{x} \cdot [t \times (R \hat{x}')] = 0 \quad \Rightarrow \quad \hat{x}^T E \hat{x}' = 0 \quad \text{with} \quad E = [t]_{\times} R$$

Skew-symmetric matrix

Properties of the Essential matrix

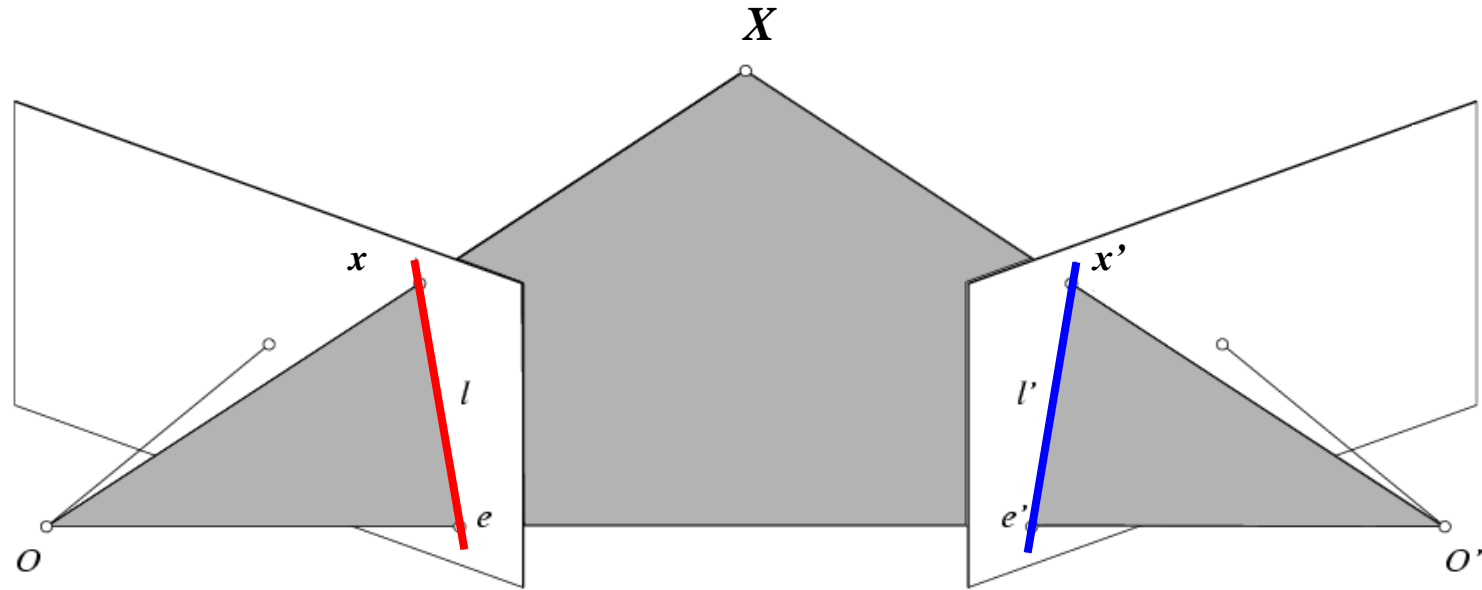


$$\hat{x} \cdot [t \times (R \hat{x}')] = 0 \quad \Rightarrow \quad \hat{x}^T E \hat{x}' = 0 \quad \text{with} \quad E = [t]_{\times} R$$

- $E x'$ is the epipolar line associated with x' ($l = E x'$)

Skew-symmetric matrix

Properties of the Essential matrix

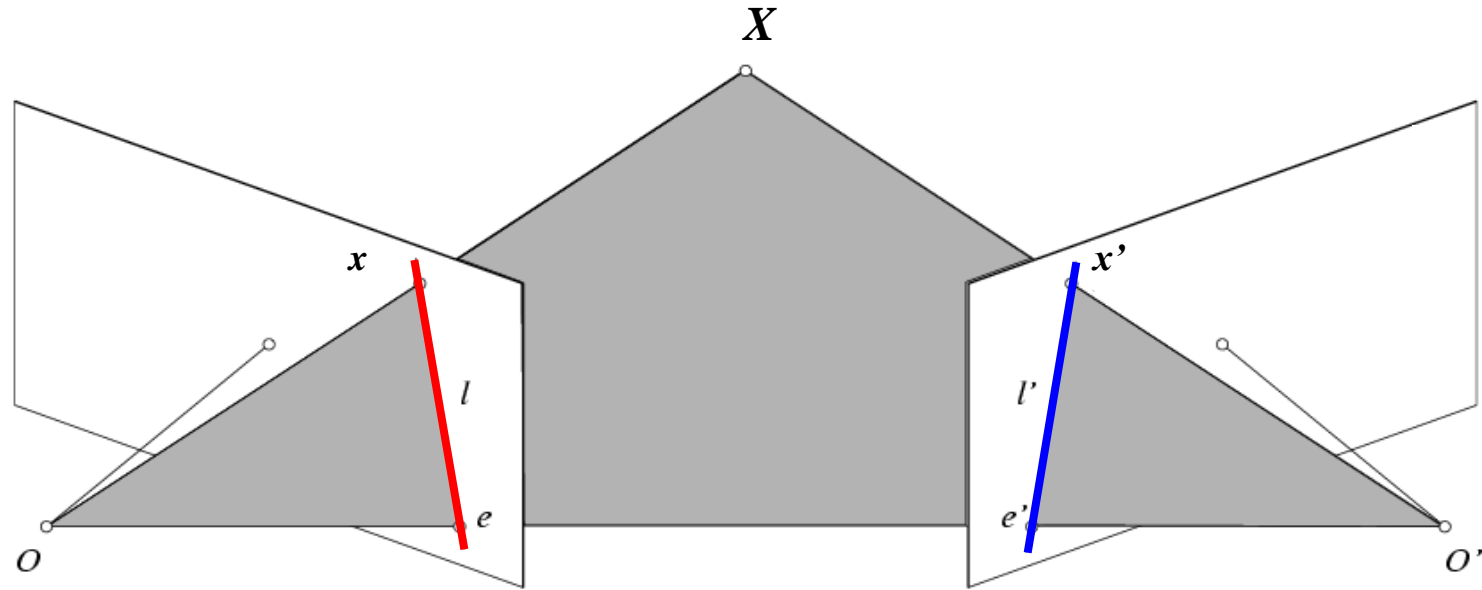


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- $E x'$ is the epipolar line associated with x' ($l = E x'$)
- $E^T x$ is the epipolar line associated with x ($l' = E^T x$)

Skew-symmetric matrix

Properties of the Essential matrix

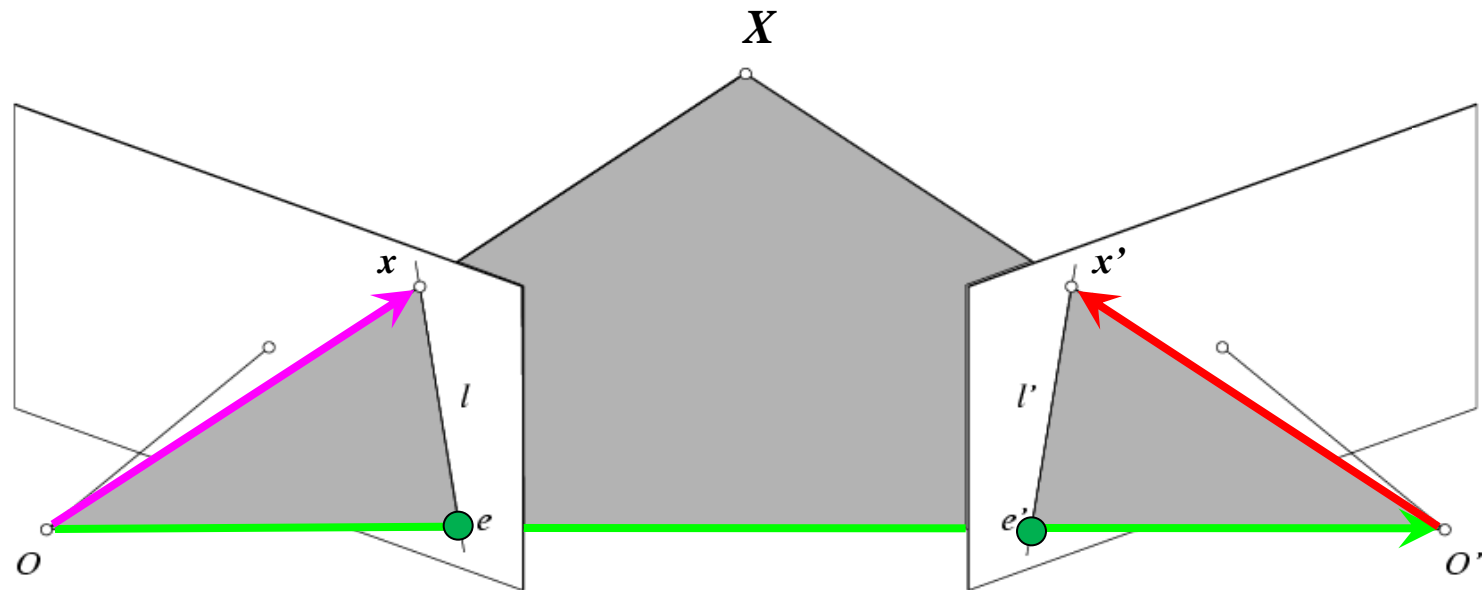


$$\hat{x} \cdot [t \times (R \hat{x}')] = 0 \quad \Rightarrow \quad \hat{x}^T E \hat{x}' = 0 \quad \text{with} \quad E = [t]_{\times} R$$

- $E x'$ is the epipolar line associated with x' ($l = E x'$)
- $E^T x$ is the epipolar line associated with x ($l' = E^T x$)
- E is singular (rank two): $\det(E)=0$

Skew-symmetric matrix

Epipolar constraint: Uncalibrated case



- If we don't know K and K' , then we can write the epipolar constraint in terms of *unknown* normalized coordinates:

$$\hat{x}^T E \hat{x}' = 0$$

$$x = K \hat{x}, \quad x' = K' \hat{x}'$$

The Fundamental Matrix

Without knowing K and K' , we can define a similar relation using *unknown* normalized coordinates

$$\hat{x}^T E \hat{x}' = 0$$

$$\hat{x} = K^{-1} x$$

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

The Fundamental Matrix

Without knowing K and K' , we can define a similar relation using *unknown* normalized coordinates

$$\hat{x}^T E \hat{x}' = 0$$

$$\hat{x} = K^{-1} x$$

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


$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

The Fundamental Matrix

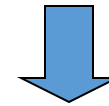
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$$\hat{x}^T E \hat{x}' = 0$$

$$\hat{x} = K^{-1} x$$

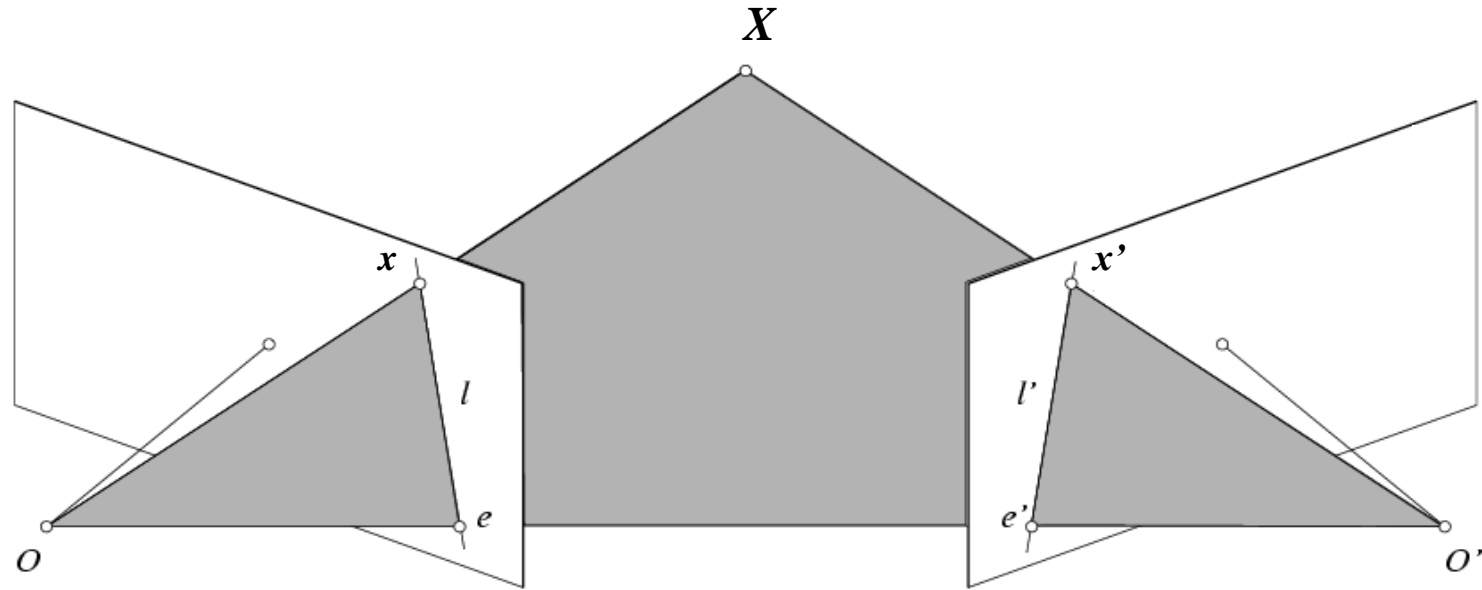
$$\hat{x}' = K'^{-1} x'$$


$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$



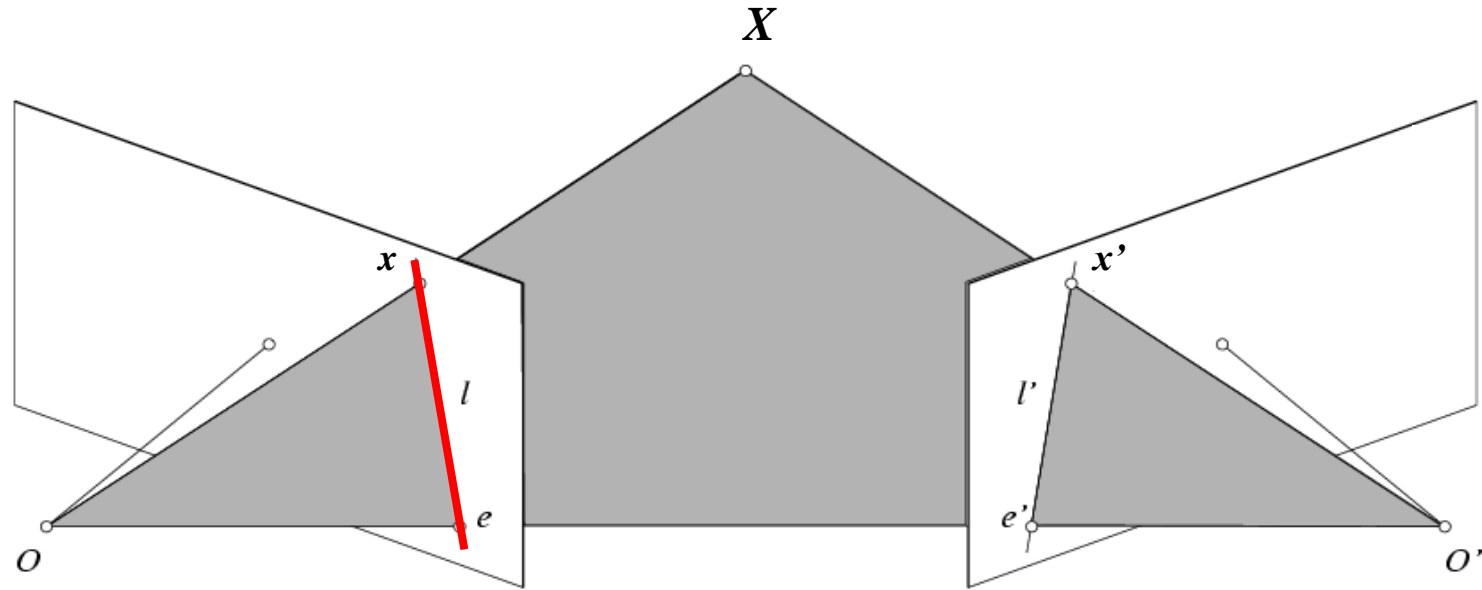
Fundamental Matrix
(Faugeras and Luong, 1992)

Properties of the Fundamental matrix



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

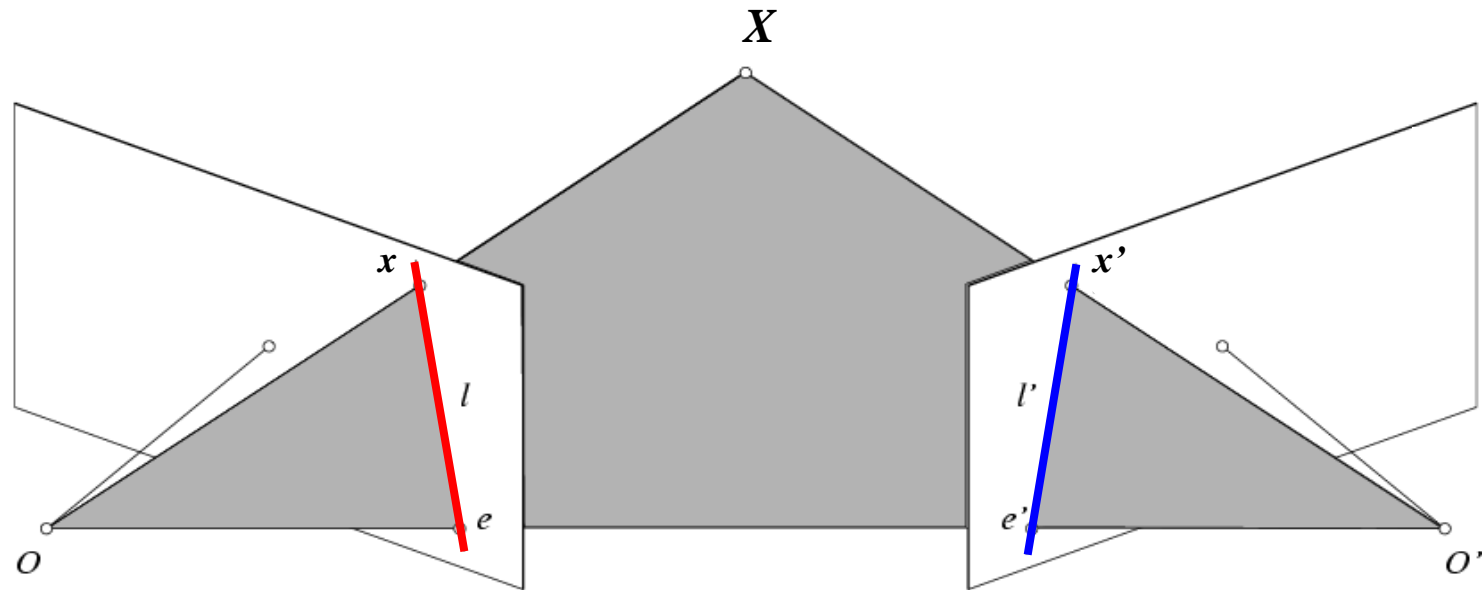
Properties of the Fundamental matrix



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

- $F x'$ is the epipolar line associated with x' ($l = F x'$)

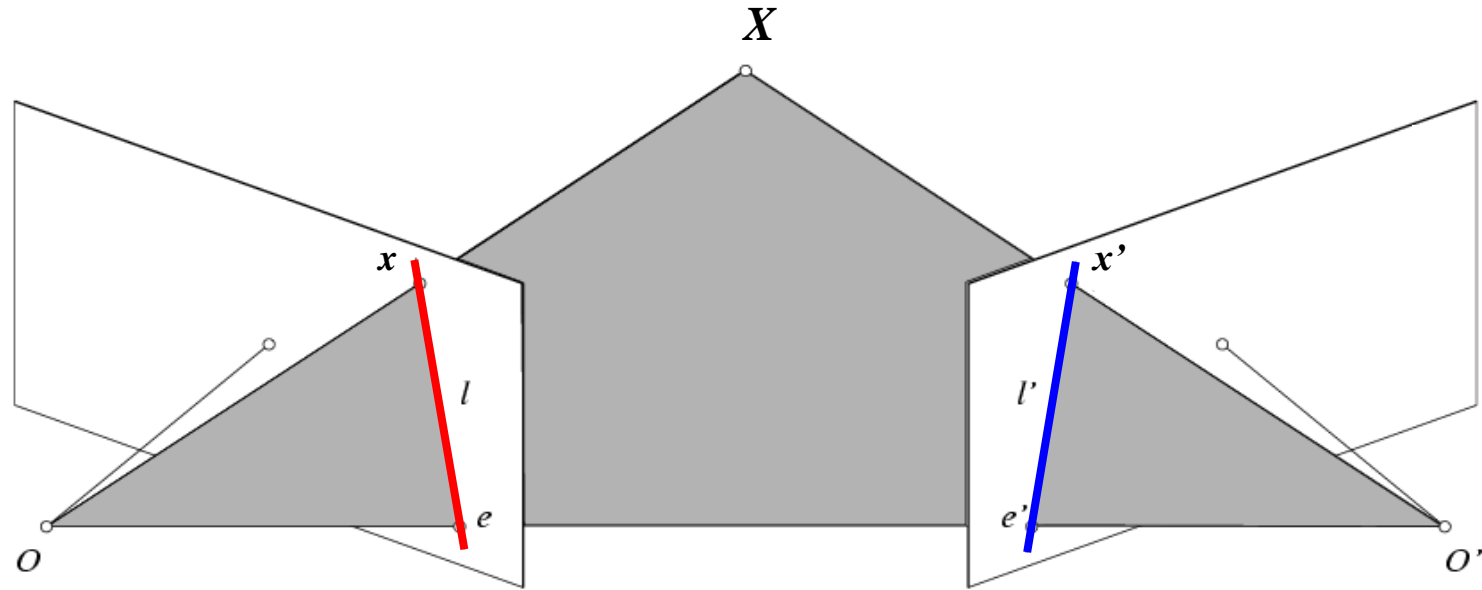
Properties of the Fundamental matrix



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

- $F x'$ is the epipolar line associated with x' ($l = F x'$)
- $F^T x$ is the epipolar line associated with x ($l' = F^T x$)

Properties of the Fundamental matrix



$$x^T F x' = 0 \quad \text{with} \quad F = K^{-T} E K'^{-1}$$

- $F x'$ is the epipolar line associated with x' ($l = F x'$)
- $F^T x$ is the epipolar line associated with x ($l' = F^T x$)
- F is singular (rank two): $\det(F)=0$

Estimating the Fundamental Matrix

- 8-point algorithm
 - Least squares solution using SVD on equations from 8 pairs of correspondences
 - Enforce $\det(F)=0$ constraint using SVD on F

Note: estimation of F (or E) is degenerate for a planar scene.

8-point algorithm

1. Solve a system of homogeneous linear equations
 - a. Write down the system of equations

$$\mathbf{x}^T F \mathbf{x}' = 0$$

$$uu'f_{11} + uv'f_{12} + uf_{13} + vu'f_{21} + vv'f_{22} + vf_{23} + u'f_{31} + v'f_{32} + f_{33} = 0$$

8-point algorithm

1. Solve a system of homogeneous linear equations

a. Write down the system of equations

$$\mathbf{x}^T F \mathbf{x}' = 0$$

$$uu'f_{11} + uv'f_{12} + uf_{13} + vu'f_{21} + vv'f_{22} + vf_{23} + u'f_{31} + v'f_{32} + f_{33} = 0$$

$$A\mathbf{f} = \begin{bmatrix} u_1u_1' & u_1v_1' & u_1 & v_1u_1' & v_1v_1' & v_1 & u_1' & v_1' & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u_nu_n' & u_nv_n' & u_n & v_nu_n' & v_nv_n' & v_n & u_n' & v_n' & 1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ \vdots \\ f_{33} \end{bmatrix} = \mathbf{0}$$

8-point algorithm

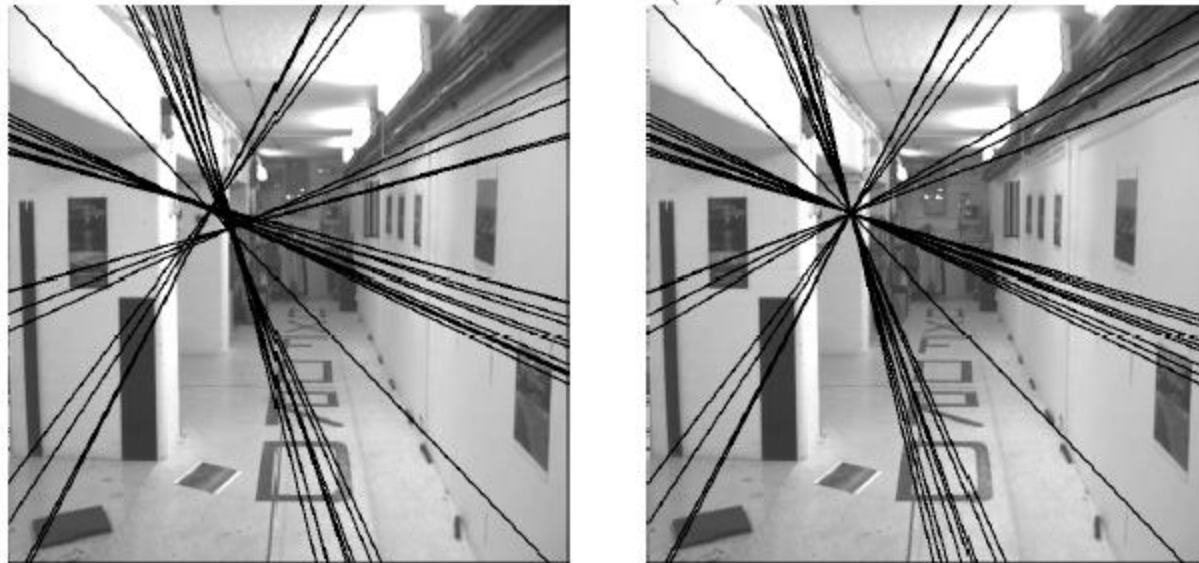
1. Solve a system of homogeneous linear equations
 - a. Write down the system of equations
 - b. Solve \mathbf{f} from $\mathbf{A}\mathbf{f}=\mathbf{0}$ using SVD

Matlab:

```
[U, S, V] = svd(A);  
f = V(:, end);  
F = reshape(f, [3 3])';
```

Need to enforce singularity constraint

Fundamental matrix has rank 2 : $\det(\mathbf{F}) = 0$.



Left : Uncorrected \mathbf{F} – epipolar lines are not coincident.

Right : Epipolar lines from corrected \mathbf{F} .

8-point algorithm

1. Solve a system of homogeneous linear equations

a. Write down the system of equations

b. Solve \mathbf{f} from $\mathbf{A}\mathbf{f}=\mathbf{0}$ using SVD

Matlab:

```
[U, S, V] = svd(A);  
f = V(:, end);  
F = reshape(f, [3 3])';
```

2. Resolve $\det(\mathbf{F}) = 0$ constraint using SVD

Matlab:

```
[U, S, V] = svd(F);  
S(3,3) = 0;  
F = U*S*V';
```

8-point algorithm

Notes:

- Use RANSAC to deal with outliers (sample 8 points)
 - How to test for outliers? $|\mathbf{x}^T \mathbf{F} \mathbf{x}'| < \textit{threshold}$
- Solve in normalized coordinates
 - mean=0
 - standard deviation $\sim (1,1,1)$

Moving on to stereo...

Fuse a calibrated binocular stereo pair to produce a depth image

image 1



image 2

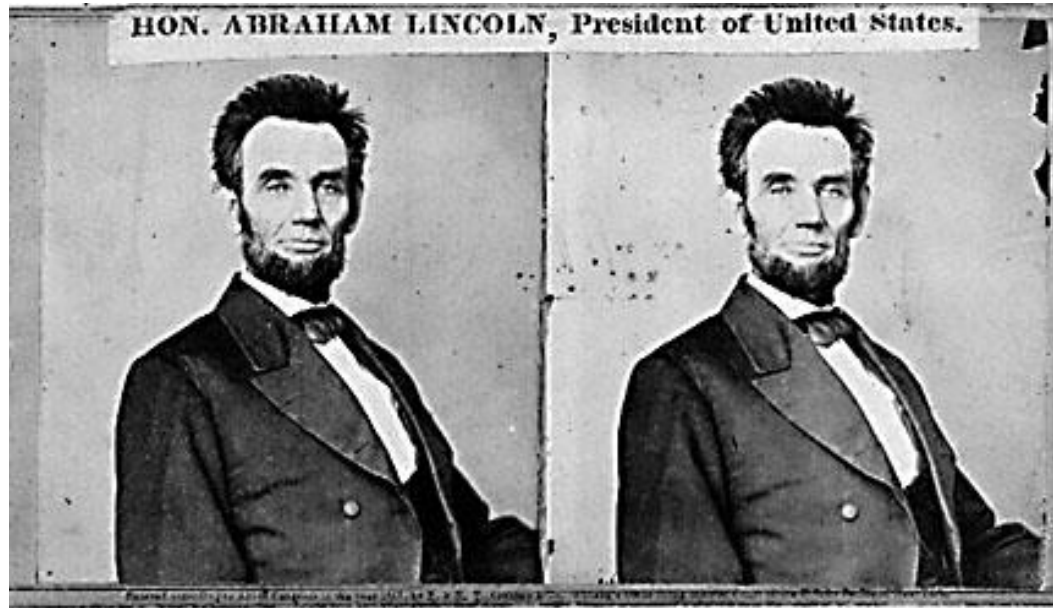


Depth map



Many of these slides adapted from
Steve Seitz and Lana Lazebnik

Basic stereo matching algorithm

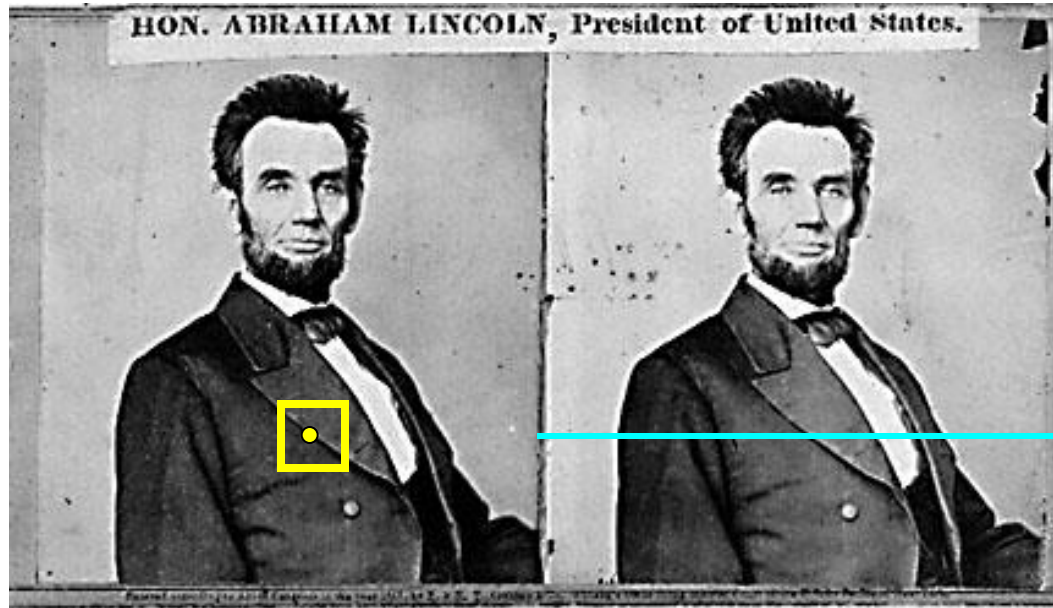


Basic stereo matching algorithm



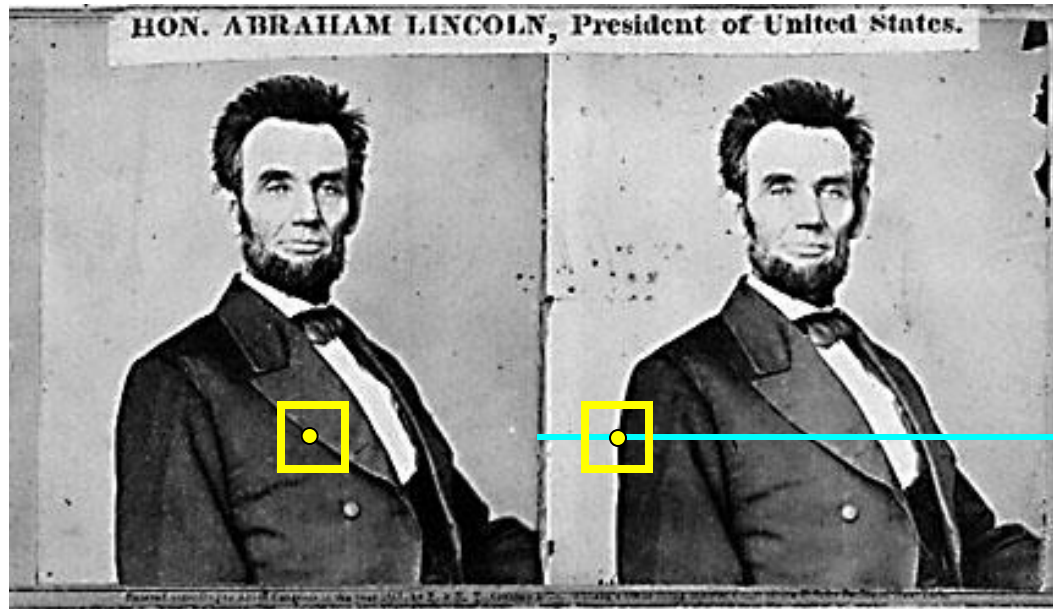
- For each pixel in the first image

Basic stereo matching algorithm



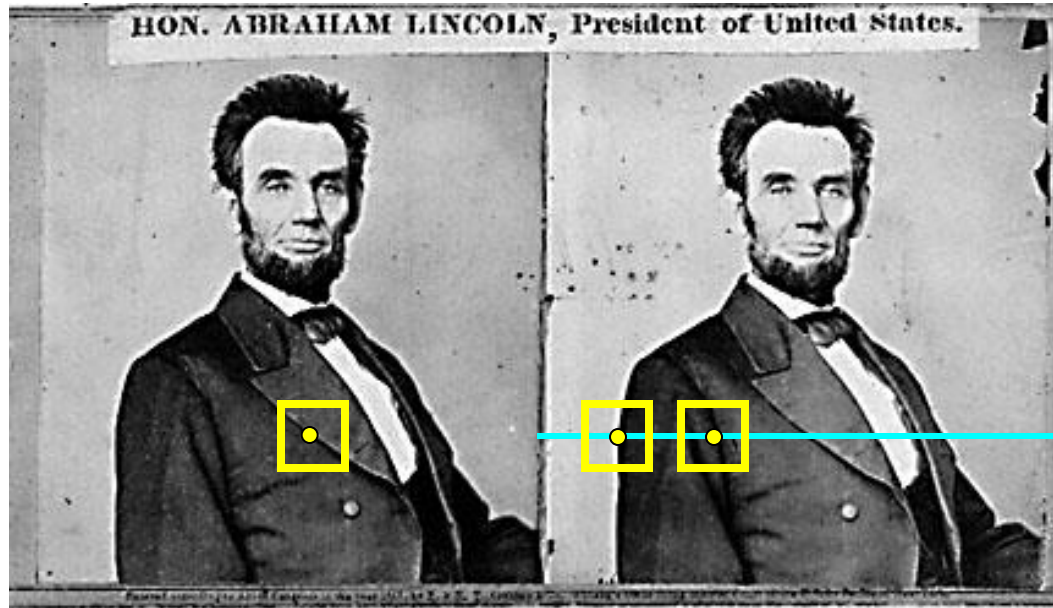
- For each pixel in the first image
 - Find corresponding epipolar line in the right image

Basic stereo matching algorithm



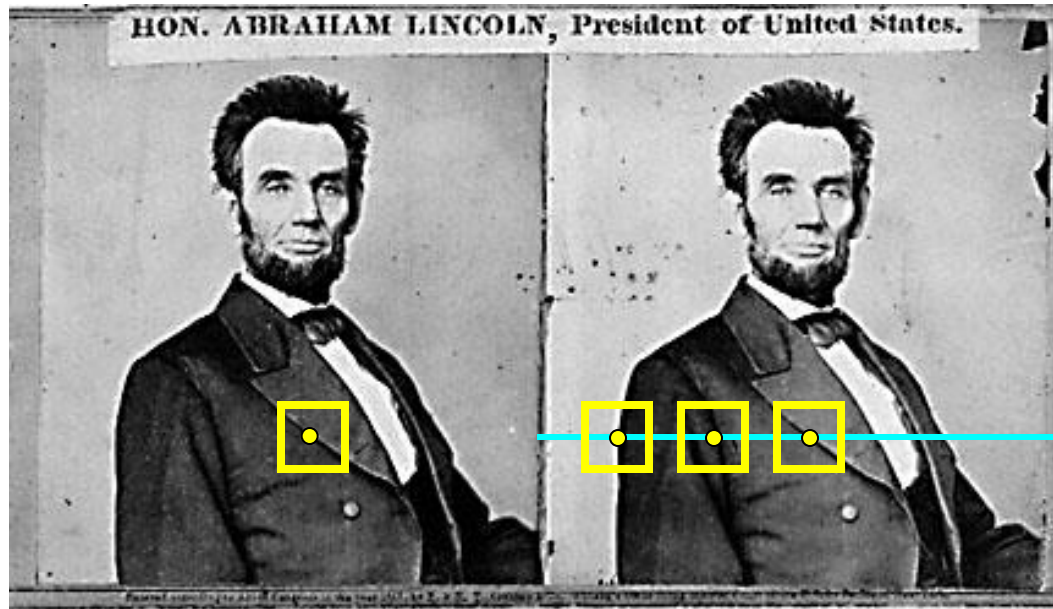
- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Search along epipolar line and pick the best match

Basic stereo matching algorithm



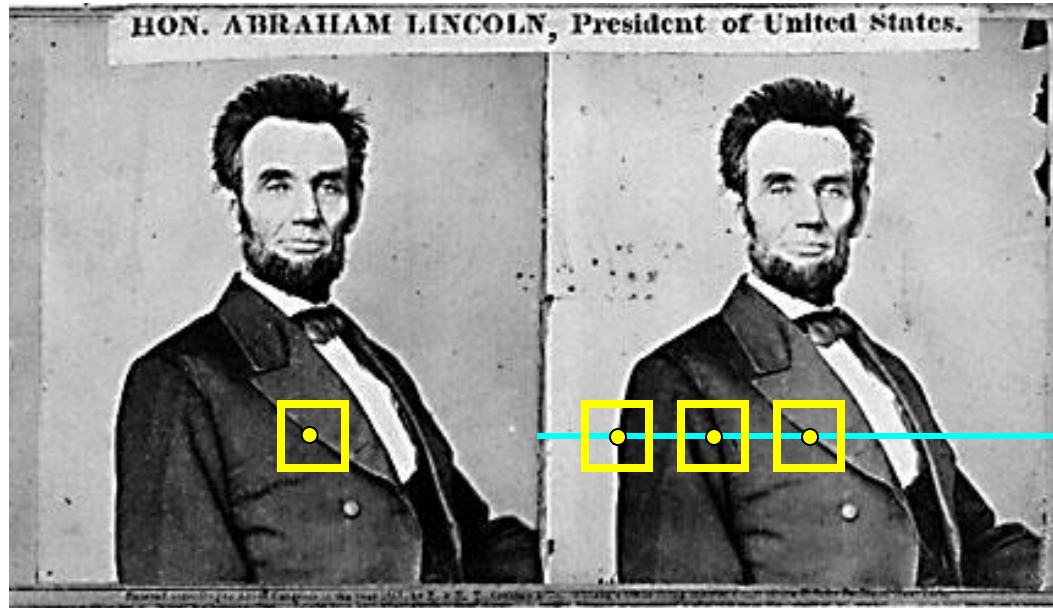
- For each pixel in the first image
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Basic stereo matching algorithm



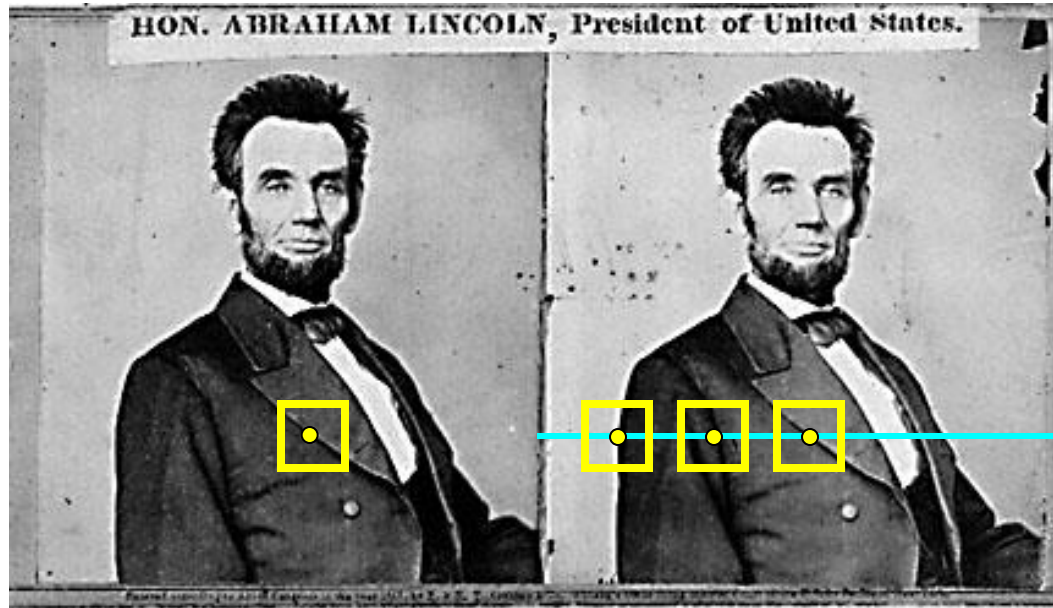
- For each pixel in the first image
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Basic stereo matching algorithm



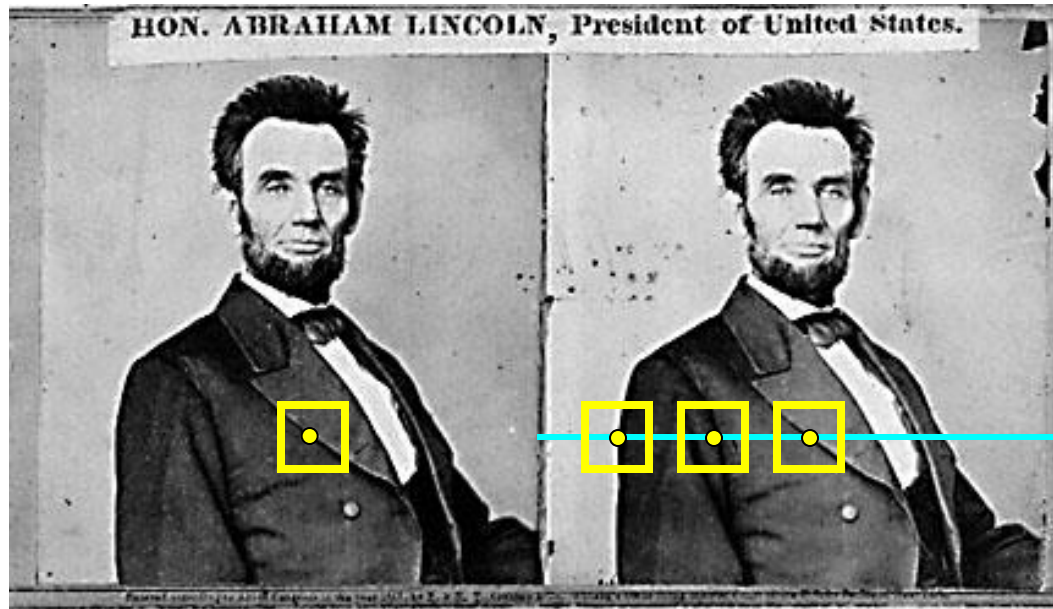
- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Search along epipolar line and pick the best match
 - Triangulate the matches to get depth information

Basic stereo matching algorithm



- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Search along epipolar line and pick the best match
 - Triangulate the matches to get depth information
- Simplest case: epipolar lines are scanlines

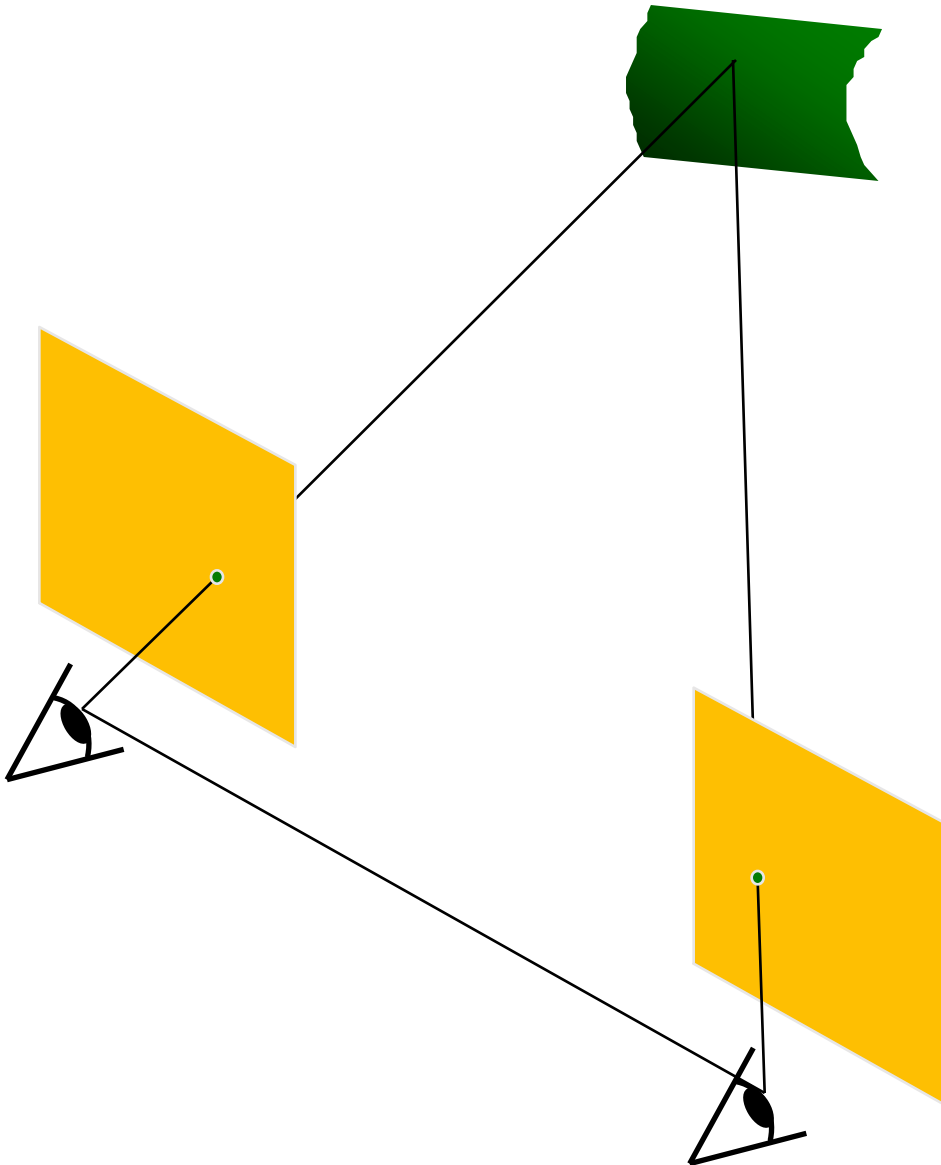
Basic stereo matching algorithm



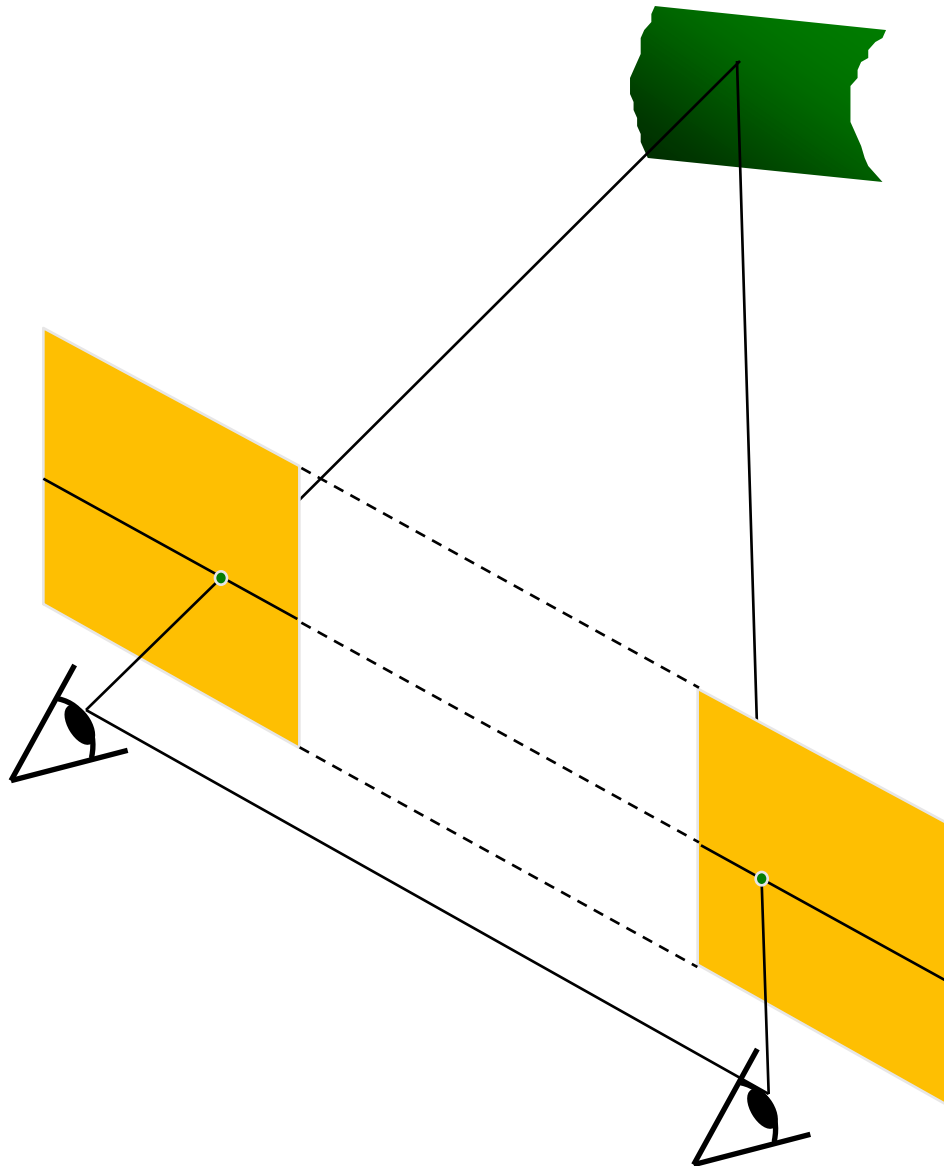
- For each pixel in the first image
 - Find corresponding epipolar line in the right image
 - Search along epipolar line and pick the best match
 - Triangulate the matches to get depth information
- Simplest case: epipolar lines are scanlines
 - When does this happen?

Simplest Case: Parallel images

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

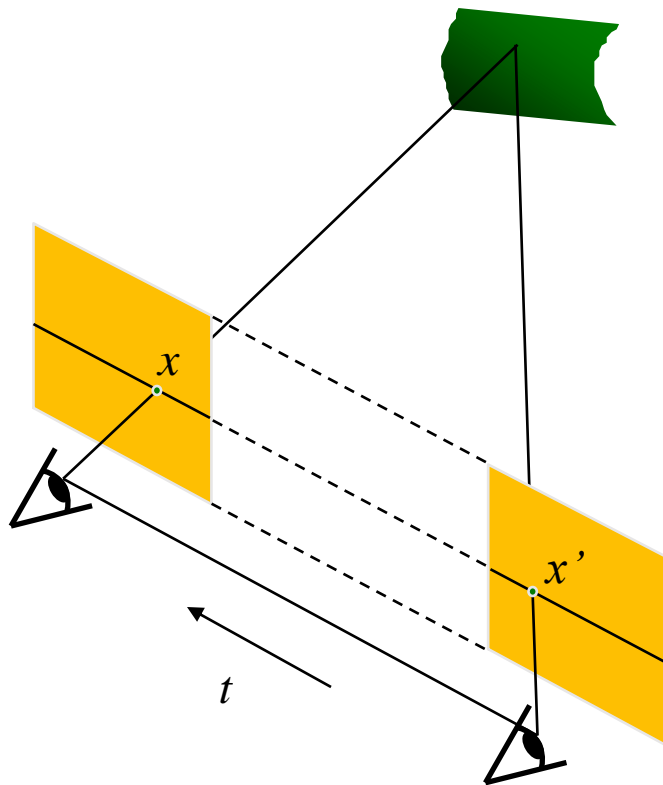


Simplest Case: Parallel images



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

Simplest Case: Parallel images



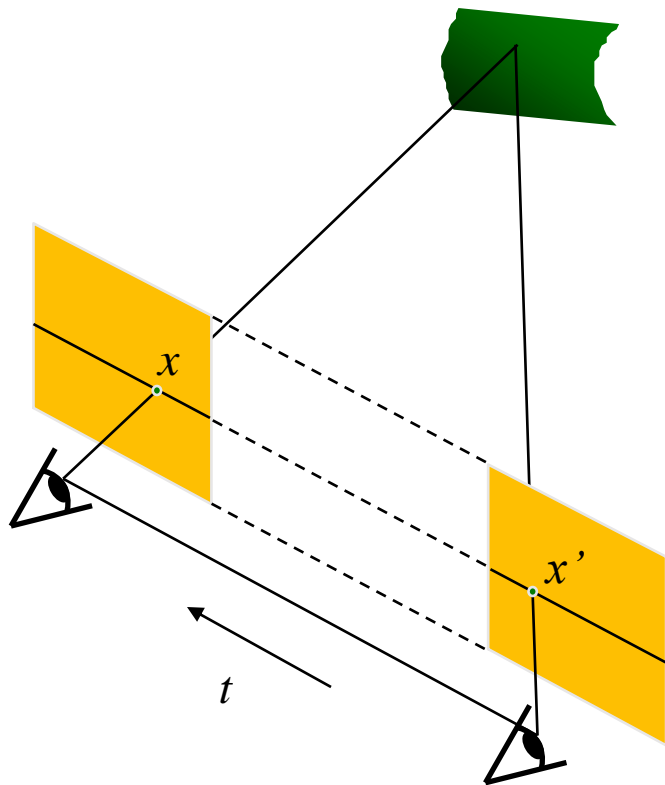
Epipolar constraint:

$$x^T E x' = 0, \quad E = t \times R$$

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

$$E = t \times R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

Simplest Case: Parallel images



Epipolar constraint:

$$x^T E x' = 0, \quad E = t \times R$$

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

$$E = t \times R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

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

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

Simplest Case: Parallel images

Epipolar constraint:

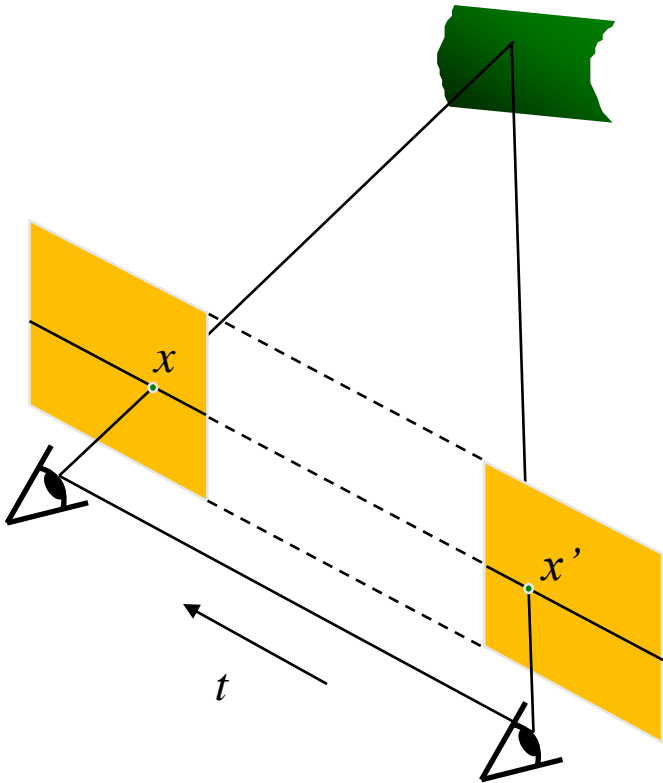
$$x^T E x' = 0, \quad E = t \times R$$

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

$$E = t \times R = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix}$$

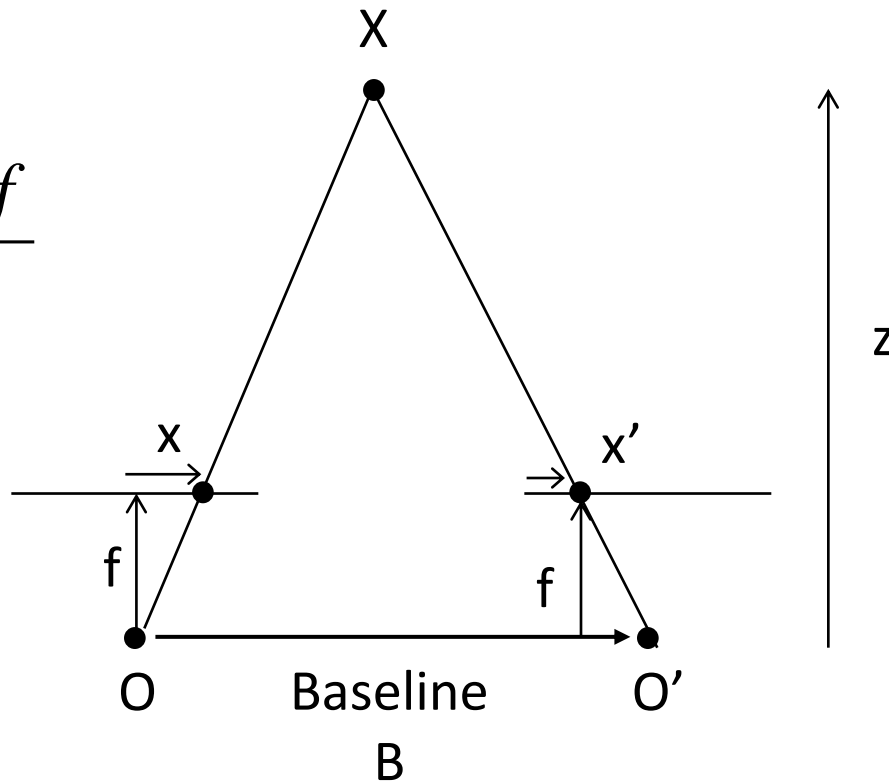
$$(u \quad v \quad 1) \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -T \\ 0 & T & 0 \end{bmatrix} \begin{pmatrix} u' \\ v' \\ 1 \end{pmatrix} = 0 \quad (u \quad v \quad 1) \begin{pmatrix} 0 \\ -T \\ Tv' \end{pmatrix} = 0 \quad Tv = Tv'$$

The y-coordinates of corresponding points are the same



Depth from disparity

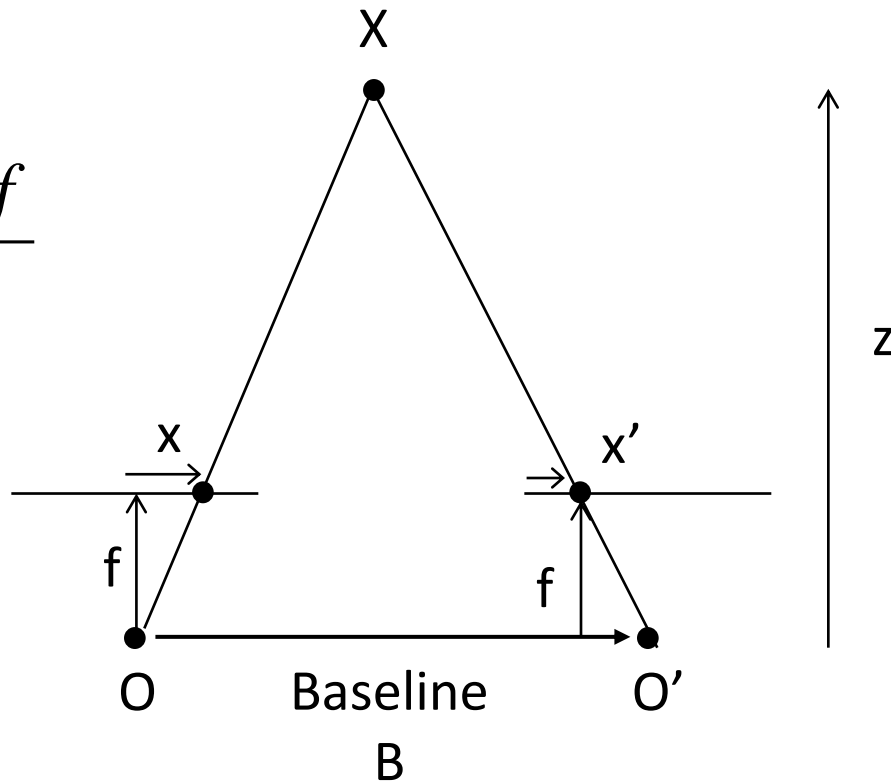
$$\frac{B - x + x'}{B} = \frac{z - f}{z}$$



Depth from disparity

$$\frac{B - x + x'}{B} = \frac{z - f}{z}$$

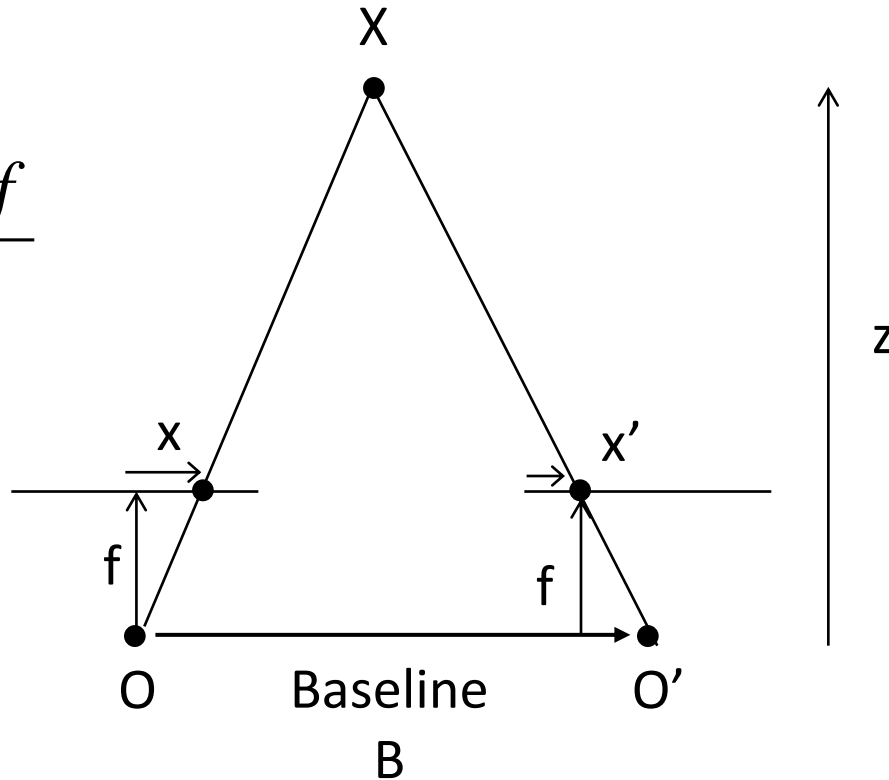
➔
$$\frac{x - x'}{B} = \frac{f}{z}$$



Depth from disparity

$$\frac{B - x + x'}{B} = \frac{z - f}{z}$$

➔
$$\frac{x - x'}{B} = \frac{f}{z}$$

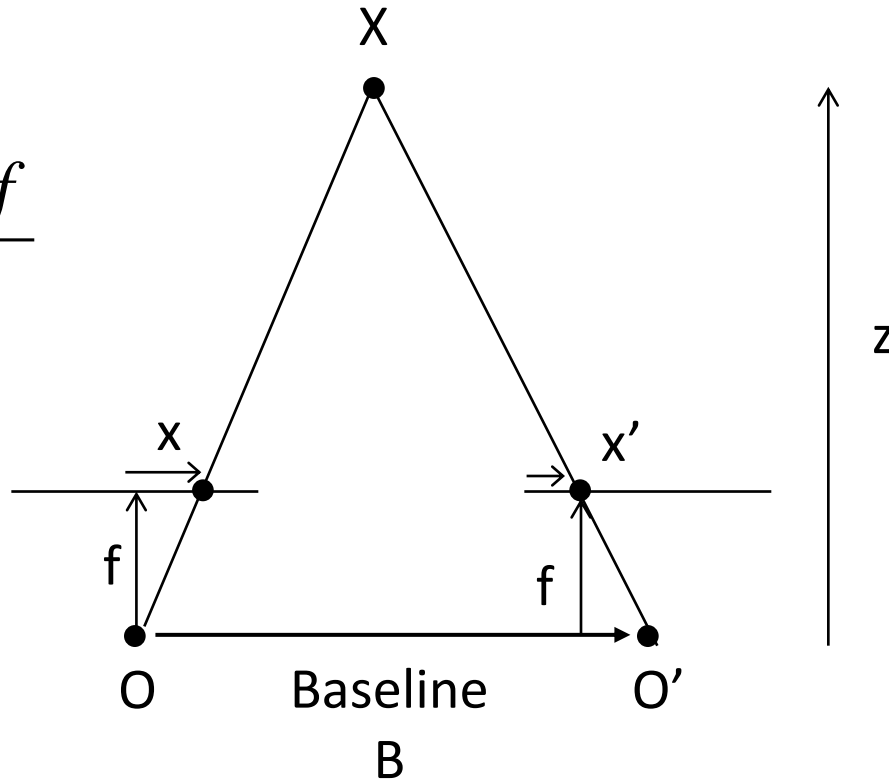


$$\text{disparity} = x - x' = \frac{B \cdot f}{z}$$

Depth from disparity

$$\frac{B - x + x'}{B} = \frac{z - f}{z}$$

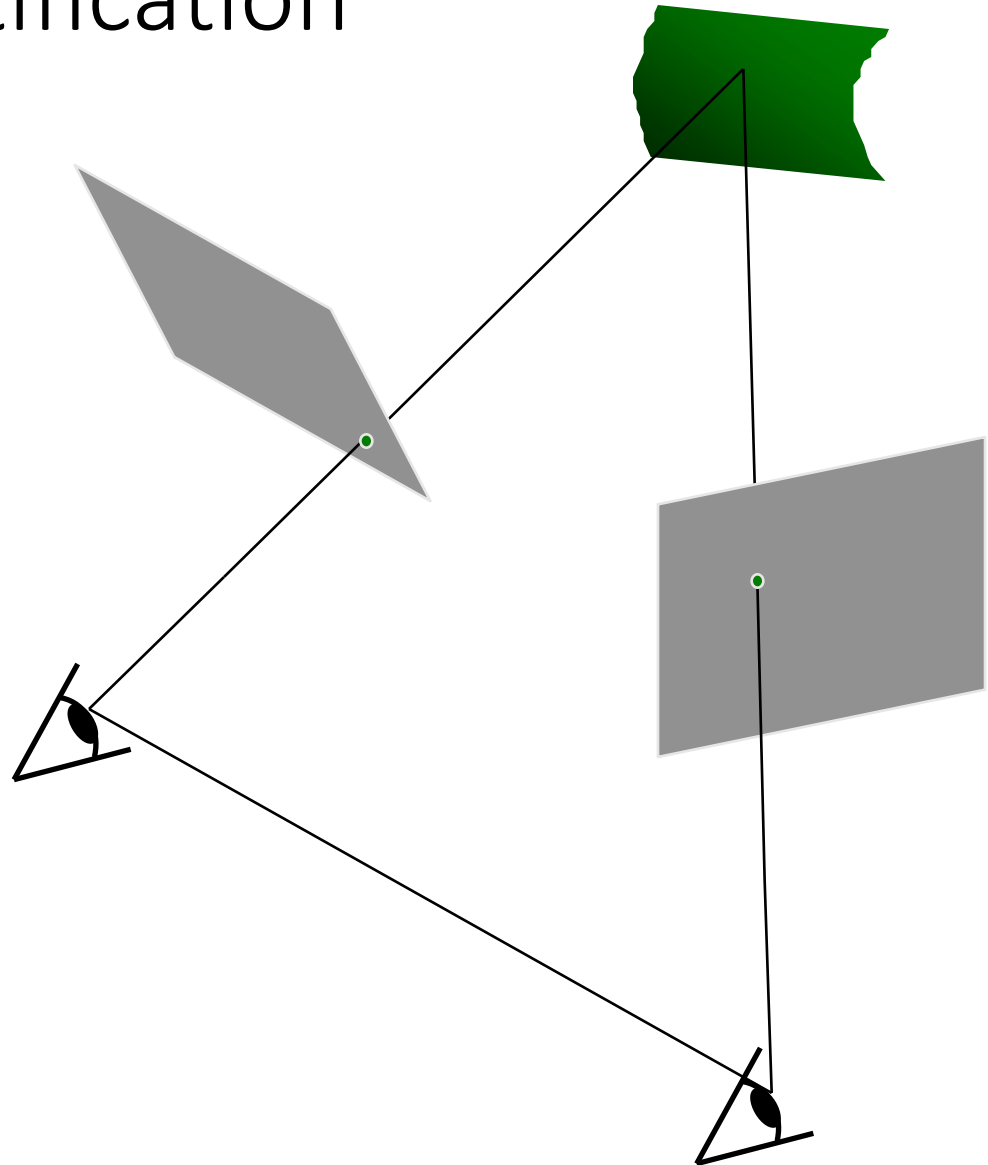
➔
$$\frac{x - x'}{B} = \frac{f}{z}$$



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

Disparity is inversely proportional to depth.

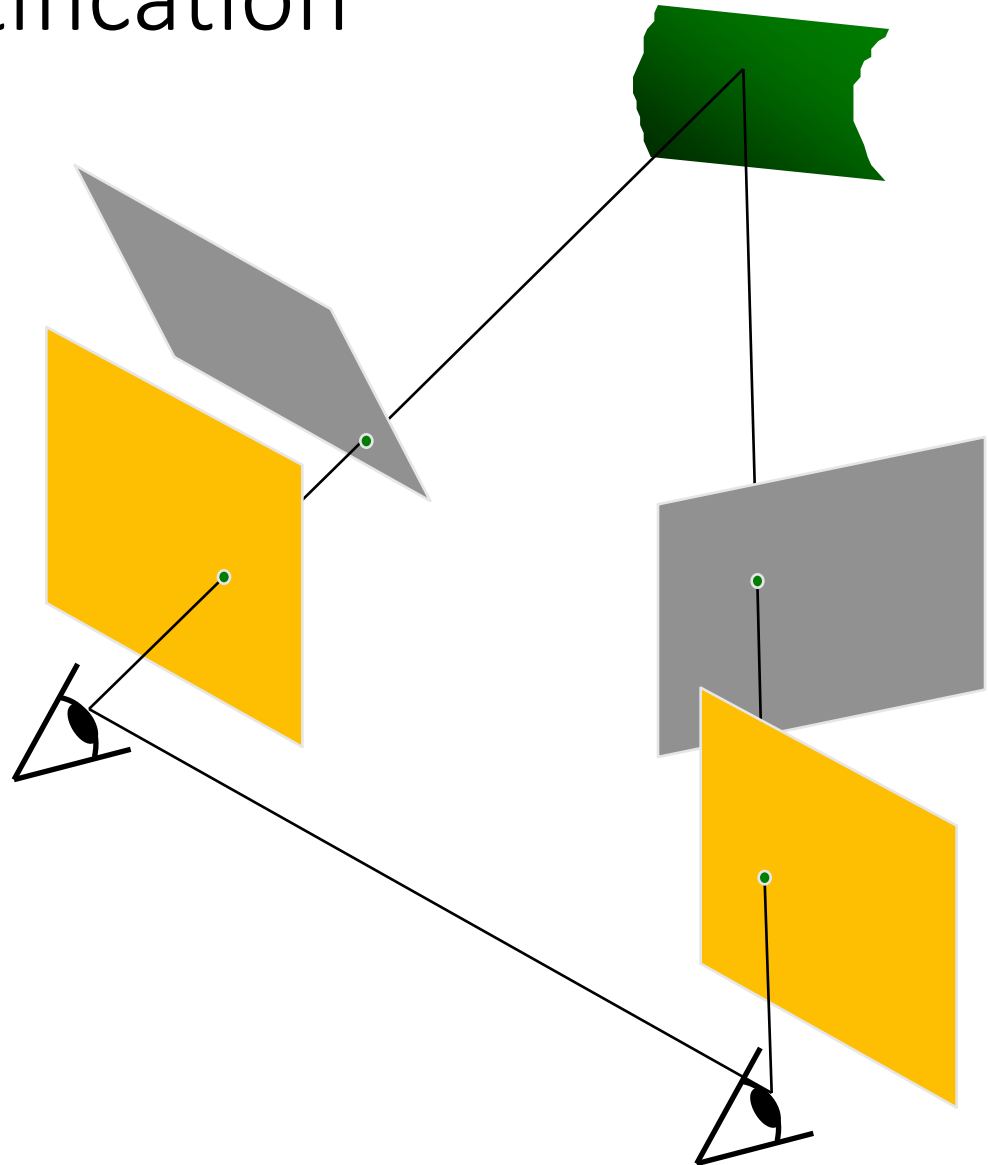
Stereo image rectification



C. Loop and Z. Zhang. [Computing Rectifying Homographies for Stereo Vision](#).
IEEE Conf. Computer Vision and Pattern Recognition, 1999.

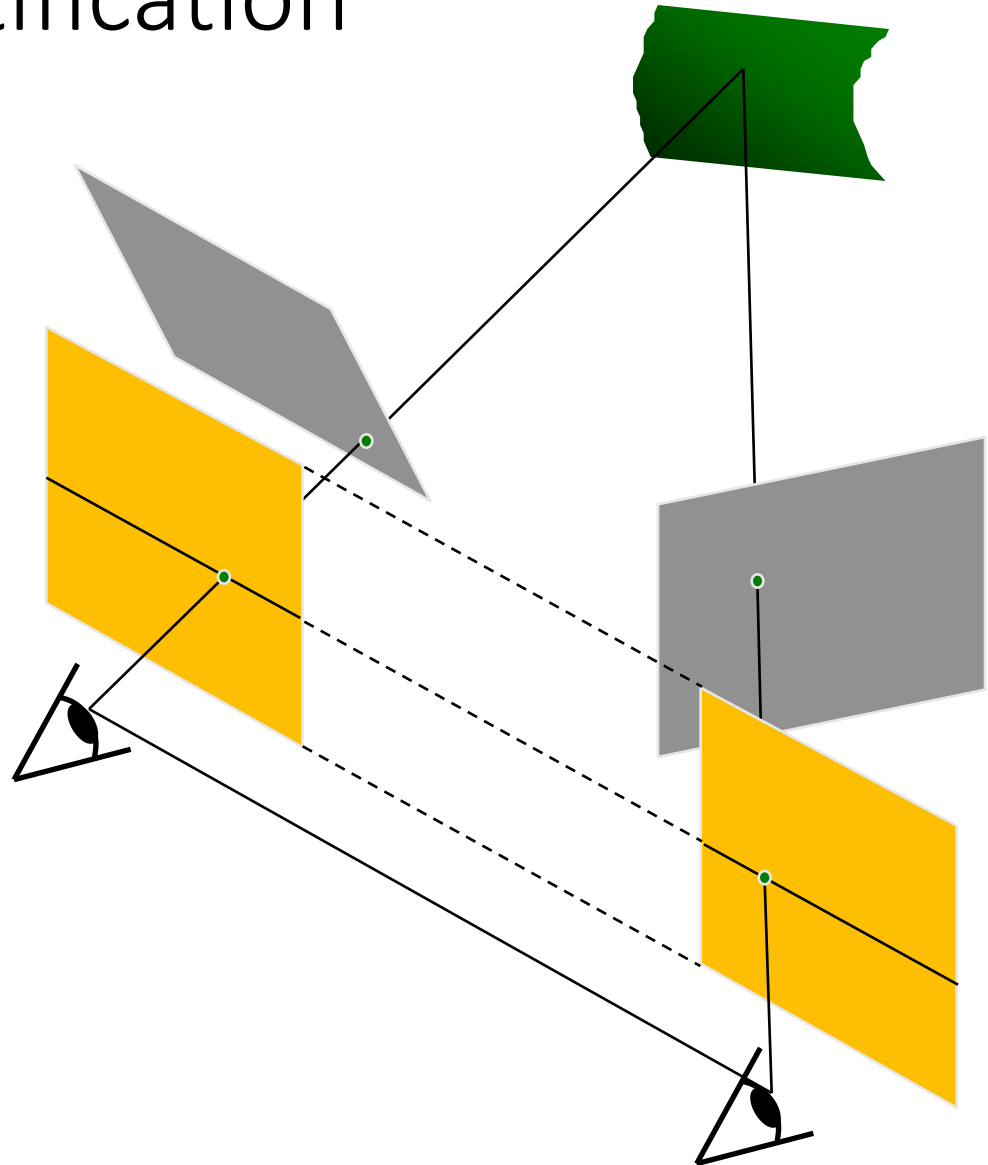
Stereo image rectification

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



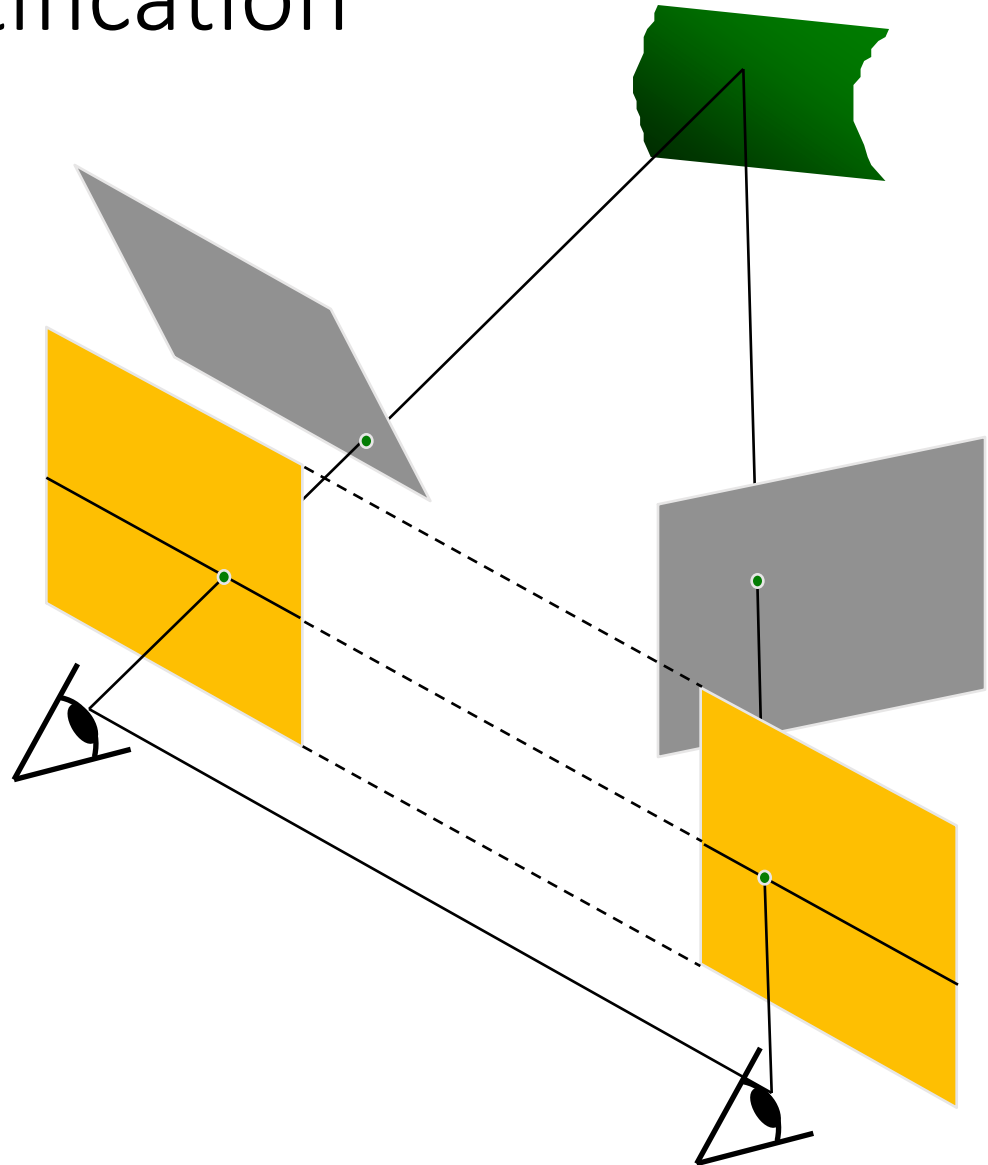
Stereo image rectification

- Reproject image planes onto a common plane parallel to the line between camera centers
- Pixel motion is horizontal after this transformation

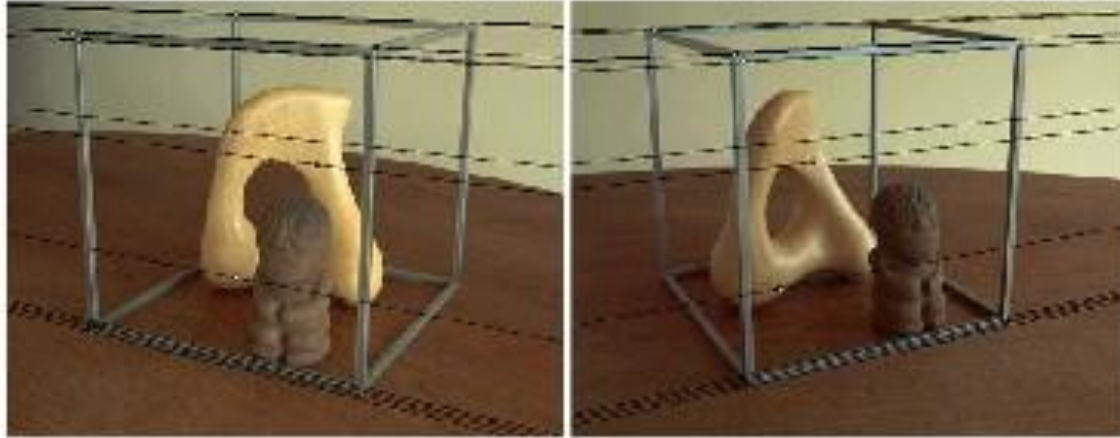


Stereo image rectification

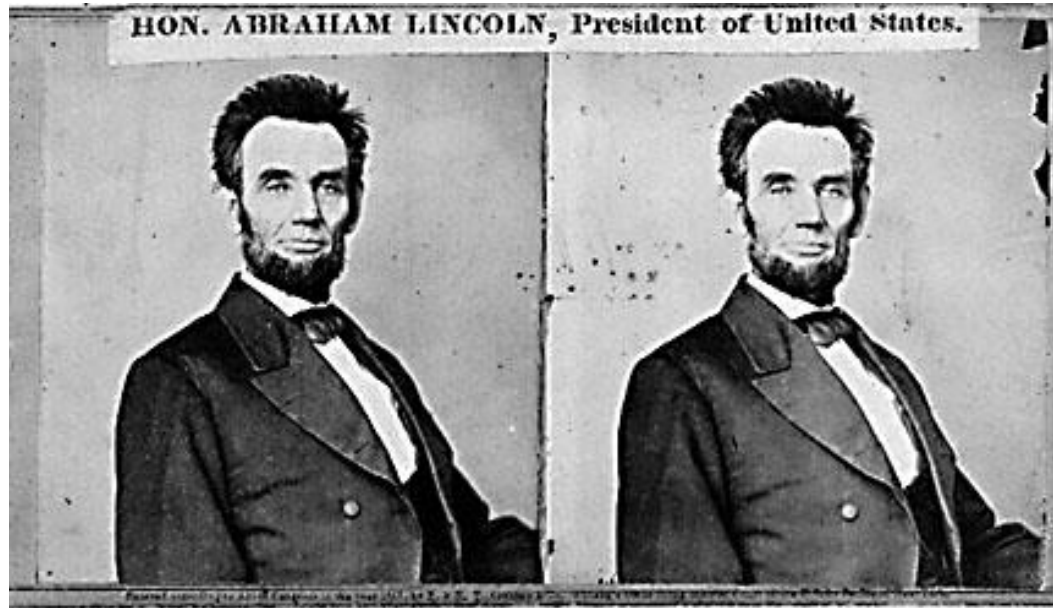
- Reproject image planes onto a common plane parallel to the line between camera centers
- Pixel motion is horizontal after this transformation
- Two homographies (3x3 transform), one for each input image reprojection



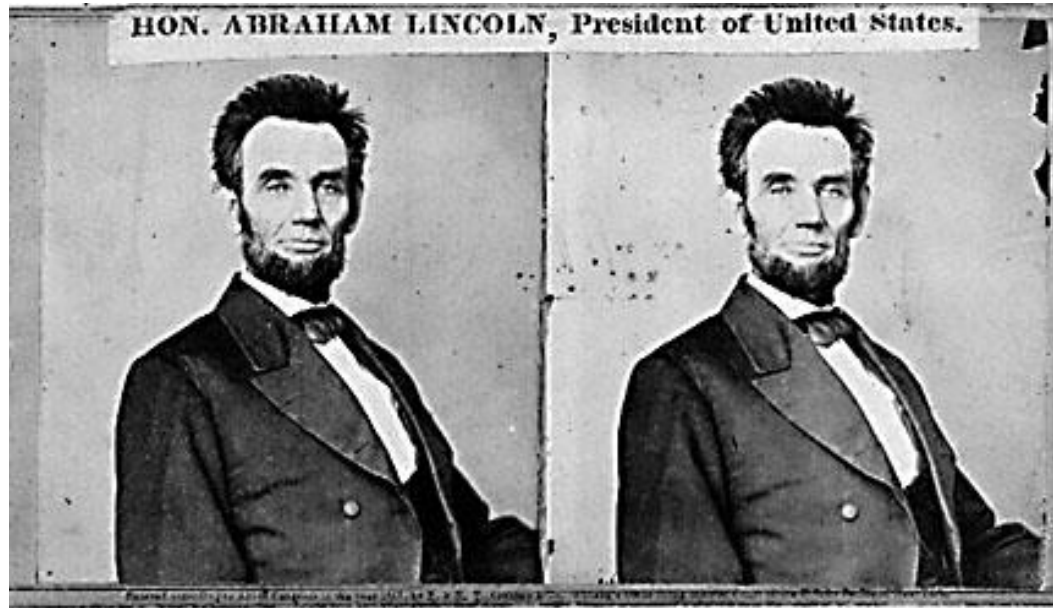
Rectification example



Basic stereo matching algorithm



Basic stereo matching algorithm



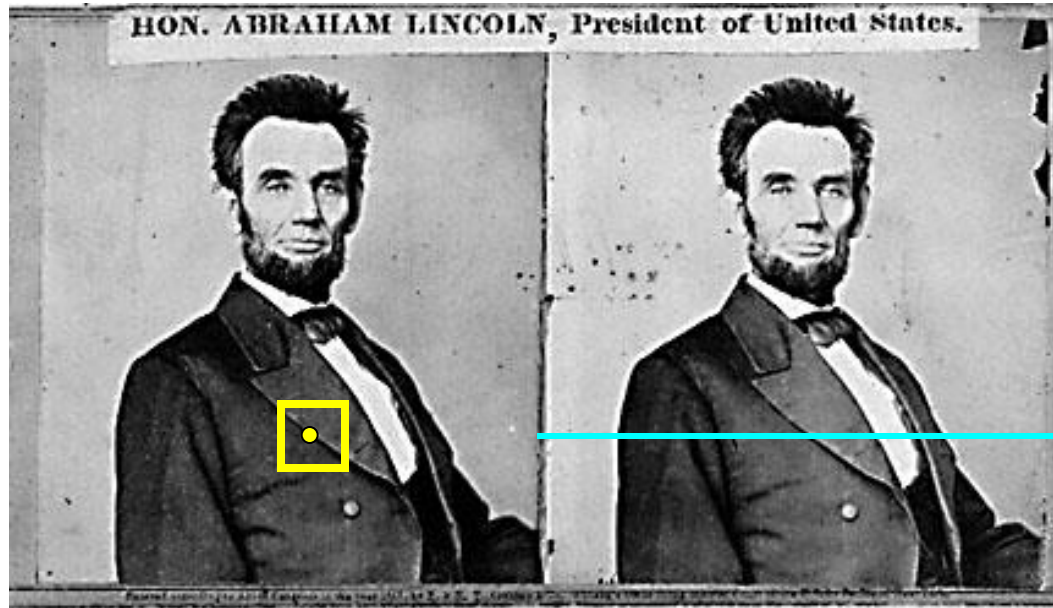
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines

Basic stereo matching algorithm



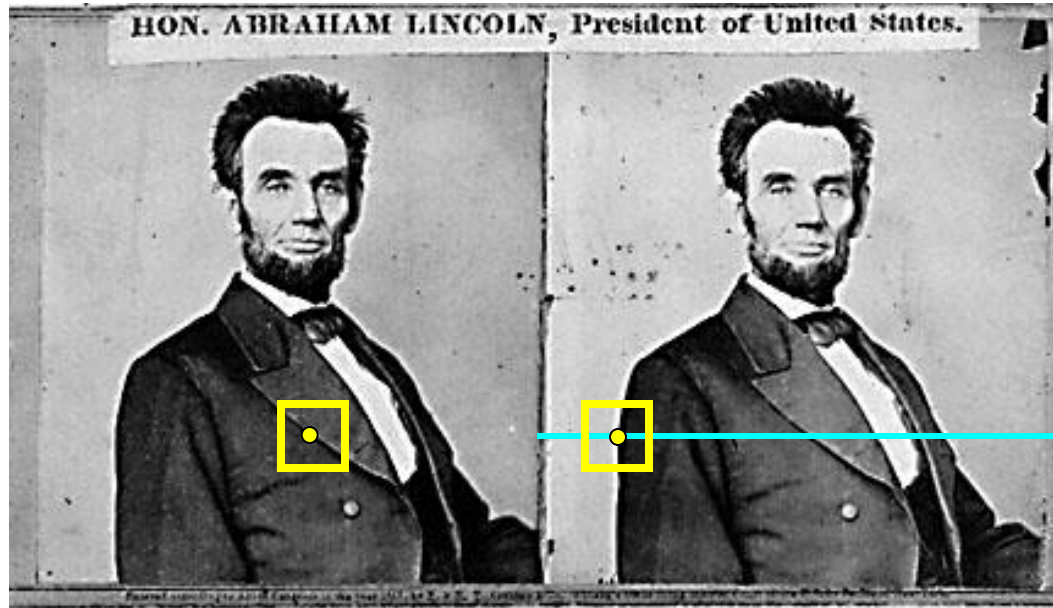
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image

Basic stereo matching algorithm



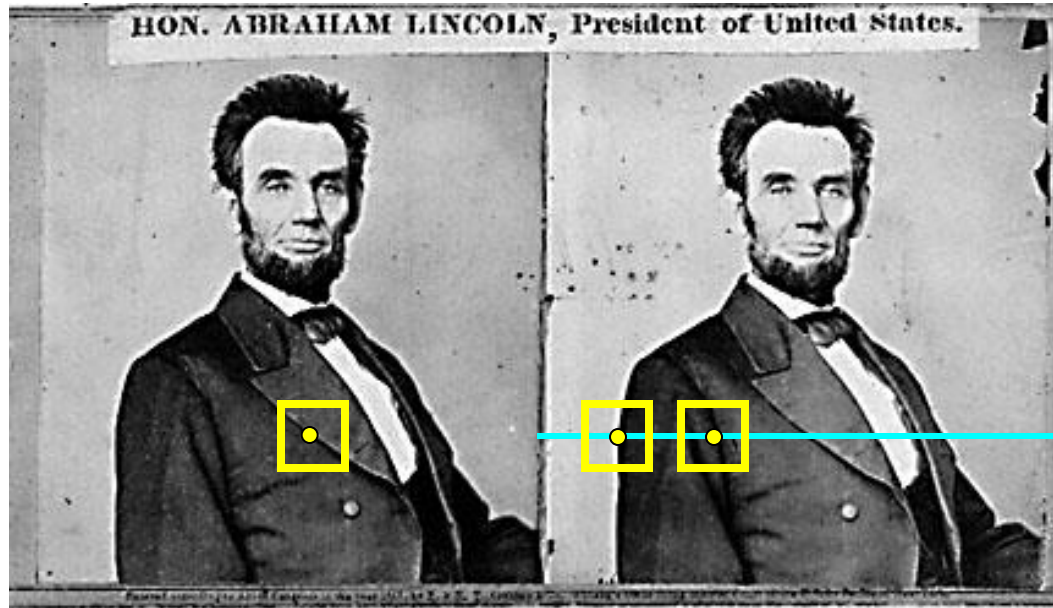
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image

Basic stereo matching algorithm



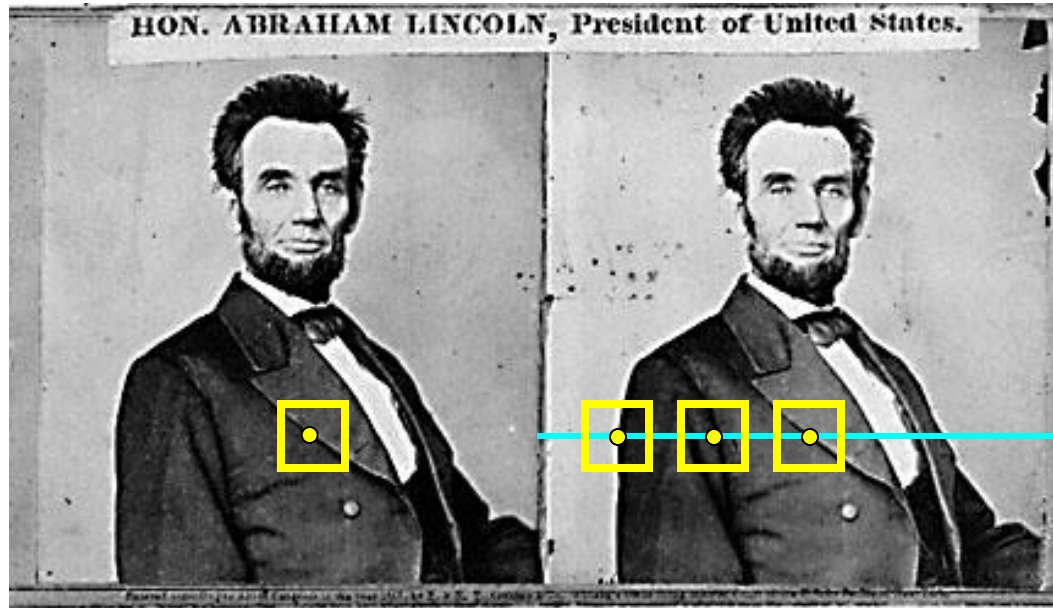
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image
 - Search the scanline and pick the best match x'

Basic stereo matching algorithm



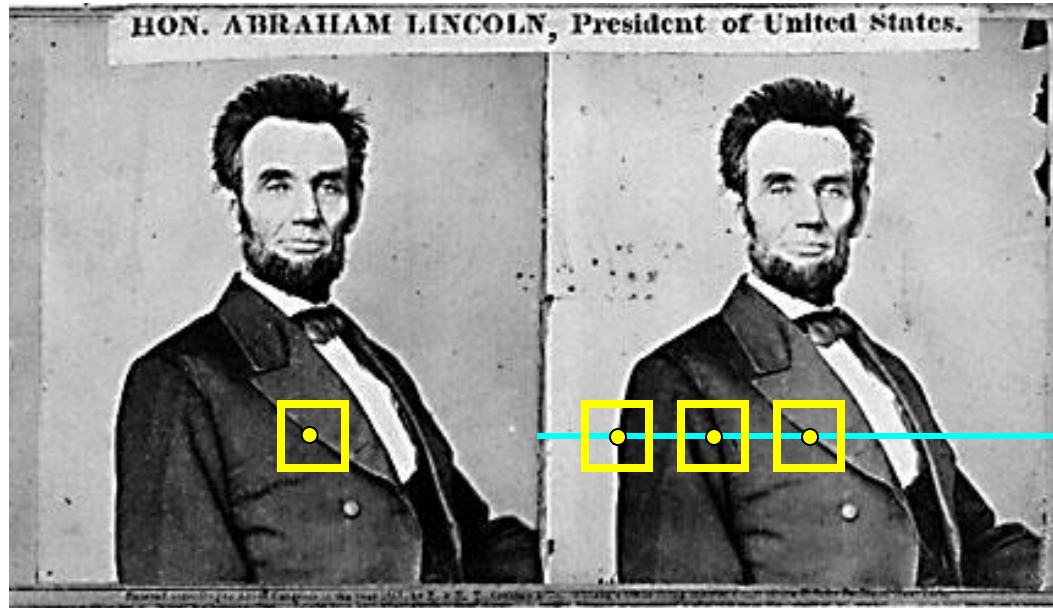
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image
 - Search the scanline and pick the best match x'

Basic stereo matching algorithm



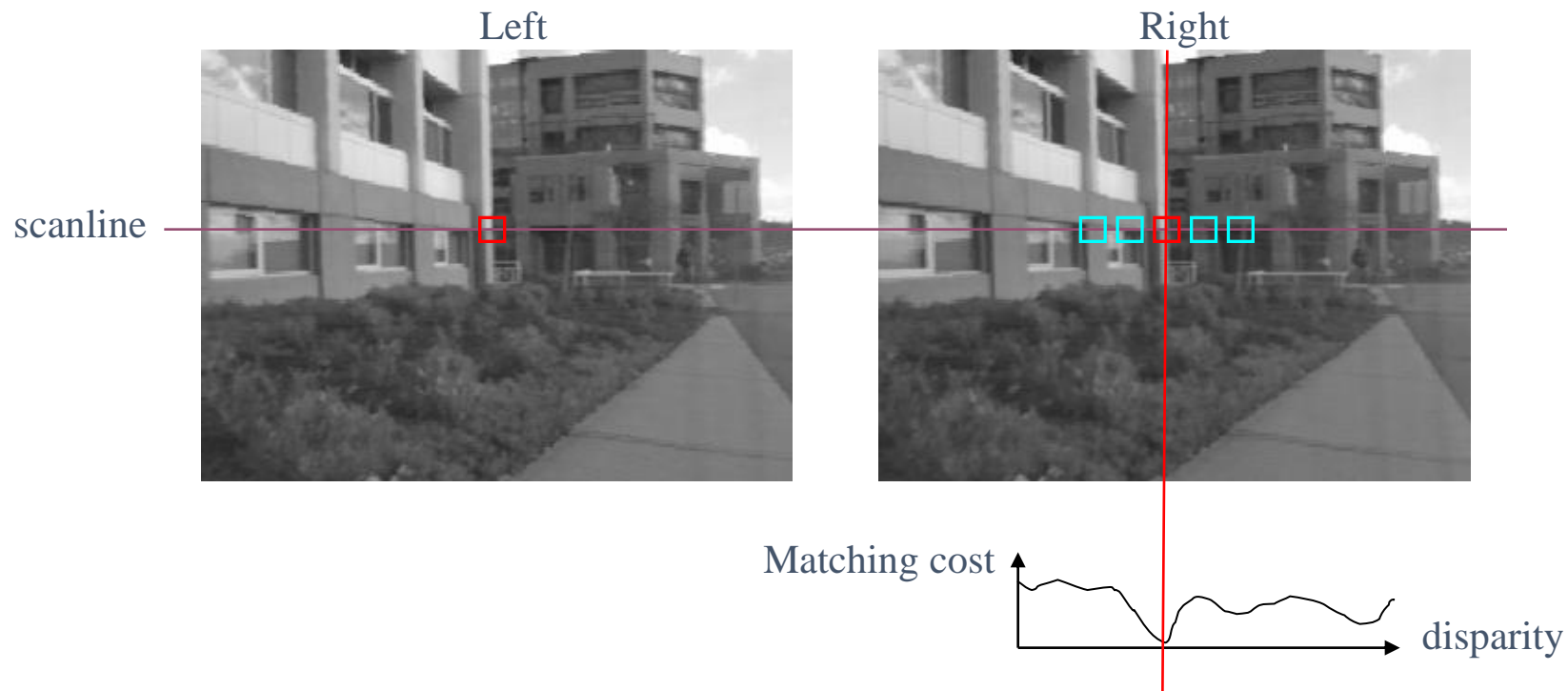
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image
 - Search the scanline and pick the best match x'

Basic stereo matching algorithm



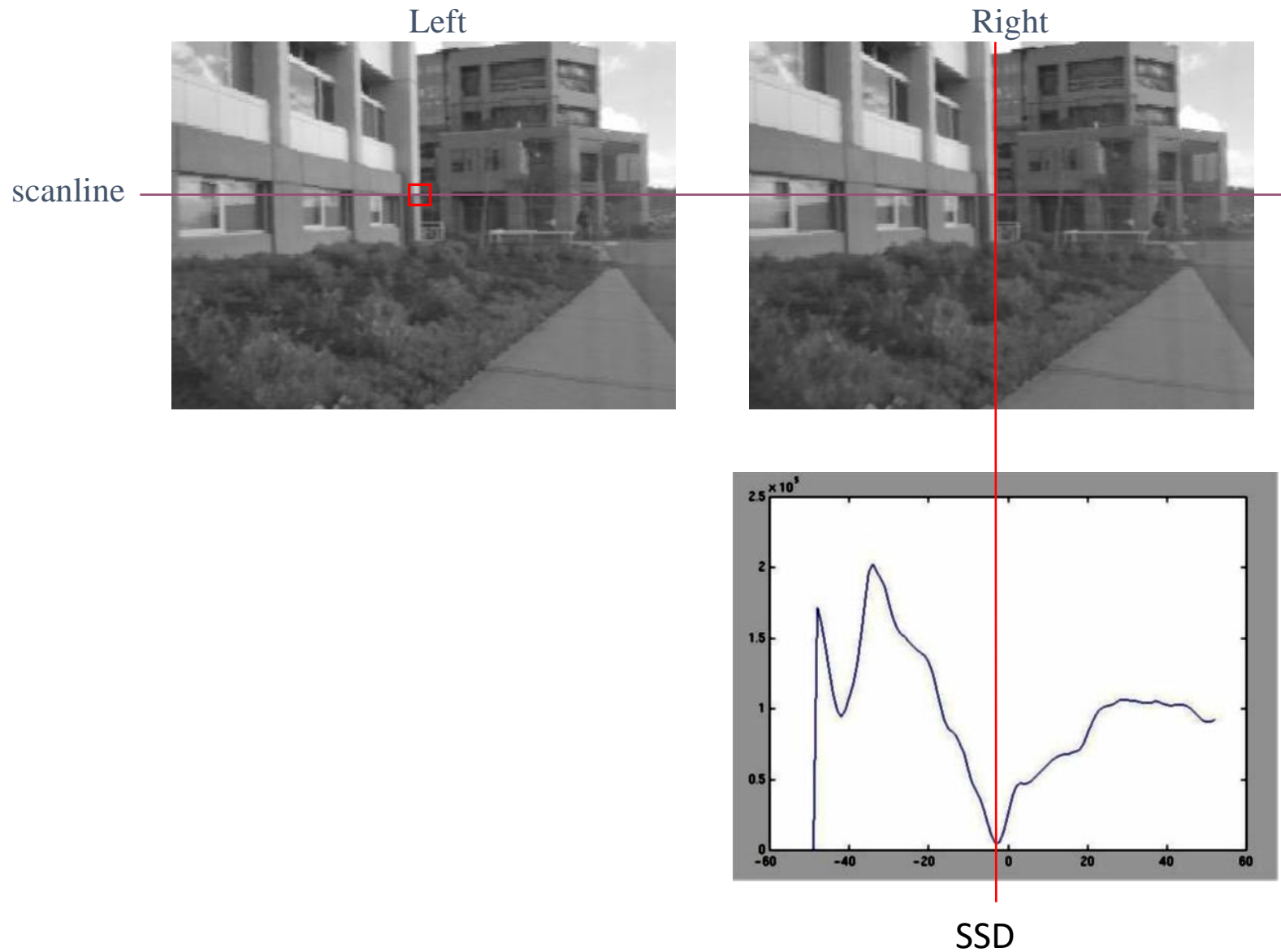
- If necessary, rectify the two stereo images to transform epipolar lines into scanlines
- For each pixel x in the first image
 - Find corresponding epipolar scanline in the right image
 - Search the scanline and pick the best match x'
 - Compute disparity $x - x'$ and set $\text{depth}(x) = fB/(x -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

Correspondence search



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

Correspondence search



Correspondence search

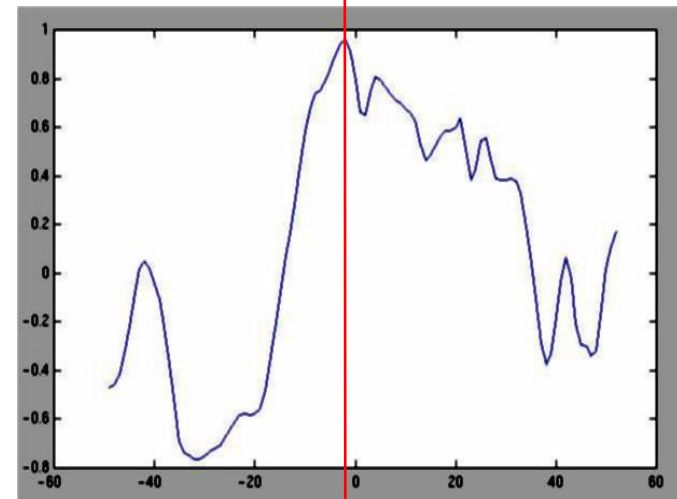
Left



Right



scanline

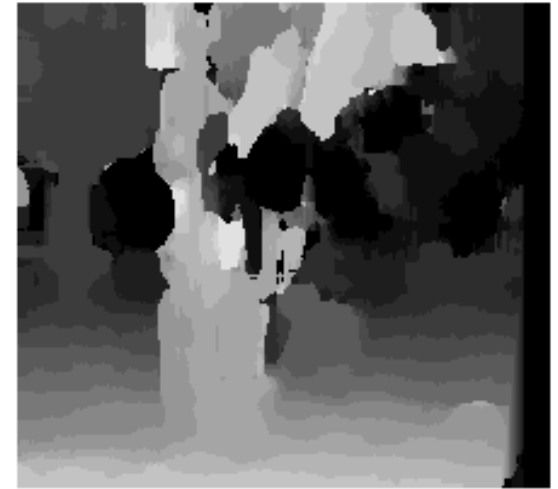


Norm. corr

Effect of window size



$W = 3$

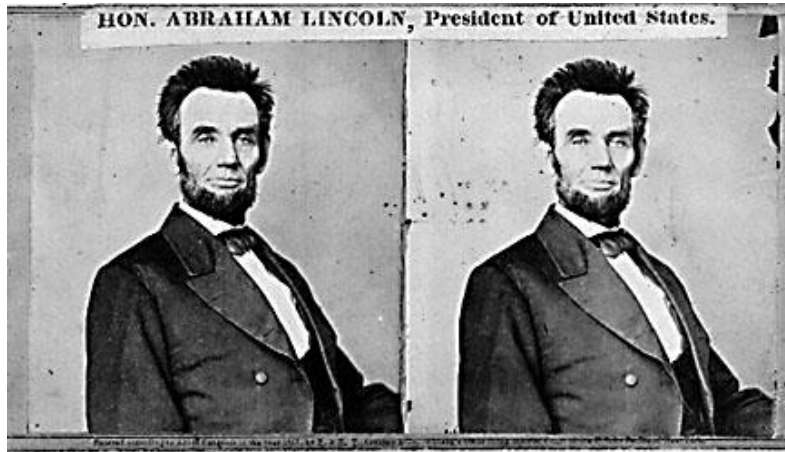


$W = 20$

- **Smaller window**
 - + More detail
 - More noise
- **Larger window**
 - + Smoother disparity maps
 - Less detail
 - Fails near boundaries

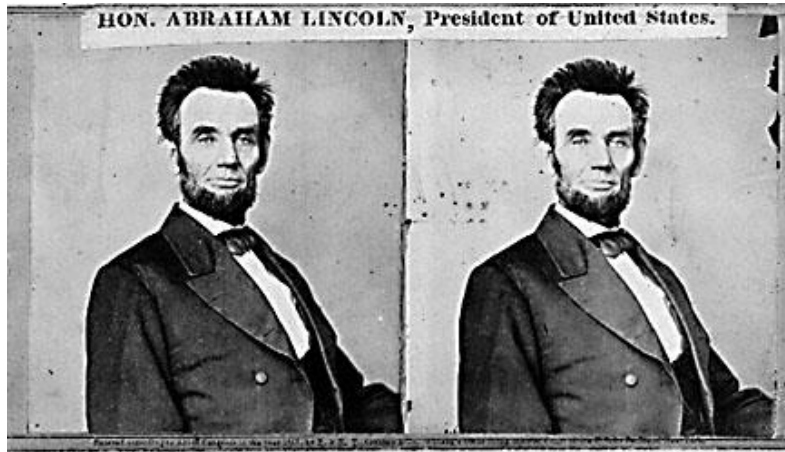
Failures of correspondence search

Failures of correspondence search



Textureless surfaces

Failures of correspondence search

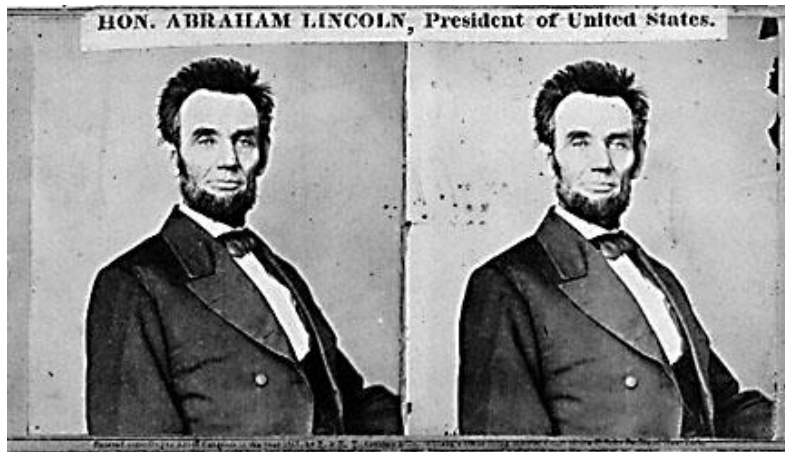


Textureless surfaces



Occlusions, repetition

Failures of correspondence search



Textureless surfaces



Occlusions, repetition



Non-Lambertian surfaces, specularities

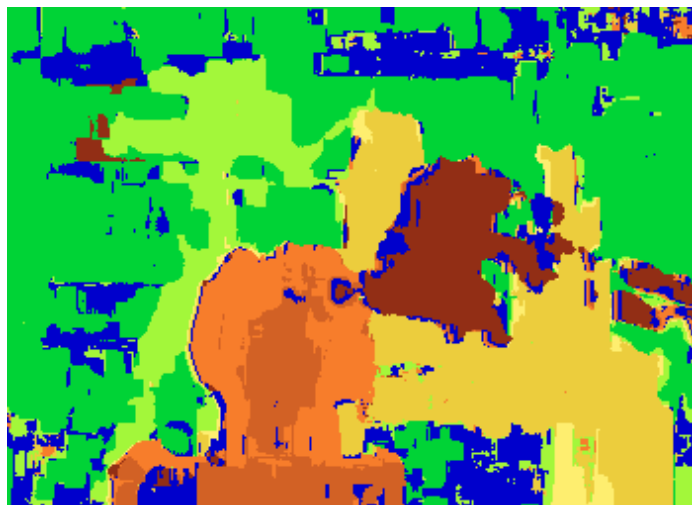


Results with window search

Data



Window-based matching



Ground truth



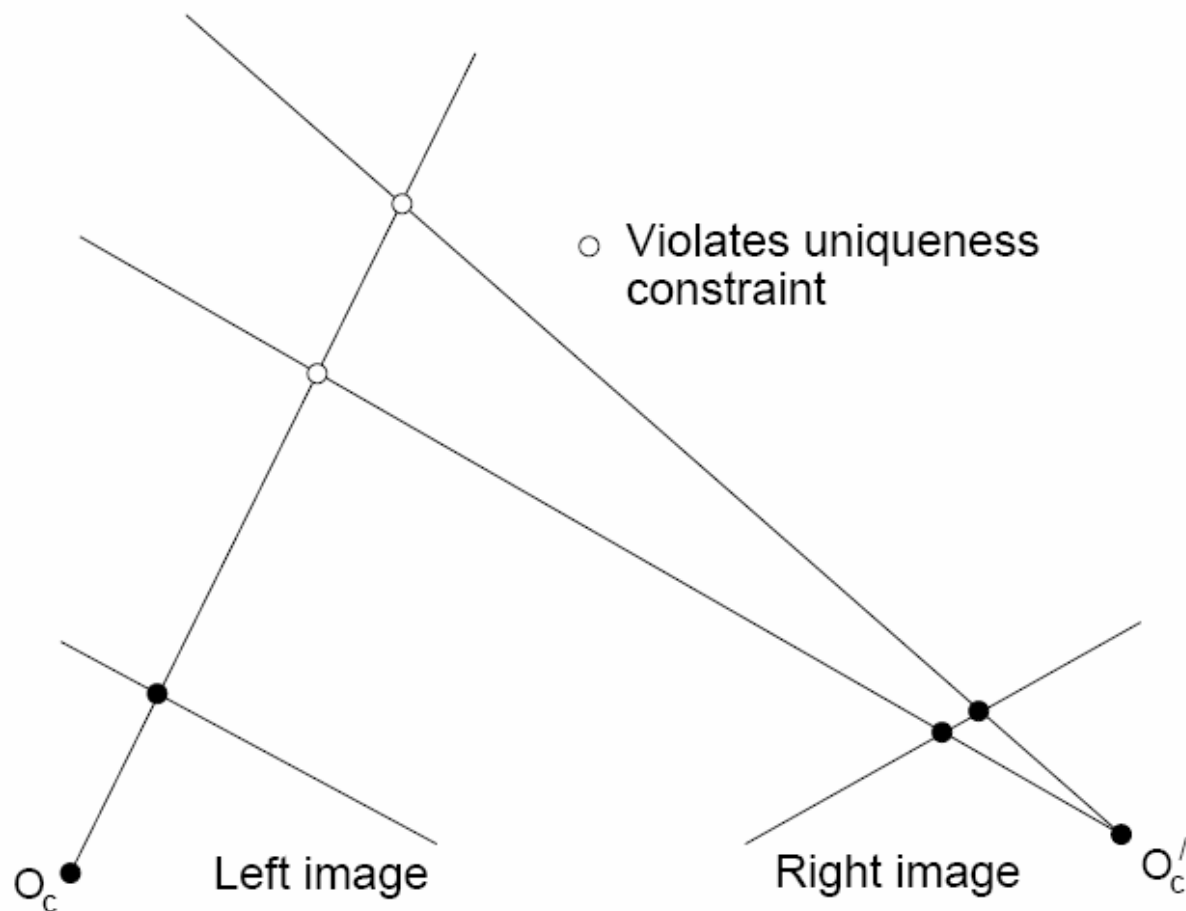
How can we improve window-based matching?

- So far, matches are independent for each point
- What constraints or priors can we add?

Stereo constraints/priors

- Uniqueness

- For any point in one image, there should be at most one matching point in the other image



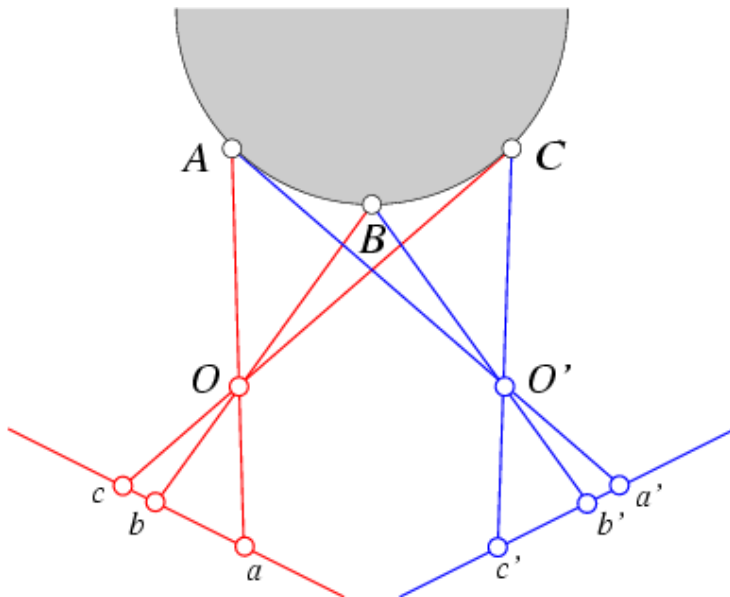
Stereo constraints/priors

- Uniqueness

- For any point in one image, there should be at most one matching point in the other image

- Ordering

- Corresponding points should be in the same order in both views



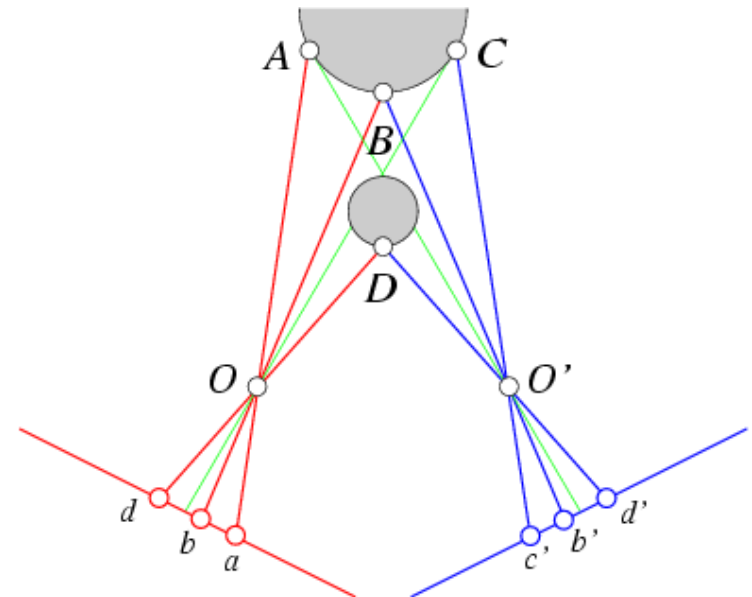
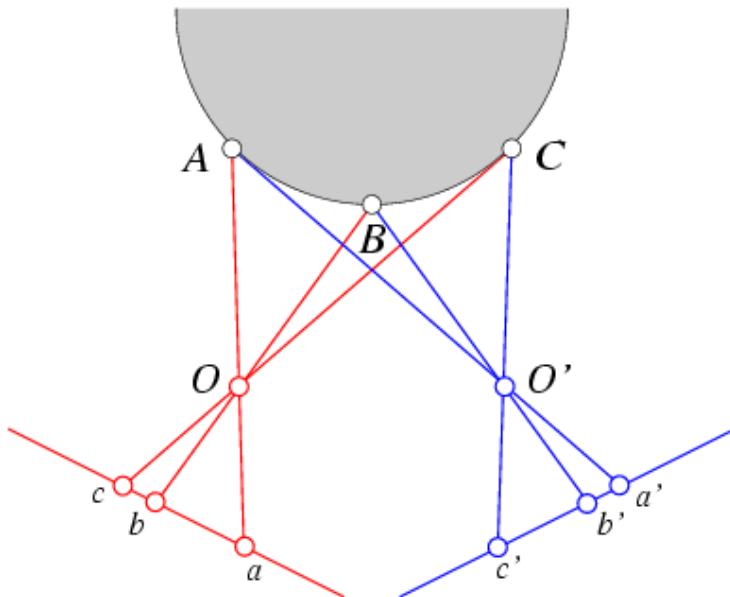
Stereo constraints/priors

- Uniqueness

- For any point in one image, there should be at most one matching point in the other image

- Ordering

- Corresponding points should be in the same order in both views



Ordering constraint doesn't hold

Stereo constraints/priors

- Uniqueness

- For any point in one image, there should be at most one matching point in the other image

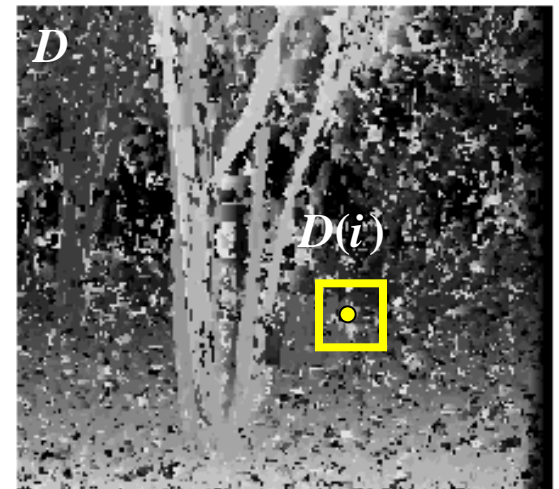
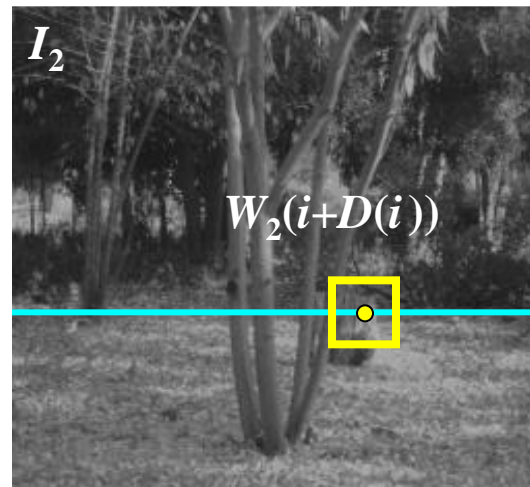
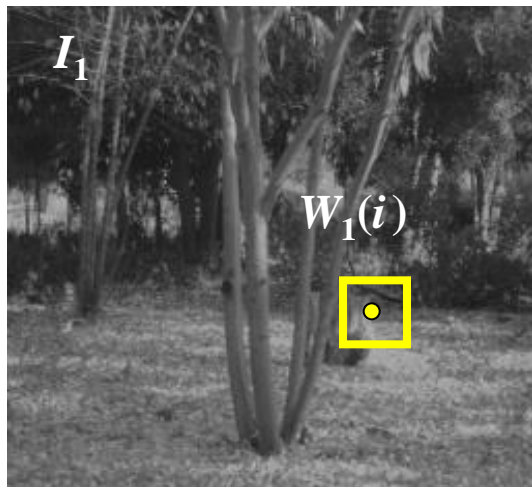
- Ordering

- Corresponding points should be in the same order in both views

- Smoothness

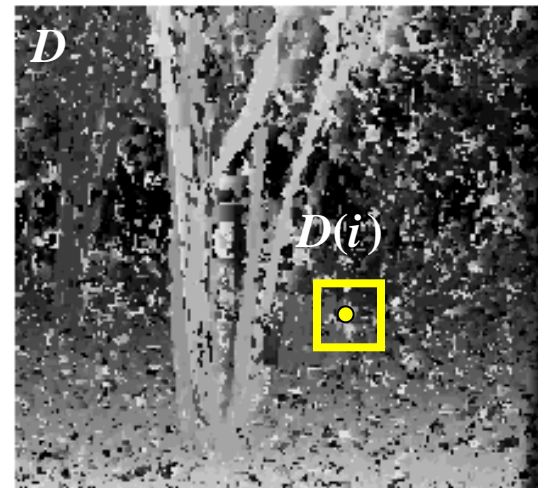
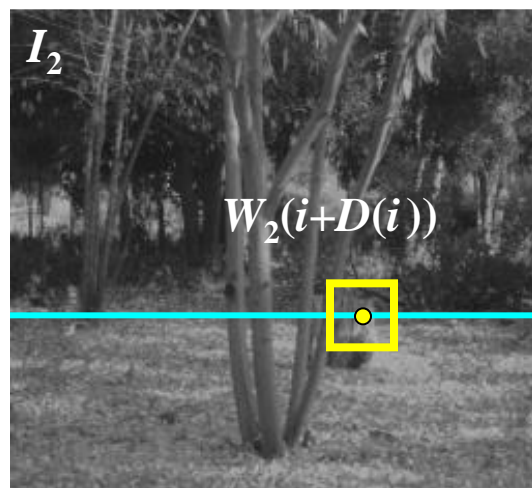
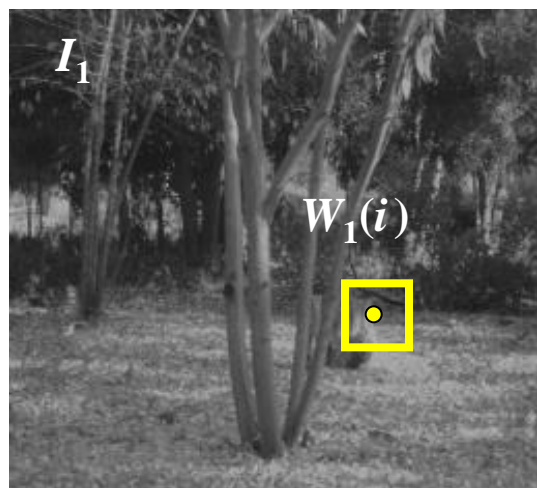
- We expect disparity values to change slowly (for the most part)

Stereo matching as energy minimization



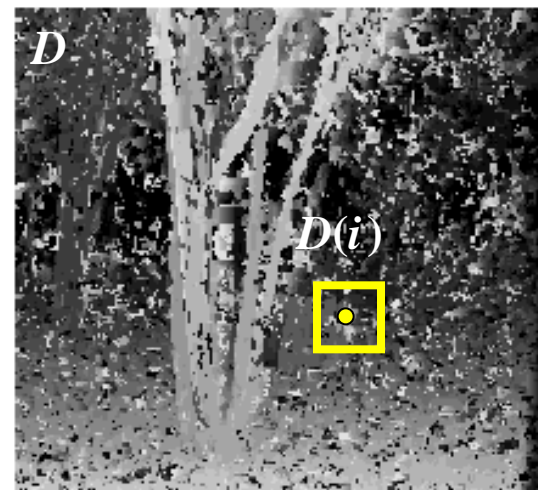
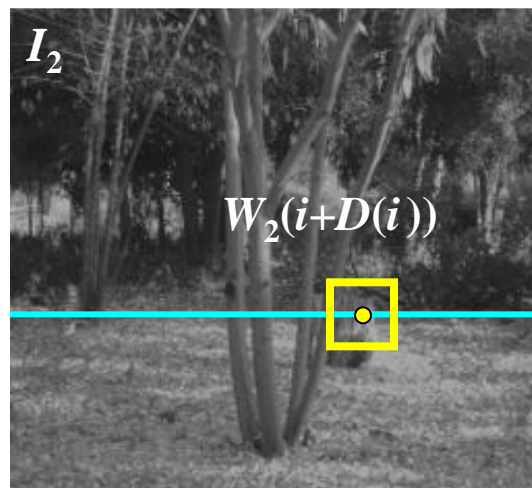
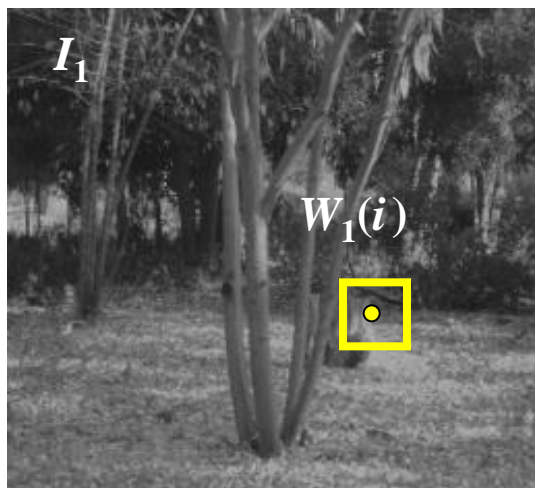
$$E_{\text{data}} = \sum_i (W_1(i) - W_2(i + D(i)))^2$$

Stereo matching as energy minimization



$$E_{\text{data}} = \sum_i (W_1(i) - W_2(i + D(i)))^2 \quad E_{\text{smooth}} = \sum_{\text{neighbors } i, j} \|D(i) - D(j)\|^2$$

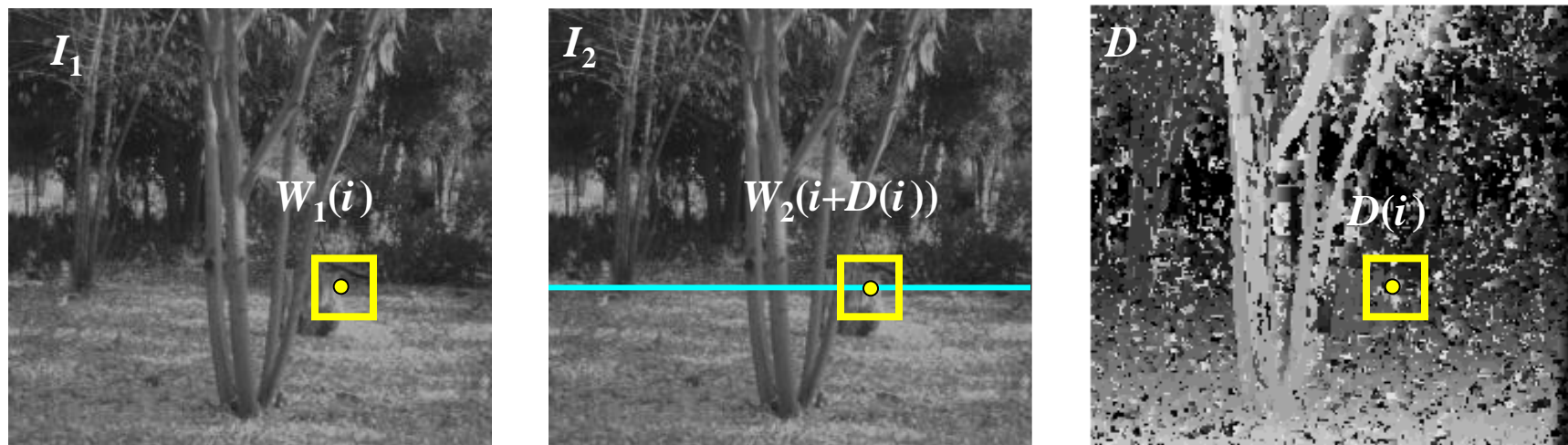
Stereo matching as energy minimization



$$E_{\text{data}} = \sum_i (W_1(i) - W_2(i + D(i)))^2 \quad E_{\text{smooth}} = \sum_{\text{neighbors } i, j} \|D(i) - D(j)\|^2$$

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

Stereo matching as energy minimization



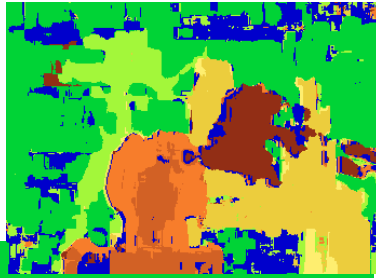
$$E_{\text{data}} = \sum_i (W_1(i) - W_2(i + D(i)))^2 \quad E_{\text{smooth}} = \sum_{\text{neighbors } i, j} \|D(i) - D(j)\|^2$$

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

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

Many of these constraints can be encoded in an energy function and solved using graph cuts

Before



Graph cuts



Ground truth

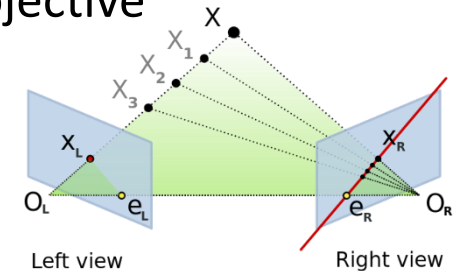
Y. Boykov, O. Veksler, and R. Zabih, [Fast Approximate Energy Minimization via Graph Cuts](#), PAMI 2001

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

Things to remember

- **Epipolar geometry**

- Epipoles are intersection of baseline with image planes
- Matching point in second image is on a line passing through its epipole
- Fundamental matrix maps from a point in one image to a line (its epipolar line) in the other
- Can solve for F given corresponding points (e.g., interest points)
- Can recover canonical camera matrices from F (with projective ambiguity)



- **Stereo depth estimation**

- Estimate disparity by finding corresponding points along scanlines
- Depth is inverse to disparity



Acknowledgements

- Thanks to the following researchers for making their teaching/research material online
 - Forsyth
 - Steve Seitz
 - Noah Snavely
 - J.B. Huang
 - Derek Hoiem
 - J. Hays
 - J. Johnson
 - R. Girshick
 - S. Lazebnik
 - K. Grauman
 - Antonio Torralba
 - Rob Fergus
 - Leibe
 - And many more

Next class:
structure from motion

