



Master in Computer Vision *Barcelona*

Module 4: 3D Vision

Lecture 5: Epipolar geometry

Lecturer: Javier Ruiz Hidalgo

Outline

- Why is stereo useful?
 - Monocular / Binocular depth perception
- Epipolar constraints
 - Calibrated cameras: Essential matrix
 - Uncalibrated cameras: Fundamental matrix
- Estimating Fundamental matrix
 - Linear: 8 point algorithm
 - Non-linear
 - Robust methods: RANSAC
- Rectification

Why is stereo useful?

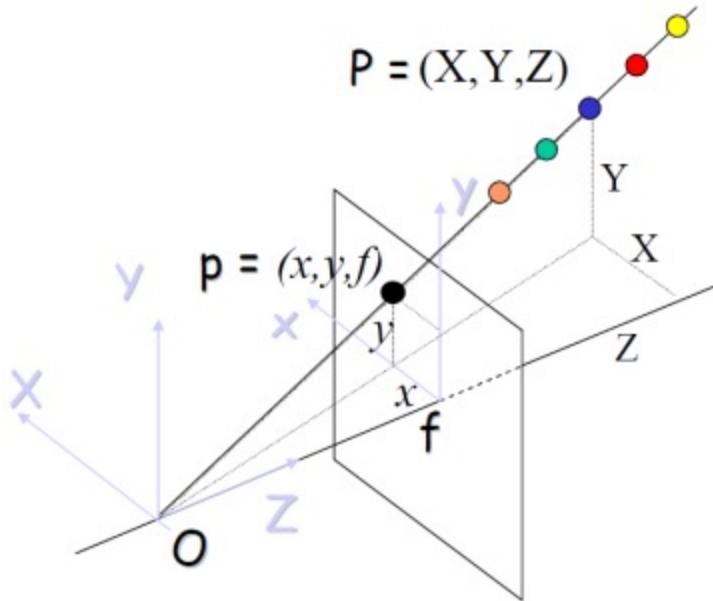
- **Structure and depth** are inherently **ambiguous** from single views



Source: L. Lazebnik

Why is stereo useful?

- **Fundamental ambiguity**
 - Any point P on the ray OP projects to the same point p in the image plane



$$x = f \frac{X}{Z} = f \frac{kX}{kZ}$$
$$y = f \frac{Y}{Z} = f \frac{kY}{kZ}$$

Source: R. Collins

Monocular depth perception

- What cues help us to perceive 3D structure and depth?

Monocular cues

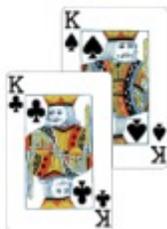
size



perspective



occlusions



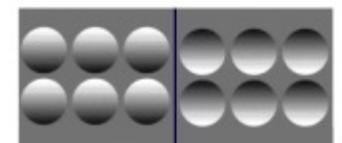
aerial perspective



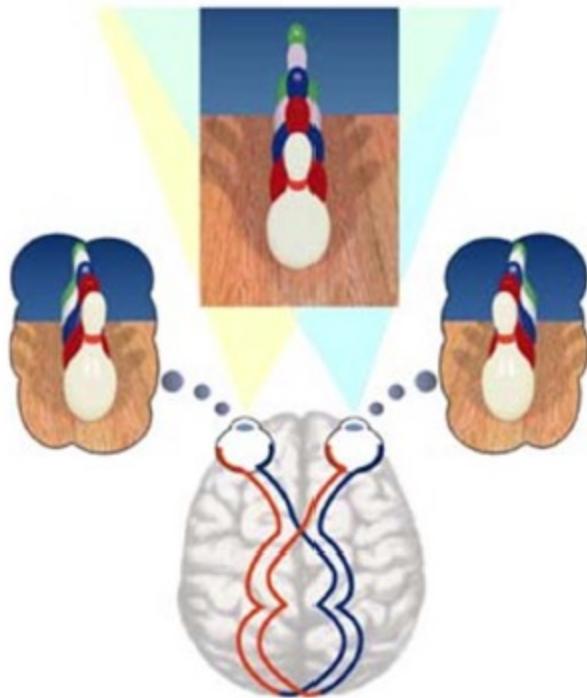
defocus blur



lighting & shading

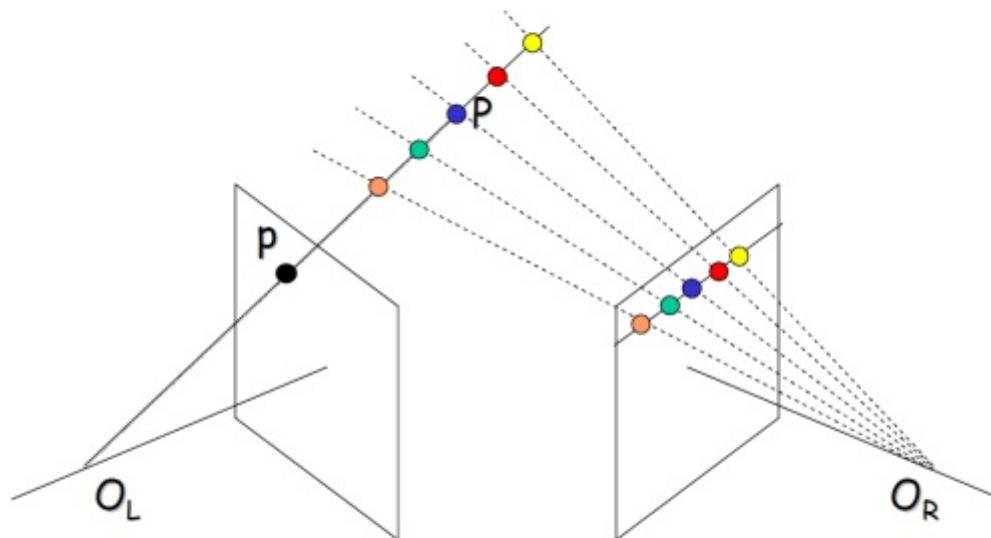


Two eyes help!



Two eyes help!

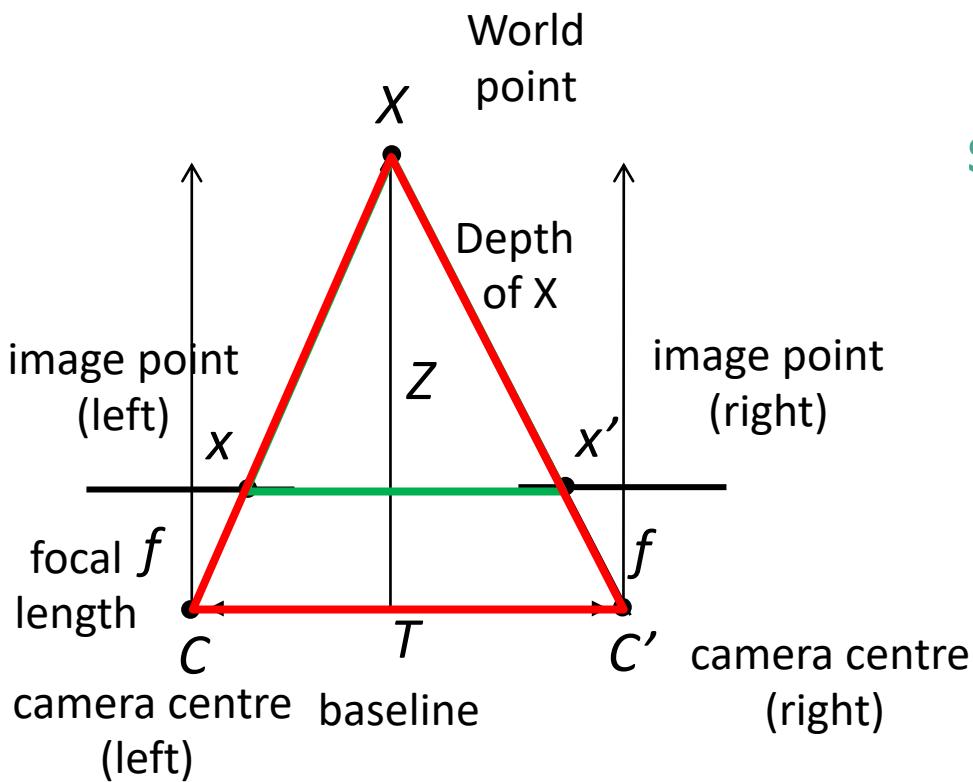
- A second camera can resolve the ambiguity, enabling measuring of depth via **triangulation**
 - Camera parameters (intrinsic & extrinsic) are known



Source: R. Collins

Geometry for a simple stereo system

- Parallel optical axes and known camera parameters



Similar triangles (x, X, x') and (C, X, C'):

$$\frac{T - x + x'}{Z - f} = \frac{T}{Z}$$

$$Z = f \frac{T}{x - x'}$$

disparity

Source: K. Grauman

Depth from disparity

image $I(x,y)$



Disparity map $D(x,y)$

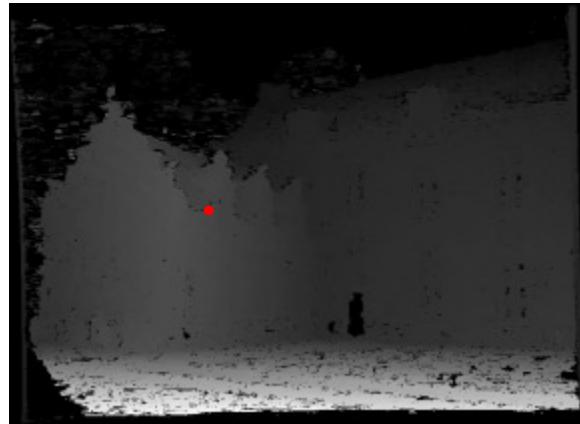


image $I'(x',y')$



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

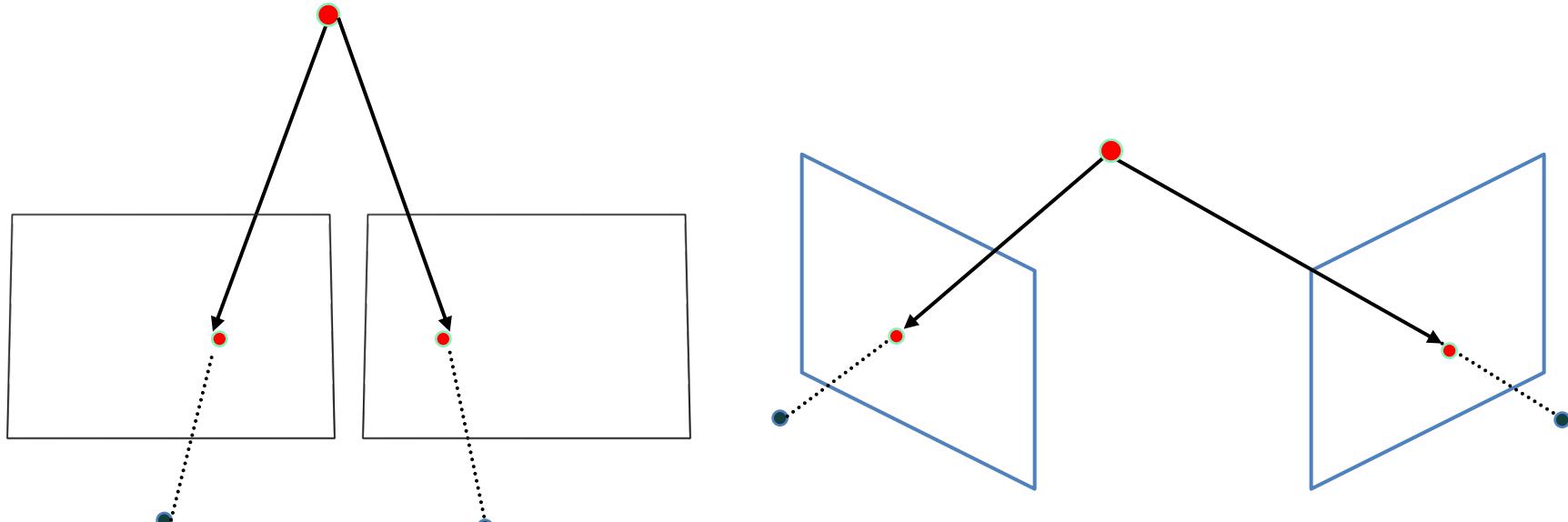
Source: K. Grauman

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General case with calibrated cameras

- Two cameras without parallel optical axes

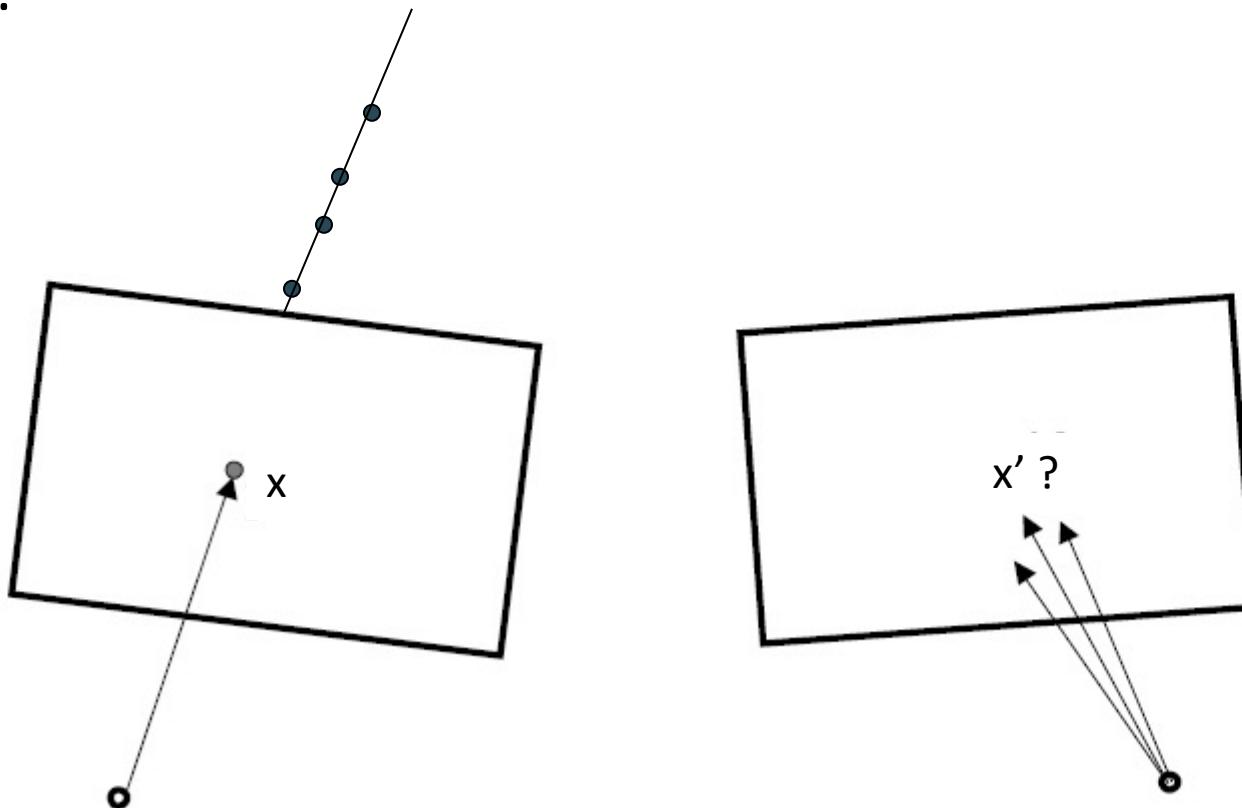


VS.

Source: K. Grauman

Stereo correspondence constraints

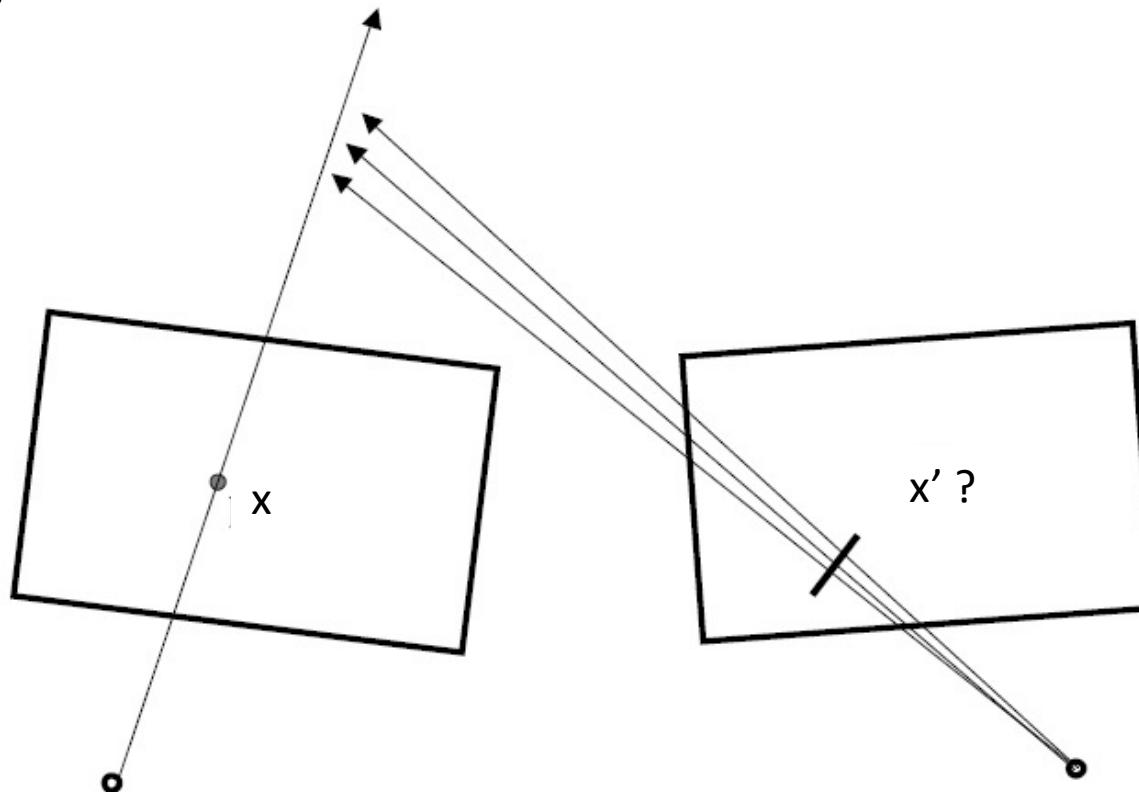
- Given x in the left image, where can the correspondence point x' be?



Source: K. Grauman

Stereo correspondence constraints

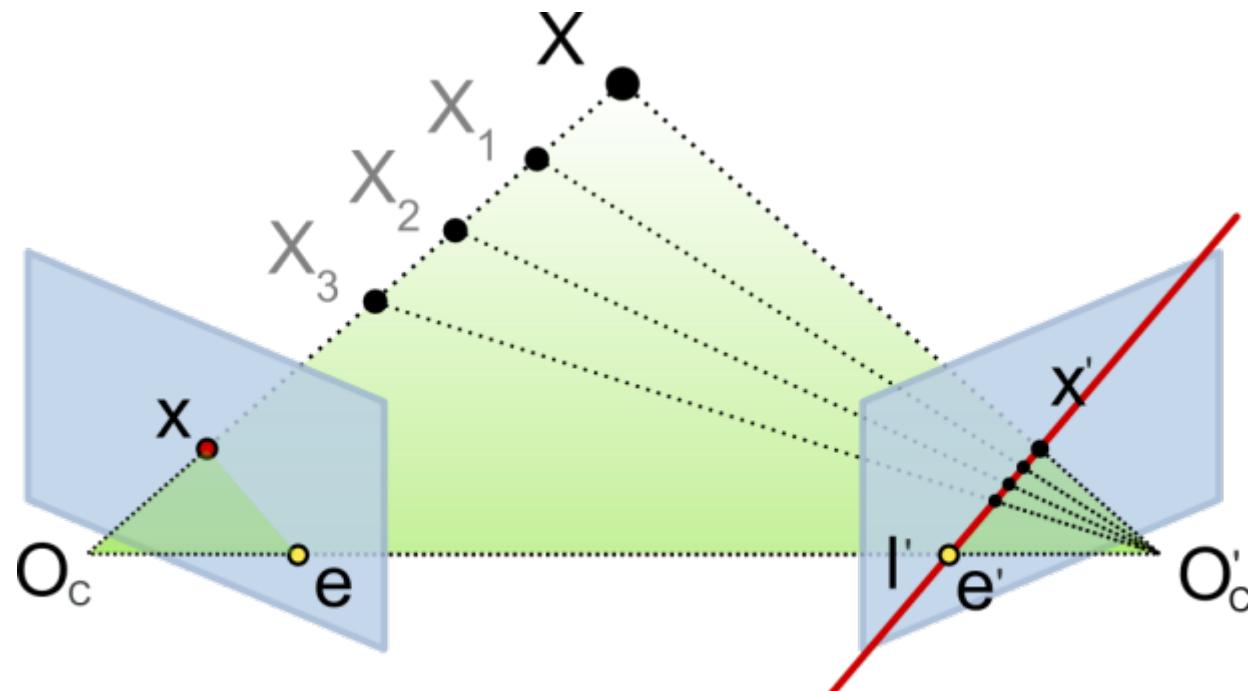
- Given x in the left image, where can the correspondence point x' be?



Source: K. Grauman

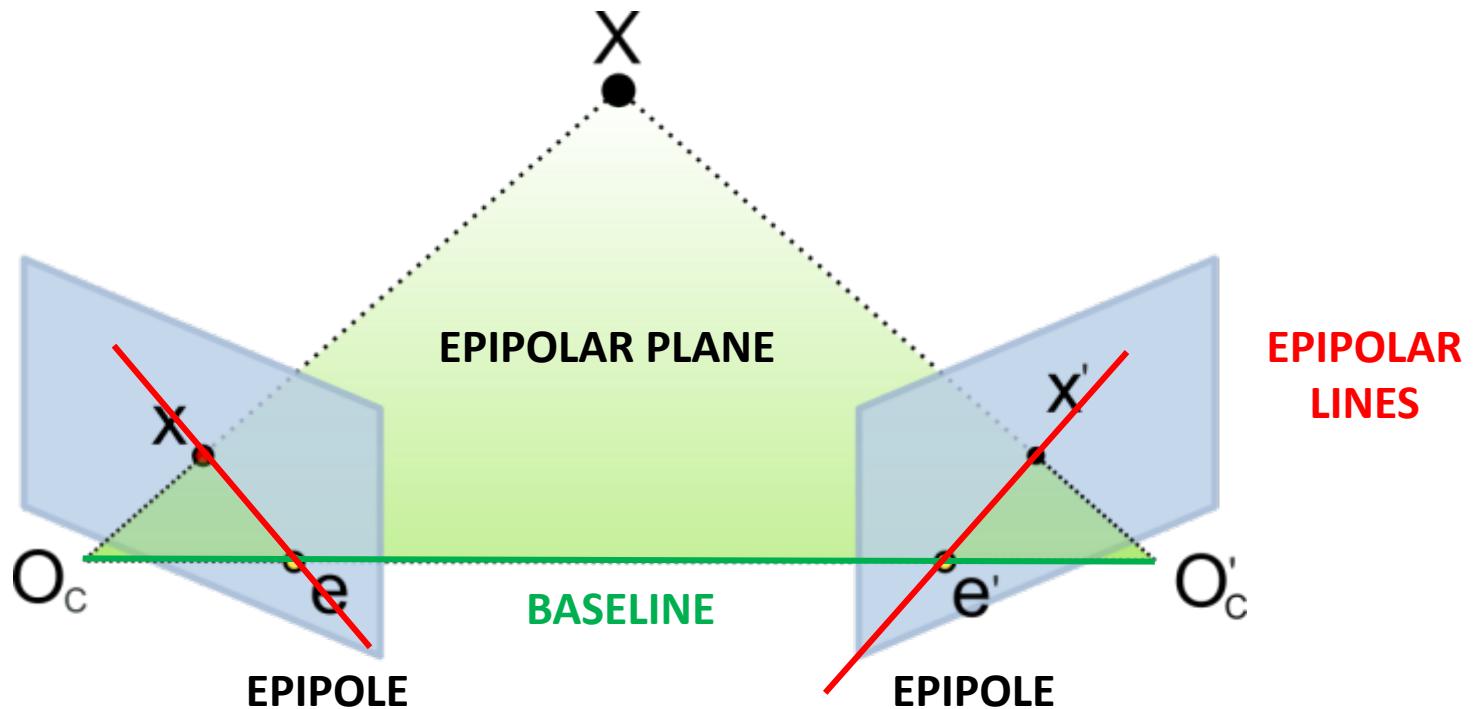
Epipolar constraint

- Geometry of two views constrains where the corresponding pixel for some image point in the left view must occur in the right view
 - It must be on the line carved out by a plane connecting the world point and optical centres



Source: K. Grauman

Epipolar geometry



<http://www.ai.sri.com/~luong/research/Meta3DViewer/EpipolarGeo.html>

Source: K. Grauman

Epipolar geometry terms

- **Baseline**: line joining the camera centres
- **Epipole**: point of intersection of baseline with image plane
- **Epipolar plane**: plane containing baseline and world point
- **Epipolar line**: intersection of epipolar plane with the image plane
- All epipolar lines intersect at the epipole
- An epipolar plane intersects the left and right image planes in epipolar lines
- **WHY IS THE EPIPOLAR CONSTRAINT USEFUL?**

Source: K. Grauman

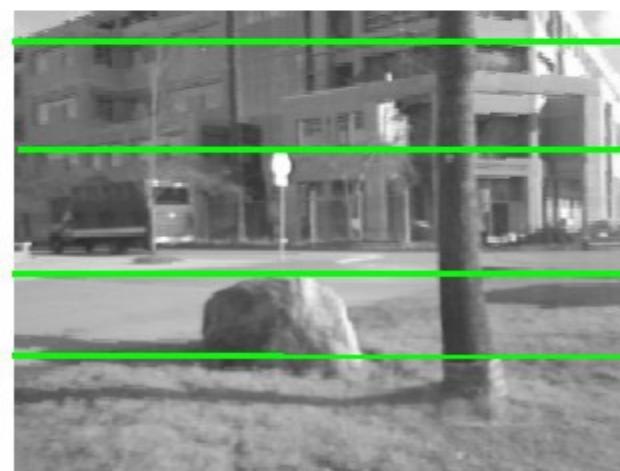
Epipolar constraint

- This is useful because it reduces the correspondence problem to a 1D search along an epipolar line



Source: K. Grauman

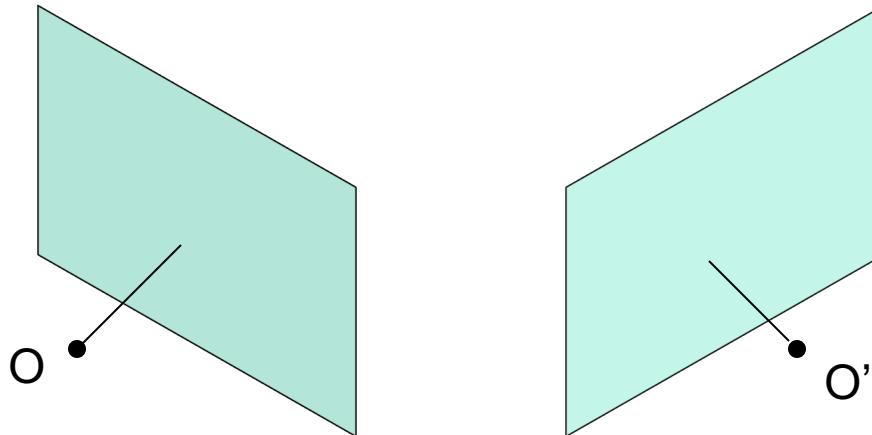
Epipolar constraint: Example



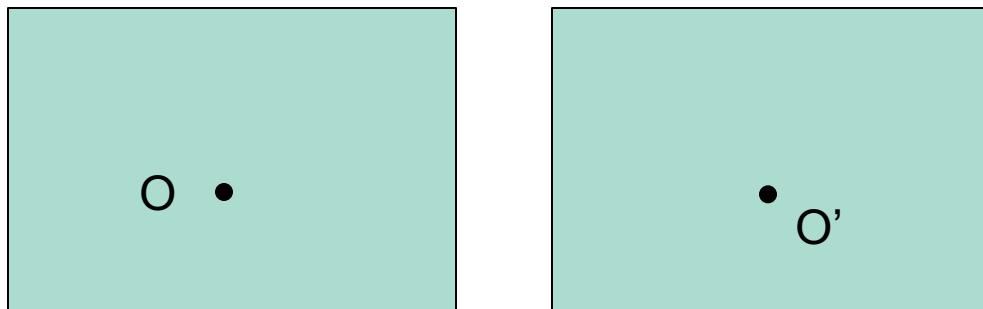
Source: K. Grauman

What do epipolar lines look like?

1.

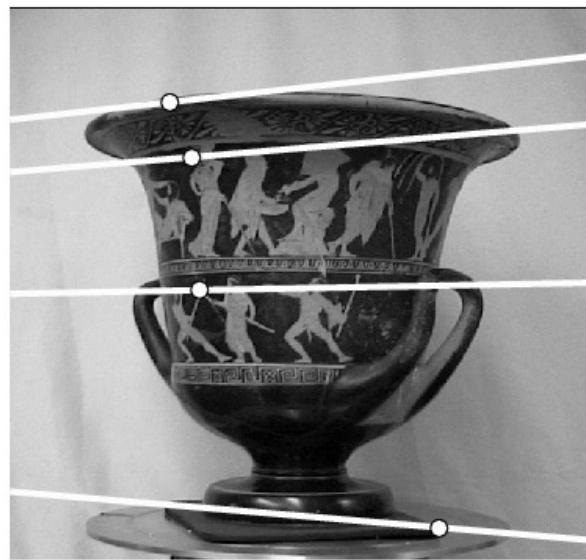
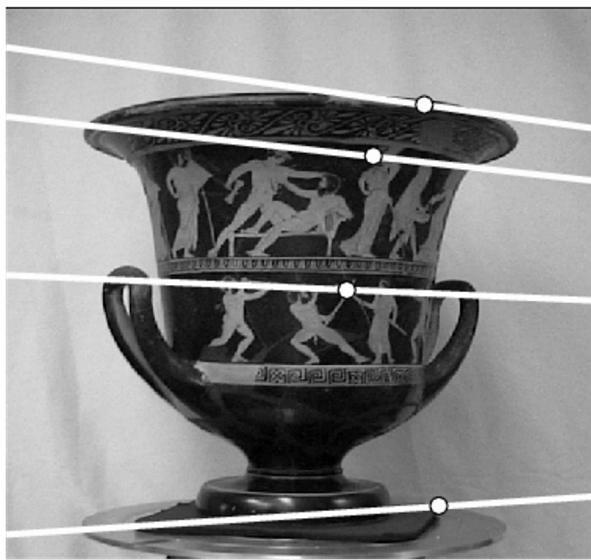
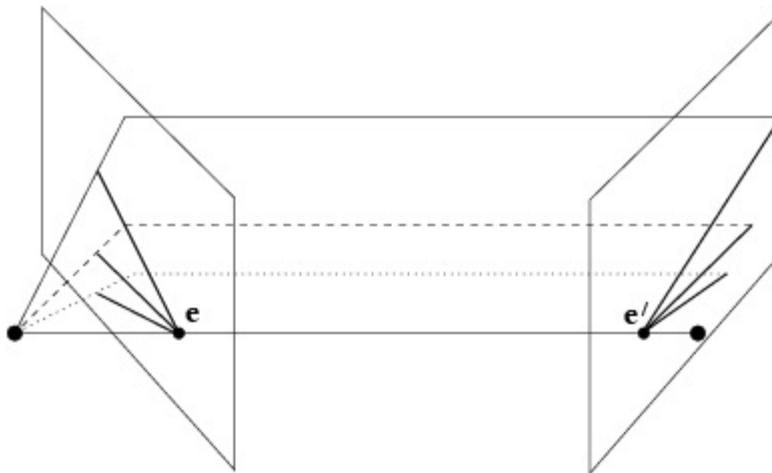


2.



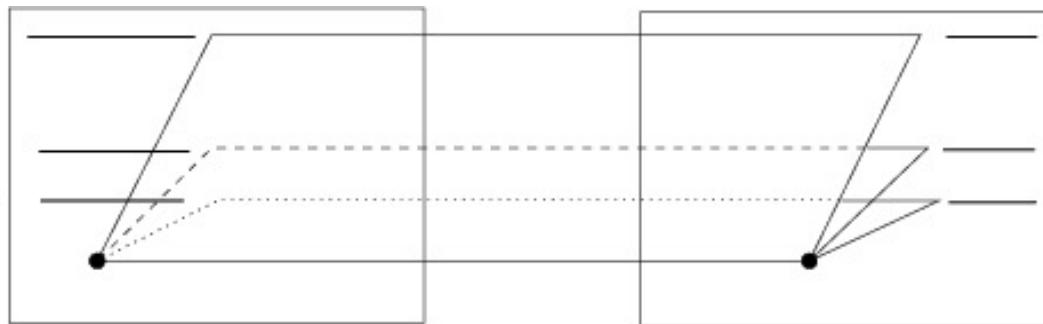
Source: K. Grauman

1. Converging cameras

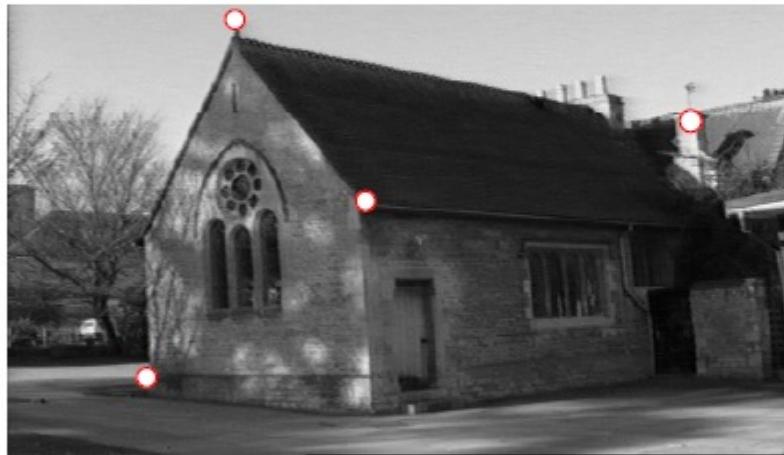


Source: K. Grauman

1. Parallel cameras



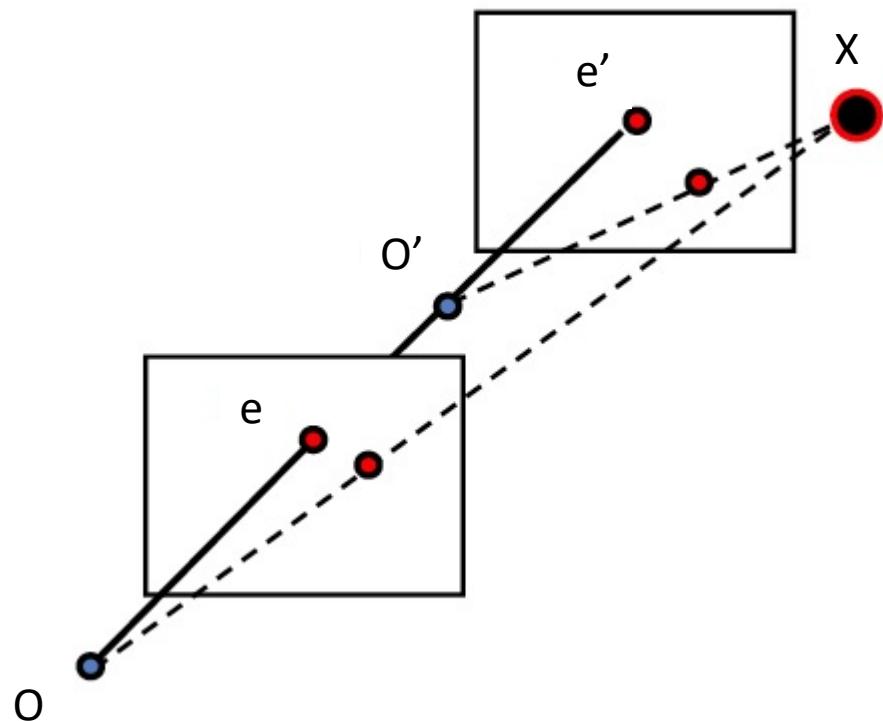
Where are the epipoles?



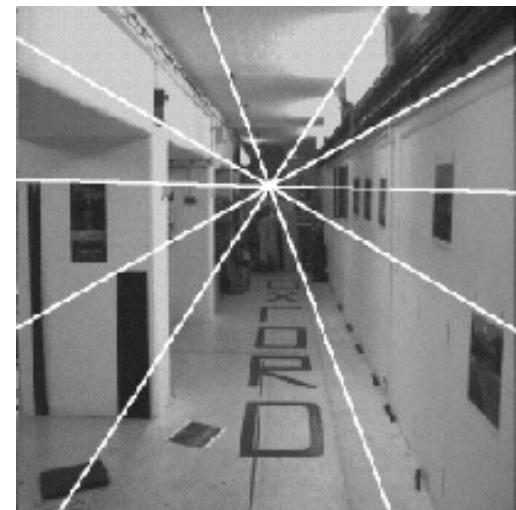
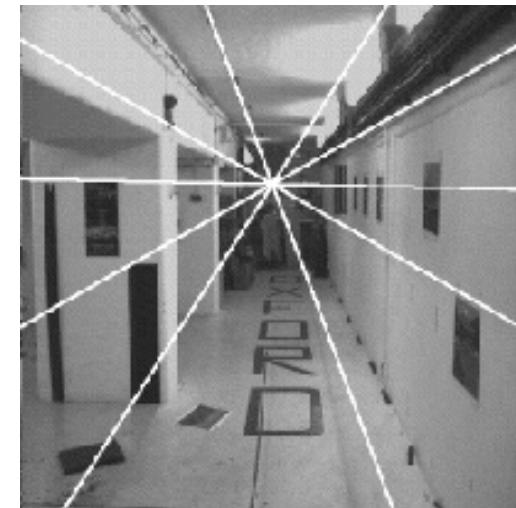
Source: K. Grauman

Another example

- Forward motion. Camera moves directly forward in the camera axes direction



- Epipoles have the same pixel position in both images
- Epipole called “Focus of expansion”

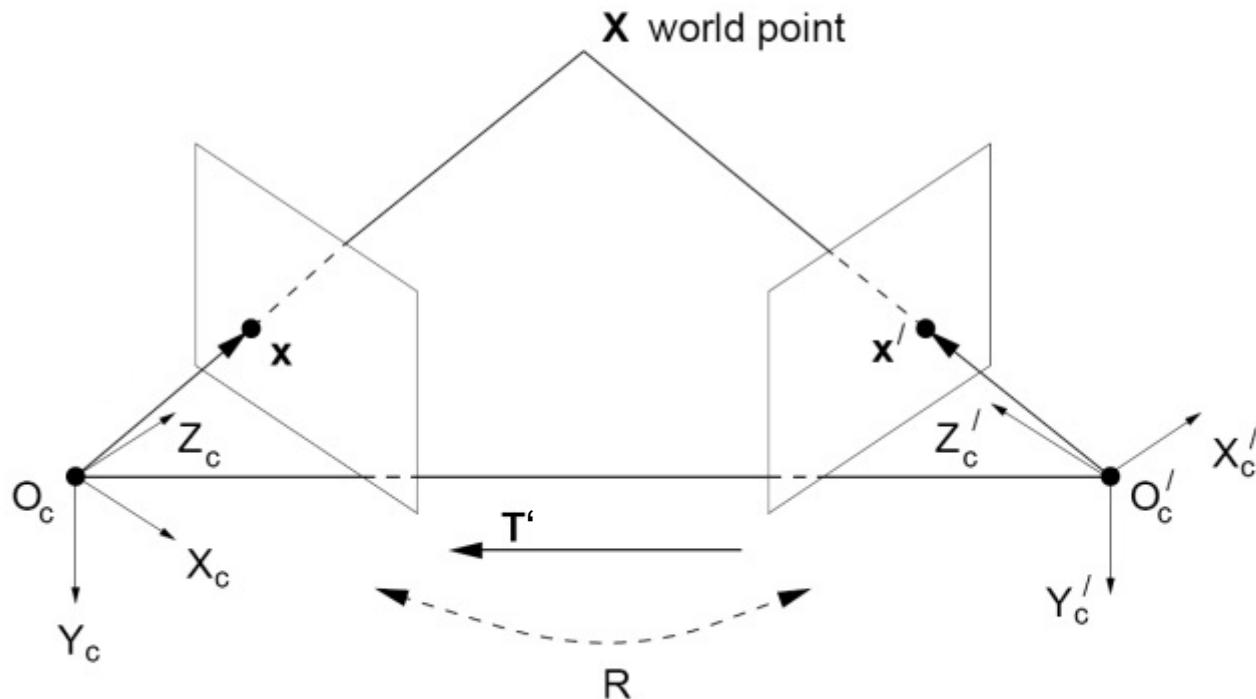


Source: K. Grauman & Fei-Fei Li

Epipolar constraint

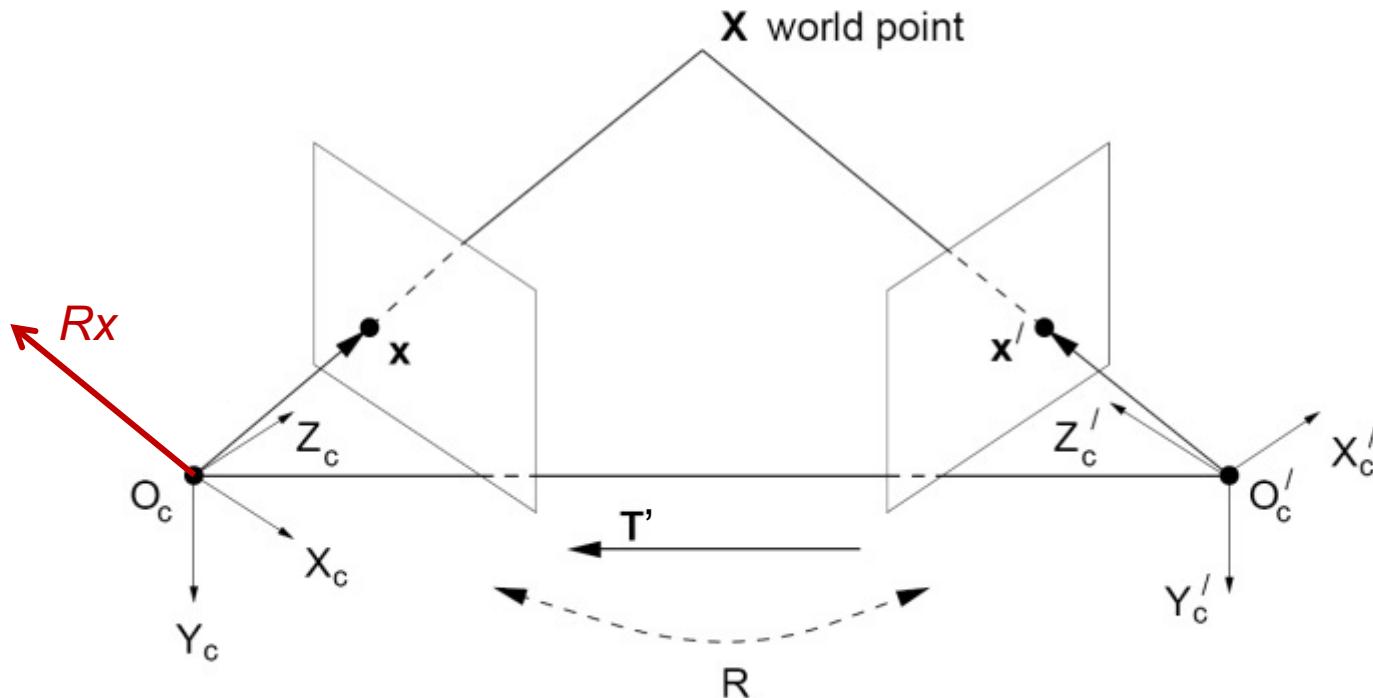
Source: K. Grauman

- Let's express this epipolar constraint algebraically



- Both cameras are calibrated
 - Know how to rotate & translate from camera 1 to camera 2 (prime)
 - Rotation: 3 x 3 matrix R ; translation: 3 vector \mathbf{T}' $X' = RX + T'$

Epipolar constraint



- Epipolar plane is defined by vectors (X, T') or (x, T') or (x', T')
- Vector Rx also included in epipolar plane
- Vector $T' \times Rx$ perpendicular to epipolar plane

$$x' \cdot (T' \times Rx) = 0$$

Source: K. Grauman

Cross product multiplication

- We can express the cross product multiplication of two vectors \mathbf{a} and \mathbf{b} as a matrix multiplication

$$\mathbf{a} \times \mathbf{b} = \begin{bmatrix} a_x \\ a_y \\ a_z \end{bmatrix} \times \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} = \underbrace{\begin{bmatrix} 0 & -a_z & a_y \\ a_z & 0 & -a_x \\ -a_y & a_x & 0 \end{bmatrix}}_{\text{skew-symmetric}} \begin{bmatrix} b_x \\ b_y \\ b_z \end{bmatrix} = [\mathbf{a}_\times] \mathbf{b}$$

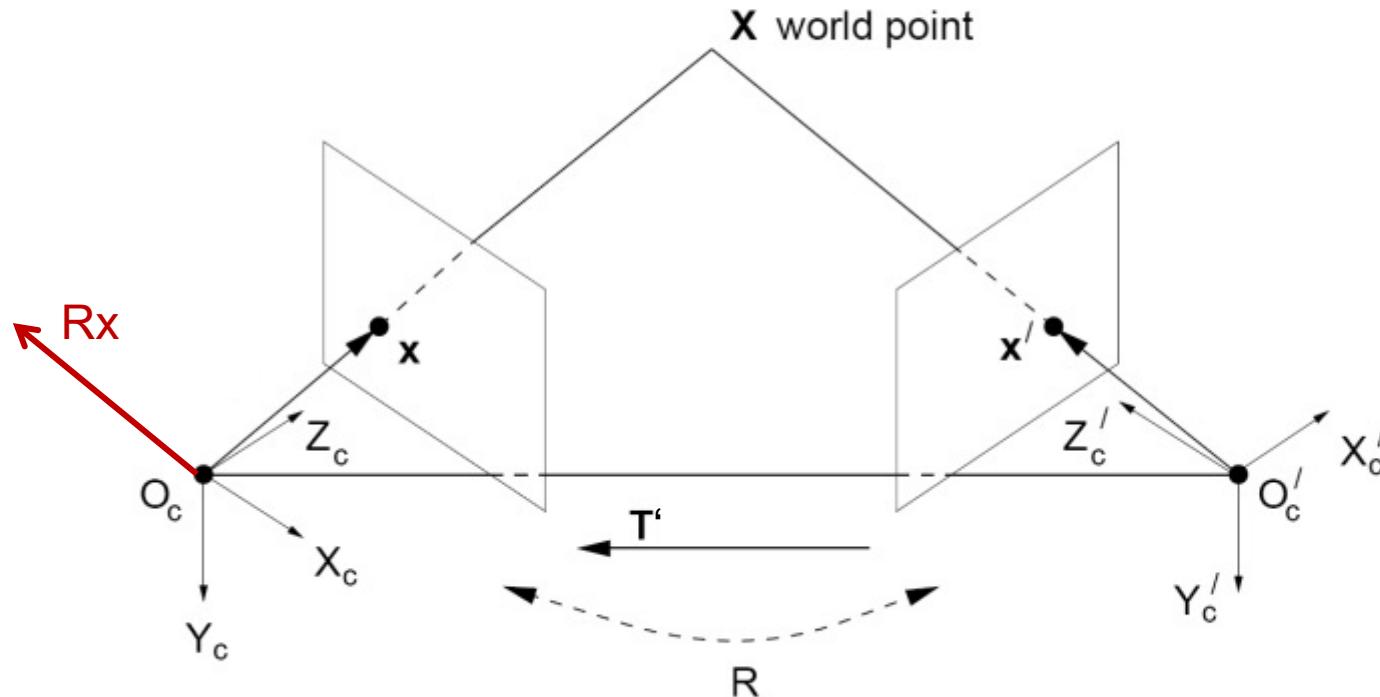
- Remember that

skew-symmetric

$$\mathbf{a} \cdot (\mathbf{a} \times \mathbf{b}) = \mathbf{a}^T [\mathbf{a}_\times] \mathbf{b} = 0$$

$$\mathbf{b} \cdot (\mathbf{a} \times \mathbf{b}) = \mathbf{b}^T [\mathbf{a}_\times] \mathbf{b} = 0$$

Epipolar constraint



- Epipolar plane is defined by vectors (X, T') or (x, T') or (x', T')
- Vector Rx also included in epipolar plane
- Vector $T' \times Rx$ perpendicular to epipolar plane

$$x' \cdot (T' \times Rx) = 0 \rightarrow x' \cdot ([T'_x] Rx) = x'^T [T'_x] Rx = 0$$

Essential matrix
(Longuet-Higgins, 1981)

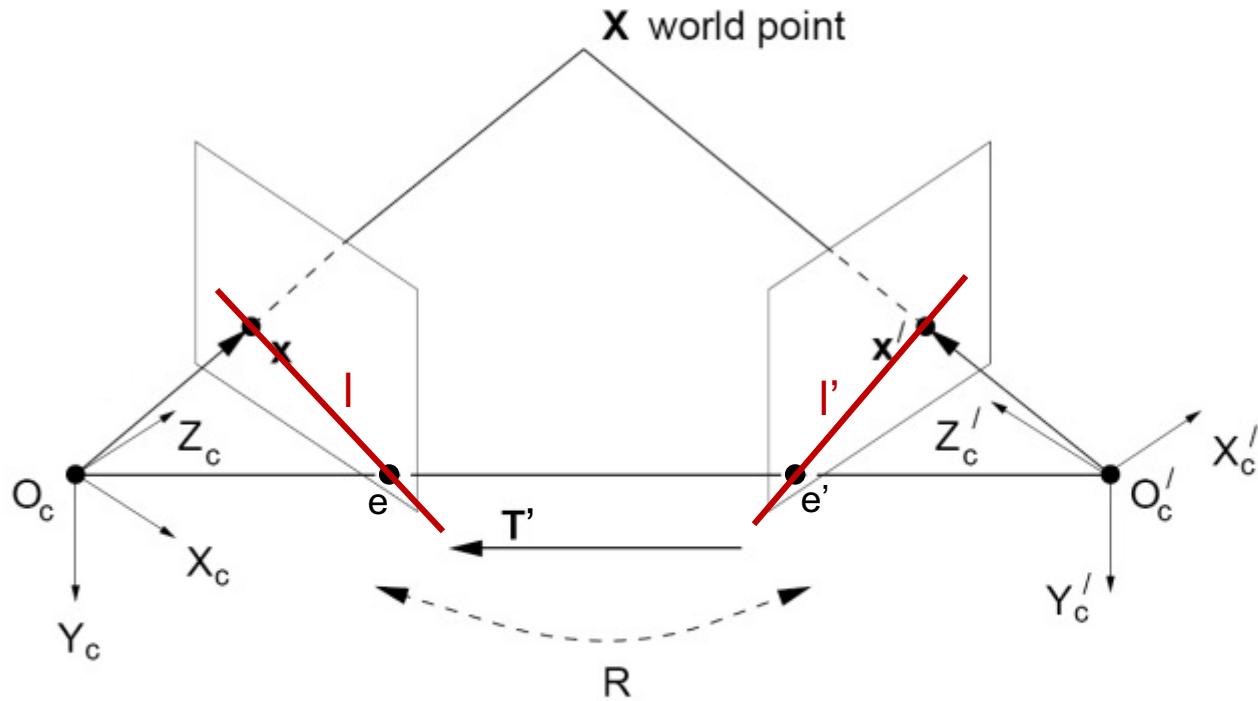
Source: K. Grauman

Essential matrix (1)

$$x'^T E x = 0$$

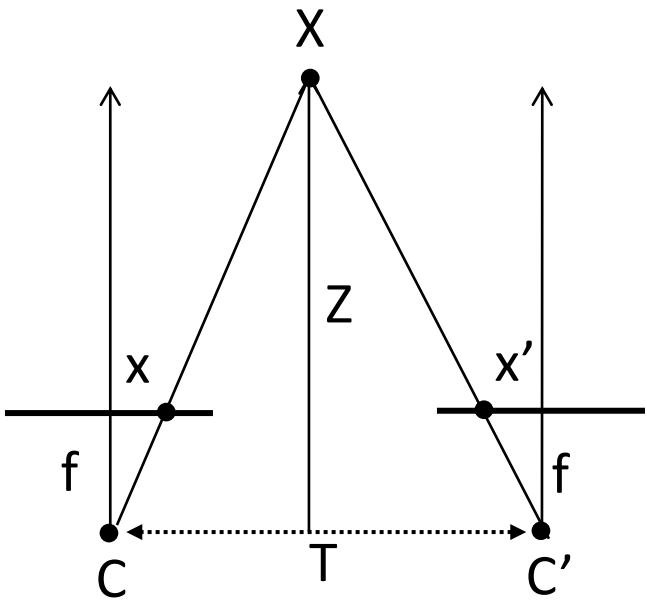
- $E=[T' \mathbf{x}]R$ is called the **essential matrix**
- Relates corresponding points between both cameras given the rotation and translation
- Defined **up-to-scale**
- x and x' are in **camera coordinates system** (3 component vectors).

Essential matrix (2)



- Epipoles
 - $Ee=0$ and $E^T e'=0$
 - Epipolar lines
 - $l=E^T x'$ and $l'=Ex$
- $$x'^T E x = 0$$

Essential matrix: Example



$$\begin{aligned}\mathbf{R} &= \mathbf{I} \\ \mathbf{T}' &= [-d, 0, 0]^T \\ \mathbf{E} &= [\mathbf{T}'] \mathbf{R}\end{aligned}$$

$$\mathbf{x} = [x, y, f]^T$$

$$\mathbf{x}' = [x', y', f]^T$$

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

$$[x' \ y' \ f] \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & d \\ 0 & -d & 0 \end{bmatrix} \begin{bmatrix} x \\ y \\ f \end{bmatrix} = 0$$

$$\Leftrightarrow [x' \ y' \ f] \begin{bmatrix} 0 \\ df \\ -dy \end{bmatrix} = 0$$

$$\Leftrightarrow y = y'$$

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

Essential matrix (3)

- 3x3 matrix with 5 degrees of freedom, $\det(E)=0$
- E is singular (rank 2)
- Two of its singular values are equal, and the third is zero

$$E = UDV^T = U \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T$$



Essential matrix: Extrinsic parameters (1)

- Computing extrinsic parameters from essential matrix is possible → factorizing
- Assume extrinsics of first camera are $P = [I | 0]$ with Essential matrix:

$$E = \begin{bmatrix} T' \\ \times \end{bmatrix} R = U \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T$$

- $E = SR$ determines S (and thus T') up to scale
- Considering that $\|T'\| = 1$ and $ST' = 0$ (S related to the cross product of T') then:

$$T' = \boxed{\mathbf{u}_3}$$

Last column of U

- Baseline between cameras normalized
 - Ground control points needed to recover true distances



Essential matrix: Extrinsic parameters (3)

- Geometrical interpretation:

$$P'_1 = \begin{bmatrix} UWV^T | +\mathbf{u}_3 \end{bmatrix} \quad P'_2 = \begin{bmatrix} UWV^T | -\mathbf{u}_3 \end{bmatrix}$$

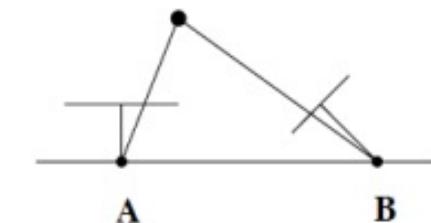
$$P'_3 = \begin{bmatrix} UW^T V^T | +\mathbf{u}_3 \end{bmatrix} \quad P'_4 = \begin{bmatrix} UW^T V^T | -\mathbf{u}_3 \end{bmatrix}$$

- Direction of translation vector is reversed: $+\mathbf{u}_3 \leftrightarrow -\mathbf{u}_3$
- Rotation of 180° along the baseline:

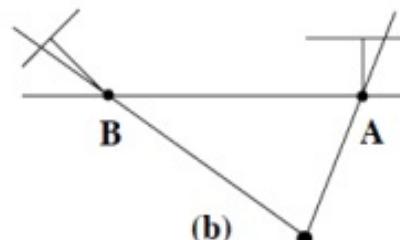
$$\begin{aligned} \begin{bmatrix} UW^T V^T | u_3 \end{bmatrix} &= \begin{bmatrix} UWV^T | u_3 \end{bmatrix} \begin{bmatrix} VW^T W^T V^T \\ 1 \end{bmatrix} = \\ &= \begin{bmatrix} UWV^T | u_3 \end{bmatrix} \begin{bmatrix} V \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 0 & 0 & 1 \end{bmatrix} V^T \\ 1 \end{bmatrix} \end{aligned}$$

Essential matrix: Extrinsic parameters (2)

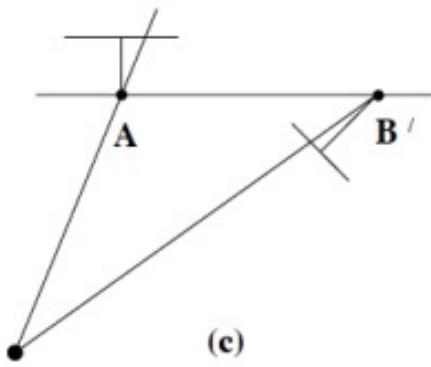
- Up to 4 possible solutions → Only one solution (a) the reconstructed point is in front of both cameras



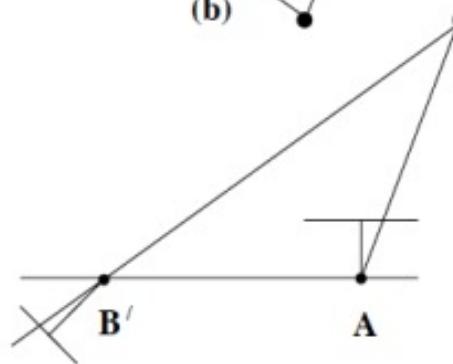
(a)



(b)



(c)



(d)

Source: R. Hartley & A. Zisserman

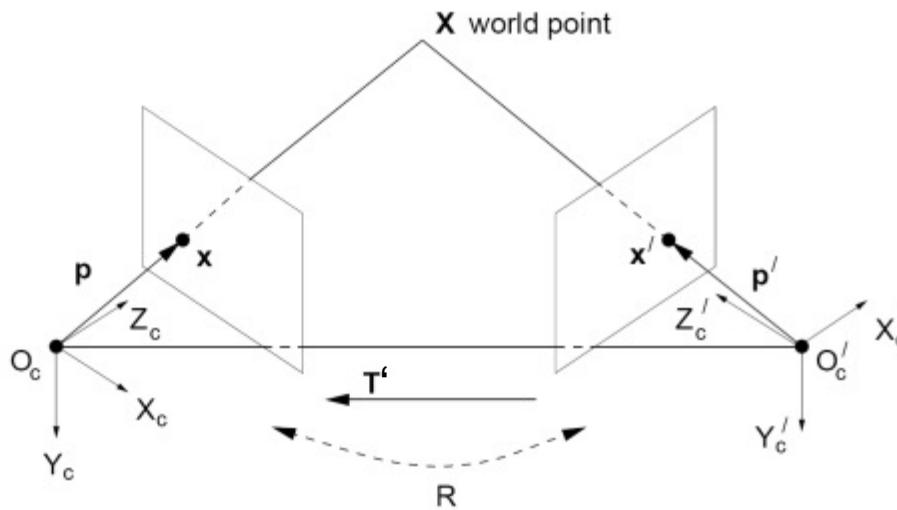
Epipolar constraint: Uncalibrated case

- Can we establish a similar relation between pixel coordinates $p=[u \ v]^T$ instead of points in camera coordinates $x=[x \ y \ z]^T$???
- Yes we can! using homogeneous coordinates
 - Points are represented as lines in a higher dimension

Epipolar constraint: Uncalibrated case

$$\tilde{p} = M\tilde{X} = K[I \quad 0]\tilde{X} = Kx \rightarrow x = K^{-1}\tilde{p}$$

$$\tilde{p}' = M' \tilde{X} = K'[R \quad T'] \tilde{X} = K' x' \rightarrow x' = K'^{-1} \tilde{p}'$$



$$x'^T E x = (K'^{-1} \tilde{p}')^T E K^{-1} \tilde{p} = \tilde{p}'^T [K'^{-T} E K^{-1}] \tilde{p} = \tilde{p}'^T [K'^{-T} [T'] R K^{-1}] \tilde{p}$$

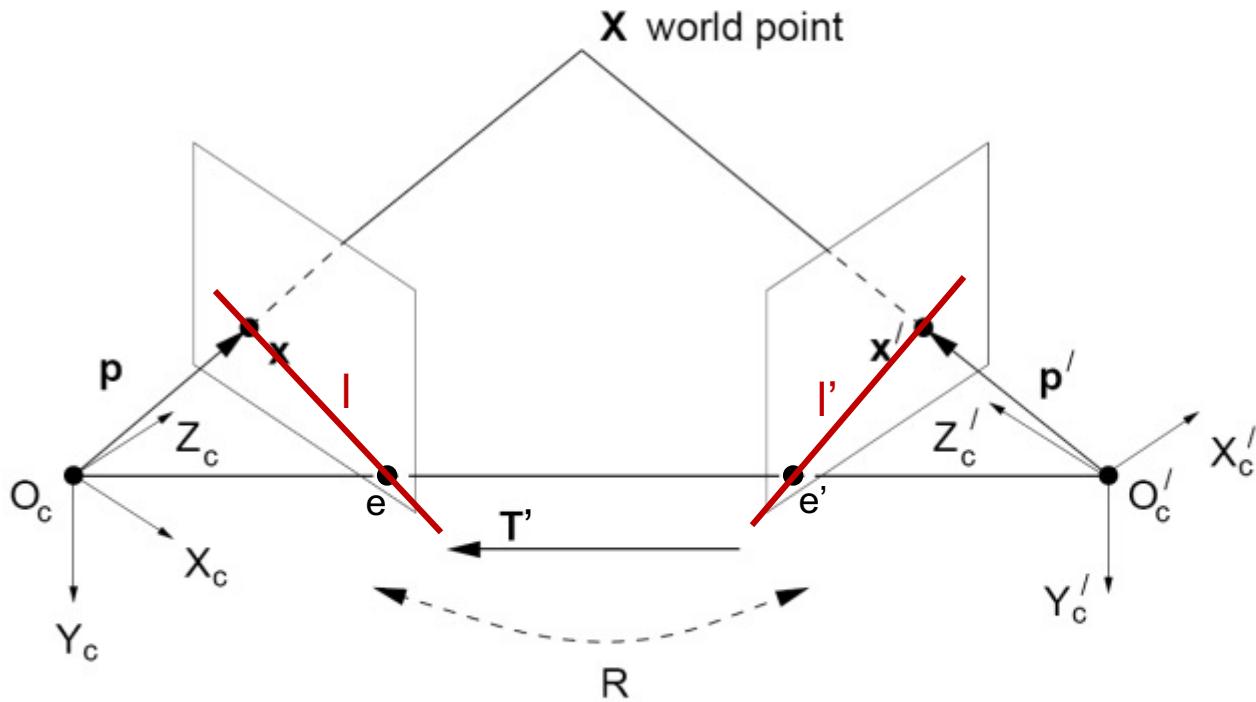
Fundamental matrix (Faugeras and Luong, 1992)

Fundamental matrix (1)

$$\tilde{p}'^T F \tilde{p} = 0$$

- $F = K'^{-T} [T'_{x'}] R K^{-1}$ is called the **fundamental matrix**
- Relates corresponding points between uncalibrated cameras
- 3×3 matrix with 7 degrees of freedom, $\det(F) = 0$
- F is singular (rank 2)
- Defined **up-to-scale**
- p and p' are expressed in **pixels** (homogeneous coordinates)

Fundamental matrix (2)



- Epipoles
 - $\mathbf{F}\tilde{\mathbf{e}}=0$ and $\mathbf{F}^T\tilde{\mathbf{e}}'=0$
 - Epipolar lines
 - $\mathbf{l}=\mathbf{F}^T\tilde{\mathbf{p}}'$ and $\mathbf{l}'=\mathbf{F}\tilde{\mathbf{p}}$
- $$\tilde{\mathbf{p}}'^T \mathbf{F} \tilde{\mathbf{p}} = 0$$

Fundamental matrix: Reconstruction ambiguity (1)

- Computing camera matrices from fundamental matrix
 - A pair of projection matrices M and M' uniquely determine F
 - However, the fundamental matrix F determines the pair of camera matrices **up to a projective transformation**

- Possible solution:

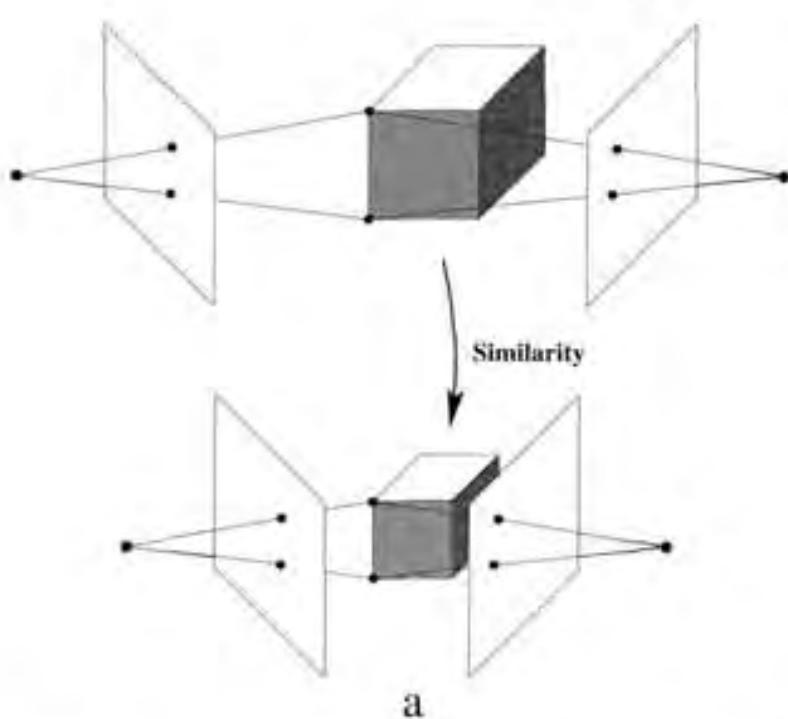
$$M = [I \mid 0] \quad M' = [SF \mid e'] = [[e'_x]F \mid e']$$

- Taking H as a 4x4 matrix representing a projective transformation
 - Fundamental matrices corresponding to the pairs of camera matrices ($M ; M'$) and ($MH ; M'H$) are the same

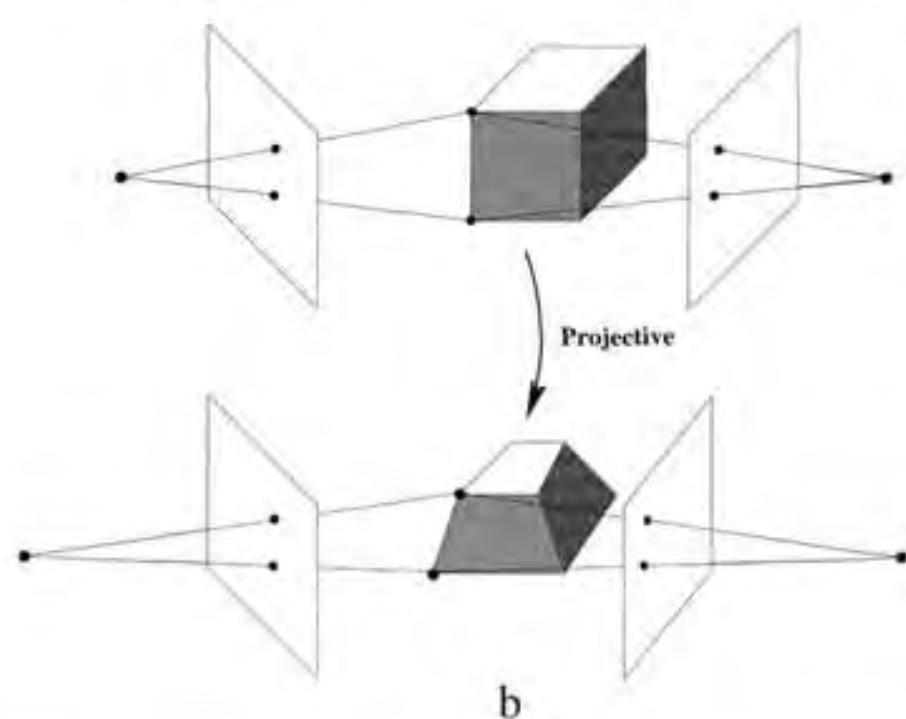
$$H = \begin{bmatrix} R & t \\ 0^T & s \end{bmatrix}$$

Fundamental matrix: Reconstruction ambiguity (2)

(a) Calibrated case



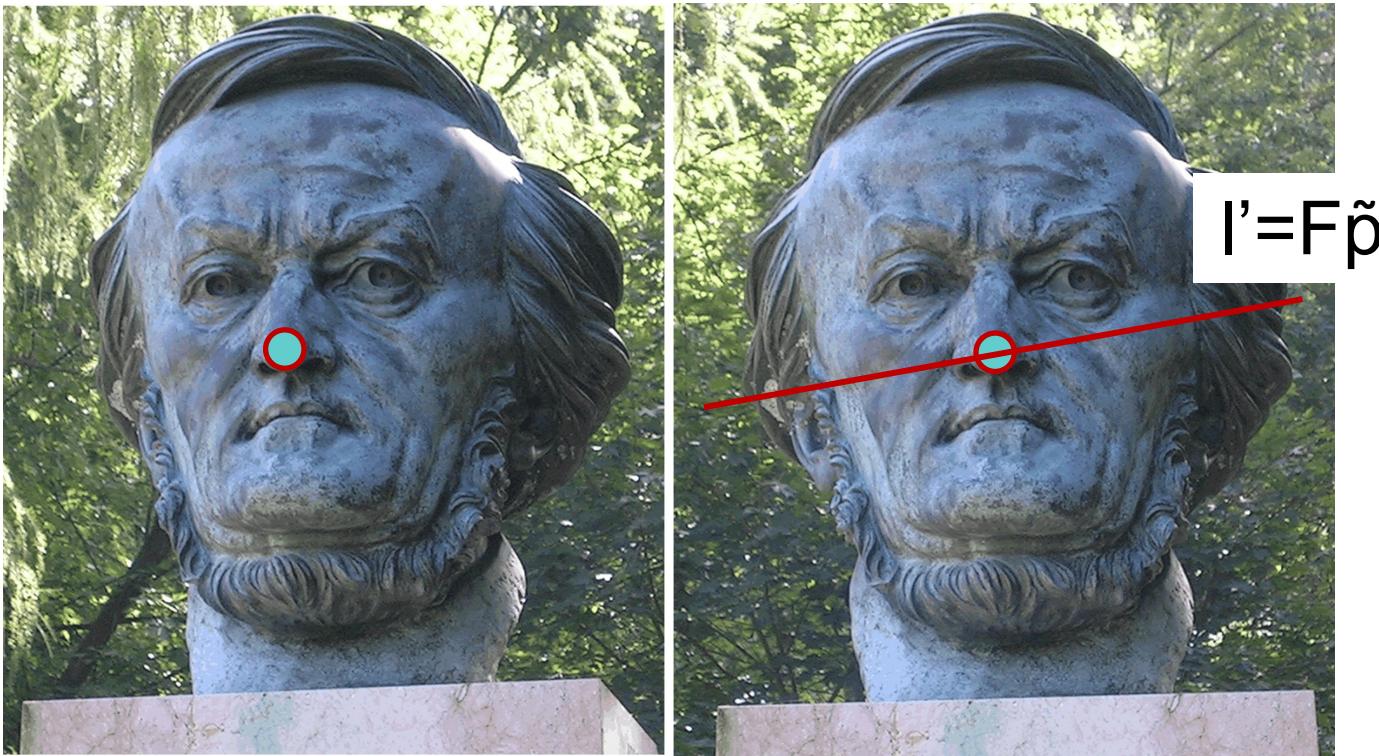
(b) Uncalibrated case



Source: R. Hartley & A. Zisserman



Why is F useful?



- Two views of the same object
 - Suppose I know the camera positions and camera matrices
- Given a point on left image, how can I find the corresponding point on right image?

Source: Fei-Fei Li

Why is F useful?

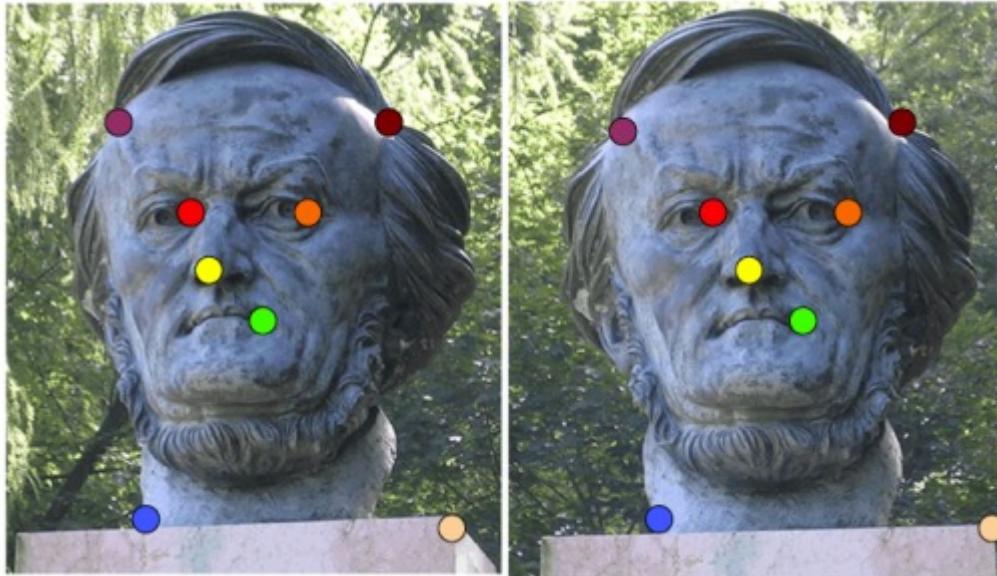
- F captures information about the epipolar geometry of 2 views + camera parameters
- **MORE IMPORTANTLY:** F gives constraints on how the scene changes under view point transformation (without reconstructing the scene!)
- Powerful tool in:
 - 3D reconstruction
 - Multi-view object/scene matching

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Estimating F

- Estimate the fundamental matrix between two images
- Intrinsic and extrinsic parameters of the camera are unknown
- A set of points p_i and p' , correspondences between the two images

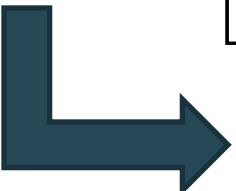


- How to obtain these points?
 - Feature detection and correspondences

Estimating F

- For each point correspondence $\tilde{p}_i = [u \ v]^T$ and $\tilde{p}'_i = [u' \ v']^T$ the fundamental matrix constrains their relation to (in homogeneous coordinates):

$$\tilde{p}'^T F \tilde{p} = 0 \rightarrow \begin{bmatrix} u' & v' & 1 \end{bmatrix} \begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = 0$$



$$\begin{bmatrix} uu' & vu' & u' & uv' & vv' & v' & u & v & 1 \end{bmatrix} \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{bmatrix} = 0$$

8-point algorithm

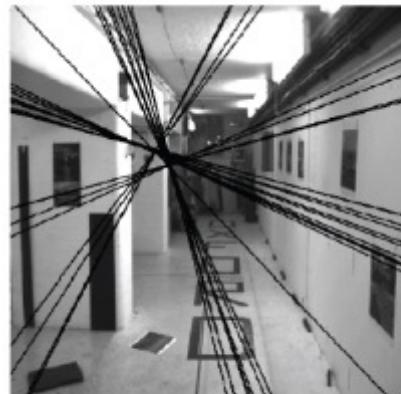
- Let's take 8 corresponding points

$$\begin{bmatrix} u_1 u'_1 & v_1 u'_1 & u'_1 & u_1 v'_1 & v_1 v'_1 & v'_1 & u_1 & v_1 & 1 \\ u_2 u'_2 & v_2 u'_2 & u'_2 & u_2 v'_2 & v_2 v'_2 & v'_2 & u_2 & v_2 & 1 \\ \vdots & & & & & & & & \\ u_8 u'_8 & v_8 u'_8 & u'_8 & u_8 v'_8 & v_8 v'_8 & v'_8 & u_8 & v_8 & 1 \end{bmatrix} \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \\ F_{33} \end{bmatrix} = 0 \rightarrow \mathbf{Wf} = 0$$

- Linear least square method
 - 0 is always a solution
 - Non-zero solution
 - Minimize $\|\mathbf{Wf}\|^2$ under the constraint $\|\mathbf{f}\|=1$

8-point algorithm

- Use singular value decomposition (SVD)
 - $\mathbf{W} = \mathbf{U}\mathbf{D}\mathbf{V}^T$ where \mathbf{U} and \mathbf{V} are orthogonal matrices and \mathbf{D} diagonal matrix with non-negative entries (descending order).
 - Last column of \mathbf{V} gives $\mathbf{f} \rightarrow \mathcal{F}$
- However, \mathcal{F} is still of rank 3
 - Epipolar lines will not coincide in the epipole!
 - Force \mathcal{F} to be of rank 2



Rank 3



Rank 2

8-point algorithm

- Use singular value decomposition (**AGAIN!**) to construct F of rank 2

$$F_{RANK_3} = U \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix} V^T$$

$$F_{RANK_2} = U \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T$$

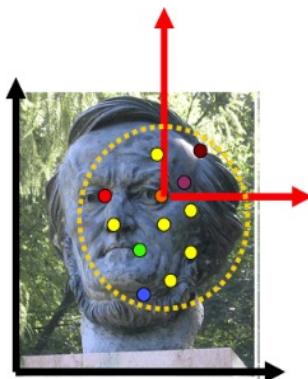
The Fundamental matrix song

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

8-point algorithm

- Least-square methods are
 - Very **sensitive** to **noise**
 - Usually more points (than 8) are used
 - Very sensitive to **false matches** (false correspondences)
 - Ransac
 - **Highly unstable** (in the numerical sense)
 - Normalize Input Data

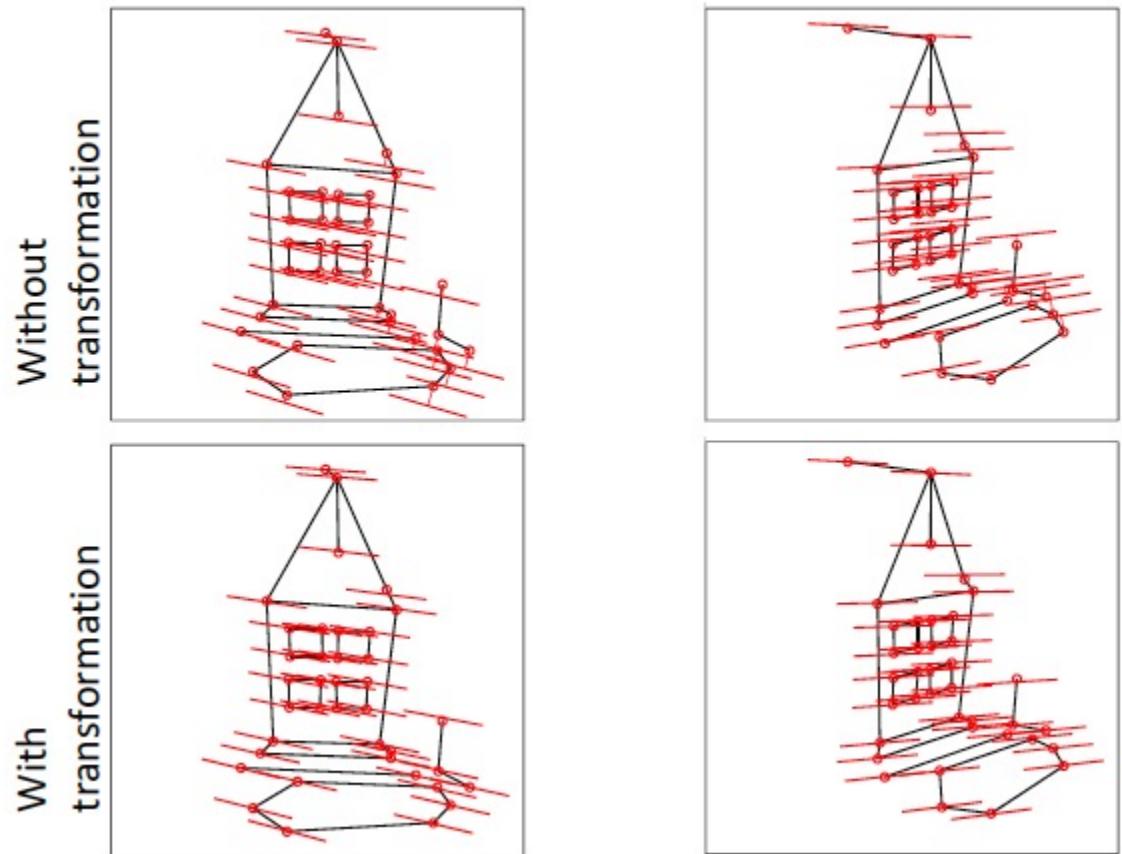
□ **IDEA:** Transform the image coordinate system to normalize input data before estimating F (Hartley,1995)



Robust methods

- Exploit heuristics
- Try to remove "outliers"
- **RAN**dom **SA**mple **C**onsensus
 - RANSAC loop (Iterate the procedure K times):
 - Randomly select 8 points
 - Estimate F from selected points
 - Determine # inliers where $d(p_i, F^T p'_i) + d(p'_i, Fp_i) < \varepsilon$
 - Re-estimate F using all inliers

Example



Mean
errors:
10.0pixel
9.1pixel

Mean
errors:
1.0pixel
0.9pixel

Non-linear methods

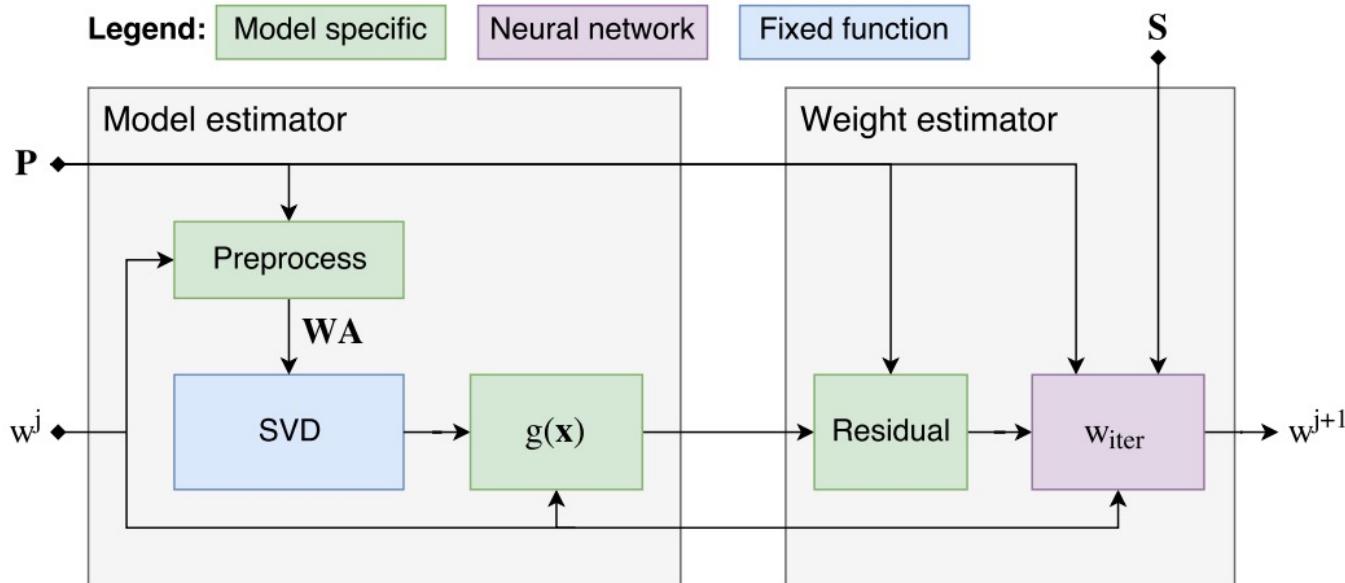
- Non-Linear Least-Squares Approach (Luong et al., 1993)
 - Minimize with respect to the coefficients of F , using an appropriate rank 2 parameterization

$$\sum_{i=1}^N \left[d^2(p_i, F^T p'_i) + d^2(p'_i, F p_i) \right]$$

- Still problems with false correspondences

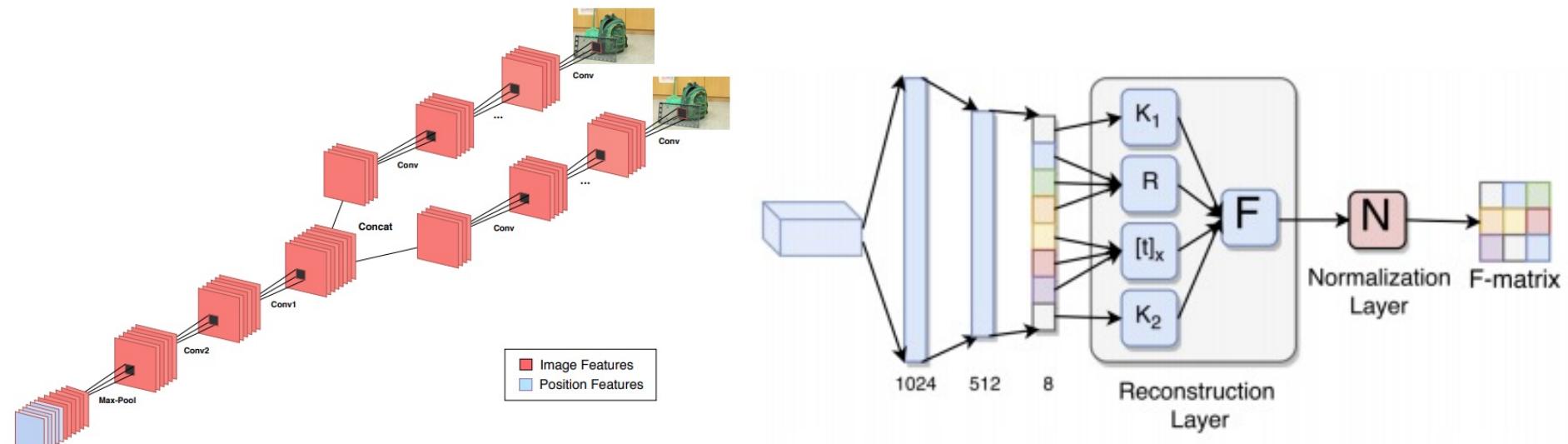
Learning methods (1)

- R. Ranftl and V. Koltun, [Deep Fundamental Matrix Estimation](#), ECCV, 2018
 - Uses neural network to refine weights for least-squares
 - Automatic detection of outliers



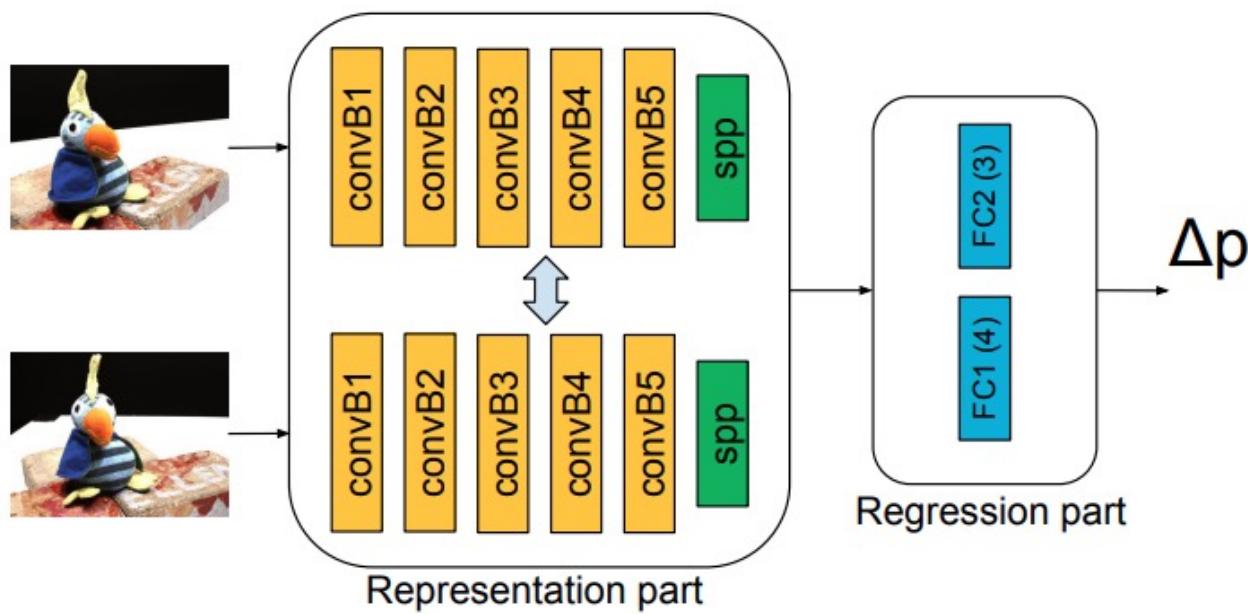
Learning methods (2)

- O. Poursaeed, G. Yang, et.al. [Deep Fundamental Matrix Estimation without Correspondences](#), 2018.
 - Directly estimate Fundamental matrix from two images using a siamese network and convolutional layers
- Reconstruction layer to force properties of \mathbf{F}



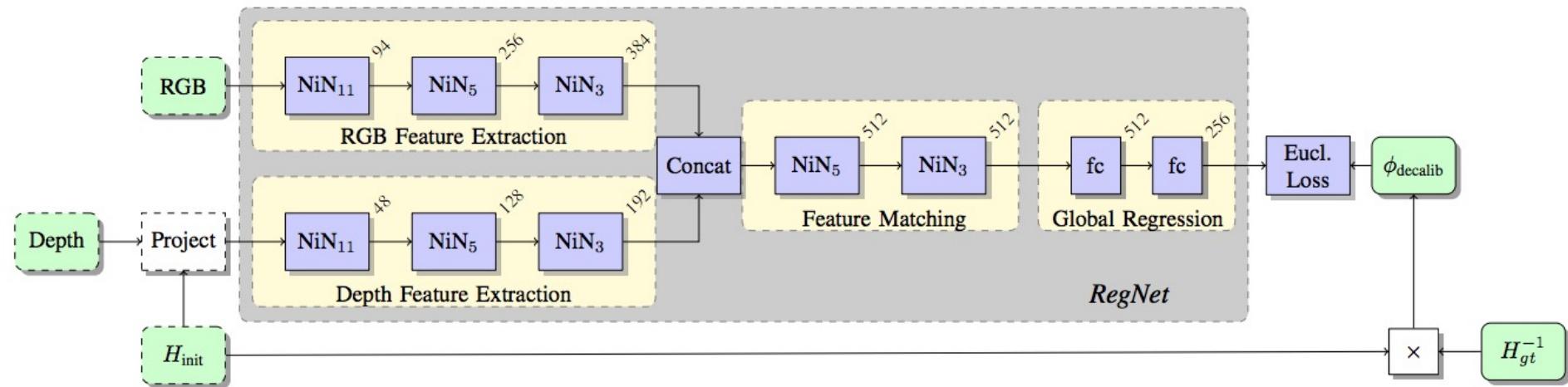
Learning methods (3)

- . Melekhov, et.al. [Relative Camera Pose Estimation Using Convolutional Neural Networks](#), ACIVS, 2017.
 - Estimate relative rotation and translation between two images



Learning methods (4)

- N. Schneider, F. Piewak, C. Stiller, U. FrankeR, [RegNet: Multimodal Sensor Registration Using Deep Neural Networks](#), IEEE Intelligent Vehicles Symposium, 2017
 - Infers extrinsic calibration between multimodal sensors
 - LiDAR and a RGB monocular camera



Outline

- Why is stereo useful?
 - Monocular / Binocular depth perception
- Epipolar constraints
 - Calibrated cameras: Essential matrix
 - Uncalibrated cameras: Fundamental matrix
- Estimating Fundamental matrix
 - Linear: 8 point algorithm
 - Non-linear
 - Robust methods: RANSAC
- Rectification

Image rectification (1)

- Transformation of two or more images into a common image plane

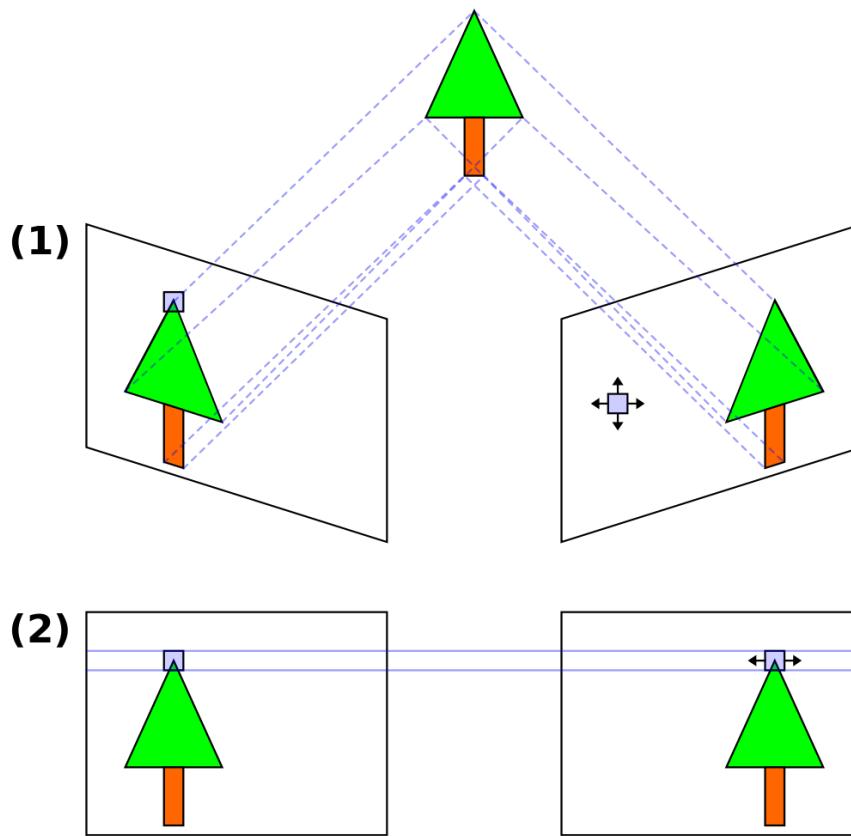
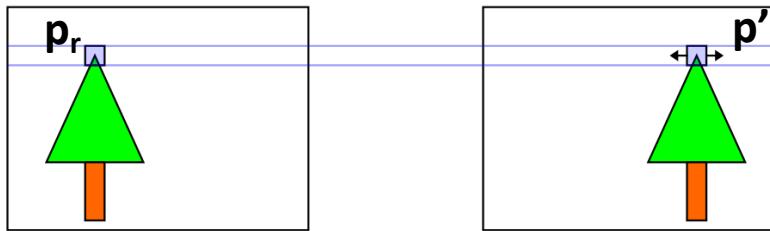


Image rectification (2)

- 3D reconstruction is a solution but ...
 - Applying 2D projective transforms, or homographies, to each image can also solve the problem (easier)
 - C. Loop and Z. Zhang, *Computing Rectifying Homographies for Stereo Vision*, Technical Report, Microsoft Research, 1998.
- Finding homographies to transform images so:
 - Epipolar lines map to horizontally aligned lines in the transformed images (parallel to X axis)
 - Epipoles are at infinity

Image rectification (3)



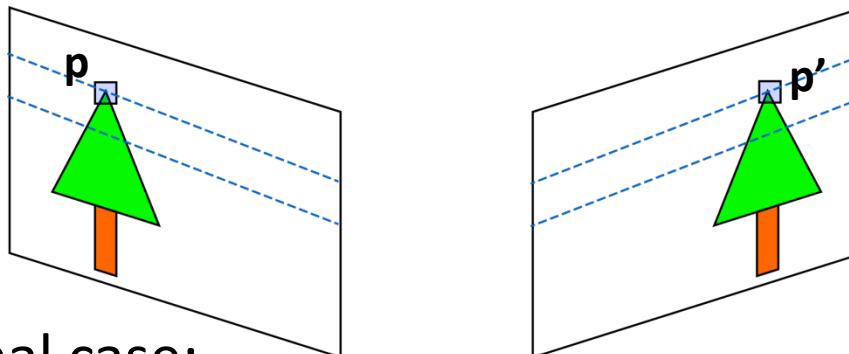
- In the rectified case:
 - Given a point p_r and its correspondence p'_r in the other image.
The epipolar constraint is defined as:

$$\tilde{p}'_r^T F_r \tilde{p}_r = 0$$

- And the fundamental matrix F_r is equal to:

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

Image rectification (4)



- In the normal case:
 - Given point \mathbf{p} and its correspondence \mathbf{p}' : $\tilde{\mathbf{p}}'^T F \tilde{\mathbf{p}} = 0$
 - Let \mathbf{H} and \mathbf{H}' be the homographies to be applied to both images and consider rectified image points \mathbf{p}_r and \mathbf{p}'_r , defined as:
 - It follows that: $\tilde{\mathbf{p}}_r = H\tilde{\mathbf{p}}$ $\tilde{\mathbf{p}}'_r = H'\tilde{\mathbf{p}}'$

$$\tilde{\mathbf{p}}_r'^T F_r \tilde{\mathbf{p}}_r = 0$$

$$\tilde{\mathbf{p}}'^T \underbrace{H'^T F_r H}_{F} \tilde{\mathbf{p}} = 0$$

Warping modes

- Different types of parametric warps include:



translation



rotation



scale



affine

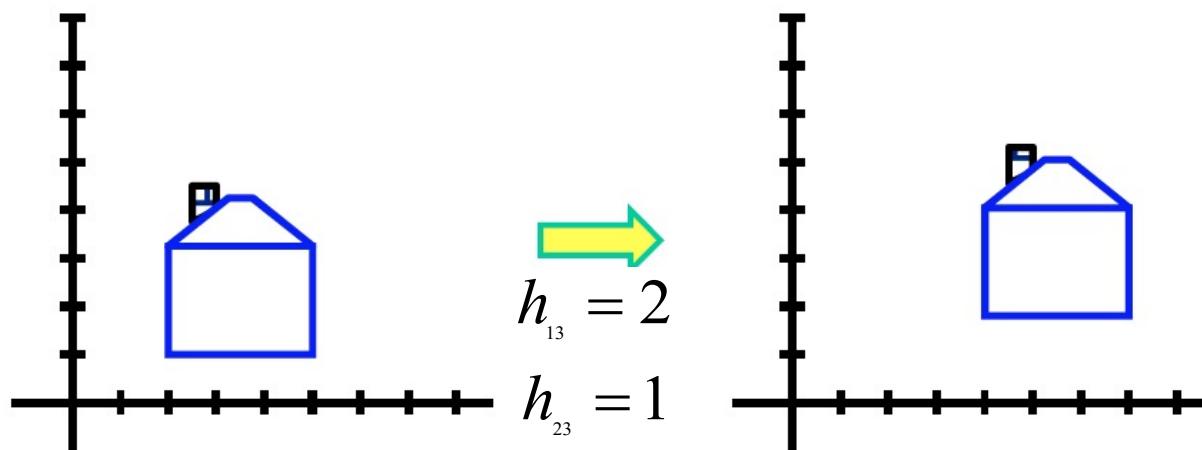


perspective

Source: R. Szeliski

Warping models: Translation

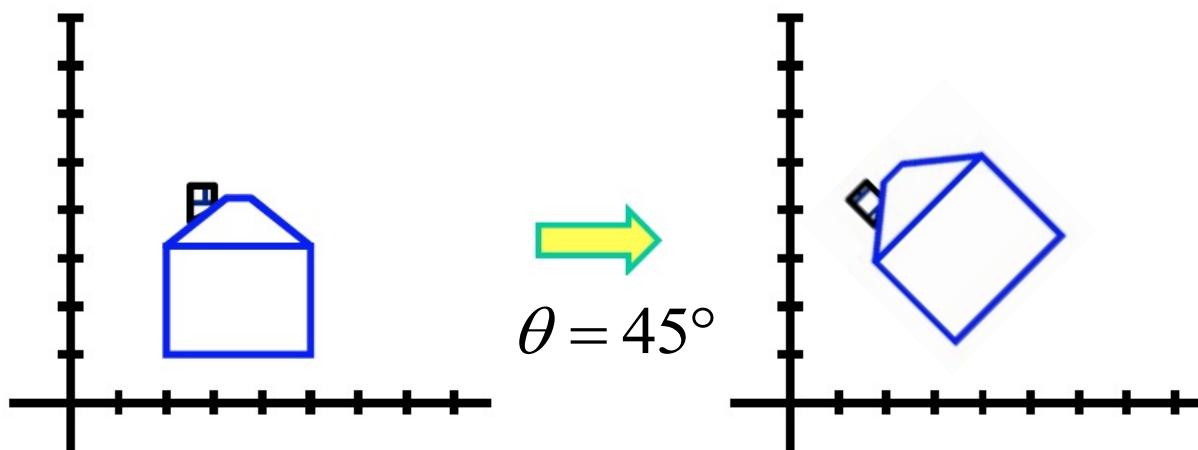
$$\begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & h_{13} \\ 0 & 1 & h_{23} \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$



Source: A. Efros

Warping models: Rotation

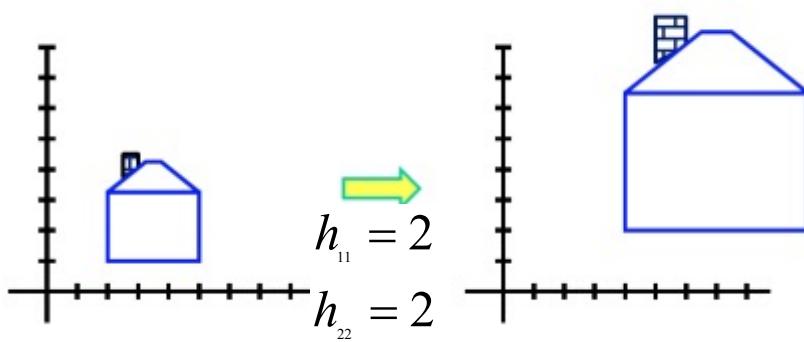
$$\begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & 0 \\ h_{21} & h_{22} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \begin{bmatrix} \cos(\theta) & -\sin(\theta) & 0 \\ \sin(\theta) & \cos(\theta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$



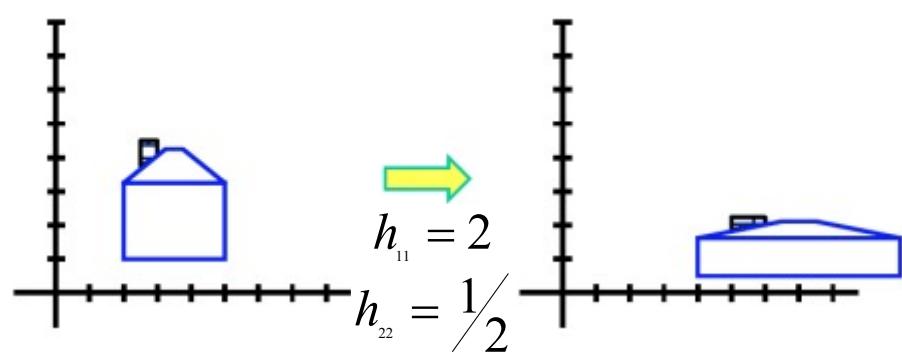
Source: A. Efros

Warping models: Scale

$$\begin{bmatrix} u' \\ v' \\ 1 \end{bmatrix} = \begin{bmatrix} h_{11} & 0 & 0 \\ 0 & h_{22} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$$



Uniform Scaling



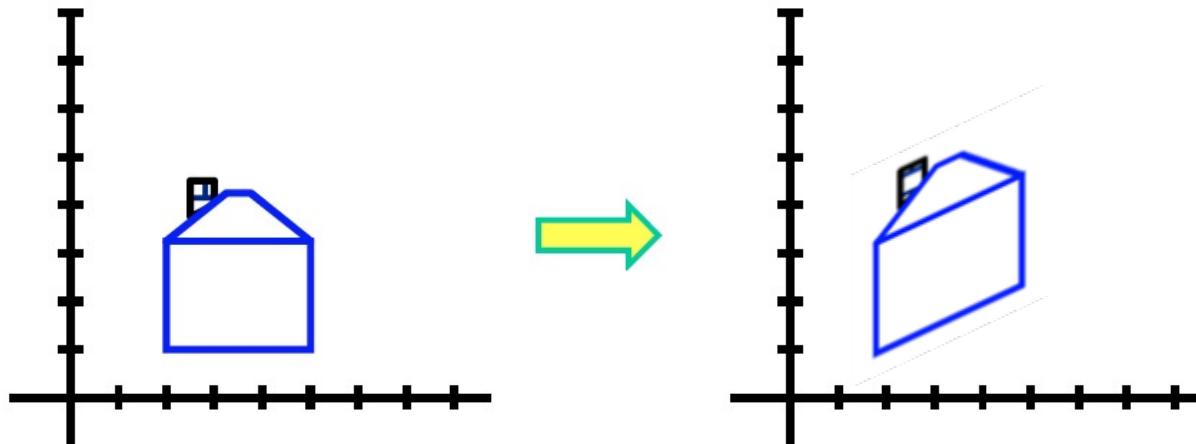
Non-uniform Scaling

Source: A. Efros

Warping models: Affine

- Combination of **rotation**, **scaling** and **translation**
- Parallel** lines remain **parallel**

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



Warping models: Perspective

- Combination of **affine** and **projective** warps
- Parallel** lines **do not** necessarily **remain parallel**

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

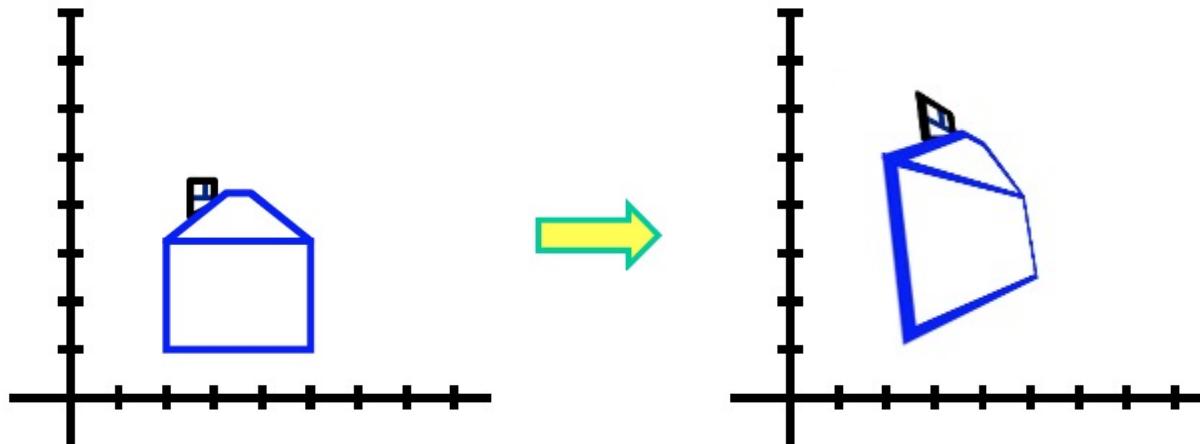


Image rectification (5) [REVIEW]

- Knowing \mathbf{F} we need to find \mathbf{H} and \mathbf{H}' so:

$$\mathbf{F} = \mathbf{H}'^T \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \mathbf{H}$$

- Multiple solutions:
 - Find \mathbf{H} and \mathbf{H}' with less distortion
 - Decompose homography \mathbf{H} (and similarly \mathbf{H}') into 3 different homographies:

$$\mathbf{H} = \mathbf{H}_s \mathbf{H}_a \mathbf{H}_p$$

Image rectification (6)

- H_p corresponds to a perspective transform

$$H_p = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ p_1 & p_2 & 1 \end{bmatrix}$$

- Map epipoles to points at infinity
- Epipolar lines become parallel
- Use a Distortion minimization criterion
 - Minimize the variation of the weights of points in the image

Image rectification (7)

Original (un-rectified images)

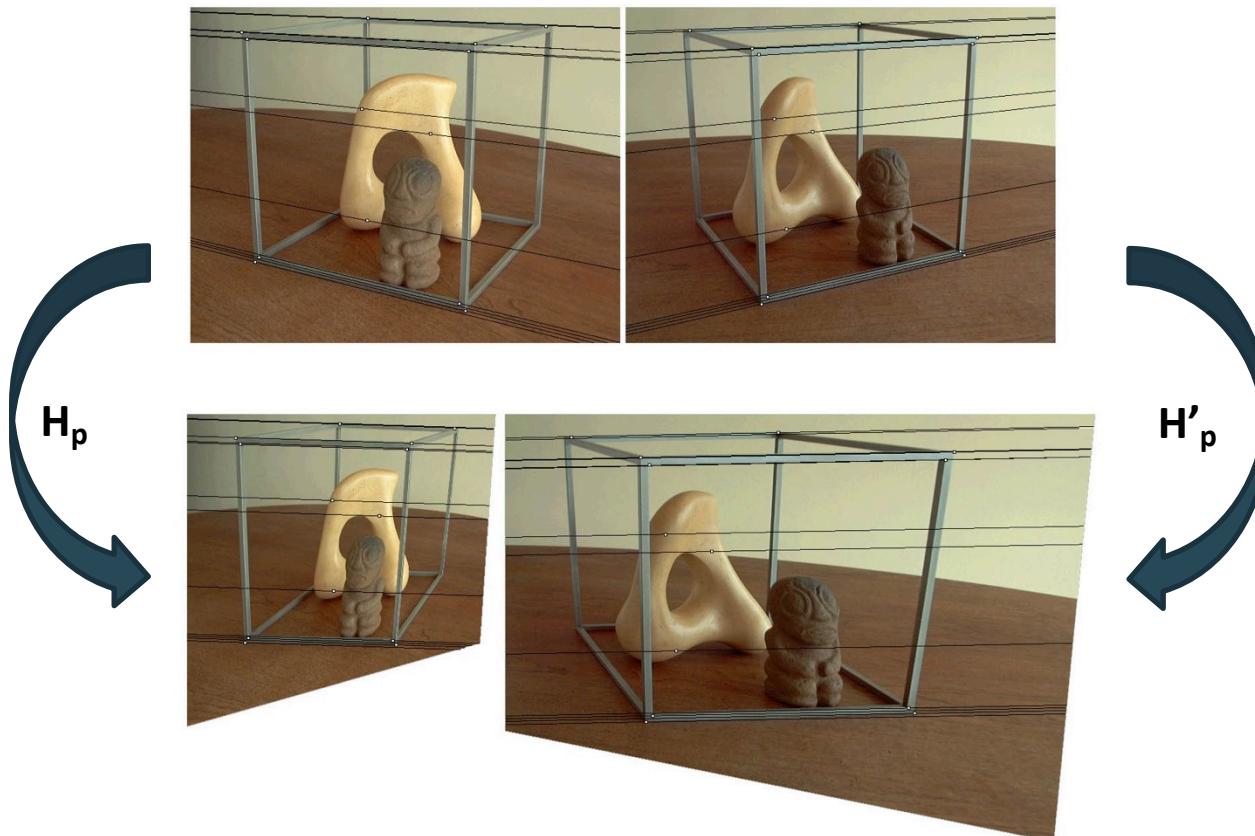


Image rectification (8)

- H_a corresponds to an affine transform
 - Rotate epipoles to be aligned in the X direction
 - Epipolar lines become rectified (parallel to X axes)

$$H_a = \begin{bmatrix} a_1 & a_2 & 0 \\ a_3 & a_4 & a_5 \\ 0 & 0 & 1 \end{bmatrix}$$

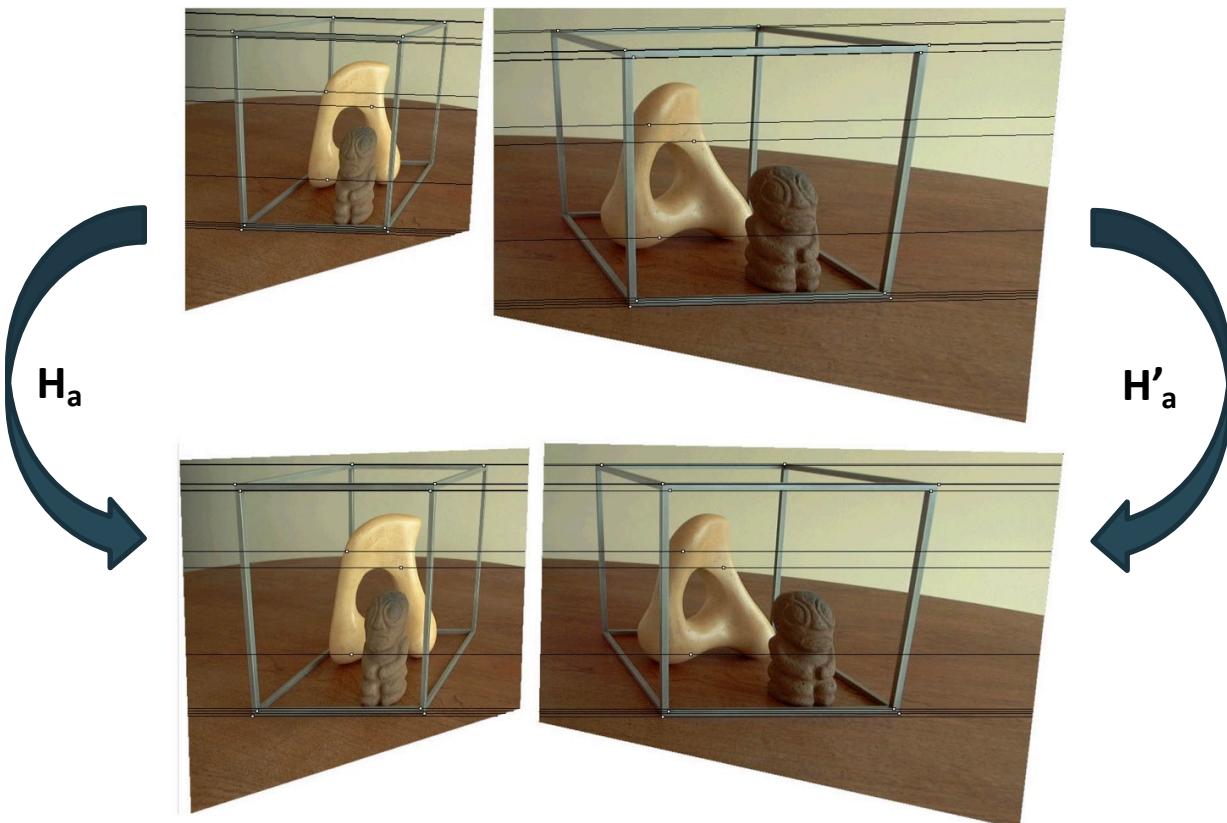
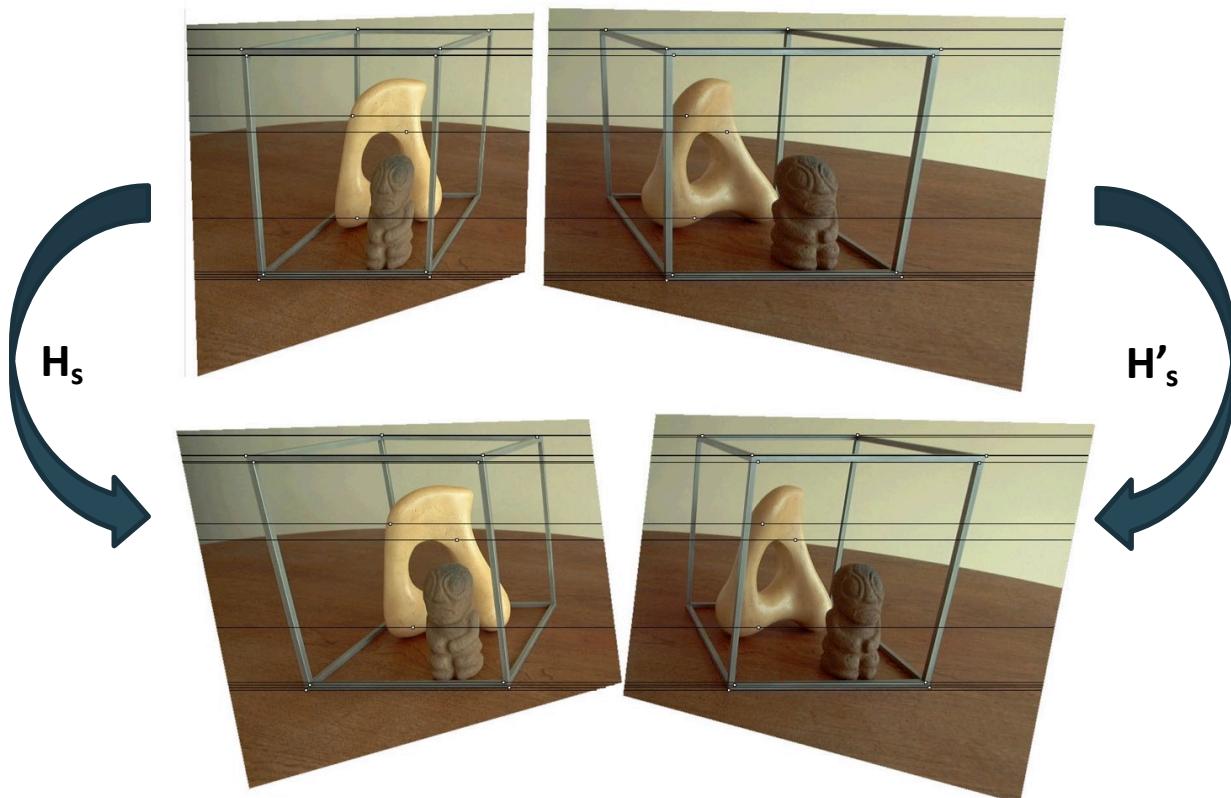


Image rectification (9)

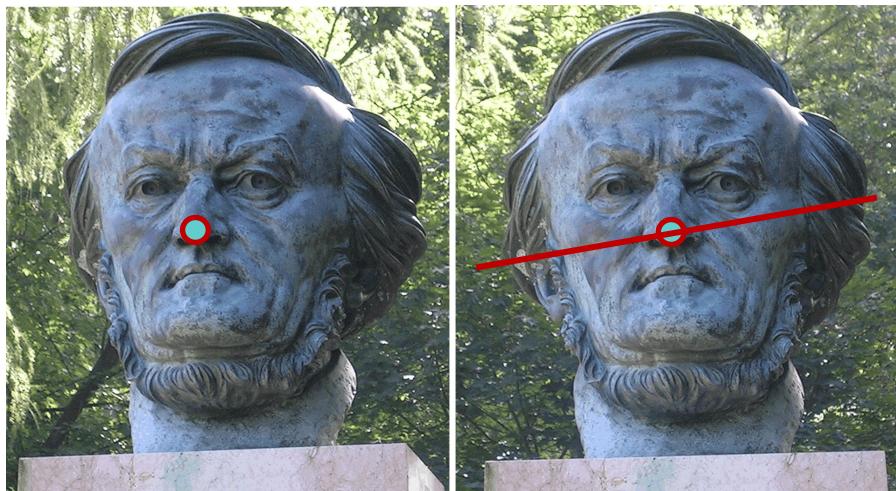
- H_s corresponds to a shearing transform
 - Reduce horizontal distortion (X coordinate)
 - No effect on rectification

$$H_s = \begin{bmatrix} s_1 & s_2 & s_3 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$



In this two lessons we have seen...

- Epipolar constraints
 - Essential and Fundamental matrices
- Estimating Fundamental matrix
 - 8 point algorithm
 - RANSAC
- Image rectification



References

- Epipolar geometry
 - R. Hartley and A. Zisserman, ***Multiple View Geometry in Computer Vision***, Cambridge University Press, June 2000. [[Chapter 9](#)]
 - G. Xu and Z. Zhang, ***Epipolar Geometry in Stereo Motion and Object Recognition***, Kluwer Academic Publishers, 1996. ISBN 0-7923-4199-6
 - R. I. Hartley, ***In Defence of the 8-point Algorithm***, IEEE transaction on pattern analysis and machine intelligence, Vol. 19, No. 6, June 1997
- Image rectification
 - C. Loop and Z. Zhang, ***Computing Rectifying Homographies for Stereo Vision***, Technical Report, Microsoft Research, 1998.