

3D Vision 2

Week 8

Two-view Geometry: Homography Estimation

Two-view Geometry: Epipolar Geometry

Announcements

- Assignment 2 due 11:59pm **today**
 - This includes a one week extension that has already been applied
 - **Zero** marks if either report or code submitted late (unless extension)
 - Submit early; you can always resubmit an updated version later
 - Depending on your internet connection and load on the TurnItIn servers, uploading can sometimes be slow, so please factor this into your submission schedule
 - Submit your report (PDF) and code (ZIP file) **separately under the correct tab** in the submission box
 - Follow the instructions under Submission Requirements

Weekly Study Plan: Overview

Wk	Starting	Lecture	Lab	Assessment
1	19 Feb	Introduction	X	
2	26 Feb	Low-level Vision 1	1	
3	4 Mar	Low-level Vision 2	1	
		Mid-level Vision 1		
4	11 Mar	Mid-level Vision 2	1	CLab1 report due Friday
		High-level Vision 1		
5	18 Mar	High-level Vision 2	2	
6	25 Mar	High-level Vision 3 ¹	2	
	1 Apr	Teaching break	X	
	8 Apr	Teaching break	X	
7	15 Apr	3D Vision 1	2	CLab2 report due Friday
8	22 Apr	3D Vision 2	3	
9	29 Apr	3D Vision 3	3	
10	6 May	3D Vision 4	3	
		Mid-level Vision 3		
11	13 May	High-level Vision 4	X	CLab3 report due Friday
12	20 May	Course Review	X	

Weekly Study Plan: Part B

Wk	Starting	Lecture	By
7	15 Apr	3D vision: introduction, camera model, single-view geometry	Dylan
8	22 Apr	3D vision: camera calibration, two-view geometry (homography)	Dylan
9	29 Apr	3D vision: two-view geometry (epipolar geometry, triangulation, stereo)	Dylan
10	6 May	3D vision: multiple-view geometry	Weijian
		Mid-level vision: optical flow, shape-from-X	Dylan
11	13 May	High-level vision: self-supervised learning, detection, segmentation	Dylan
12	20 May	Course review	Dylan

Outline

1. Two-view Geometry: Homographies
2. Two-view Geometry: Homography Estimation
3. Two-view Geometry: Epipolar Geometry

Summary: Camera Calibration

- **Estimate:** $\mathbf{P}, \mathbf{K}, \mathbf{R}, \mathbf{C}$
- **Given:** 2D–3D point correspondences $\{\mathbf{x}_i, \mathbf{X}_i\}$
- **Use:** Direct Linear Transformation (DLT) algorithm to get \mathbf{P}

- Assemble matrix \mathbf{A} , where

for each $(\mathbf{x}_i, \mathbf{X}_i)$ $\mathbf{A}_i = \begin{bmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \end{bmatrix}$

- Take SVD of \mathbf{A} , where $\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^T$; \mathbf{p} is the last column of \mathbf{V}
- Reshape vector \mathbf{p} into matrix \mathbf{P} $12 * 1 \rightarrow 3 * 4$

- **Decompose:** $\mathbf{P} \rightarrow \mathbf{C}$

- $\mathbf{P}\mathbf{C} = \mathbf{0} \Rightarrow \mathbf{C}$ is the right null space vector of \mathbf{P}
- Take SVD, where $\mathbf{P} = \mathbf{U}\Sigma\mathbf{V}^T$; \mathbf{C} is the last column of \mathbf{V}

- **Decompose:** $\mathbf{P} \rightarrow \mathbf{K}, \mathbf{R}$

- \mathbf{K} is upper triangular, \mathbf{R} is orthogonal
- Perform an RQ-decomposition of \mathbf{KR} where $\mathbf{P} = [\mathbf{KR}] - \mathbf{KRC}$

$\bullet \mathbf{P} = \mathbf{K}[\mathbf{R} \mid -\mathbf{RC}] = [\mathbf{M} \mid -\mathbf{MC}]$

1. RQ decomposition of \mathbf{M} :

- $(\mathbf{R}_\Delta, \mathbf{Q}) = \text{RQ}(\mathbf{M})$
- $\mathbf{K} = \mathbf{R}_\Delta$: upper triangular matrix (Δ is just to distinguish it from rotation)
- $\mathbf{R} = \mathbf{Q}$: orthonormal matrix

Homographies

Two-view Geometry

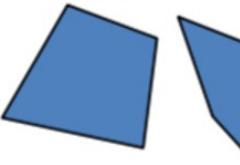
A Hierarchy of 2D Transformations

Homography

Projective
8 DoF

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

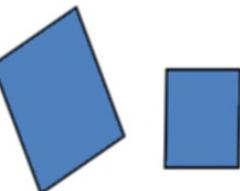
Transformed Square Invariants



- Concurrency, collinearity, order of contact (intersection, tangency, inflection, etc.), cross ratio

Affine
6 DoF

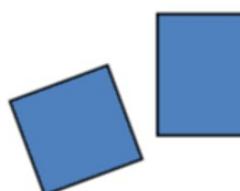
$$\begin{bmatrix} a_{11} & a_{12} & t_x \\ a_{21} & a_{22} & t_y \\ 0 & 0 & 1 \end{bmatrix}$$



- Parallelism, ratio of areas, ratio of lengths on parallel lines (e.g., midpoints), linear combinations of vectors (centroids), line at infinity I_∞

Similarity
4 DoF

$$\begin{bmatrix} sr_{11} & sr_{12} & t_x \\ sr_{21} & sr_{22} & t_y \\ 0 & 0 & 1 \end{bmatrix}$$



- Ratios of lengths, angles, circular points I, J

Euclidean
3 DoF

$$\begin{bmatrix} r_{11} & r_{12} & t_x \\ r_{21} & r_{22} & t_y \\ 0 & 0 & 1 \end{bmatrix}$$

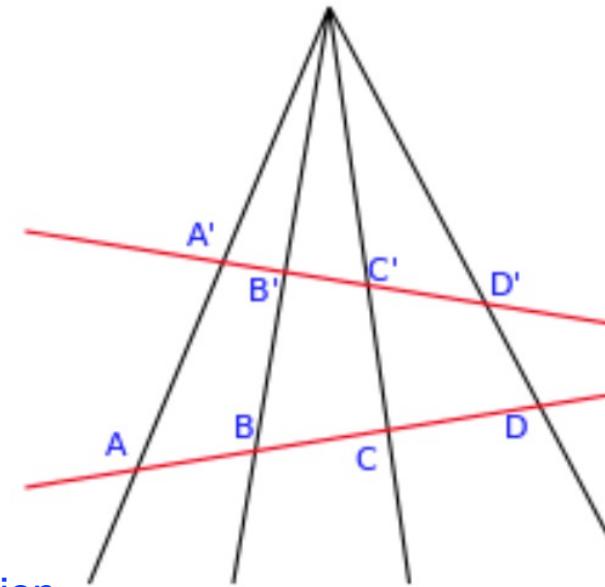


- Lengths, areas

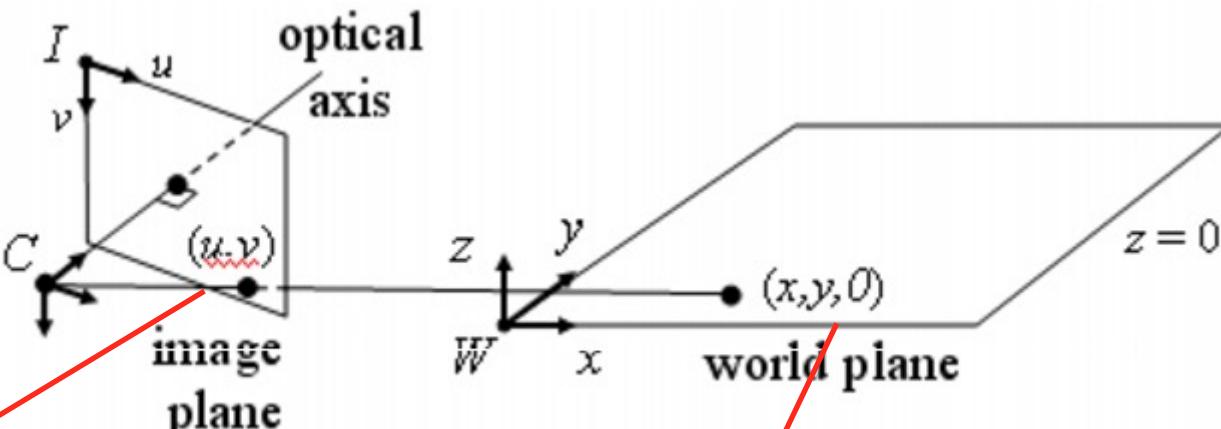
Projective Transformation (Homography)

$$\begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} A & t \\ v^T & b \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = H \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

- 8 DoF
- Preserves:
 - Cross ratio of 4 collinear points
$$(A, B; C, D) = \frac{AC \cdot BD}{BC \cdot AD}$$
 - Collinearity points lying on the same straight line after transformation
- Example:
 - Points A, B, C, D and A', B', C', D' are related by a projective transformation, so their cross ratios are equal $(A, B; C, D) = (A', B'; C', D')$



Homography Mapping from World Plane



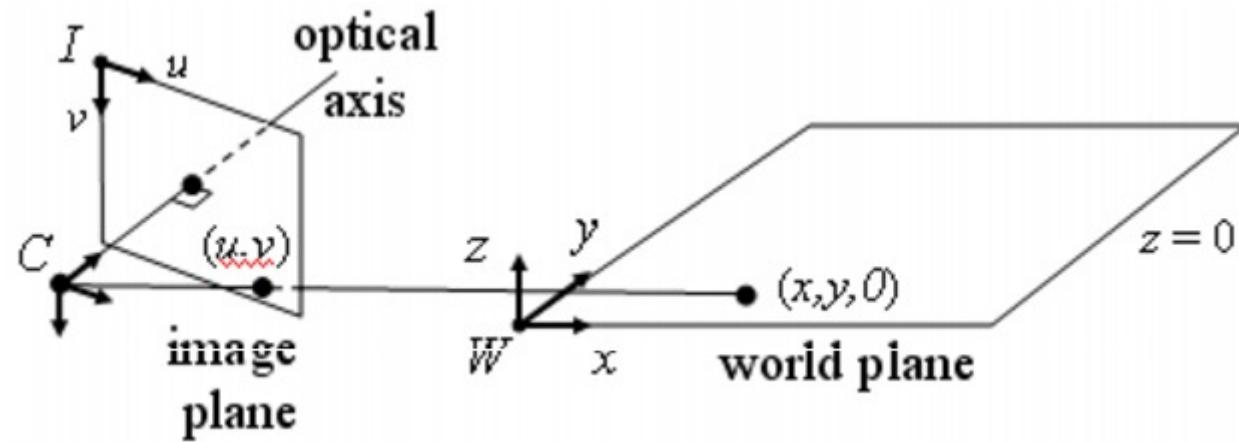
The diagram shows the projection of a point from the world plane to the image plane. A point $(x, y, 0)$ in the world plane is projected through the optical center C onto the image plane at (u, v) . The image plane has axes u and v , and the world plane has axes x , y , and z . The optical axis is shown as a dashed line.

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{K}_{\{3 \times 3\}} \text{ intrinsic}} \underbrace{\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix}}_{[\mathbf{R}_{\{3 \times 3\}} \quad \mathbf{t}_{\{3 \times 1\}}] \text{ extrinsic}} \begin{bmatrix} x \\ y \\ 0 \\ 1 \end{bmatrix}$$

Annotations:

- x_{img} points to u
- $3 * 3$ is above α, γ, u_0
- $3 * 4$ is above $\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3, \mathbf{t}$
- x_{world} points to x

Homography Mapping from World Plane



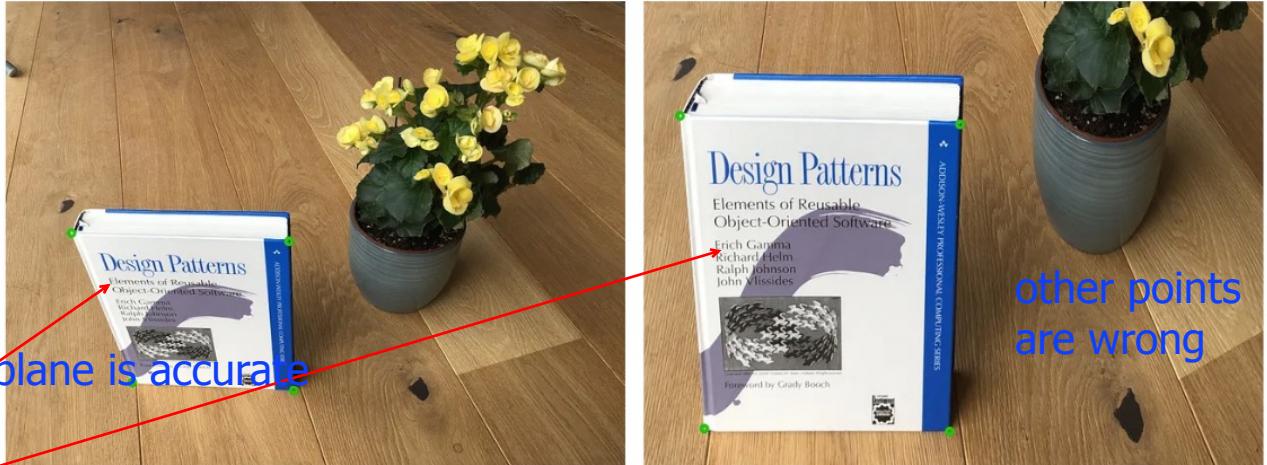
$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{K}_{\{3 \times 3\}}} \underbrace{\begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \boxed{\mathbf{r}_3} & \mathbf{t} \end{bmatrix}}_{[\mathbf{R}_{\{3 \times 3\}} \quad \mathbf{t}_{\{3 \times 1\}}]} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \boxed{\mathbf{K}[\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}]} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

$\mathbf{H}_{\{3 \times 3\}}$

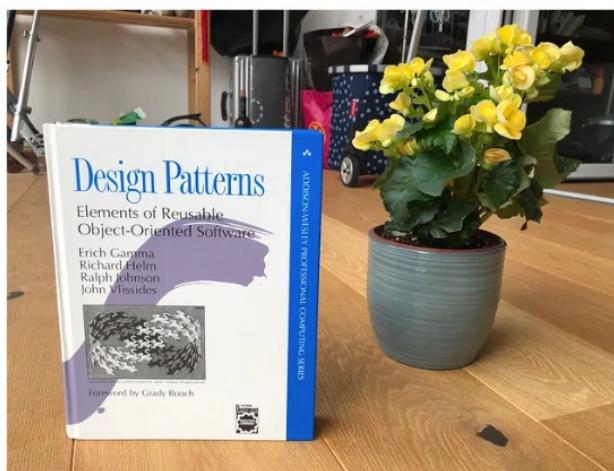
An Homography is a Planar Projectivity

- Given the homography matrix, one can transform an unfavourable view of a plane into a more desirable one

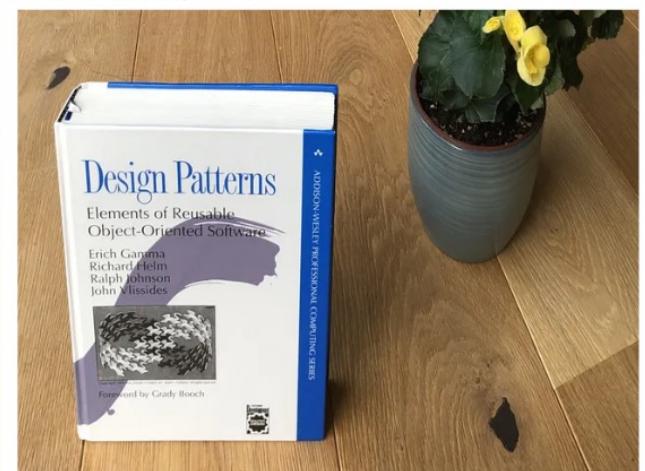
chosen plane is accurate



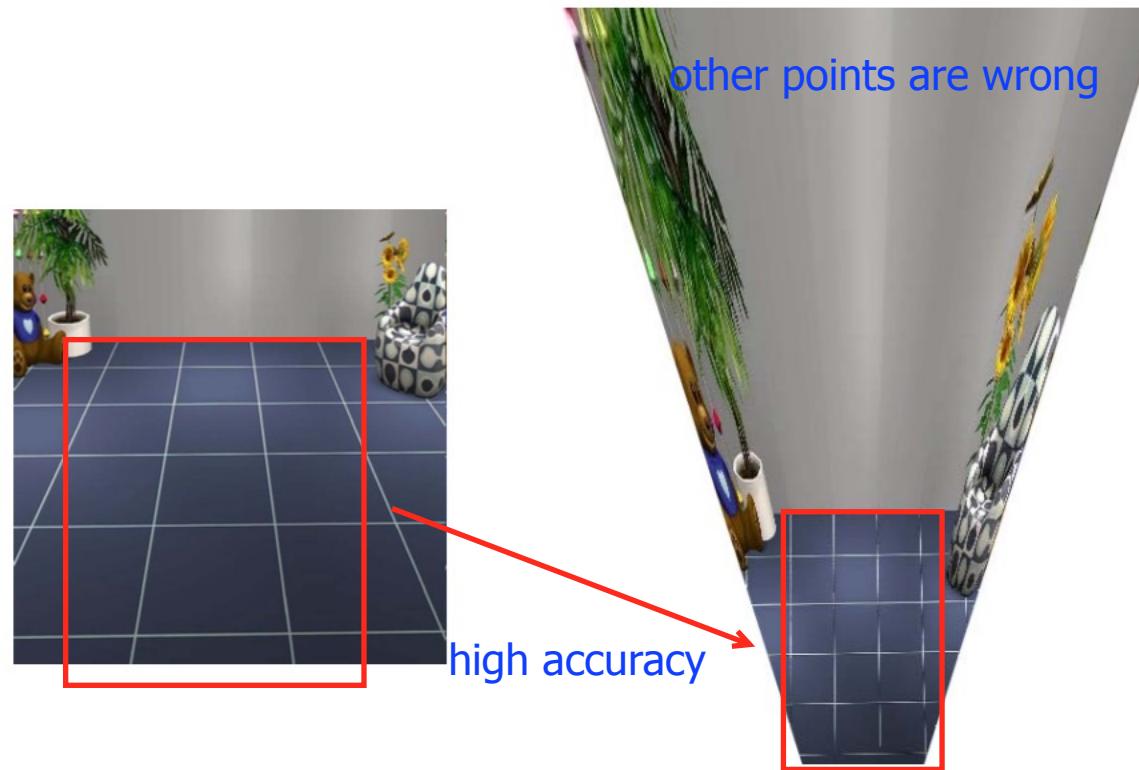
- While the chosen plane will be transformed with high accuracy, every other point in the image will suffer a wrong transformation



Left: Real view, Right: Artificially warped view

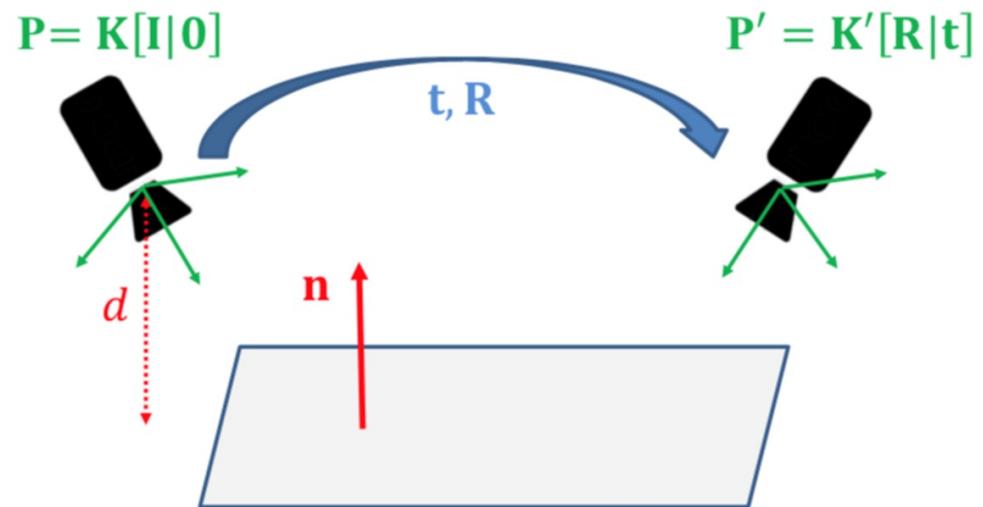


An Homography is a Planar Projectivity



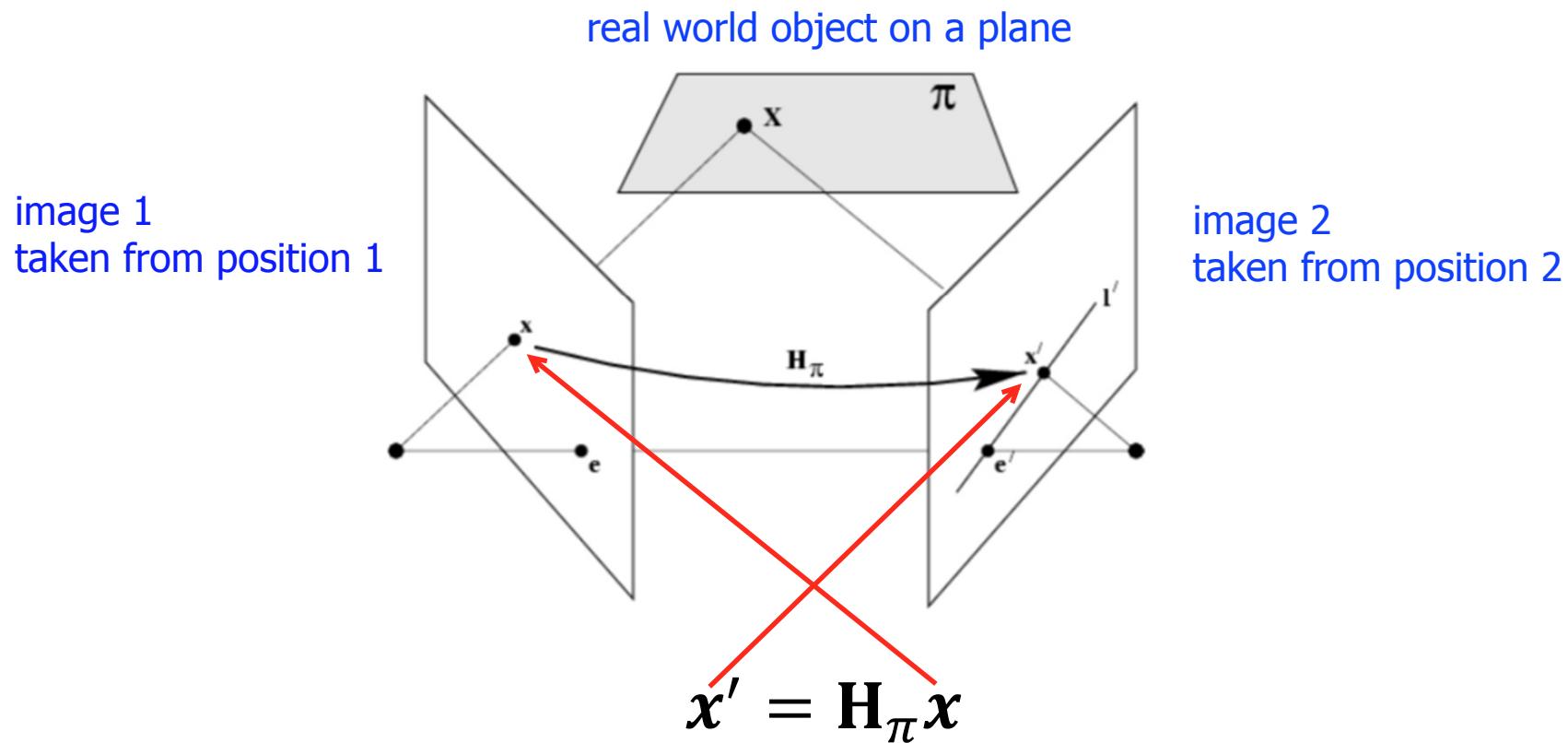
Planar Homography

- Transforms points to points
- Depends on:
 - Camera intrinsic parameters \mathbf{K}
 - Relative motion parameters \mathbf{R}, \mathbf{t}
 - 3D plane parameters (normal vector and depth) \mathbf{d}, \mathbf{n}



$$\mathbf{H} = \mathbf{K}' \left(\mathbf{R} - \frac{\mathbf{t}\mathbf{n}^\top}{d} \right) \mathbf{K}^{-1}$$

Geometric Derivation



Transformation of 2D Points and Lines

- Transforms points into points

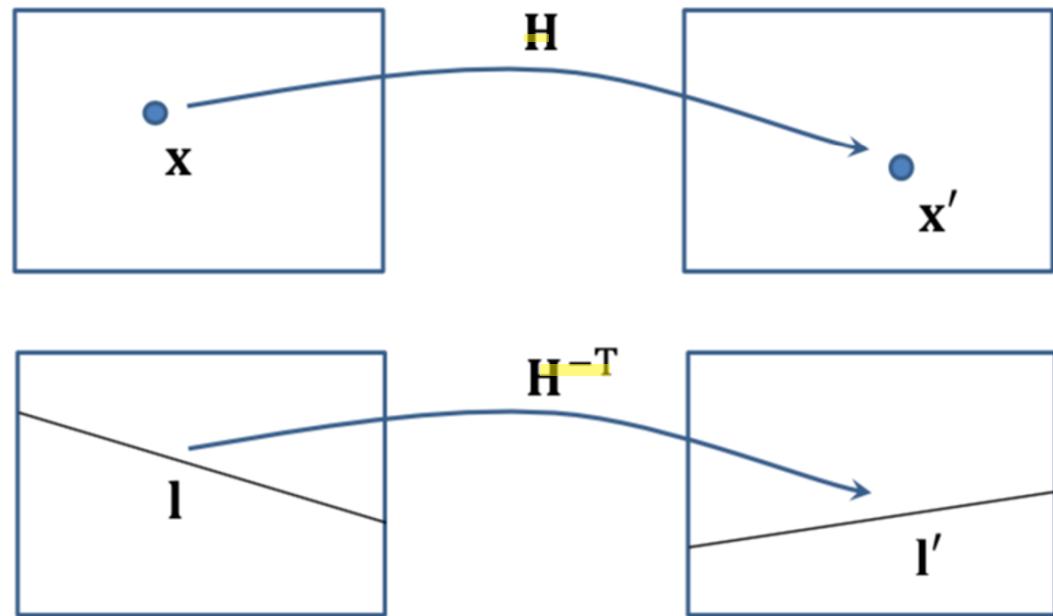
$$x' = \mathbf{H}x$$

- Also maps lines to lines

$$l' = \mathbf{H}^{-T}l$$

- Proof:

$$\begin{aligned} l^T x &= l^T (\mathbf{H}^{-1} \mathbf{H}) x \\ &= (\mathbf{H}^{-T} l)^T \mathbf{H} x \\ &= l'^T x' \\ &= 0 \end{aligned}$$



Homography Estimation

Two-view Geometry

Direct Linear Transformation (DLT) Algorithm for Homography Estimation

$$\mathbf{x}'_i = k\mathbf{H}\mathbf{x}_i \Rightarrow \mathbf{x}'_i \times \mathbf{H}\mathbf{x}_i = \mathbf{0} \quad (\mathbf{x}_i: \text{image 1 coord}; \mathbf{x}'_i: \text{image 2 coord})$$

$$[\mathbf{x}'_i]_{\times} \mathbf{H} \mathbf{x}_i = \begin{pmatrix} y'_i \mathbf{h}_3^T \mathbf{x}_i - w'_i \mathbf{h}_2^T \mathbf{x}_i \\ w'_i \mathbf{h}_1^T \mathbf{x}_i - x'_i \mathbf{h}_3^T \mathbf{x}_i \\ x'_i \mathbf{h}_2^T \mathbf{x}_i - y'_i \mathbf{h}_1^T \mathbf{x}_i \end{pmatrix} = \begin{bmatrix} \mathbf{0}^T & -w'_i \mathbf{x}_i^T & y'_i \mathbf{x}_i^T \\ w'_i \mathbf{x}_i^T & \mathbf{0}^T & -x'_i \mathbf{x}_i^T \\ -y'_i \mathbf{x}_i^T & x'_i \mathbf{x}_i^T & \mathbf{0}^T \end{bmatrix} \begin{pmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \mathbf{h}_3 \end{pmatrix} = \mathbf{A}'_i \mathbf{h} = \mathbf{0}$$

where $\mathbf{x}_i = (x_i, y_i, w_i)^T$ and $\mathbf{H} = \begin{bmatrix} \mathbf{h}_1^T \\ \mathbf{h}_2^T \\ \mathbf{h}_3^T \end{bmatrix}$; $\mathbf{h}_i \in \mathbb{R}^{3 \times 1}$

Direct Linear Transformation (DLT) Algorithm for Camera Calibration

- Cross-product trick:

- When an equation is only known up to scale, take the cross product of the LHS with both sides of the equation – no loss of information
same direction hence parallel
- $\mathbf{x}_i = k\mathbf{P}\mathbf{X}_i \Rightarrow \mathbf{x}_i \times \mathbf{P}\mathbf{X}_i = \mathbf{0}$ [Why?] (\mathbf{x}_i : image coords; \mathbf{X}_i : world coords)

$$[\mathbf{x}_i]_{\times} \mathbf{P} \mathbf{X}_i = \begin{pmatrix} y_i \mathbf{p}_3^T \mathbf{X}_i - w_i \mathbf{p}_2^T \mathbf{X}_i \\ w_i \mathbf{p}_1^T \mathbf{X}_i - x_i \mathbf{p}_3^T \mathbf{X}_i \\ x_i \mathbf{p}_2^T \mathbf{X}_i - y_i \mathbf{p}_1^T \mathbf{X}_i \end{pmatrix} = \begin{bmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & \mathbf{0}^T \end{bmatrix} \begin{pmatrix} \mathbf{p}_1 \\ \mathbf{p}_2 \\ \mathbf{p}_3 \end{pmatrix} = \mathbf{A}' \mathbf{p} = \mathbf{0}$$

where $\mathbf{x}_i^{\text{image}} = (x_i, y_i, w_i)^T$ and $\mathbf{P} = \begin{bmatrix} \mathbf{p}_1^T \\ \mathbf{p}_2^T \\ \mathbf{p}_3^T \end{bmatrix}$; $\mathbf{p}_i \in \mathbb{R}^{4 \times 1}$

Direct Linear Transformation (DLT) Algorithm for Homography Estimation

- Equations are linear in h
 - Only 2 out of 3 equations are linearly independent, so pick two

$$\begin{bmatrix} \mathbf{0}^\top & -w_i' \mathbf{x}_i^\top & y_i' \mathbf{x}_i^\top \\ w_i' \mathbf{x}_i^\top & \mathbf{0}^\top & -x_i' \mathbf{x}_i^\top \end{bmatrix} \begin{pmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \mathbf{h}_3 \end{pmatrix} = \mathbf{A}_i \mathbf{h} = \mathbf{0}$$

- Holds for any homogeneous representation, e.g., $(x'_i, y'_i, 1)$
 - Homography matrix has 8 DoF:
 - 9 parameters defined up to scale
 - Linear solution requires at least 4 points (two DoF per point)

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \propto \underbrace{\begin{bmatrix} \alpha & \gamma & u_0 \\ 0 & \beta & v_0 \\ 0 & 0 & 1 \end{bmatrix}}_K \underbrace{\begin{bmatrix} r_1 & r_2 & r_3 & t \end{bmatrix}}_{\begin{bmatrix} R_{[3 \times 3]} & t_{[3 \times 1]} \end{bmatrix}} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \underbrace{\mathbf{K} \begin{bmatrix} r_1 & r_2 & t \end{bmatrix}}_{\mathbf{H}_{[3 \times 3]}} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

Direct Linear Transformation (DLT) Algorithm for Homography Estimation

- Using 4 points to solve for \mathbf{H} :

$$\mathbf{A}\mathbf{h} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \mathbf{A}_3 \\ \mathbf{A}_4 \end{bmatrix} \mathbf{h} = \mathbf{0}$$

(2 * 4) * 9

- $\mathbf{A} \in \mathbb{R}^{8 \times 9}$ but $\text{rank}(\mathbf{A}) = 8$
- How to solve?
 - The trivial solution $\mathbf{h} = \mathbf{0}$ is not interesting
 - Compute the 1D null-space (e.g., via SVD)
 - Fix norm of \mathbf{h} afterwards (e.g., set $\|\mathbf{h}\| = 1$)

Direct Linear Transformation (DLT) Algorithm for Homography Estimation

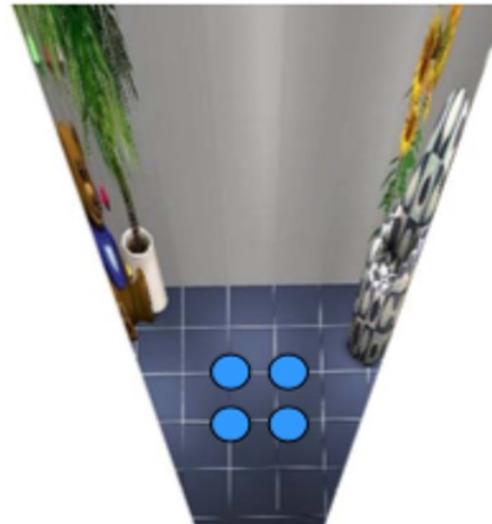
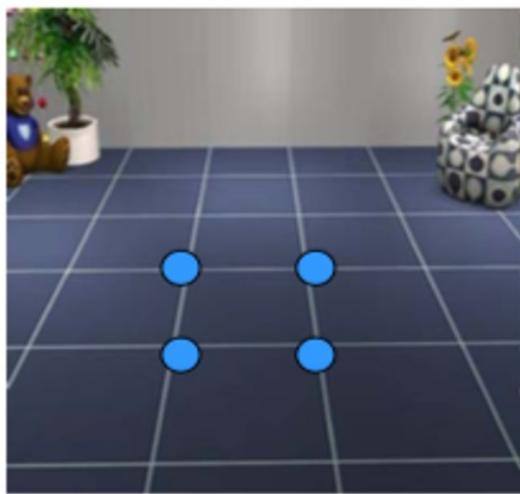
$n \geq 4$

- Using n points to solve for \mathbf{H} : the over-determined case

$$\mathbf{A}\mathbf{h} = \begin{bmatrix} \mathbf{A}_1 \\ \mathbf{A}_2 \\ \vdots \\ \mathbf{A}_n \end{bmatrix} \mathbf{h} = \mathbf{0}$$

- How to solve?
 - No exact non-trivial solution due to inexact measurements (e.g., noise)
 - $\mathbf{A}\mathbf{h} = \mathbf{0}$ is not possible, so minimise $\|\mathbf{A}\mathbf{h}\|$ subject to $\|\mathbf{h}\| = 1$
 - 1. Take the singular value decomposition (SVD) of $\mathbf{A} = \mathbf{U}\Sigma\mathbf{V}^\top$
 - 2. Take the rightmost column of \mathbf{V}
 - The right-singular vector of \mathbf{A} , corresponding to the smallest singular value (arranged in decreasing singular value order)

Computing \mathbf{H}_p



- At least 4 point correspondences needed (8 DoF)

Direct Linear Transformation (DLT) Algorithm for Homography Estimation

- Objective:
 - Given $n \geq 4$ 2D–2D point correspondences $\{\mathbf{x}_i \leftrightarrow \mathbf{x}'_i\}$, determine the 3×3 homography matrix \mathbf{H} such that $\mathbf{x}'_i \approx \mathbf{H}\mathbf{x}_i$
- Algorithm:
 1. For each correspondence $\{\mathbf{x}_i \leftrightarrow \mathbf{x}'_i\}$ compute \mathbf{A}_i , taking only the first 2 rows
 2. Assemble the n 2×9 \mathbf{A}_i matrices into a single $2n \times 9$ matrix \mathbf{A}
 3. Compute the SVD of \mathbf{A} : $\mathbf{U}\Sigma\mathbf{V}^T$
 4. Take the last column of \mathbf{V} as the solution for \mathbf{h}
 5. Rearrange \mathbf{h} to obtain \mathbf{H} $9*1 \rightarrow 3*3$

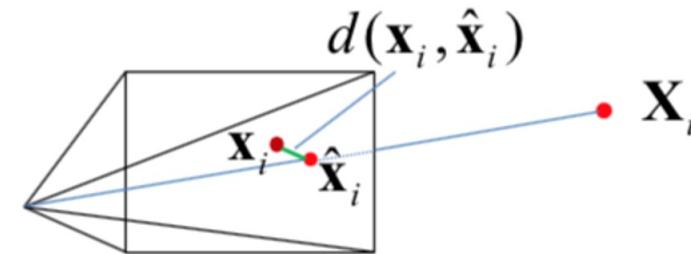
Normalised Direct Linear Transformation (DLT) Algorithm for Homography Estimation

- Objective:
 - Given $n \geq 4$ 2D–2D point correspondences $\{\mathbf{x}_i \leftrightarrow \mathbf{x}'_i\}$, determine the 3×3 homography matrix \mathbf{H} such that $\mathbf{x}'_i \approx \mathbf{H}\mathbf{x}_i$
- Algorithm:
 1. Normalise 2D points: $\tilde{\mathbf{x}}_i = \mathbf{T}\mathbf{x}_i$, $\tilde{\mathbf{x}}'_i = \mathbf{T}'\mathbf{x}'_i$
 2. Apply the DLT algorithm to $\{\tilde{\mathbf{x}}_i \leftrightarrow \tilde{\mathbf{x}}'_i\}$
 3. Denormalise the recovered solution $\tilde{\mathbf{H}}$ using $\mathbf{H} = \mathbf{T}'^{-1}\tilde{\mathbf{H}}\mathbf{T}$
- Example normalisation matrices:

$$\mathbf{T} = \begin{bmatrix} w+h & 0 & w/2 \\ 0 & w+h & h/2 \\ 0 & 0 & 1 \end{bmatrix}^{-1}; \quad \mathbf{T}' = \begin{bmatrix} w'+h' & 0 & w'/2 \\ 0 & w'+h' & h'/2 \\ 0 & 0 & 1 \end{bmatrix}^{-1}$$

Geometric Solvers for Homography Estimation

- So far, minimisation of an **algebraic error** criterion
 - Advantage: **linear solutions**
 - Disadvantage: **no explicit geometric meaning**
- Refinement:
 - Nonlinear minimisation of a **geometric error**
 - (Same as for calibration)



Geometric Solvers for Homography Estimation

- Notation:

- \mathbf{x} measured coordinates
- $\hat{\mathbf{x}}$ estimated coordinates
- $d(\cdot, \cdot)$ Euclidean distance in image

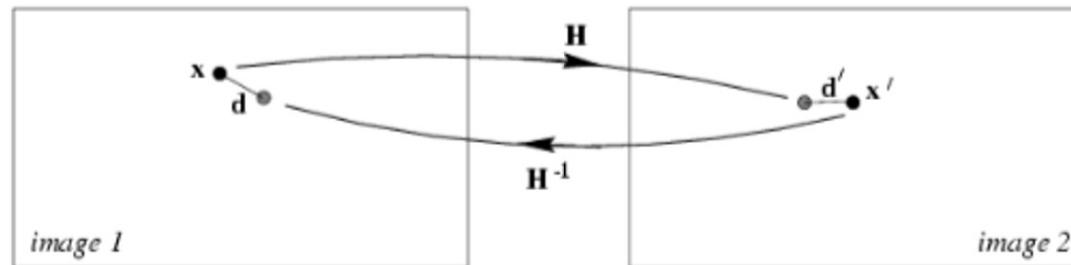
- Single-image error: $\hat{\mathbf{H}} = \operatorname{argmin}_{\mathbf{H}} \sum_i d(\mathbf{x}'_i, \mathbf{H}\mathbf{x}_i)^2$
sum of errors from transformations in both ways
- Symmetric transfer error: $\hat{\mathbf{H}} = \operatorname{argmin}_{\mathbf{H}} \sum_i d(\mathbf{x}_i, \mathbf{H}^{-1}\mathbf{x}'_i)^2 + d(\mathbf{x}'_i, \mathbf{H}\mathbf{x}_i)^2$
- Reprojection error:

$$(\hat{\mathbf{H}}, \hat{\mathbf{x}}_i, \hat{\mathbf{x}}'_i) = \operatorname{argmin}_{\mathbf{H}, \hat{\mathbf{x}}_i, \hat{\mathbf{x}}'_i} \sum_i d(\mathbf{x}_i, \hat{\mathbf{x}}_i)^2 + d(\mathbf{x}'_i, \hat{\mathbf{x}}'_i)^2$$

subject to $\hat{\mathbf{x}}'_i = \hat{\mathbf{H}}\hat{\mathbf{x}}_i$

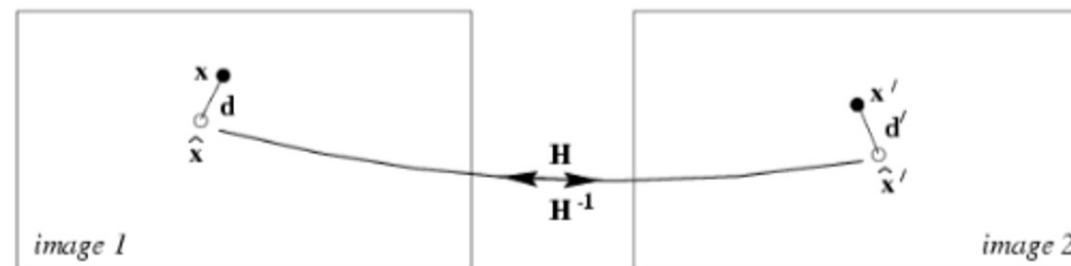
Geometric Solvers for Homography Estimation

symmetric
transfer error



$$d(\mathbf{x}, \mathbf{H}^{-1}\mathbf{x}')^2 + d(\mathbf{x}', \mathbf{H}\mathbf{x})^2$$

reprojection
error



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

Iterative Refinement

Required to minimise geometric error:

- (i) Often slower than DLT
- (ii) Requires initialisation
- (iii) No guaranteed convergence, local minima
- (iv) Stopping criterion required

Initialisation

- Typically, use linear solution e.g. DLT
- If have outliers, use robust algorithm (e.g., M-estimator, or RANSAC)

Robust M-estimators

- General approach: find model parameters θ that minimise

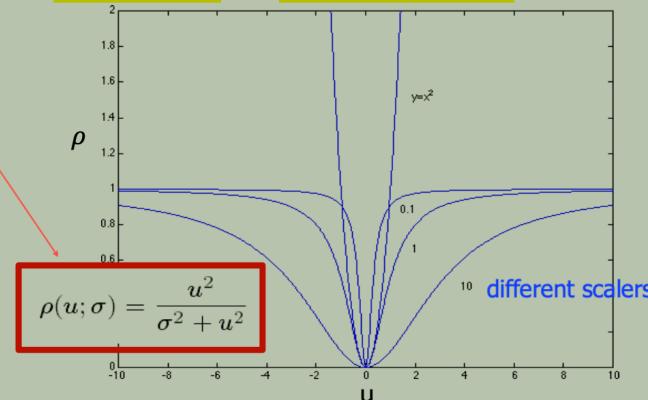
$$\sum_i \rho(r_i(x_i, \theta); \sigma)$$

where:

- r_i is the residual/loss of the i th point w.r.t. model parameters θ
- ρ is a robust function with scale parameter σ

outliers contribute large residuals, where robust m-estimators can moderate its influence

- Robust function behaves like squared distance for small values of the residual but saturates for larger values



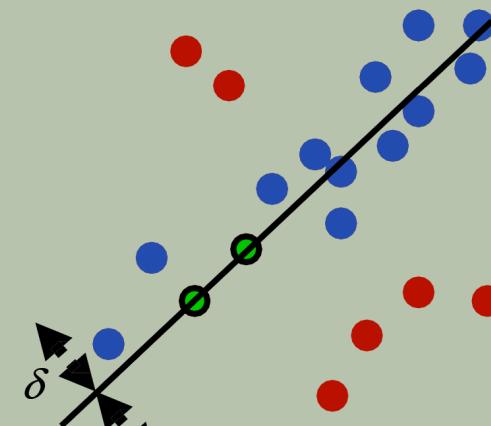
RANSAC

$$N_I = 14$$

Algorithm:

1. Sample (randomly) the minimum number of points required to fit the model ($n=2$)
2. Solve for model parameters
3. Score by the fraction of inliers within a preset threshold

Repeat 1–3 until the best model is found



Iterative Methods

Many iterative algorithms exist

- Newton's method
- Levenberg-Marquardt
- Powell's method
- Simplex method

“Gold Standard” Algorithm for Homography Estimation

- Objective:
 - Given $n \geq 4$ 2D–2D point correspondences $\{\mathbf{x}_i \leftrightarrow \mathbf{x}'_i\}$, determine the 3×3 homography matrix \mathbf{H} such that $\mathbf{x}'_i \approx \mathbf{H}\mathbf{x}_i$
- Algorithm:
 1. Initialisation: compute an initial estimate using normalised DLT or RANSAC
 2. Geometric minimisation of reprojection error:
 1. Minimise using Levenberg–Marquardt over the 9 entries of \mathbf{H}
 2. Compute initial estimate for optimal $\{\mathbf{x}_i\}$
 3. Minimise cost $\sum d(\mathbf{x}_i, \hat{\mathbf{x}}_i)^2 + d(\mathbf{x}'_i, \hat{\mathbf{x}}'_i)^2$ over $\{\mathbf{H}, \mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$
 3. Denormalise the recovered solution

“Gold Standard” Algorithm for Homography Estimation

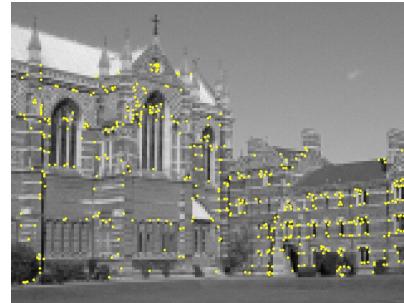
Objective

Compute homography between two images

Algorithm

- (i) Interest points:** Compute interest points in each image
- (ii) Putative correspondences:** Compute a set of interest point matches based on some similarity measure
- (iii) RANSAC robust estimation:** Repeat for n samples
 - (a) Select 4 correspondences and compute \mathbf{H} with DLT
 - (b) Calculate the distance d_{\perp} for each putative match for each chosen correspondence
 - (c) Compute the number of inliers consistent with \mathbf{H} ($d_{\perp} < t$) where d_{\perp} is lower than a threshold t
 - (d) Choose \mathbf{H} with most inliers initialised from the last step
- (iv) Optimal estimation:** re-estimate \mathbf{H} from all inliers by minimising geometric cost function with the Levenberg-Marquardt algorithm
- (v) Guided matching:** Determine more matches using prediction with computed \mathbf{H}
Optionally iterate last two steps until convergence

Example: Robust Computation

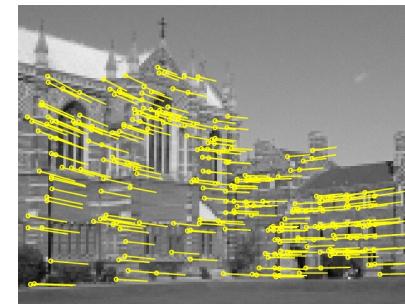
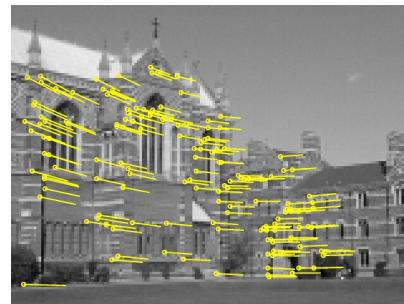


Interest points
(500/image)



Left: Putative
correspondences (268)

Right: Outliers (117)

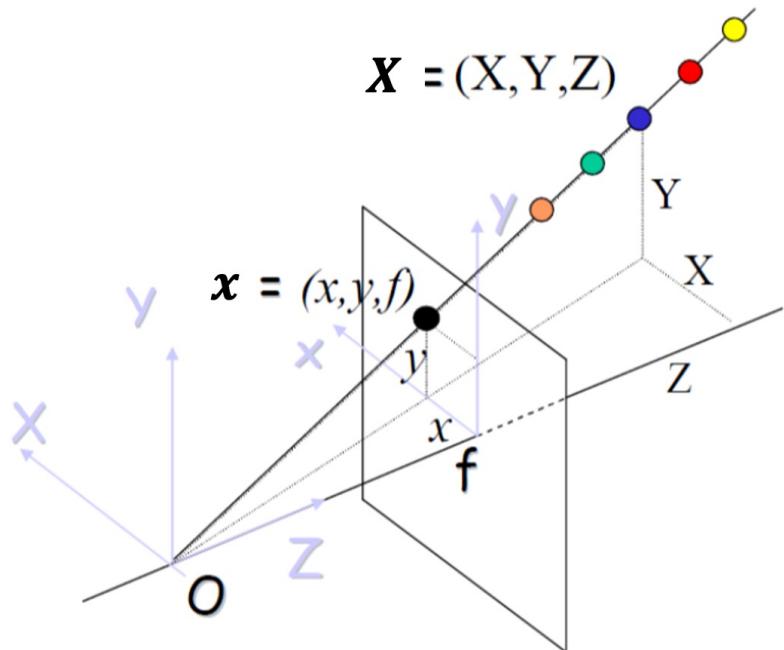


Left: Inliers (151) after
RANSAC with DLT
Right: Final inliers (262)
after Levenberg-Marquardt and
guided matching

Epipolar Geometry

Two-view Geometry

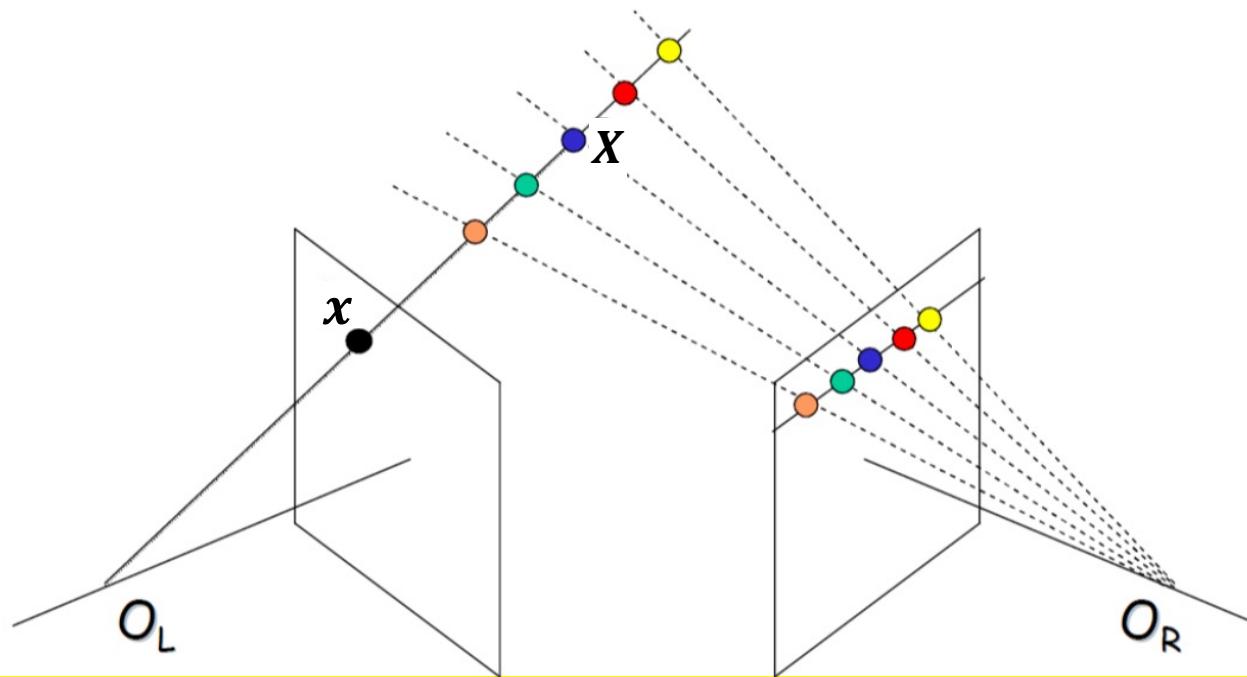
Why Two Views?



- A fundamental *ambiguity*: any point on the ray OX has projection point x on the image plane
 - Note that here the camera center is $(0,0,0)$ in the world coordinate system

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

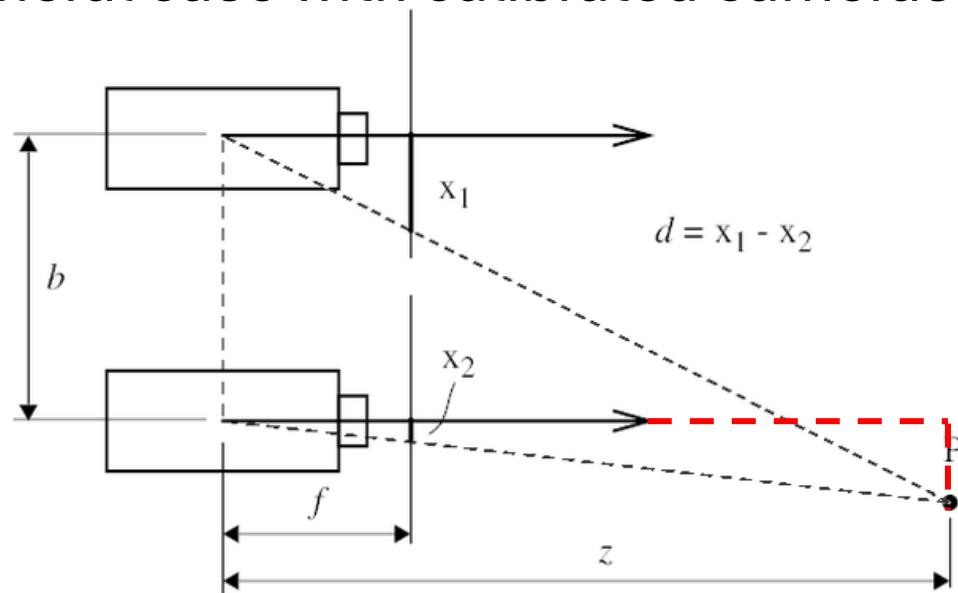
Why Two Views?



- A second camera can resolve the ambiguity, enabling measurement of depth via triangulation

General Two-view Geometry

- Human stereopsis
- Stereograms
- Epipolar geometry and the epipolar constraint
 - Parallel optical axes
 - General case with calibrated cameras



For similar triangles,

$$\frac{d}{b} = \frac{f}{z}$$

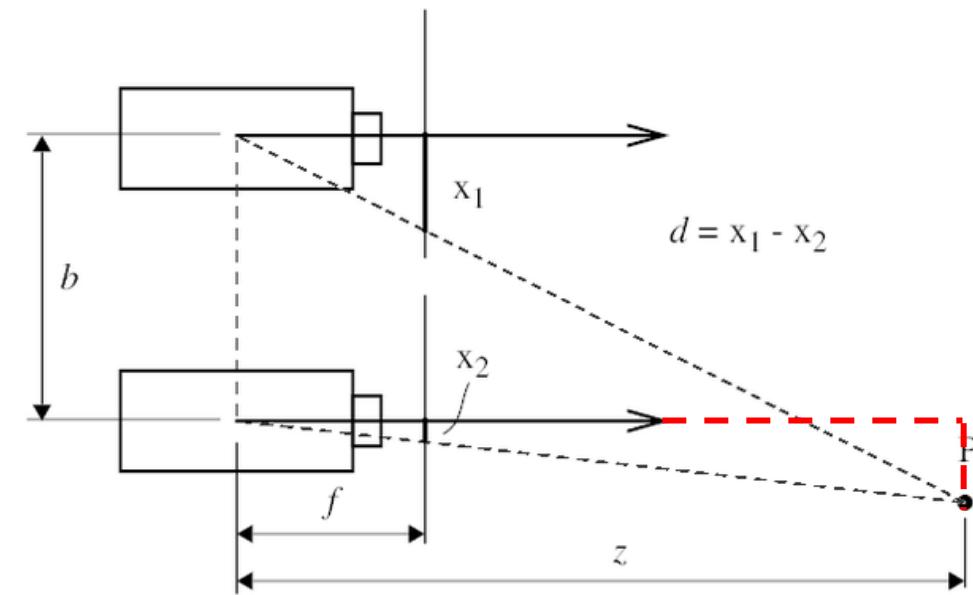
Parallel Optical Axes

- Depth from disparity d

$$1. \frac{z-f}{z} = \frac{b-x_1+x_2}{b} \text{ [similar } \triangle s\text{]}$$

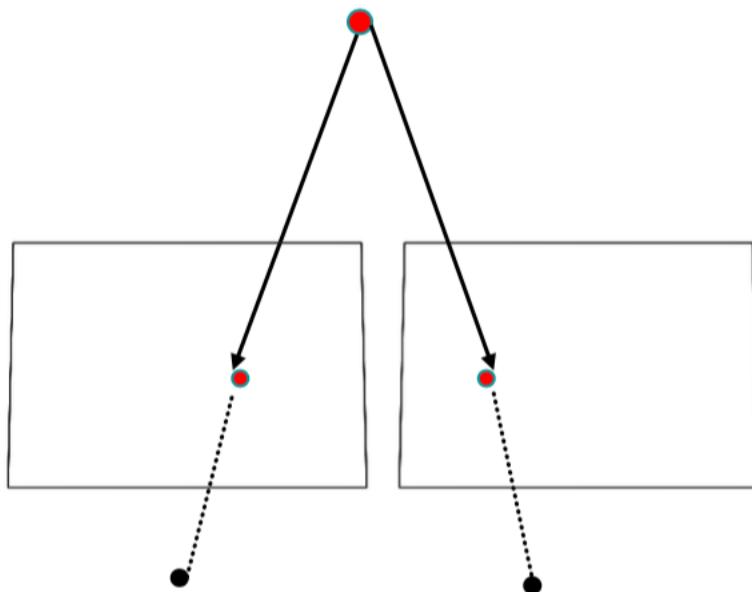
$$2. 1 - \frac{f}{z} = 1 - \frac{d}{b}$$

$$3. z = \frac{bf}{d} \text{ [depth of 3D point]}$$



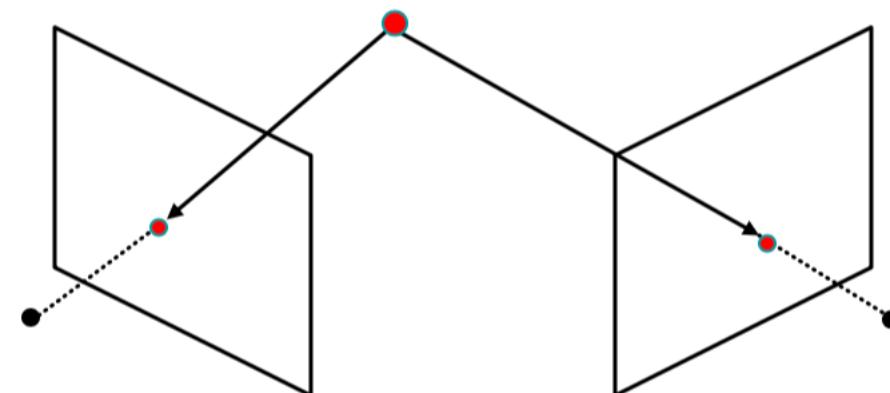
General Case with Calibrated Cameras

- The two cameras need not have parallel optical axes



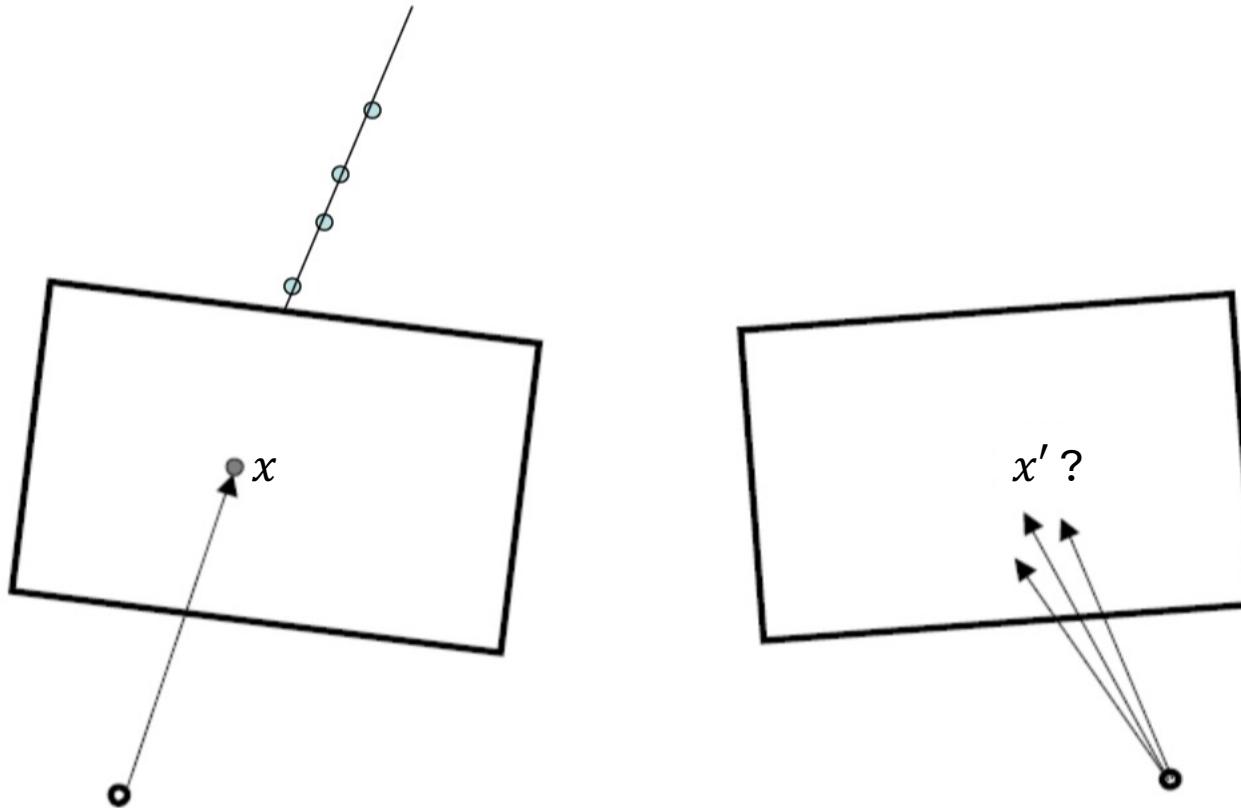
Parallel

Vs.



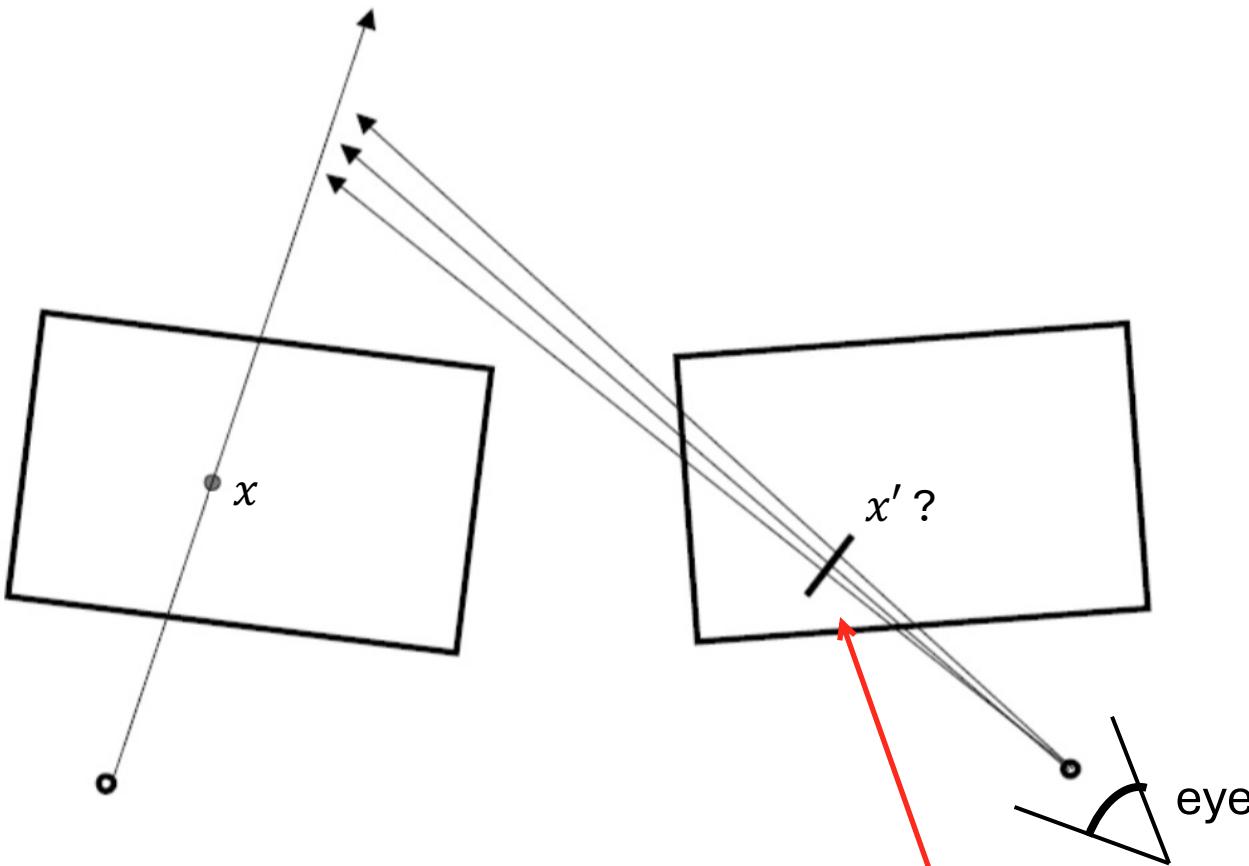
Non-parallel

Stereo Correspondence Constraints



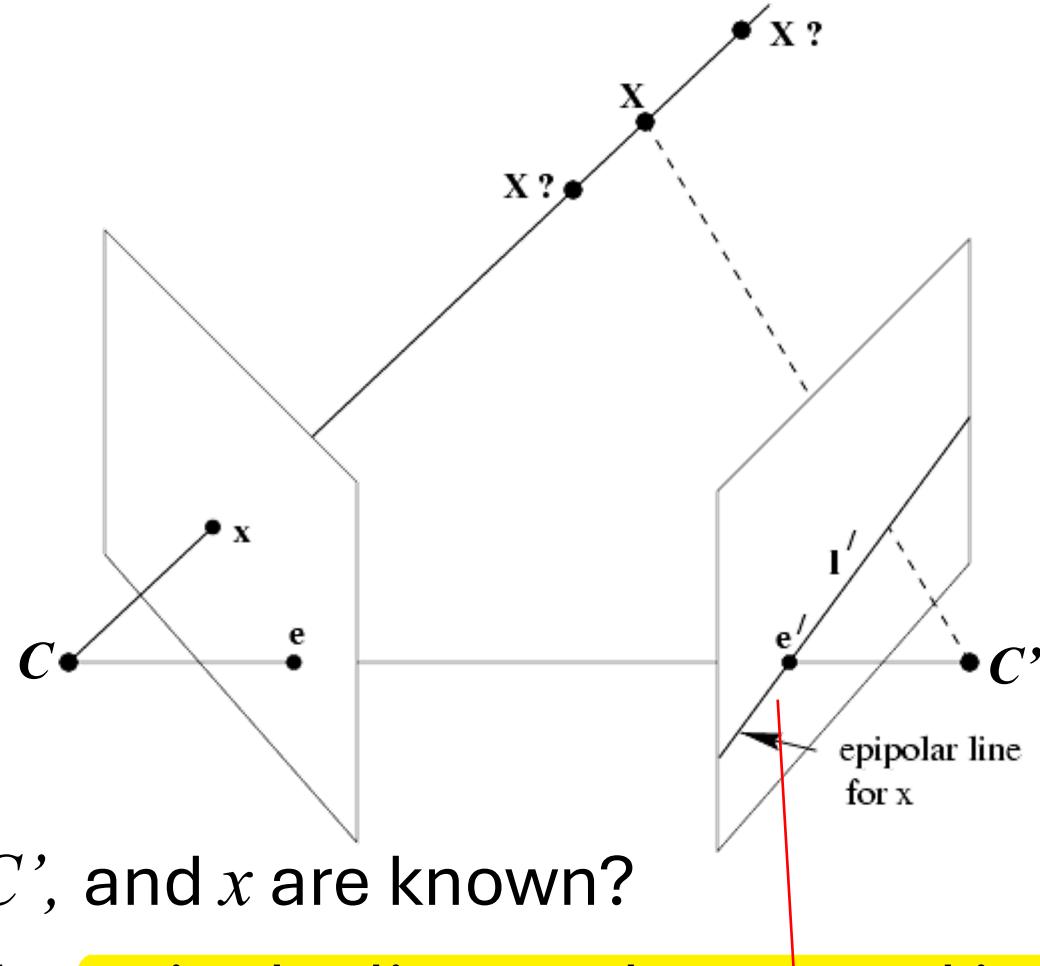
- Given x in the left image, where can the corresponding point x' be?

Stereo Correspondence Constraints



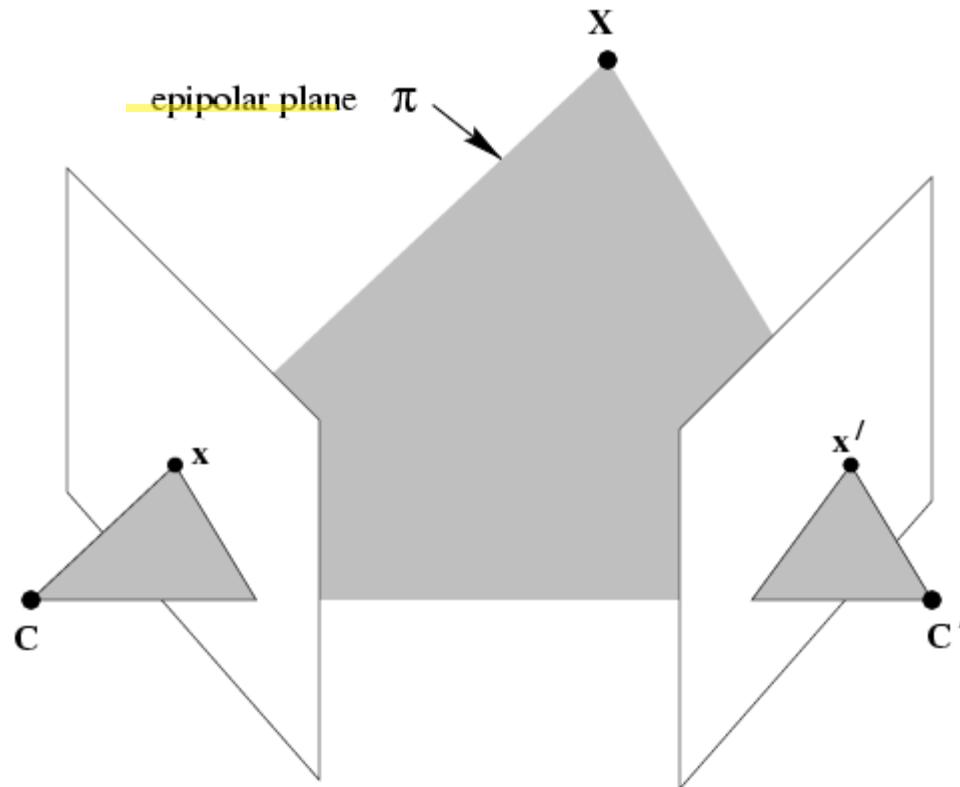
- If we, from the second image, view the ray going through x , this ray will form a **line** on the second image
- Point x' will be on this line in the second image

Epipolar Geometry



- What if only C , C' , and x are known?
- We can obtain the **epipolar line on the second image**

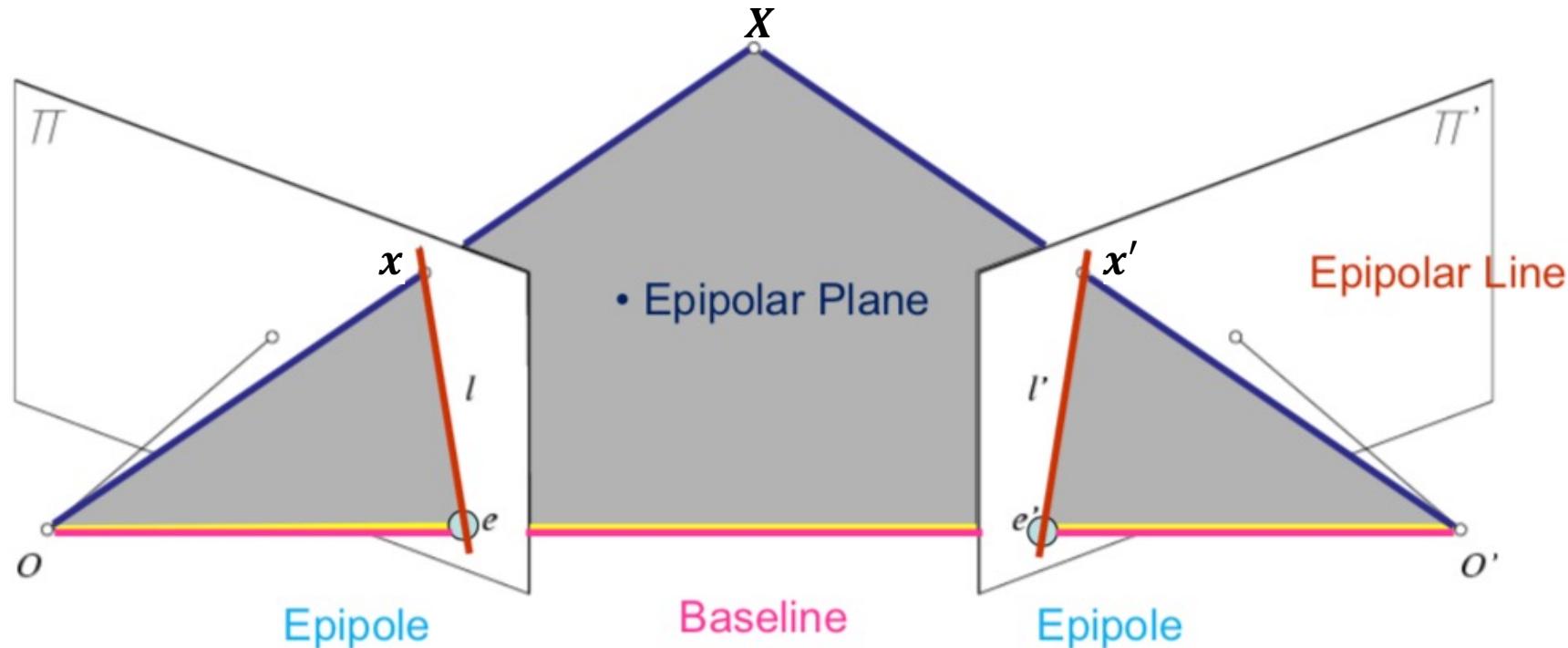
Epipolar Geometry



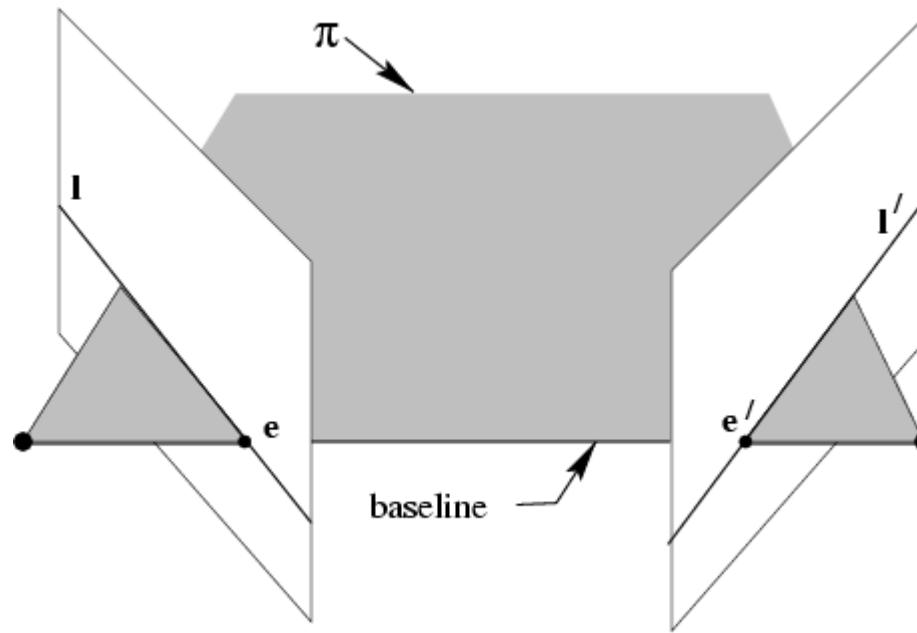
- C, C', x, x' and X are coplanar

Epipolar Geometry Terminology

- **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



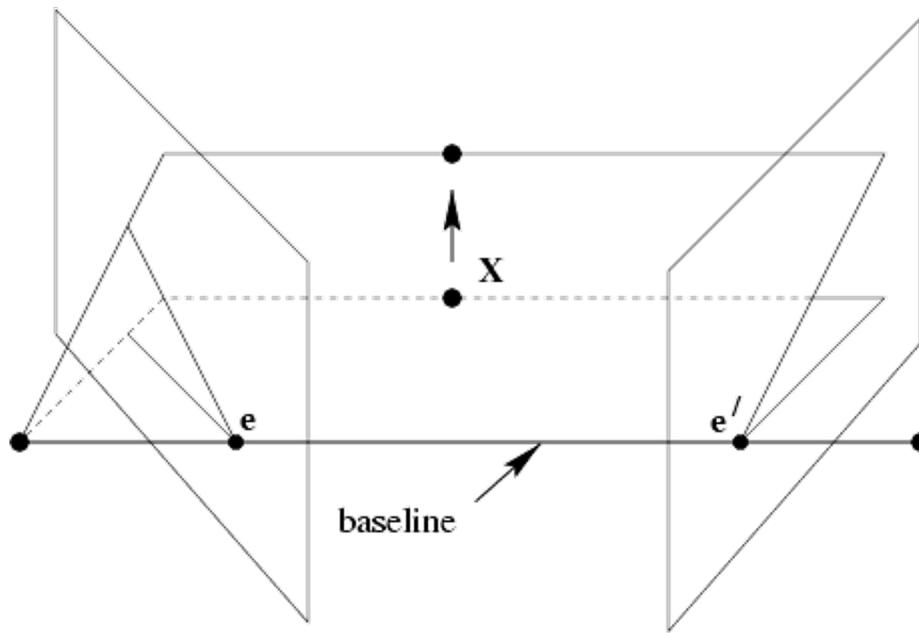
The Epipolar Plane



- All points on π project on l and l'

Epipolar Geometry

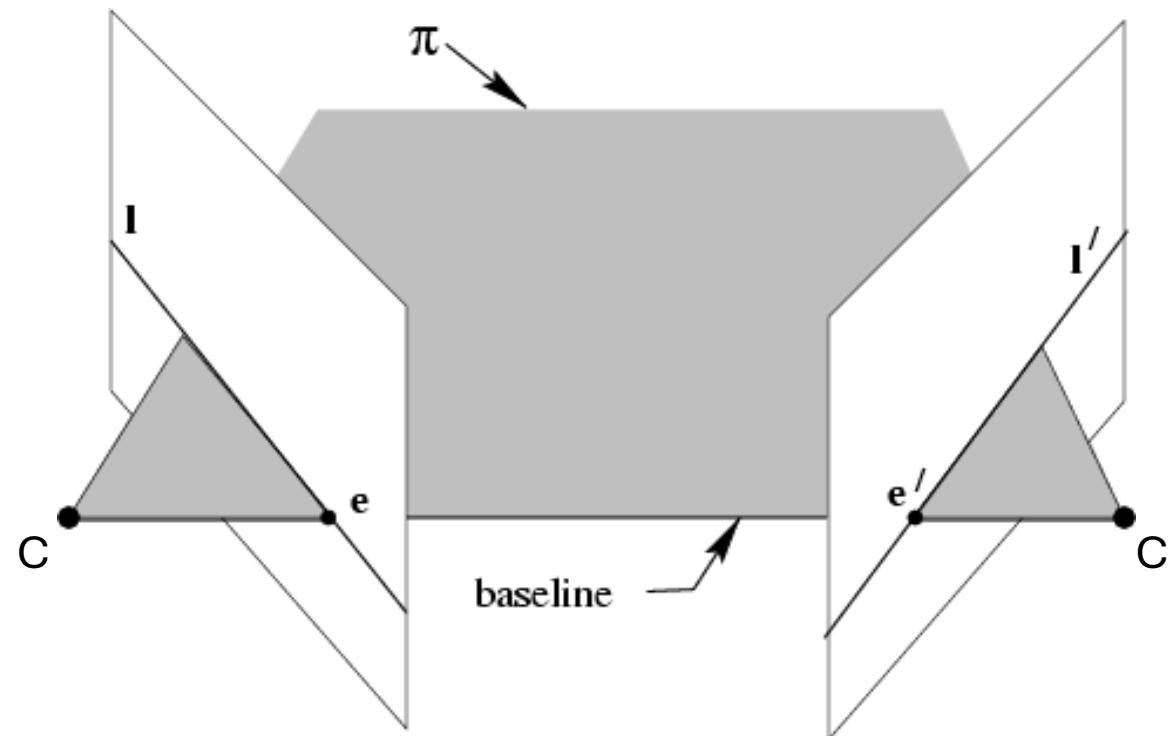
- All epipolar lines intersect at the epipole



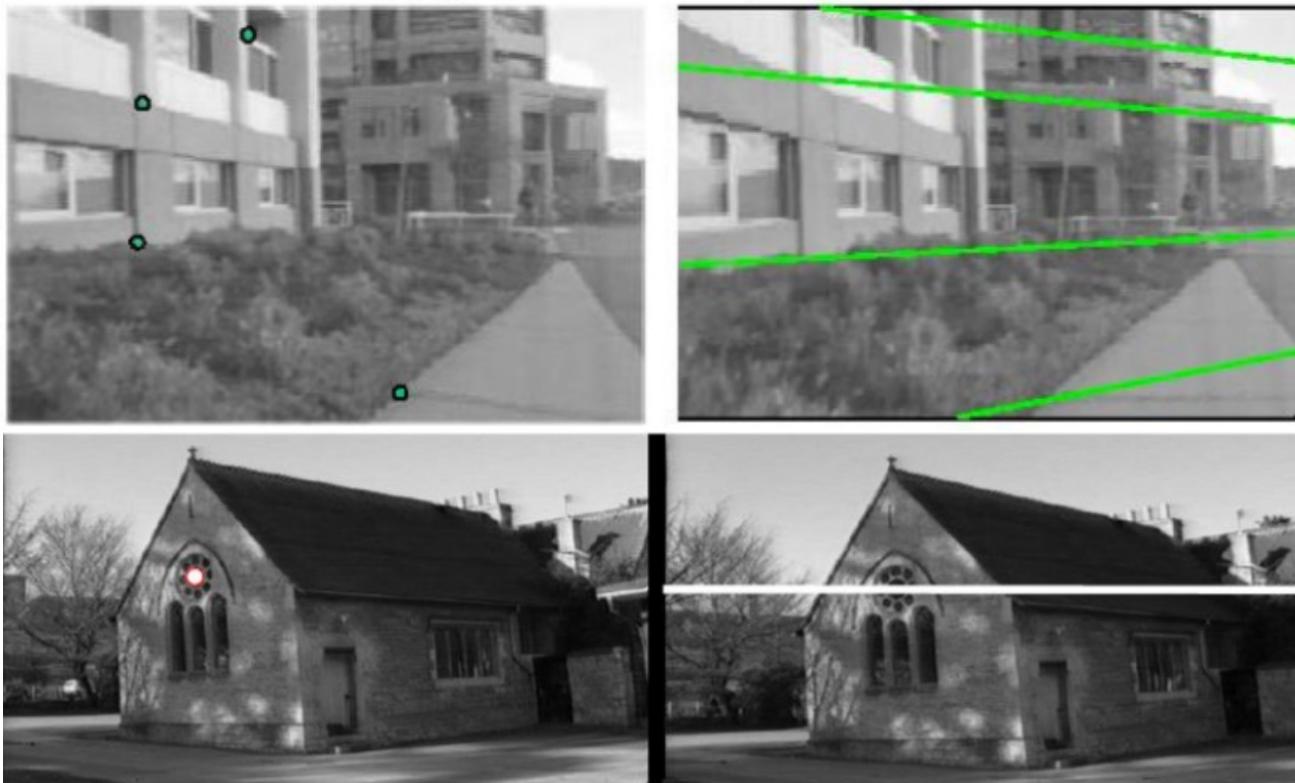
- Family of planes π and lines l and l' intersect at e and e'

Epipolar Geometry

- Epipole = intersection of baseline with image plane
= projection of one optical centre in the other image

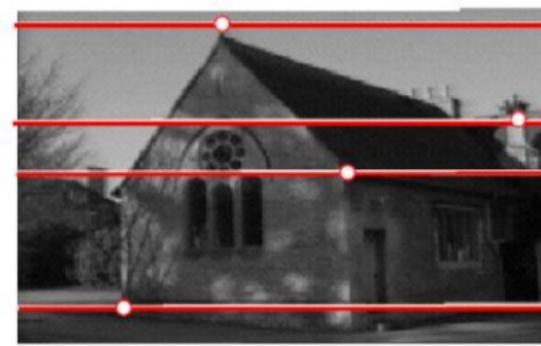
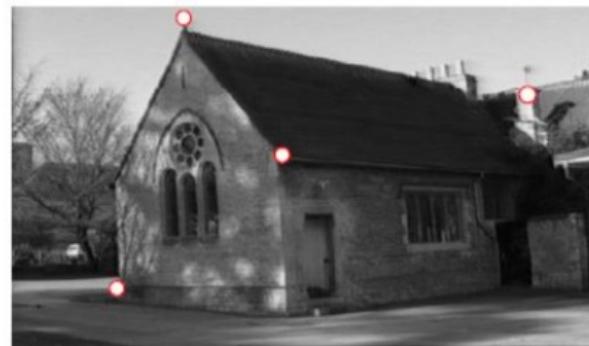


Examples



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

Examples

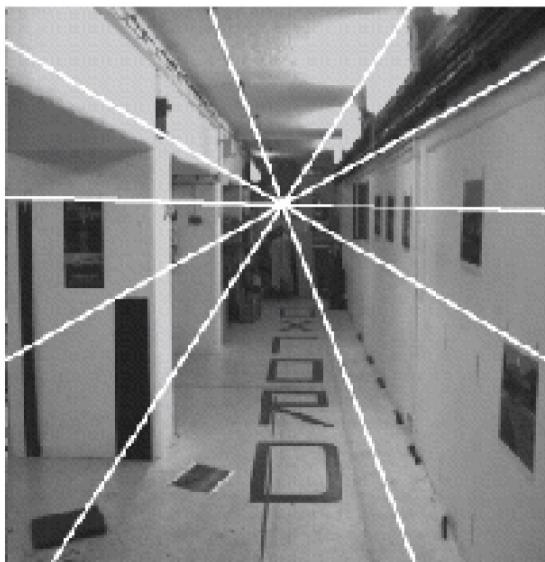
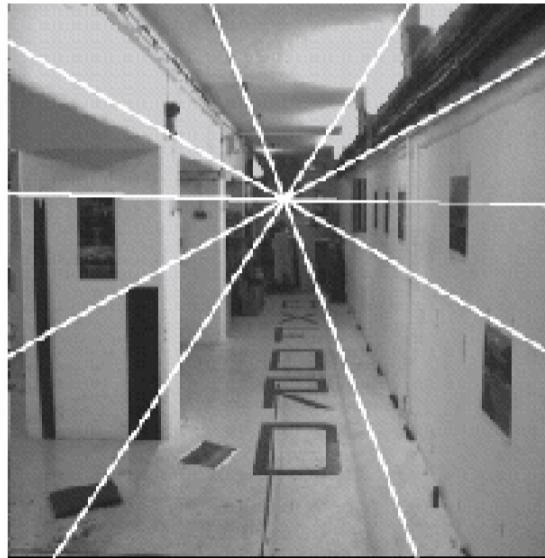


Examples

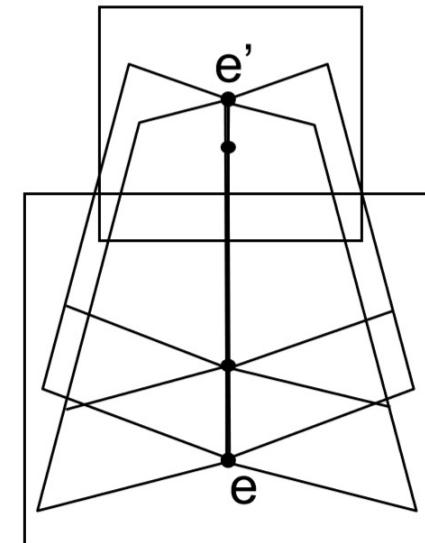


Image Credit: .gs8 50

Example: Forward Motion



- All epipolar lines go through the epipole, which is visible in the image plane in this case



- The epipole is the projection of an optical centre onto the other image

Epipolar Geometry: Summary

- The intrinsic geometry of 2 different views of the same 3D scene

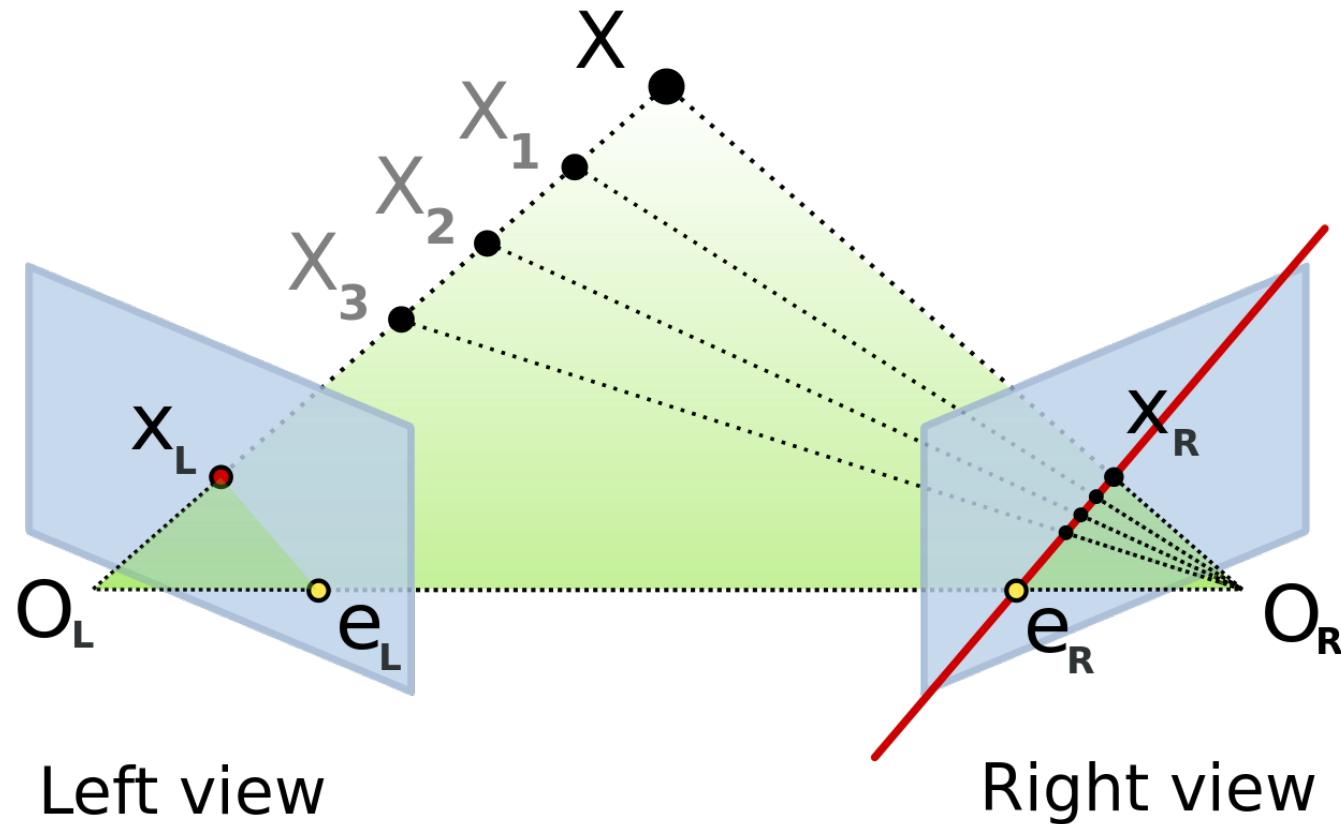


Image Credit: Arne Nordmann 52

Next Week

- Two-view geometry:
 - Epipolar geometry: Essential and Fundamental matrices
 - Triangulation
 - Stereo