

# VAN course

## Lesson 4

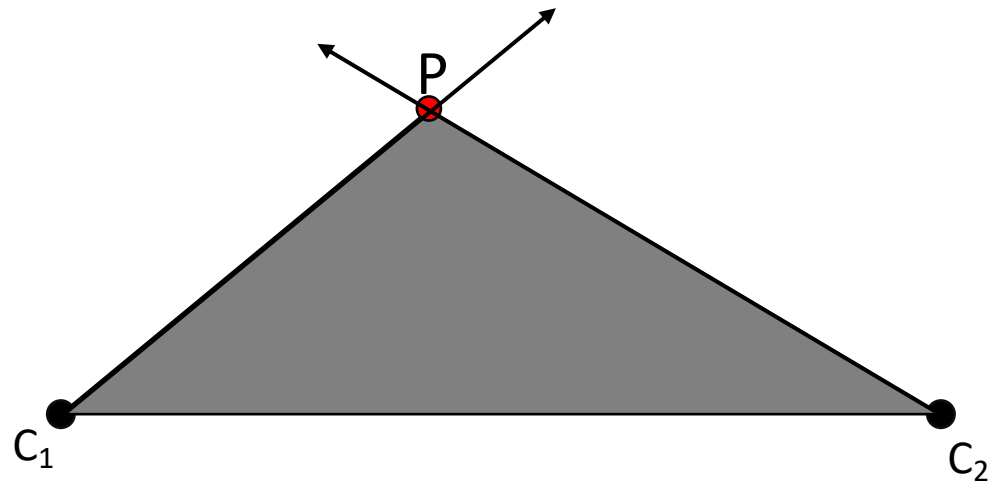
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# Today's topics

- Epipolar geometry
- Epipolar lines, Epipole
- Fundamental Matrix Calculation
- Rectification
- RANSAC

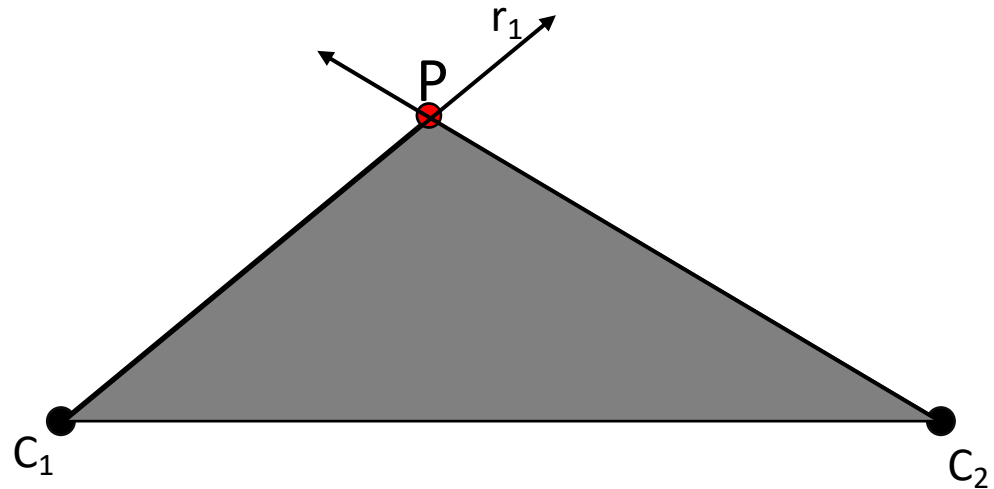
# Epipolar geometry

- The relations between views as appeared in the image



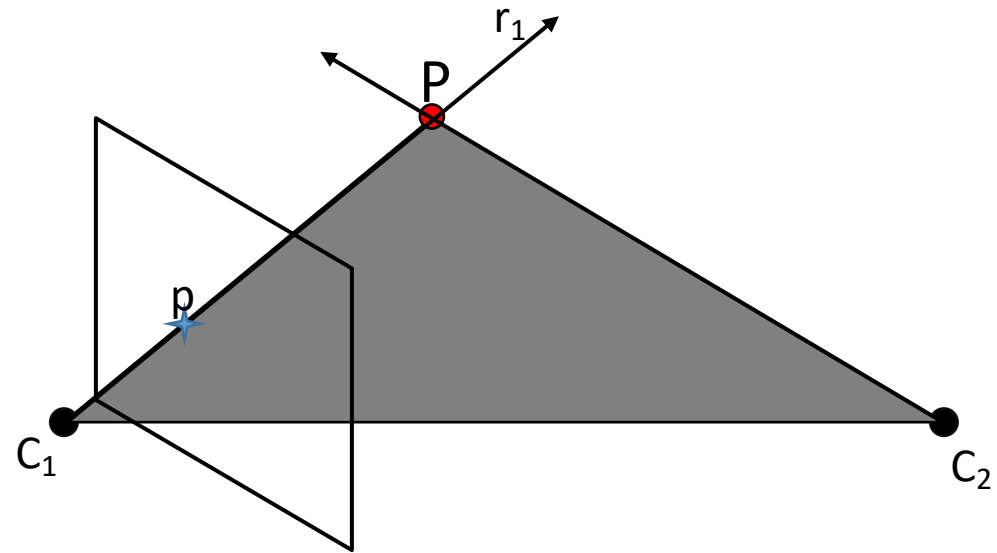
# Epipolar geometry

- The relations between views as appeared in the image
- **In 3D:** Ray  $r_1$  intersects  $P$



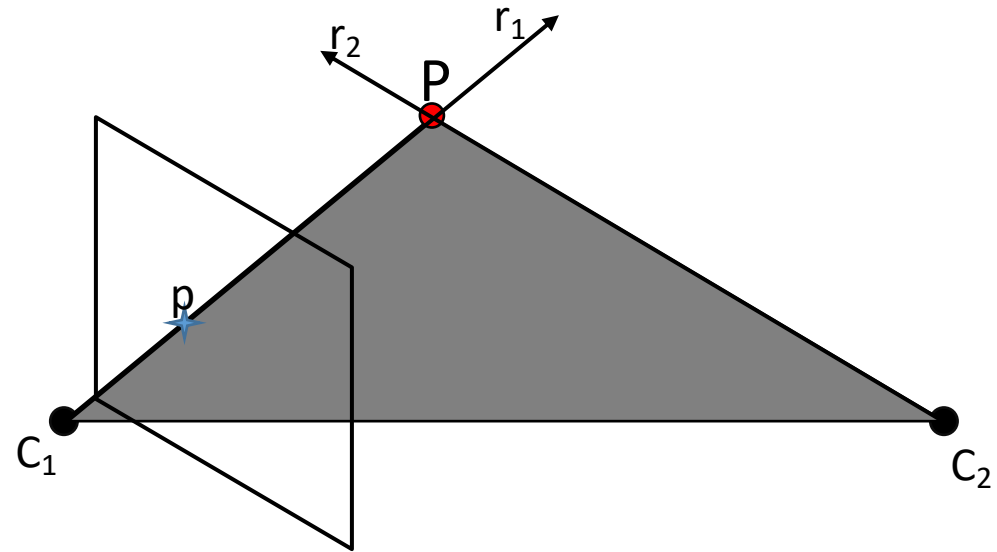
# Epipolar geometry

- The relations between views as appeared in the image
- **In 3D:** Ray  $r_1$  intersects  $P$       **In image:**  $P$  is projected to  $p$



# Epipolar geometry

- The relations between views as appeared in the image
- **In 3D:** Ray  $r_1$  intersects  $P$       **In image:**  $P$  is projected to  $p$
- **In 3D:** Ray  $r_2$  intersect  $P$



# Epipolar geometry

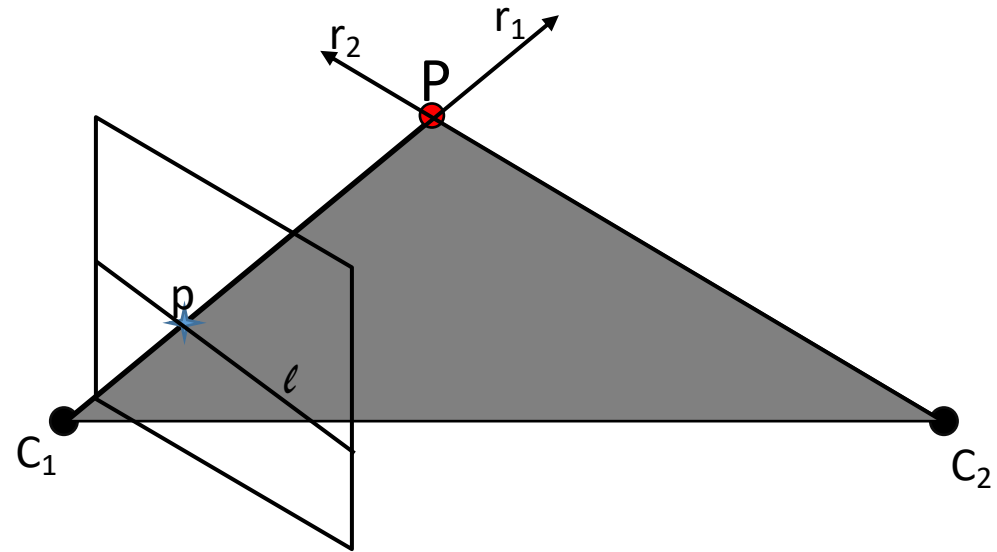
- The relations between views as appeared in the image

- **In 3D:** Ray  $r_1$  intersects  $P$

**In image:**  $P$  is projected to  $p$

- **In 3D:** Ray  $r_2$  intersect  $P$

**In Image:**  $r_2$  is projected to line  $\ell$



# Epipolar geometry

- The relations between views as appeared in the image

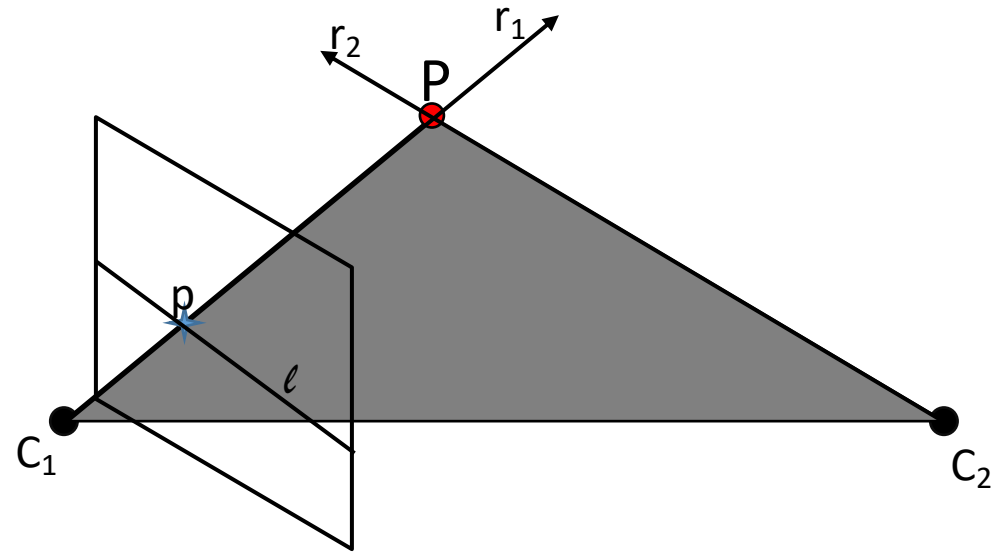
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- **In 3D:** Ray  $r_2$  intersect  $P$

**In Image:**  $r_2$  is projected to line  $\ell$

- $\ell$  is the **epipolar line**





# Epipolar geometry

- The relations between views as appeared in the image

- **In 3D:** Ray  $r_1$  intersects  $P$

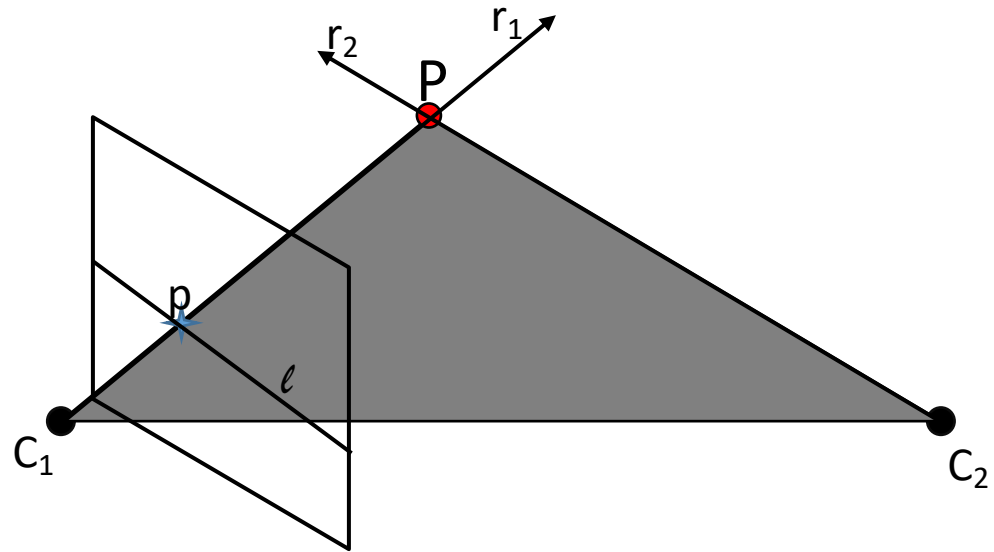
**In image:**  $P$  is projected to  $p$

- **In 3D:** Ray  $r_2$  intersect  $P$

**In Image:**  $r_2$  is projected to line  $\ell$

- $\ell$  is the **epipolar line**

- $\ell$  intersects  $p$  in image 1

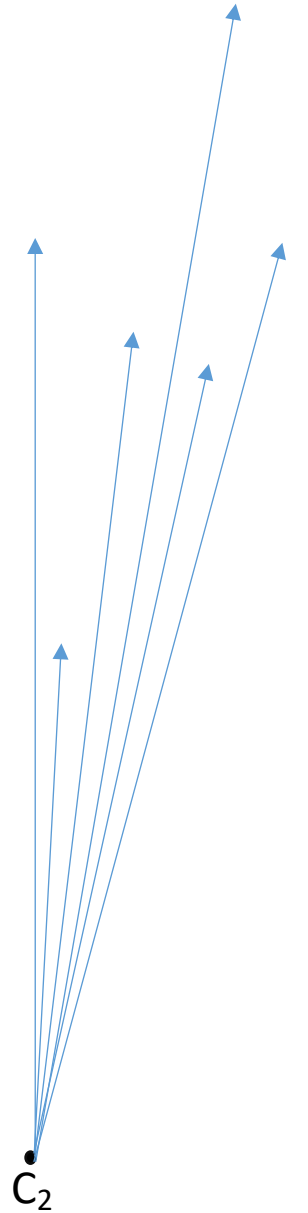


# Epipolar geometry

- What epipolar line is good for?
- If we search for a match for  $p_1$ 
  - It will be on the epipolar line  $\ell$
- If we suspect the match is wrong
  - We can decide it is an outlier if it's not on  $\ell$

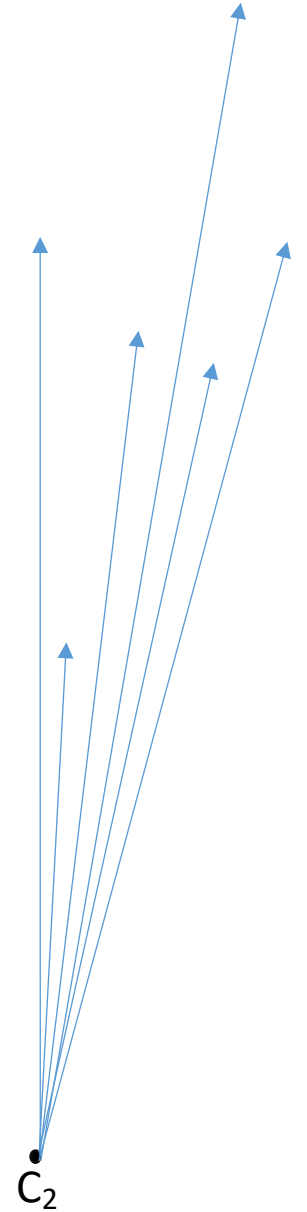
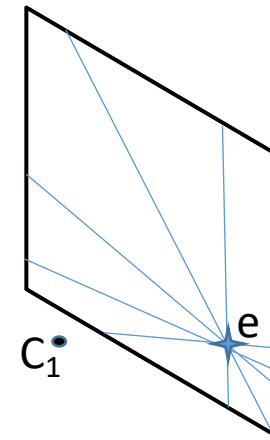
# Epipolar geometry

- **In 3D:** All 3D rays coming from  $C_2$  create a pencil



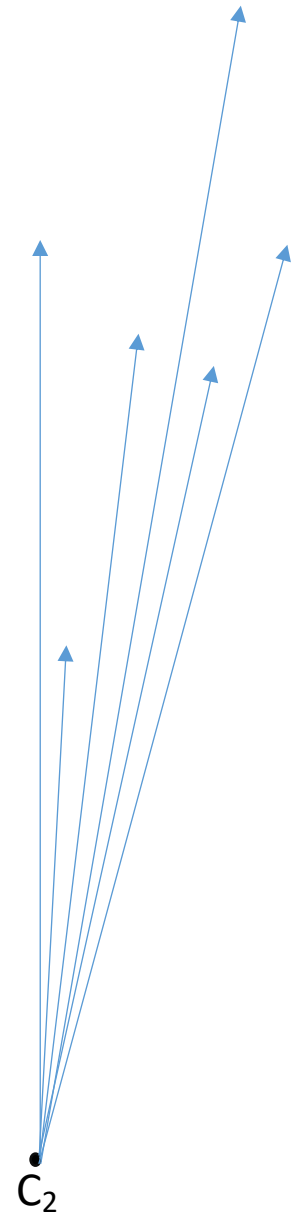
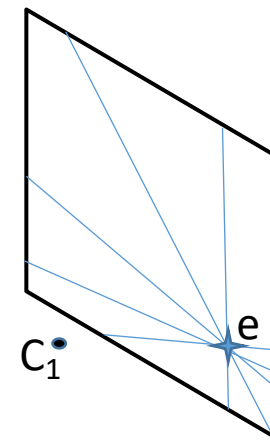
# Epipolar geometry

- **In 3D:** All 3D rays coming from  $C_2$  create a pencil
- **In image:** all epipolar lines intersect at point  $e$



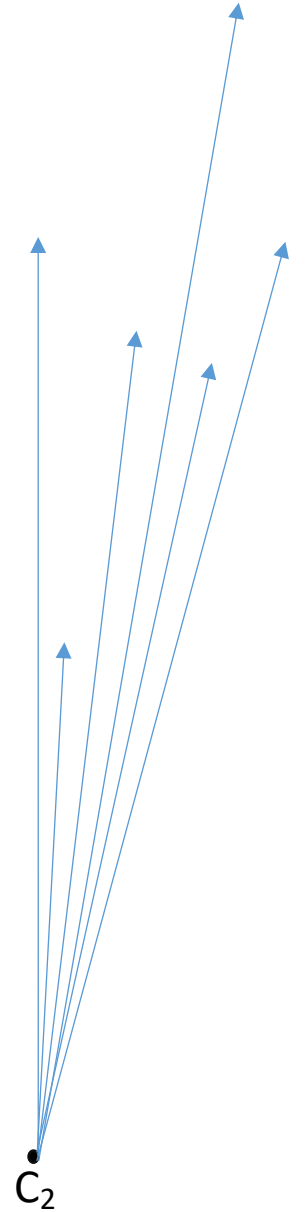
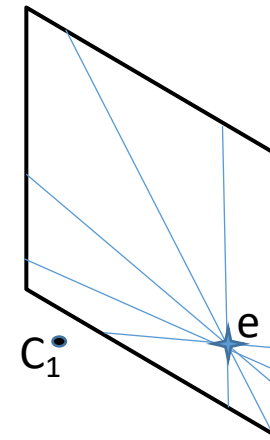
# Epipolar geometry

- **In 3D:** All 3D rays coming from  $C_2$  create a pencil
- **In image:** all epipolar lines intersect at point  $e$
- $e$  is the **epipole**



# Epipolar geometry

- **In 3D:** All 3D rays coming from  $C_2$  create a pencil
- **In image:** all epipolar lines intersect at point  $e$
- $e$  is the **epipole**
- $e$  is the projection of  $c_2$  3D location



# Epipolar geometry

- How can we calculate the epipolar line?
  - Project pixel to ray, rotate ray, project ray to line.
- Using the Fundamental Matrix  $F$ :
  - Algebraic representation of the epipolar geometry
  - Mapping from points in  $Im1$  to lines in  $Im2$ :

$$l^T_{1 \times 3} = F_{3 \times 3} x_{3 \times 1} \Leftrightarrow x_2^T F x_1 = 0$$

- Properties:
  - The null space is the Epipole:
$$\begin{aligned} \forall x: x^T F e &= 0 \\ F e &= 0 \end{aligned}$$
  - $F$  has 7 Degrees Of Freedom
    - It has rank 2
    - It is determined up to scale

# Epipolar geometry

$$Y = RX + t$$

$$[t]_{\times} Y = [t]_{\times} (RX + t)$$

$$[t]_{\times} Y = [t]_{\times} RX$$

$$Y^T [t]_{\times} Y = Y^T [t]_{\times} RX$$

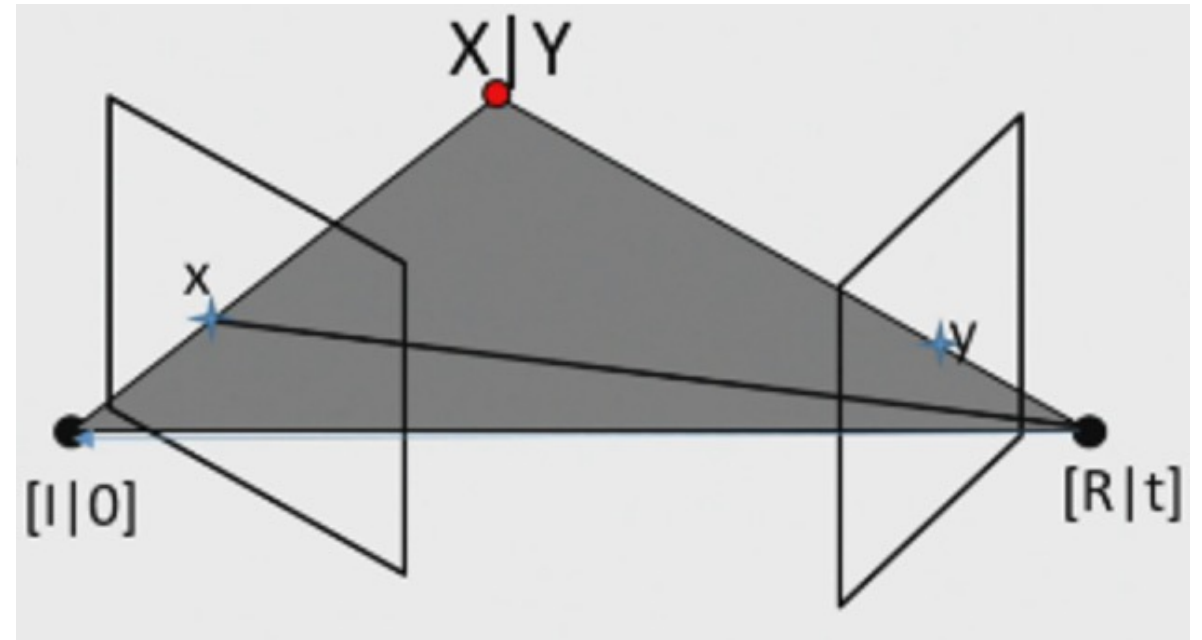
$$Y^T [t]_{\times} RX = 0$$

$$q = K_1 X, p = K_2 Y$$

$$X = K_1^{-1} q, Y = K_2^{-1} p$$

$$p^T K_2^{-T} [t]_{\times} R K_1^{-1} q = 0$$

$$p^T F q = 0$$





# Epipolar geometry

- If we don't know  $\mathbf{K}_1$ ,  $\mathbf{K}_2$ ,  $\mathbf{R}$ , or  $\mathbf{t}$ , can we still estimate  $\mathbf{F}$ ?
- Yes, given enough correspondences.
- **Many algorithms:**
  - Linear (the normalized 8-point algorithm)
  - Minimal (7-point)
  - Robust (RANSAC)
  - Non-linear refinement (MLE, Algebraic minimization)
- We use 8-point algorithm
  - Although it's inaccurate
  - Because it's fast

# Estimating F: 8-point algorithm

- The fundamental matrix  $F$  is defined by

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

for any pair of matches  $x$  and  $x'$  in two images.

- Let  $x=(u,v,1)^T$  and  $x'=(u',v',1)^T$ ,  
each match gives a linear equation

$$\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$$

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

# 8-point algorithm

$$\begin{bmatrix} u_1 u_1' & v_1 u_1' & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 & 1 \\ u_2 u_2' & v_2 u_2' & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ u_n u_n' & v_n u_n' & u_n' & u_n v_n' & v_n v_n' & v_n' & u_n & v_n & 1 \end{bmatrix} \begin{bmatrix} f_{11} \\ f_{12} \\ f_{13} \\ f_{21} \\ f_{22} \\ f_{23} \\ f_{31} \\ f_{32} \\ f_{33} \end{bmatrix} = 0$$

# 8-point algorithm

$$\begin{bmatrix}
 u_1 u_1' & v_1 u_1' & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 & 1 \\
 u_2 u_2' & v_2 u_2' & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 & 1 \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
 u_n u_n' & v_n u_n' & u_n' & u_n v_n' & v_n v_n' & v_n' & u_n & v_n & 1
 \end{bmatrix}
 \mathbf{A}
 \begin{bmatrix}
 f_{11} \\
 f_{12} \\
 f_{13} \\
 f_{21} \\
 f_{22} \\
 f_{23} \\
 f_{31} \\
 f_{32} \\
 f_{33}
 \end{bmatrix}
 = \mathbf{0}$$

# 8-point algorithm

- We solve it as before, using SDV:

$$Af = 0 \text{ s.t. } \|f\| = 1$$

$$A = U\Sigma V^T$$

$$f = V_N^T$$

- $f_{9 \times 1} \Rightarrow F_{3 \times 3}$
- Same method if  $N > 8$ 
  - We minimize  $\|Af\|$  s.t.  $\|f\| = 1$

# 8-point algorithm

- $\mathbf{F}_{3 \times 3}$  should have rank 2. It doesn't.
- To enforce that  $\mathbf{F}$  is of rank 2,  $\mathbf{F}$  is replaced by  $\mathbf{F}'_{3 \times 3}$  that minimizes  $\|\mathbf{F} - \mathbf{F}'\|$ .
- This too is achieved by SVD. Let  $\mathbf{F} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$ , where

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix} \quad \mathbf{\Sigma}' = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

then  $\mathbf{F}' = \mathbf{U}\mathbf{\Sigma}'\mathbf{V}^T$  is the solution.

# 8-point algorithm



# 8-point algorithm

$$\begin{bmatrix}
 u_1 u_1' & v_1 u_1' & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 & 1 \\
 u_2 u_2' & v_2 u_2' & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 & 1 \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
 u_n u_n' & v_n u_n' & u_n' & u_n v_n' & v_n v_n' & v_n' & u_n & v_n & 1
 \end{bmatrix}
 \begin{bmatrix}
 f_{11} \\
 f_{12} \\
 f_{13} \\
 f_{21} \\
 f_{22} \\
 f_{23} \\
 f_{31} \\
 f_{32} \\
 f_{33}
 \end{bmatrix} = 0$$

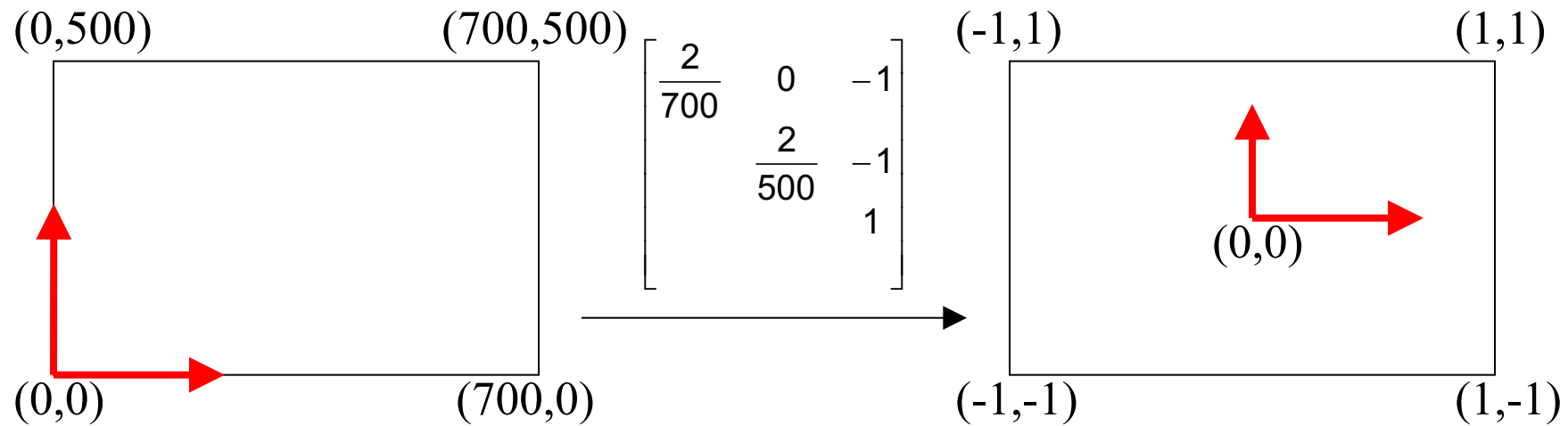
$\sim 10000 \quad \sim 10000 \quad \sim 100 \quad \sim 10000 \quad \sim 10000 \quad \sim 100 \quad \sim 100 \quad \sim 100 \quad 1$

Orders of magnitude difference  
between column of data matrix  
→ least-squares yields poor results



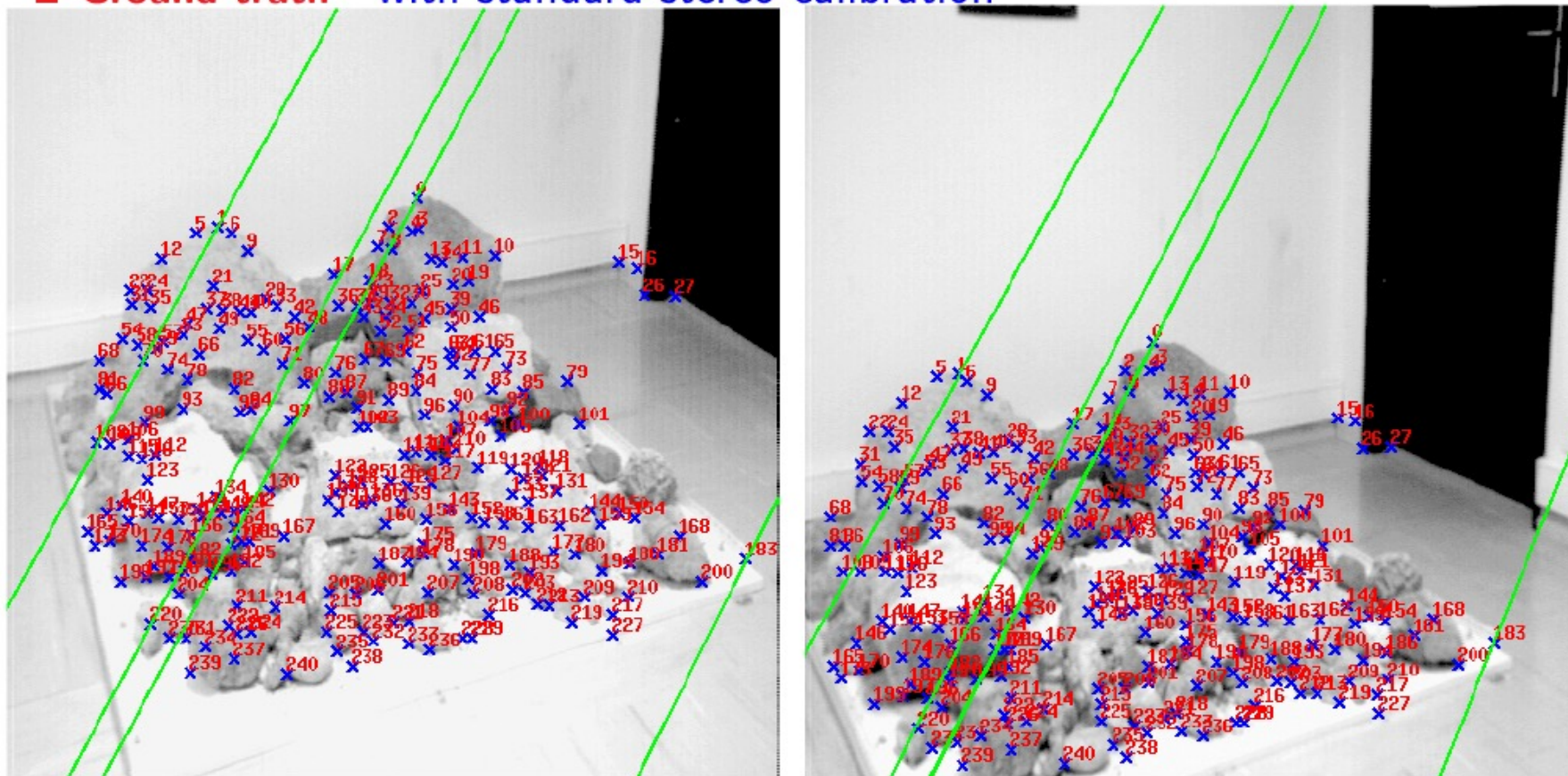
# 8-point algorithm

- normalized least squares yields good results
- Transform image to  $\sim[-1,1] \times [-1,1]$



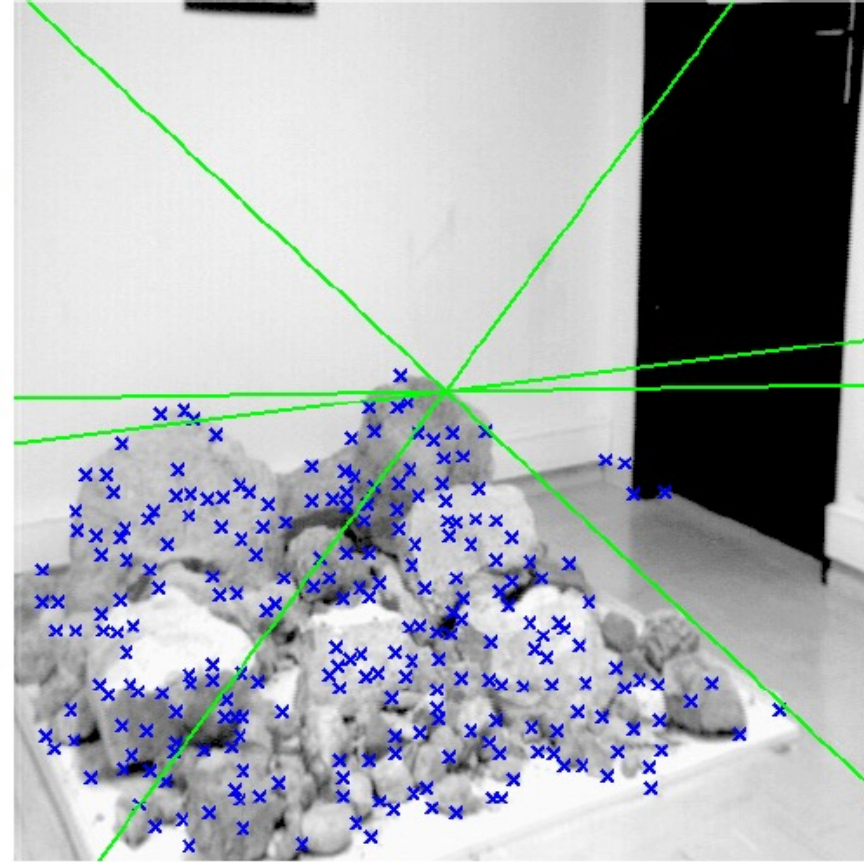
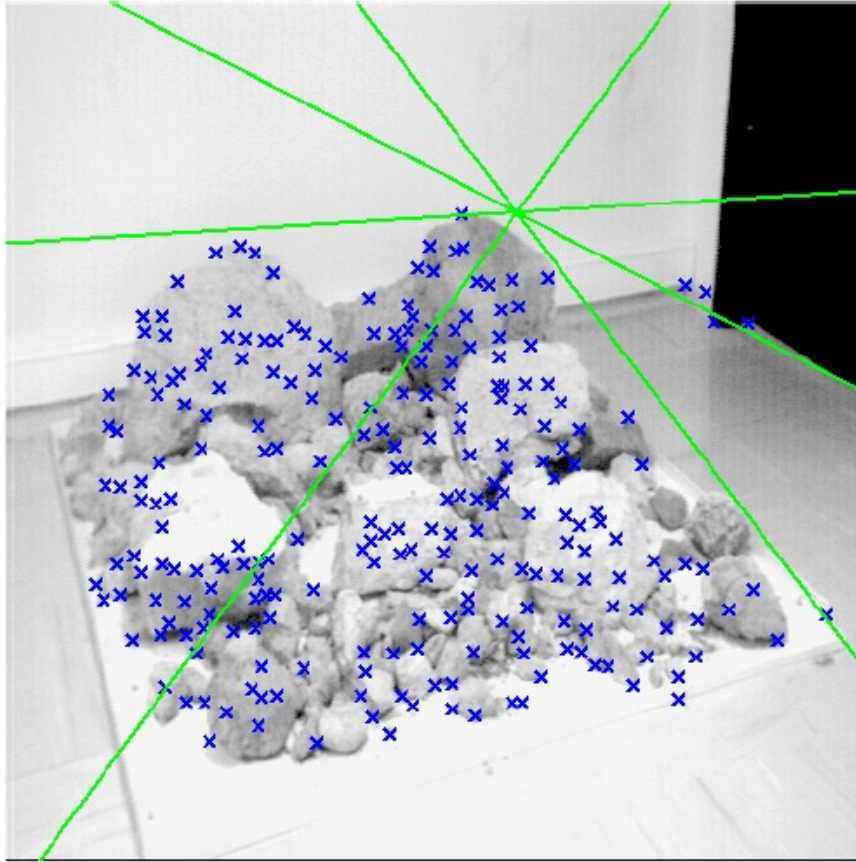
# Results (ground truth)

■ Ground truth with standard stereo calibration



# Results (8-point algorithm)

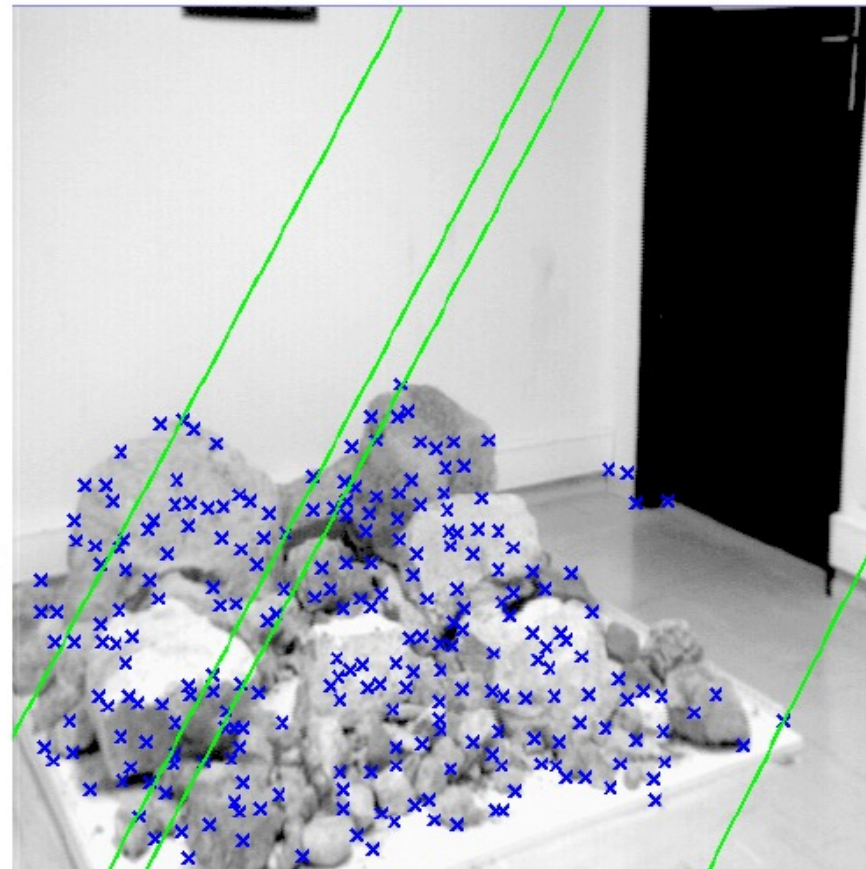
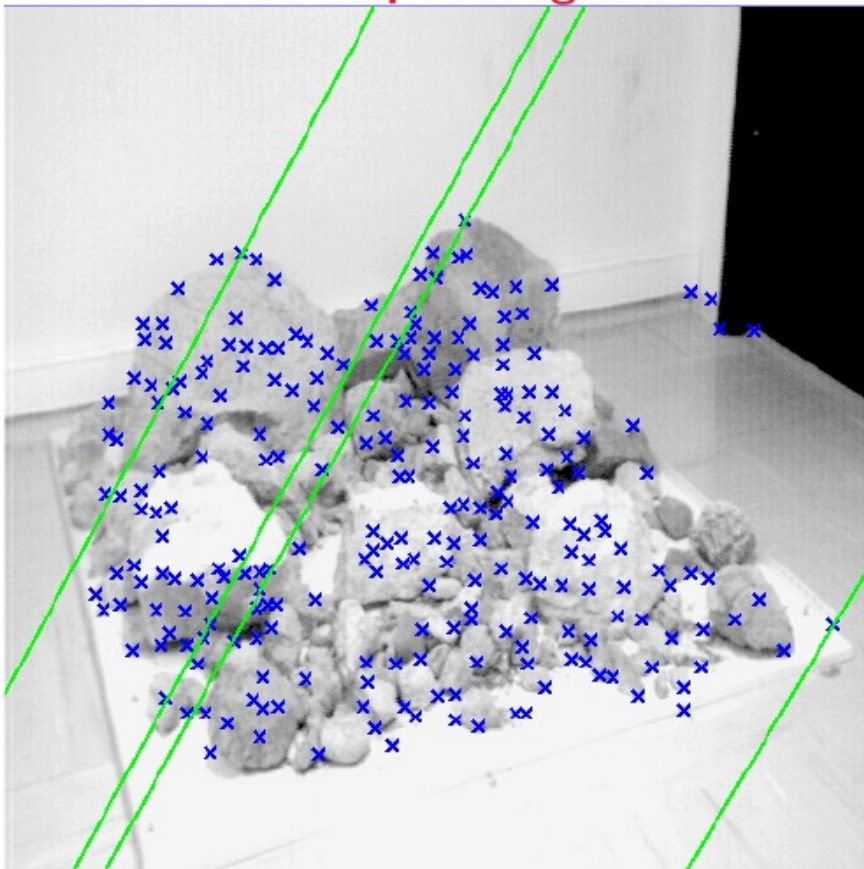
■ 8-point algorithm





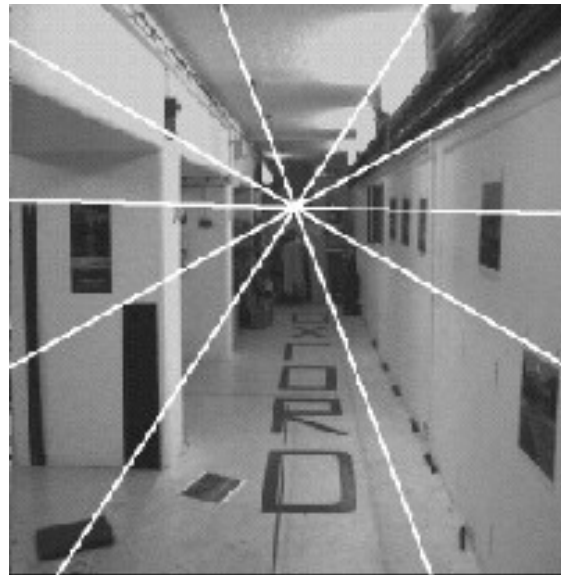
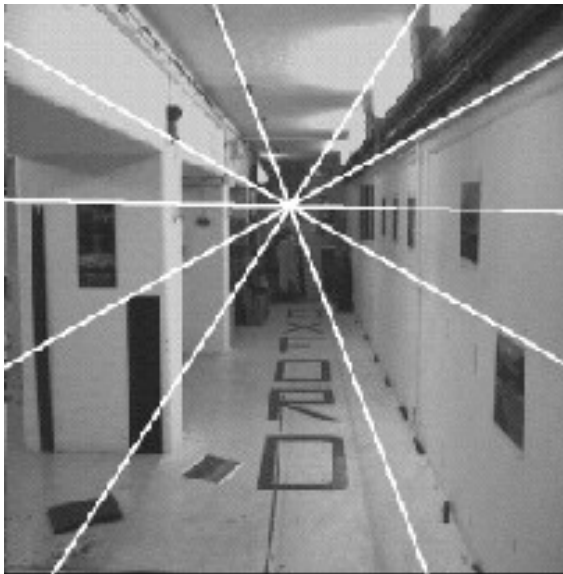
# Results (normalized 8-point algorithm)

■ Normalized 8-point algorithm



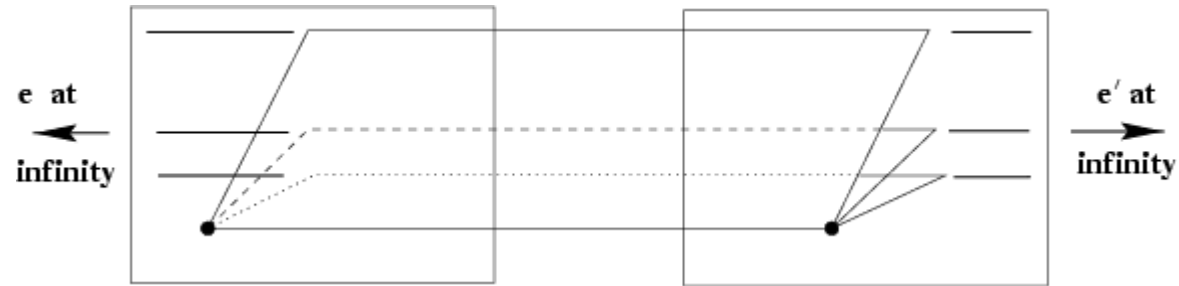
# Epipolar geometry

## Example: forward motion

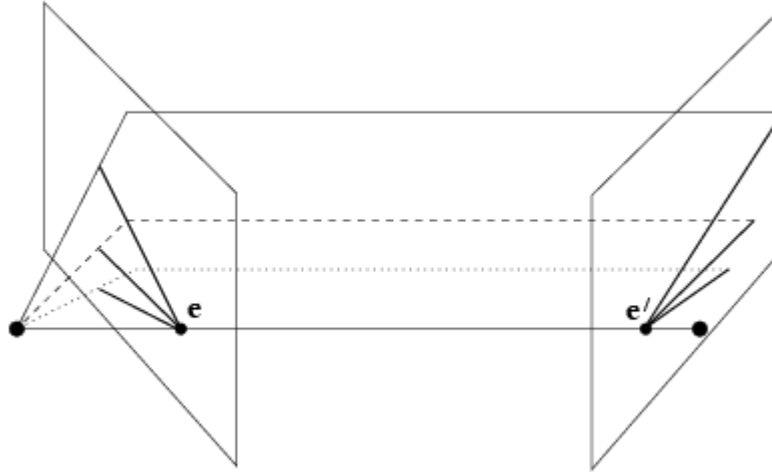


# Epipolar geometry

**Example: motion parallel with image plane**



# Example: converging cameras



Courtesy of Marc Pollefeys

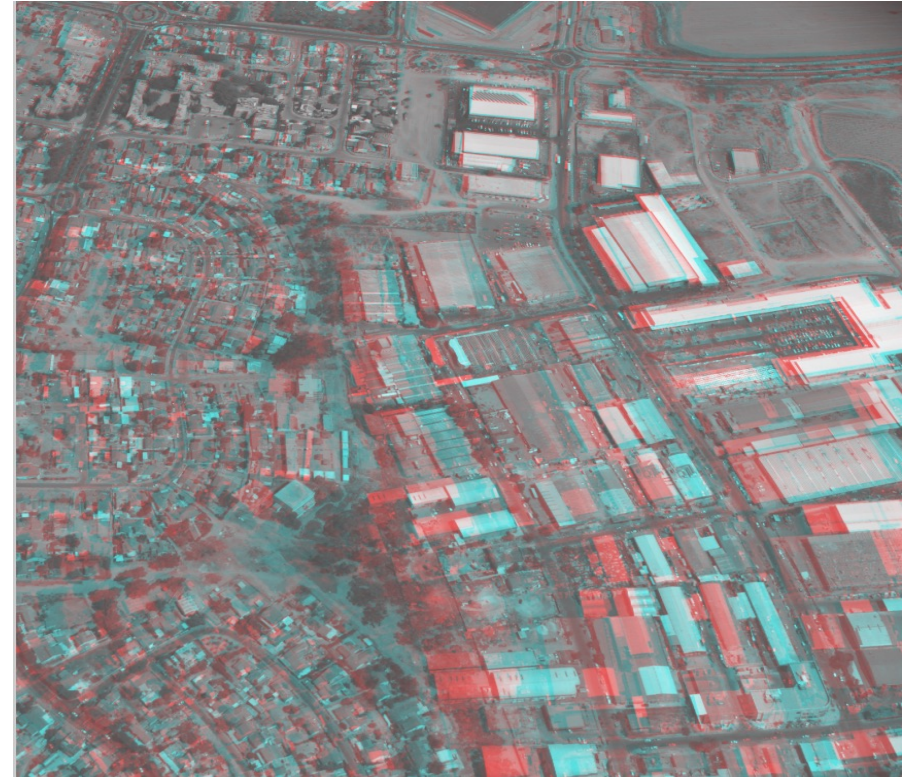
# Epipolar geometry

- After stereo rectification:

$$F \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = [0, 1, -y]$$

So F is from the shape:

$$F = \begin{bmatrix} & & 1 \\ -1 & & \\ & & \end{bmatrix} = \begin{bmatrix} 1 \\ 0 \\ 0 \end{bmatrix}_{\times} = [t]_{\times}$$





# RANSAC

- **RAN**dom **SA**mples **C**onsensus
- Problem:
  - All inliers obey some model
  - But there are some unknown outliers.
- Example: inliers are on a curve
- Chicken and egg situation:
  - If we had the curve, we could spot the outliers
  - If we knew the inliers, we could estimate the curve
- Key to solution:
  - The model can be estimated using a small set



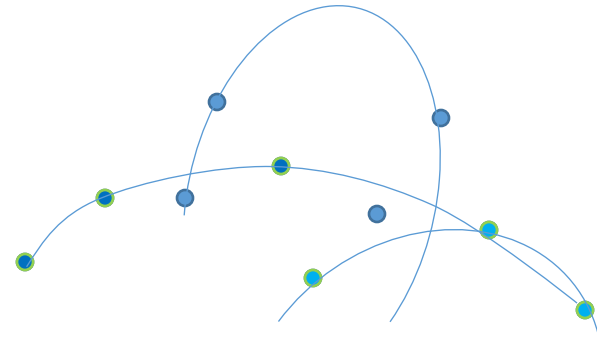
Courtesy of: ET Wales

# RANSAC

- Algorithm:
  1. Repeat:
    1. Sample a minimal set
    2. Estimate a model
    3. Check how many points obey the model
  2. Choose model with maximal #points
  3. Repeat:
    1. Estimate model from all inliers
    2. Calc inliers of new model
- Output: inliers, outliers, and model

# RANSAC

- Example:
- $\#inliers = 3$ .  $\max \#inliers = 3$
- $\#inliers = 5$ .  **$\max \#inliers = 5$**
- $\#inliers = 3$ .  $\max \#inliers = 5$
- .
- .
- Output:  $\#inliers = 5$



# RANSAC

- When to stop the first loop of RANSAC?
- Goal: one sample that will have only inliers, with high prob  $p$ .
- Prob of being an outlier:  $\epsilon$
- P(being an inlier) =  $1 - \epsilon$
- P(all inliers-sample) =  $(1 - \epsilon)^s$
- P(bad sample)=  $1 - (1 - \epsilon)^s$
- P(All samples are bad) =  $(1 - (1 - \epsilon)^s)^I$
- We wish it to be small:  $(1 - (1 - \epsilon)^s)^I < 1 - p$

$$\log(1 - (1 - \epsilon)^s)^I < \log(1 - p)$$

$$I \log(1 - (1 - \epsilon)^s) < \log(1 - p)$$

$$I > \log(1 - p) / \log(1 - (1 - \epsilon)^s)$$

# RANSAC

- This can get high:

<b>s \ <math>\epsilon</math></b>	<b>25%</b>	<b>50%</b>	<b>60%</b>	<b>70%</b>	<b>80%</b>	<b>85%</b>
<b>2</b>	6	16	26	49	113	202
<b>3</b>	8	34	70	168	573	1362
<b>7</b>	33	588	2808	21055	2.5E05	2.6E06

- What if we don't know  $\epsilon$ ?
- We can estimate it online:
  - We calc #inliers at each sample
  - This gives an ever-decreasing upper-bound on  $\epsilon$
  - Hence the needed iteration number  $I$  is also decreasing

# RANSAC

- Which models are used with RANSAC?
- 2D points matching:
  - Fundamental matrix
  - Homography transformation
  - Essential Matrix
  - Trifocal Tensor
- 3D points:
  - Point cloud registration
  - Perspective-n-Point (PNP)
  - Plane fitting
  - Curve fitting

# RANSAC

- Limitations of RANSAC with FM:
  - Efficiency: unknown
    - because outlier ratio  $\varepsilon$  is unknown
  - Accuracy
    - Even good sample may give a bad model
    - Sensitive to inlier threshold
  - Degeneracy
    - The plain+parallax problem
  - Many tricks and extensions:
    - PROSAC
    - USAC

