

CS5670: Computer Vision

Two-view geometry



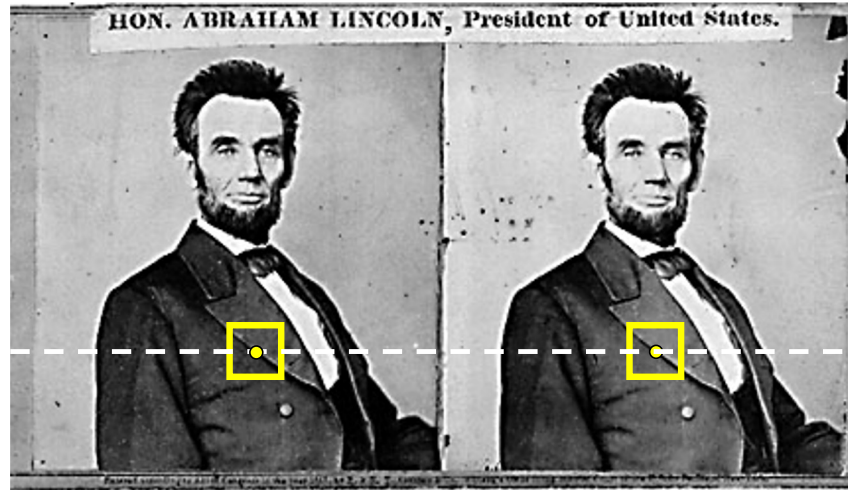
Reading

- Reading: Szeliski (2nd Edition), Chapter 11.3 and 12.1

Announcements

- Project 4 (stereo) due this Friday, March 29, at 8pm

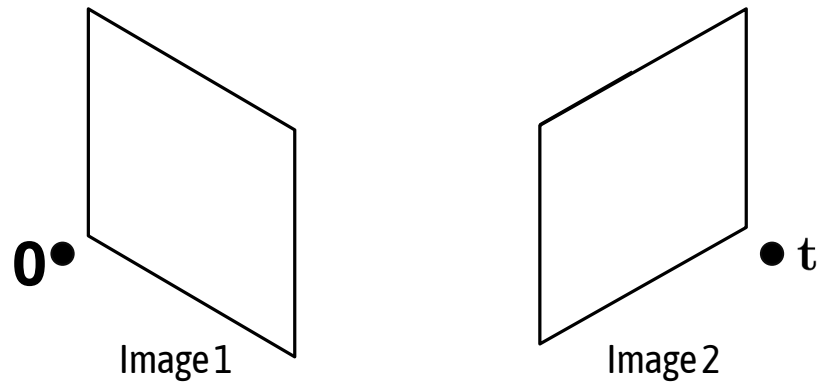
Back to stereo



- Where do epipolar lines come from?

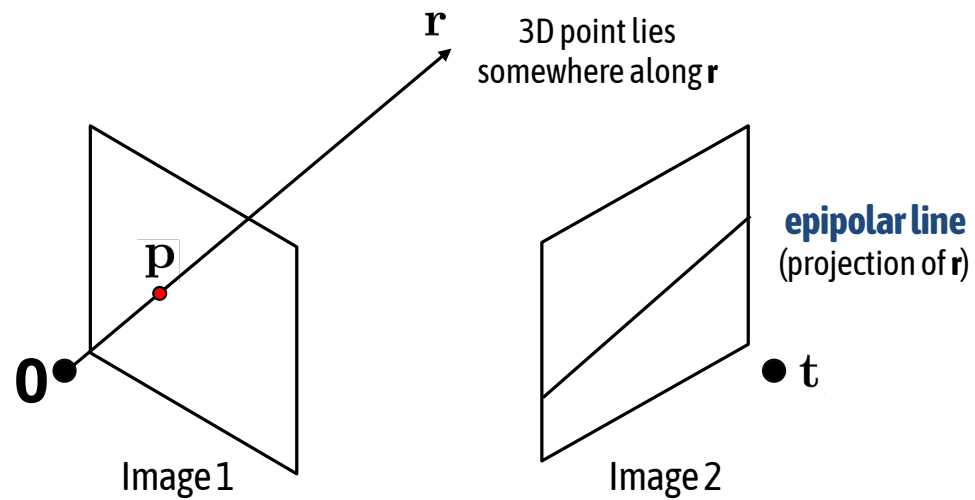
Two-view geometry

- Where do epipolar lines come from?



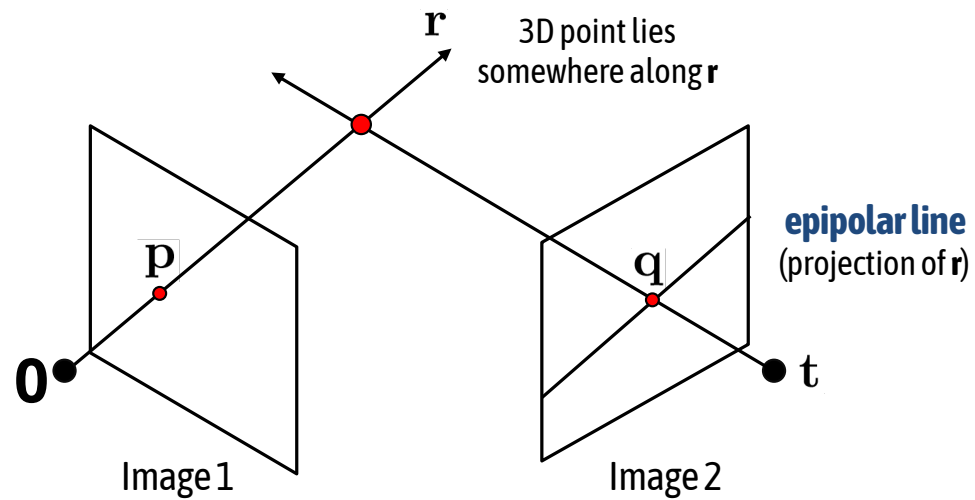
Two-view geometry

- Where do epipolar lines come from?



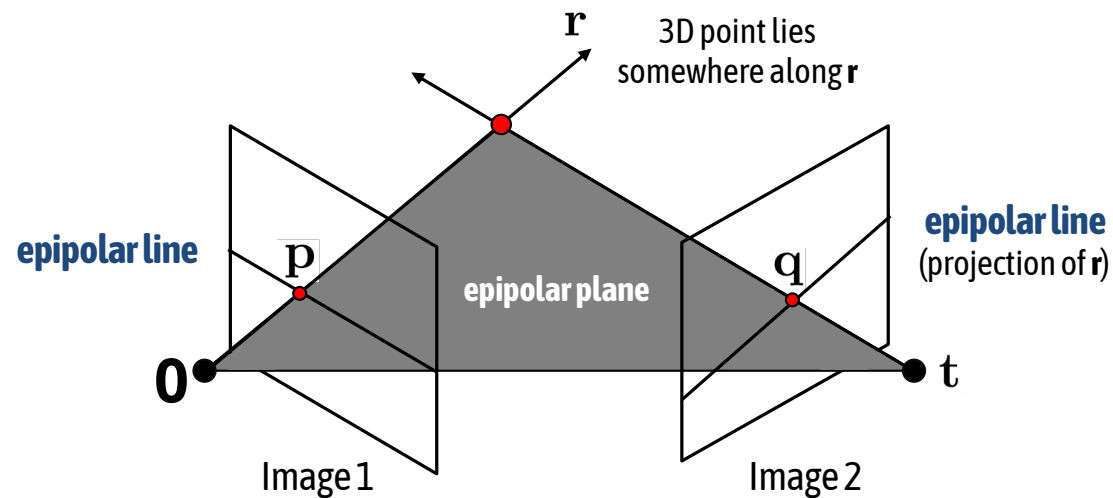
Two-view geometry

- Where do epipolar lines come from?

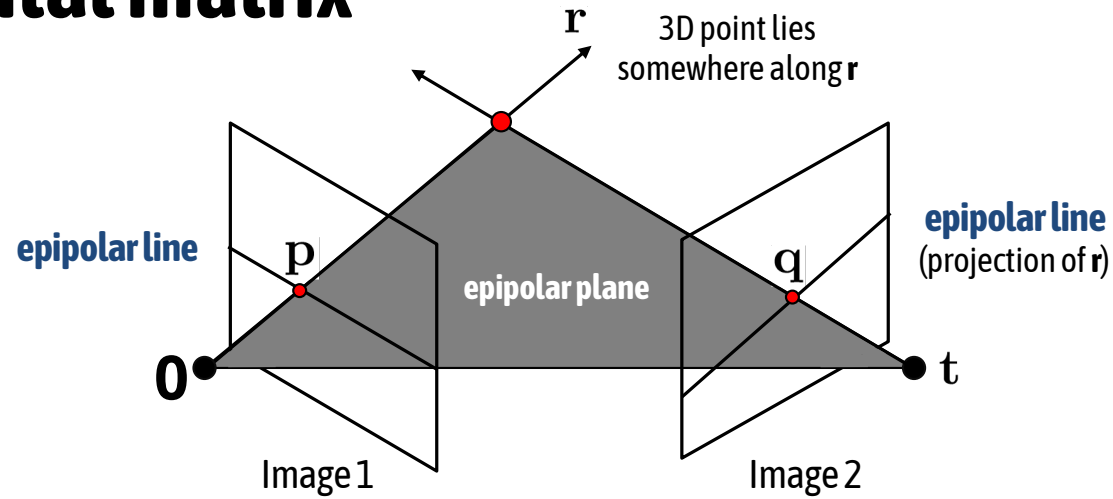


Two-view geometry

- Where do epipolar lines come from?

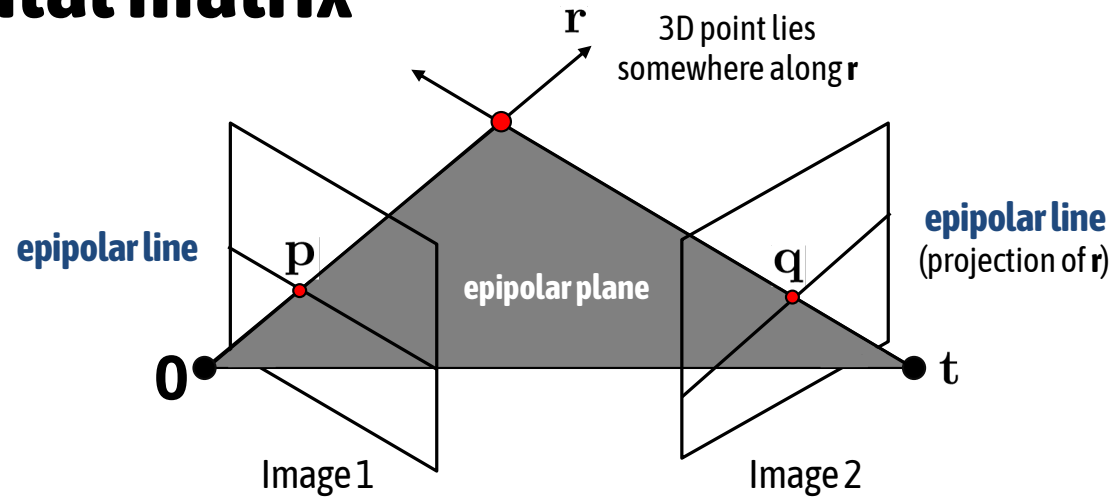


Fundamental matrix



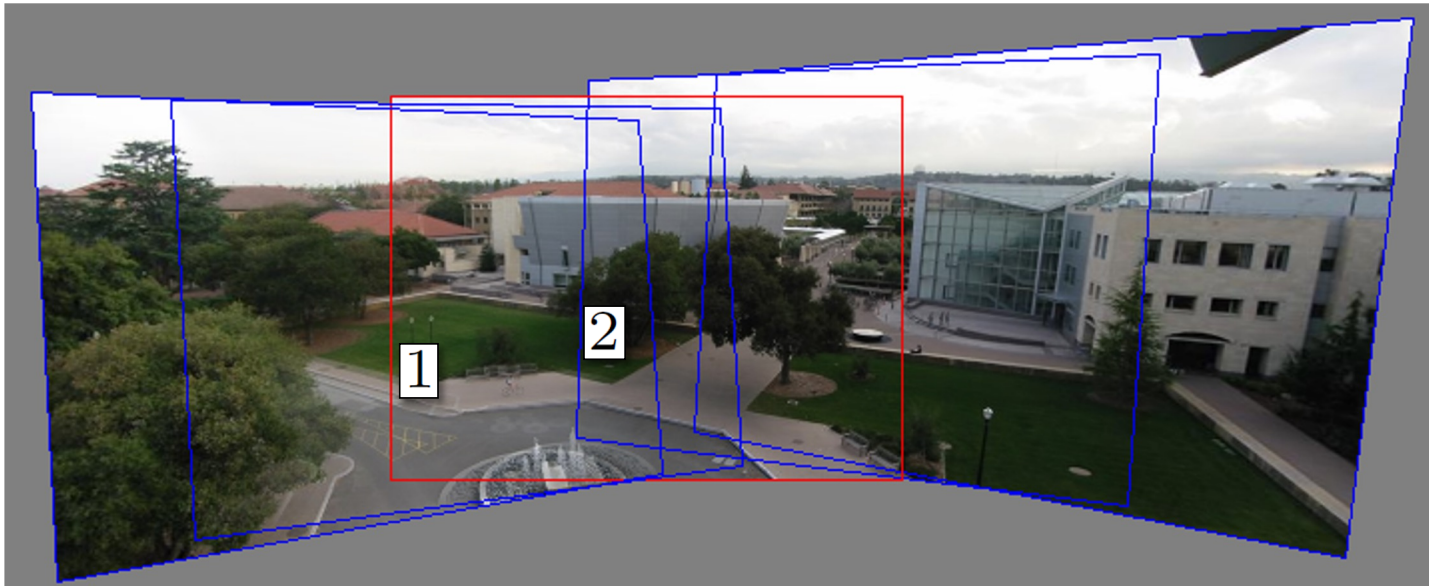
- This *epipolar geometry* of two views is described by a very special 3×3 matrix, called the *fundamental matrix* \mathbf{F}

Fundamental matrix



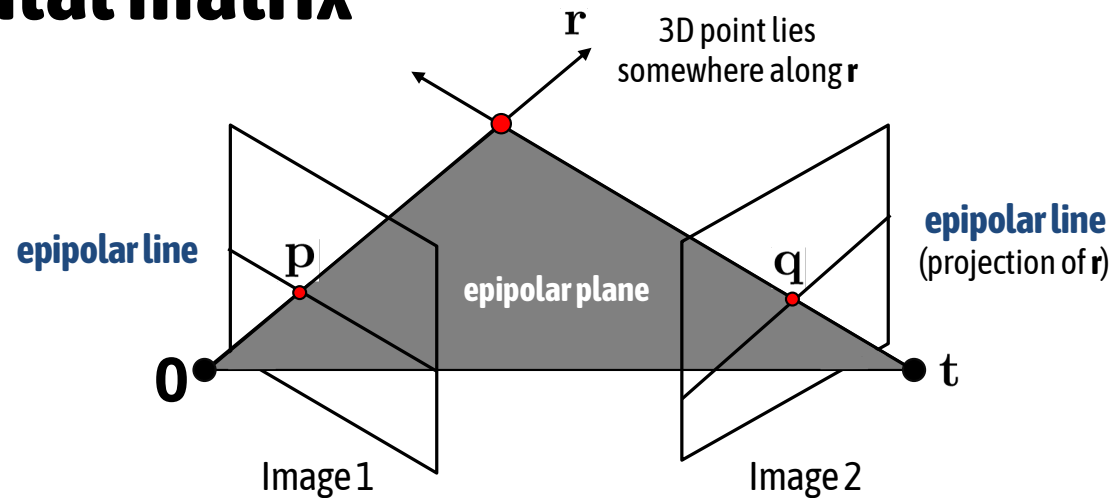
- Epipolar geometry, very special 3x3 fundamental matrix \mathbf{F}
- \mathbf{F} maps (homogeneous) *points* in image 1 to *lines* in image 2!

Relationship between F matrix and homography?



Images taken from the same center of projection? Use a homography!

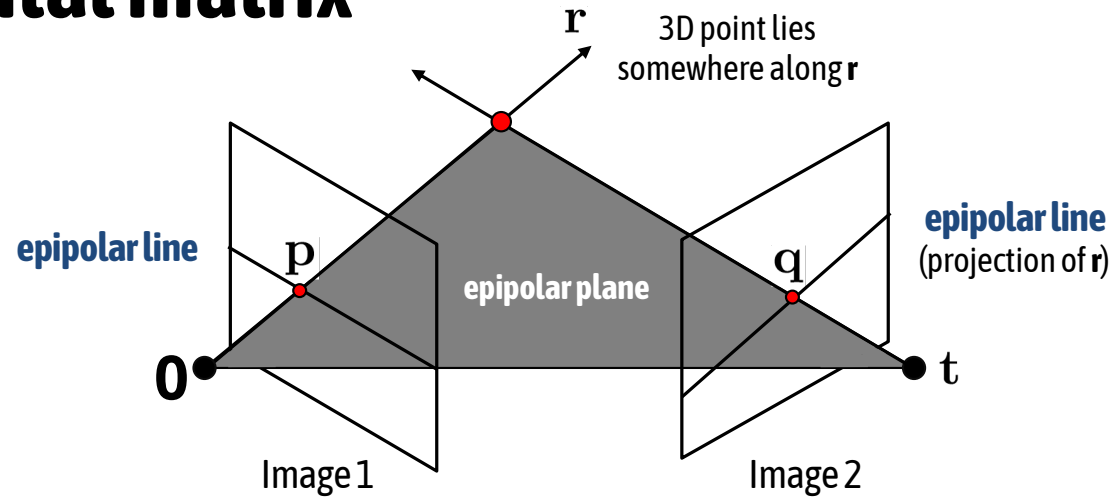
Fundamental matrix



- Epipolar geometry, very special 3x3 fundamental matrix \mathbf{F}
- \mathbf{F} maps (homogeneous) *points* in image 1 to *lines* in image 2!
- The epipolar line (in image 2) of point p is: $\mathbf{F}p$

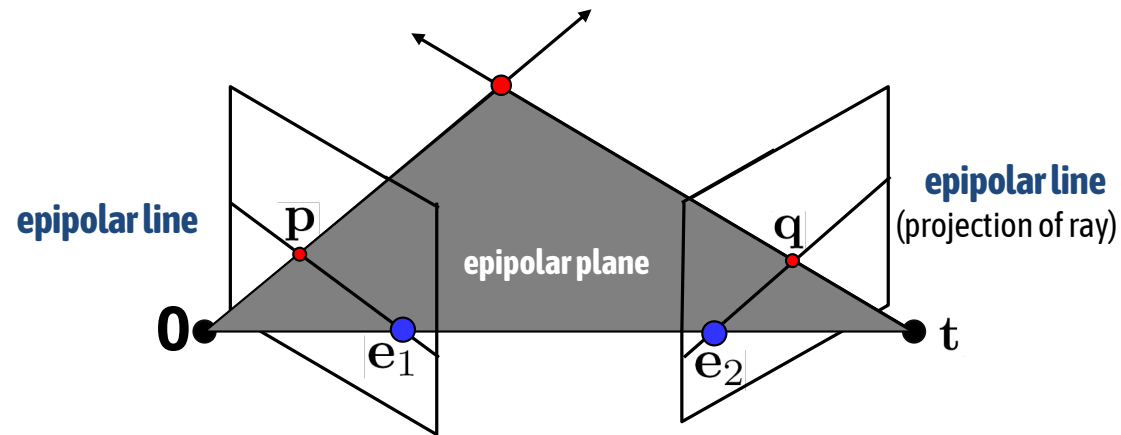
$$\mathbf{p} = \begin{bmatrix} p_x \\ p_y \\ 1 \end{bmatrix}, \quad \mathbf{q} = \begin{bmatrix} q_x \\ q_y \\ 1 \end{bmatrix} \quad \mathbf{l}' = \mathbf{F}\mathbf{p} = \begin{bmatrix} l'_a \\ l'_b \\ l'_c \end{bmatrix} \quad \mathbf{q}^T \mathbf{l}' = [q_x \quad q_y \quad 1] \begin{bmatrix} l'_a \\ l'_b \\ l'_c \end{bmatrix} = q_x l'_a + q_y l'_b + l'_c = 0$$

Fundamental matrix



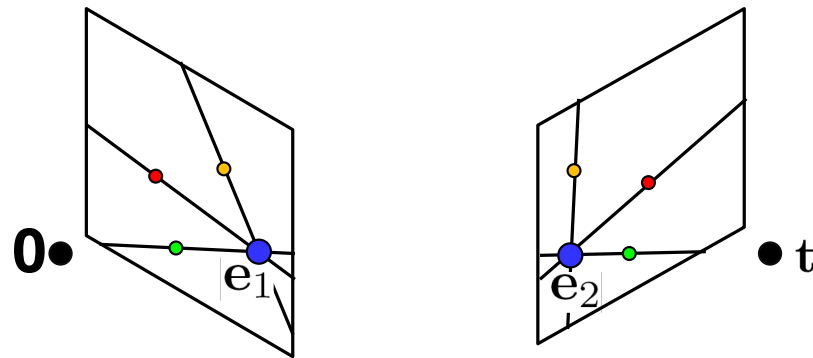
- Epipolar geometry, very special 3x3 fundamental matrix \mathbf{F}
- \mathbf{F} maps (homogeneous) *points* in image 1 to *lines* in image 2!
- The epipolar line (in image 2) of point \mathbf{p} is: $\mathbf{F}\mathbf{p}$
- Epipolar constraint on corresponding points: $\mathbf{q}^T \mathbf{F}\mathbf{p} = 0$

Fundamental matrix



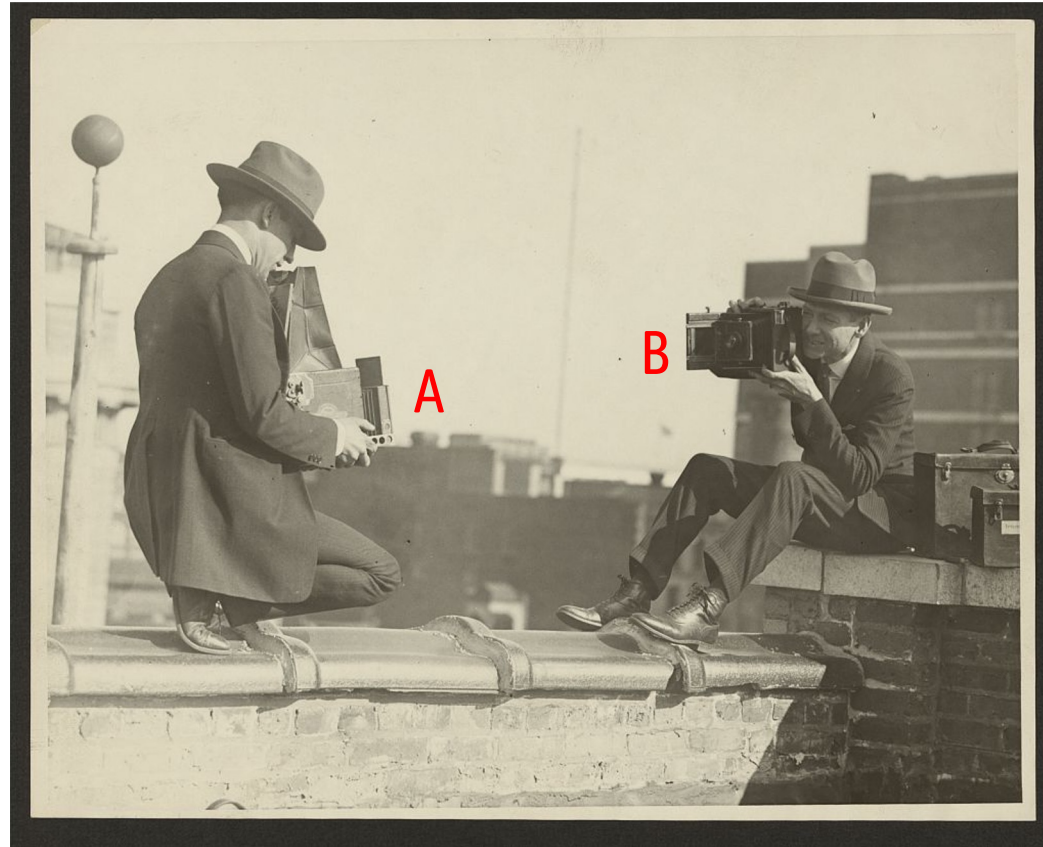
- Two Special points: e_1 and e_2 (the *epipoles*): projection of one camera into the other

Fundamental matrix



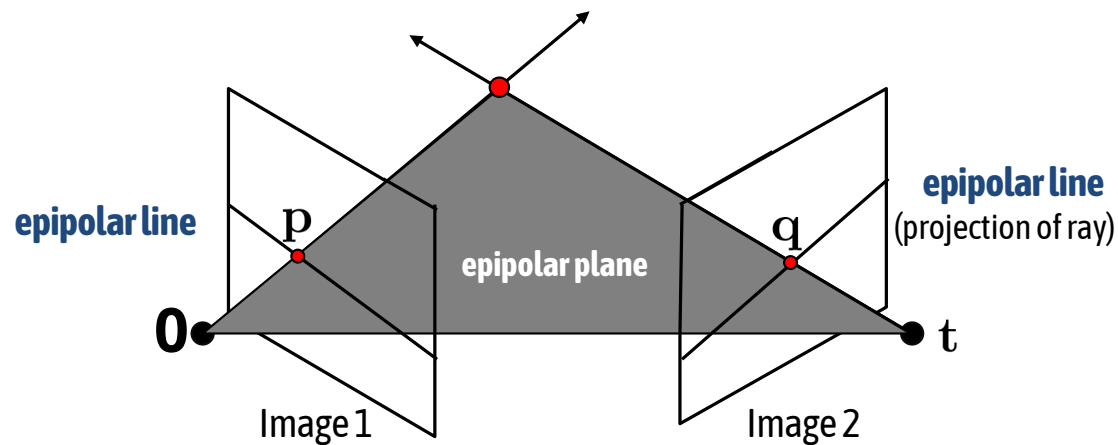
- Two Special points: e_1 and e_2 (the *epipoles*): projection of one camera into the other
- All of the epipolar lines in an image pass through the epipole
- Epipoles may or may not be inside the image

Epipoles



Properties of the Fundamental Matrix

- $\mathbf{F}\mathbf{p}$ is the epipolar line associated with \mathbf{p}
- $\mathbf{F}^T\mathbf{q}$ is the epipolar line associated with \mathbf{q}



$$\mathbf{q}^T \mathbf{F} \mathbf{p} = 0 \quad \Rightarrow \quad (\mathbf{F}^T \mathbf{q})^T \mathbf{p} = 0$$

Properties of the Fundamental Matrix

- $\overline{\mathbf{F}p}$ is the epipolar line associated with p
- $\mathbf{F}^T q$ is the epipolar line associated with q
- $\mathbf{F}e_1 = 0$ and $\mathbf{F}^T e_2 = 0$

$$q^T \mathbf{F} p = 0$$

$$e_2^T \mathbf{F} p = 0$$

$$\mathbf{F}^T e_2 = 0$$

$$\mathbf{F} e_1 = 0$$

Properties of the Fundamental Matrix

- $\overline{\mathbf{F}}\mathbf{p}$ is the epipolar line associated with \mathbf{p}
- $\mathbf{F}^T\mathbf{q}$ is the epipolar line associated with \mathbf{q}
- $\mathbf{F}\mathbf{e}_1 = \mathbf{0}$ and $\mathbf{F}^T\mathbf{e}_2 = \mathbf{0}$
- \mathbf{F} is rank 2

Properties of the Fundamental Matrix

- $\overline{\mathbf{Fp}}$ is the epipolar line associated with \mathbf{p}
- $\mathbf{F}^T \mathbf{q}$ is the epipolar line associated with \mathbf{q}
- $\mathbf{F}\mathbf{e}_1 = \mathbf{0}$ and $\mathbf{F}^T \mathbf{e}_2 = \mathbf{0}$
- \mathbf{F} is rank 2

Q: How many parameters (degrees of freedom) does \mathbf{F} have?

$$\mathbf{q}^T \mathbf{Fp} = 0$$

\mathbf{F} is rank 2

7 degrees of freedom

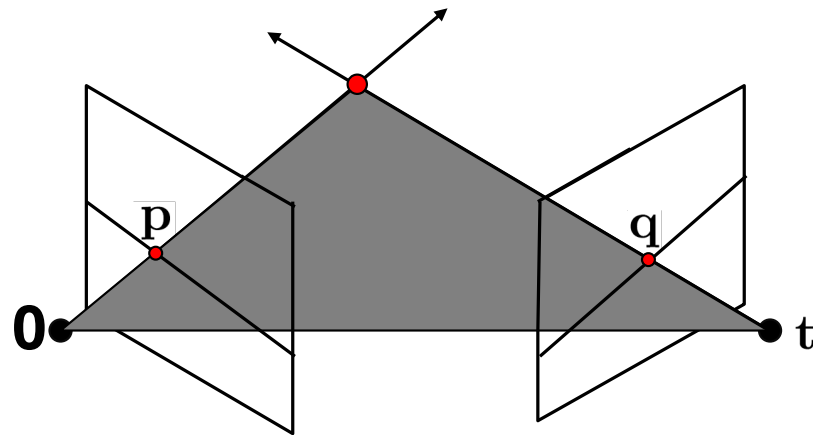
Example



Demo

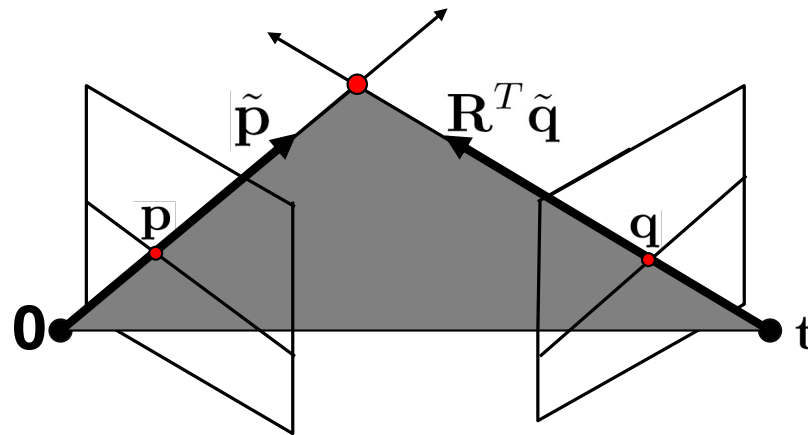
<https://www.cs.cornell.edu/courses/cs5670/2023sp/demos/FundamentalMatrix/?demo=demo1>

Fundamental matrix



- Why does \mathbf{F} exist?
- Let's derive it...

Fundamental matrix – calibrated case



\mathbf{K}_1 : intrinsics of camera 1

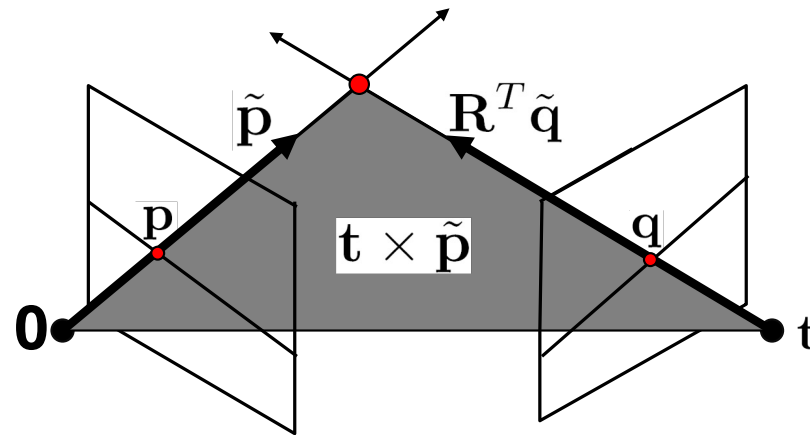
\mathbf{K}_2 : intrinsics of camera 2

\mathbf{R} : rotation of image 2 w.r.t. camera 1

$\tilde{\mathbf{p}} = \mathbf{K}_1^{-1} \mathbf{p}$: ray through \mathbf{p} in camera 1's (and world) coordinate system

$\tilde{\mathbf{q}} = \mathbf{K}_2^{-1} \mathbf{q}$: ray through \mathbf{q} in camera 2's coordinate system

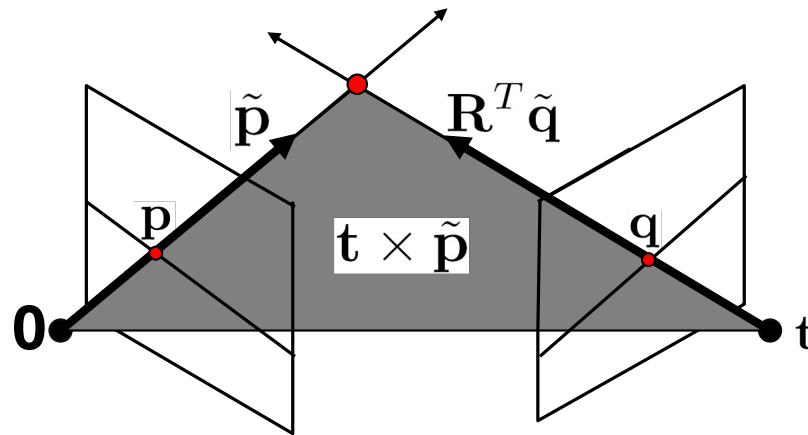
Fundamental matrix – calibrated case



- $\tilde{\mathbf{p}}, \mathbf{R}^T \tilde{\mathbf{q}}$ and \mathbf{t} are coplanar
- epipolar plane can be represented as with its normal $\mathbf{t} \times \tilde{\mathbf{p}}$

$$(\mathbf{R}^T \tilde{\mathbf{q}})^T (\mathbf{t} \times \tilde{\mathbf{p}}) = 0$$

Fundamental matrix – calibrated case

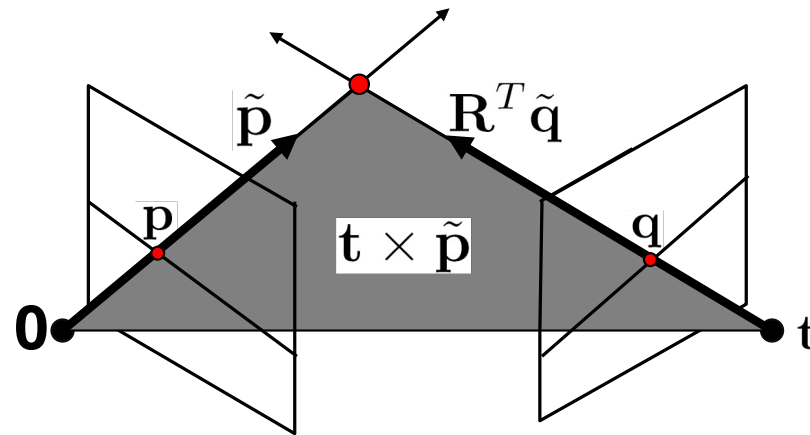


$$(\mathbf{R}^T \tilde{\mathbf{q}})^T (\mathbf{t} \times \tilde{\mathbf{p}}) = 0$$



$$\tilde{\mathbf{q}}^T \mathbf{R}(\mathbf{t} \times \tilde{\mathbf{p}}) = 0$$

Fundamental matrix – calibrated case

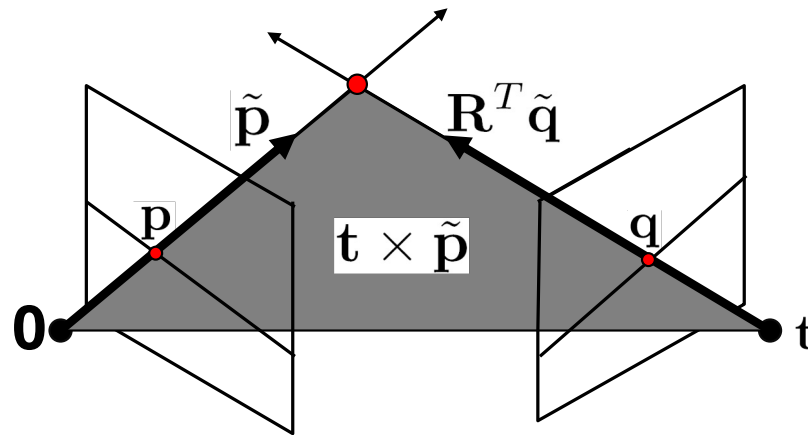


- One more substitution:

- Cross product with $\mathbf{t} = [t_x \ t_y \ t_z]$ (on left) can be represented as a 3x3 matrix

$$[\mathbf{t}]_{\times} = \begin{bmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{bmatrix} \quad \mathbf{t} \times \tilde{\mathbf{p}} = [\mathbf{t}]_{\times} \tilde{\mathbf{p}}$$

Fundamental matrix – calibrated case

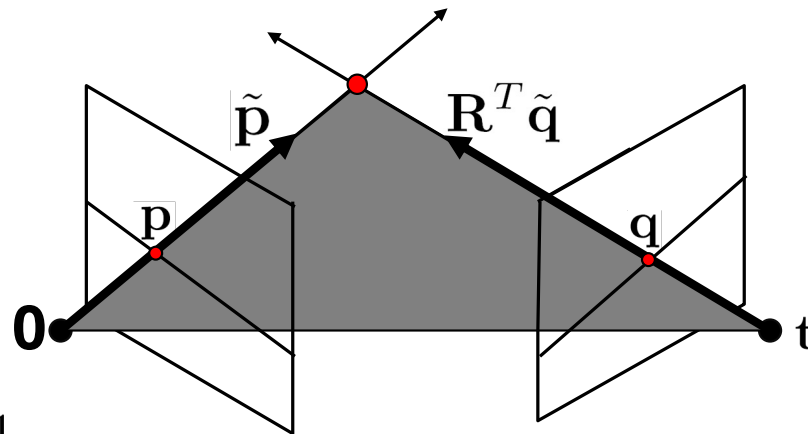


$$\tilde{q}^T \mathbf{R} (t \times \tilde{p}) = 0$$



$$\tilde{q}^T \mathbf{R} [t]_{\times} \tilde{p} = 0$$

Fundamental matrix – calibrated case



$\tilde{\mathbf{p}} = \mathbf{K}_1^{-1} \mathbf{p}$: ray through \mathbf{p} in camera 1's (and world) coordinate system

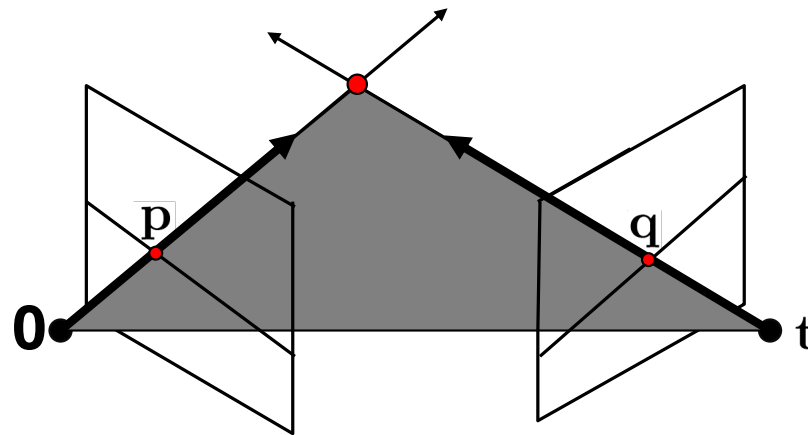
$\tilde{\mathbf{q}} = \mathbf{K}_2^{-1} \mathbf{q}$: ray through \mathbf{q} in camera 2's coordinate system

$$\underbrace{\tilde{\mathbf{q}}^T \mathbf{R} [\mathbf{t}]_{\times}}_{\mathbf{E}} \tilde{\mathbf{p}} = 0 \quad \tilde{\mathbf{q}}^T \mathbf{E} \tilde{\mathbf{p}} = 0$$

$$\mathbf{q}^T \mathbf{F} \mathbf{p} = 0$$

\mathbf{E} ← the Essential matrix

Fundamental matrix – uncalibrated case



\mathbf{K}_1 : intrinsics of camera 1

\mathbf{K}_2 : intrinsics of camera 2

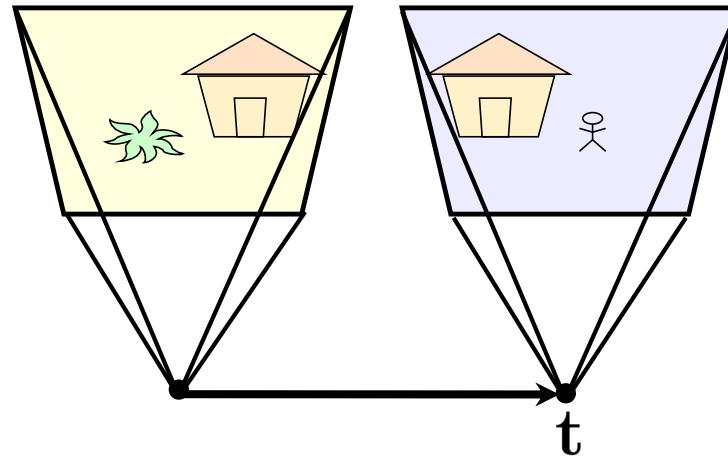
\mathbf{R} : rotation of image 2 w.r.t. camera 1

$$\mathbf{q}^T \underbrace{\mathbf{K}_2^{-T} \mathbf{R} [\mathbf{t}]_{\times} \mathbf{K}_1^{-1}}_{\mathbf{F}} \mathbf{p} = 0$$

$$\mathbf{q}^T \mathbf{F} \mathbf{p} = 0$$

\mathbf{F} ← the Fundamental matrix

Rectified case



$$\mathbf{R} = \mathbf{I}_{3 \times 3}$$

$$\mathbf{t} = [1 \quad 0 \quad 0]^T$$

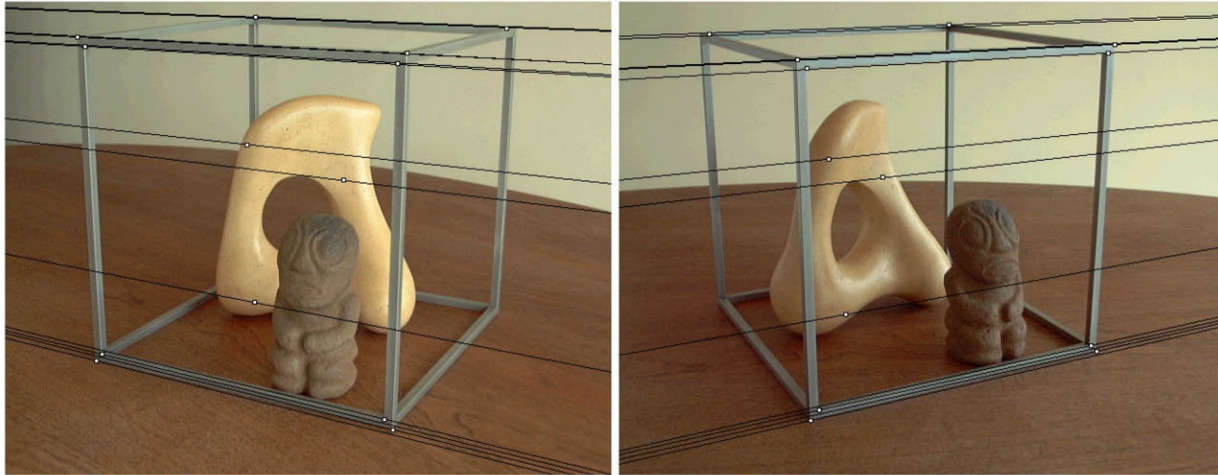
$$\mathbf{E} = \mathbf{R} [\mathbf{t}]_{\times} = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

Working out the math

- For a point $[a, b, 1]^T$ in image 1:
$$\begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix} \begin{bmatrix} a \\ b \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ -1 \\ b \end{bmatrix}$$

- Its corresponding point $[x, y, 1]^T$ in image 2 must satisfy:

$$[x \quad y \quad 1] \cdot \begin{bmatrix} 0 \\ -1 \\ b \end{bmatrix} = 0 \quad \Rightarrow \quad y = b$$



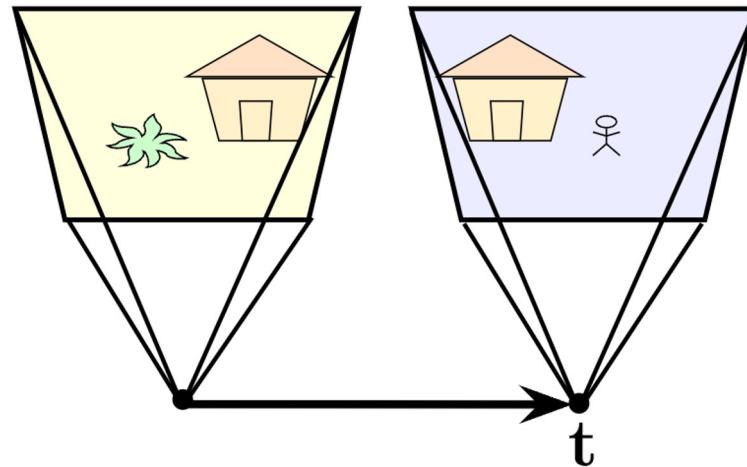
Original stereo pair



After rectification

$$y = b$$

Rectified case



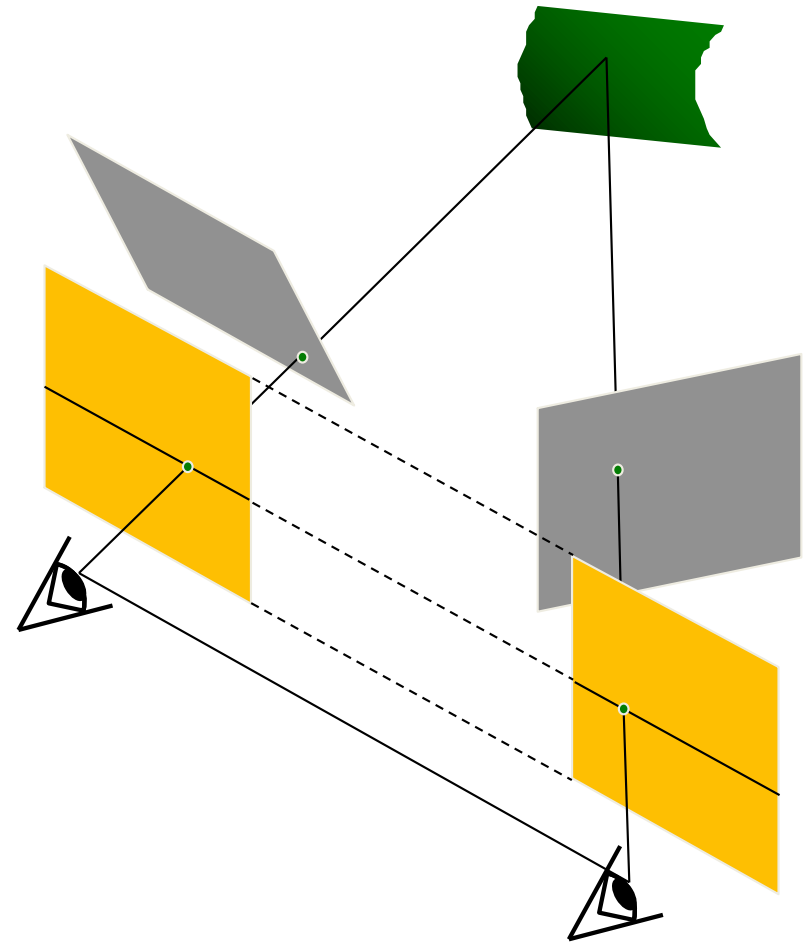
$$\mathbf{R} = \mathbf{I}_{3 \times 3}$$

$$\mathbf{t} = [1 \quad 0 \quad 0]^T$$

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

Stereo image rectification

- Reproject image planes onto a common plane
 - Plane parallel to the line between optical centers
- Pixel motion is horizontal after this transformation
- Two homographies, one for each input image
 - C. Loop and Z. Zhang. [Computing Rectifying Homographies for Stereo Vision](#). CVPR1999.



Questions?

Estimating \mathbf{F}



- If we don't know \mathbf{K}_1 , \mathbf{K}_2 , \mathbf{R} , or \mathbf{t} , can we estimate \mathbf{F} for two images?
- Yes, given enough correspondences

Estimating \mathbf{F} – 8-point algorithm

- The fundamental matrix \mathbf{F} is defined by

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

for any pair of matches \mathbf{x} and \mathbf{x}' in two images.

- Let $\mathbf{x}=(u,v,1)^T$ and $\mathbf{x}'=(u',v',1)^T$ $\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$

each match gives a linear equation

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

8-point algorithm

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

- Like with homographies, instead of solving $\mathbf{A}\mathbf{f} = \mathbf{0}$ we seek unit length \mathbf{f} to minimize $\|\mathbf{A}\mathbf{f}\|$: least eigenvector of $\mathbf{A}^T\mathbf{A}$

8-point algorithm – Problem?

- \mathbf{F} should have rank 2
- To enforce that \mathbf{F} is of rank 2, \mathbf{F} is replaced by \mathbf{F}' that minimizes $\|\mathbf{F} - \mathbf{F}'\|$ subject to the rank constraint.
- This is achieved by SVD. Let $\mathbf{F} = \mathbf{U}\Sigma\mathbf{V}^T$, where

$$\Sigma = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix}, \text{ let } \Sigma' = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

then $\mathbf{F}' = \mathbf{U}\Sigma'\mathbf{V}^T$ is the solution (closest rank-2 matrix to \mathbf{F})

8-point algorithm

```
% Build the constraint matrix
A = [x2(1,:)'.*x1(1,:) '  x2(1,:)'.*x1(2,:) '  x2(1,:) ' ...
     x2(2,:)'.*x1(1,:) '  x2(2,:)'.*x1(2,:) '  x2(2,:) ' ...
     x1(1,:) '           x1(2,:) '           ones(npts,1) ];
```

```
[U,D,V] = svd(A);
```

```
% Extract fundamental matrix from the column of V
% corresponding to the smallest singular value.
```

```
F = reshape(V(:,9),3,3)';
```

```
% Enforce rank2 constraint
```

```
[U,D,V] = svd(F);
```

```
F = U*diag([D(1,1) D(2,2) 0])*V';
```

$$\begin{aligned} A &= U\Sigma V^T && \text{SVD of A (V is orthogonal)} \\ A^T A &= (U\Sigma V^T)^T (U\Sigma V^T) \\ A^T A &= V\Sigma^T U^T U\Sigma V^T \\ A^T A &= V\Sigma^2 V^T && \text{Eigen decomposition of } A^T A \end{aligned}$$

8-point algorithm

- Pros: linear, easy to implement and fast
- Cons: sensitive to noise

Problem with 8-point algorithm

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

~ 10000 ~ 10000 ~ 100 ~ 10000 ~ 10000 ~ 100 ~ 100 ~ 100 1

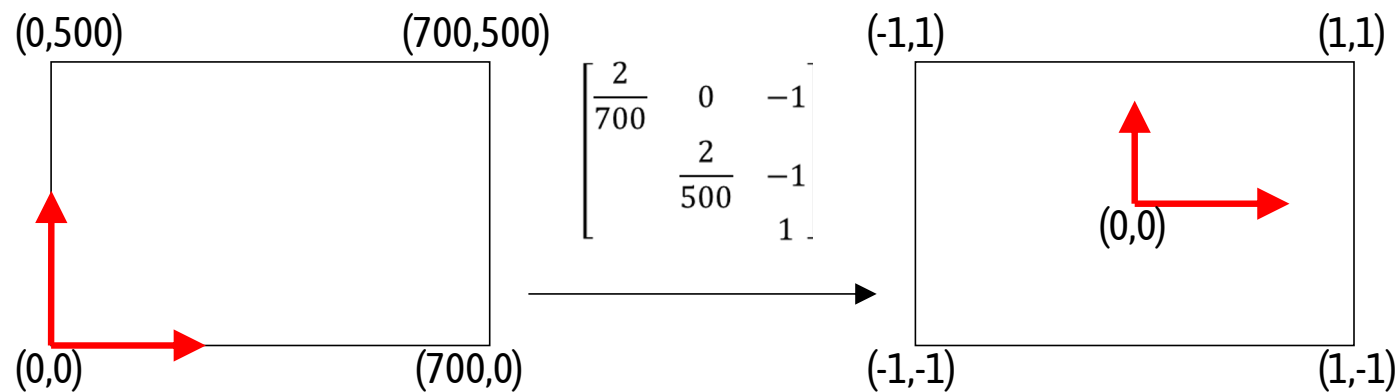


Orders of magnitude difference
 between column of data matrix
 → least-squares yields poor results

Normalized 8-point algorithm

normalized least squares yields good results

Transform image to $\sim[-1,1] \times [-1,1]$



Normalized 8-point algorithm

- Transform input by $\hat{\mathbf{x}}_i = \mathbf{T}\mathbf{x}_i$, $\hat{\mathbf{x}}'_i = \mathbf{T}'\mathbf{x}'_i$
- Call 8-point on $\hat{\mathbf{x}}_i, \hat{\mathbf{x}}'_i$ to obtain $\hat{\mathbf{F}}$
- $\mathbf{F} = \mathbf{T}'^T \hat{\mathbf{F}} \mathbf{T}$

$$\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0$$
$$\hat{\mathbf{x}}'^T \mathbf{T}'^{-T} \mathbf{F} \mathbf{T}^{-1} \hat{\mathbf{x}} = 0$$

$\hat{\mathbf{F}}$

Normalized 8-point algorithm

```
[x1, T1] = normalise2dpts(x1);
[x2, T2] = normalise2dpts(x2);

A = [x2(1,:)'.*x1(1,:) '   x2(1,:)'.*x1(2,:) '   x2(1,:) '   ...
     x2(2,:)'.*x1(1,:) '   x2(2,:)'.*x1(2,:) '   x2(2,:) '   ...
     x1(1,:) '             x1(2,:) '             ones(npts,1)
     ];

[U,D,V] = svd(A);

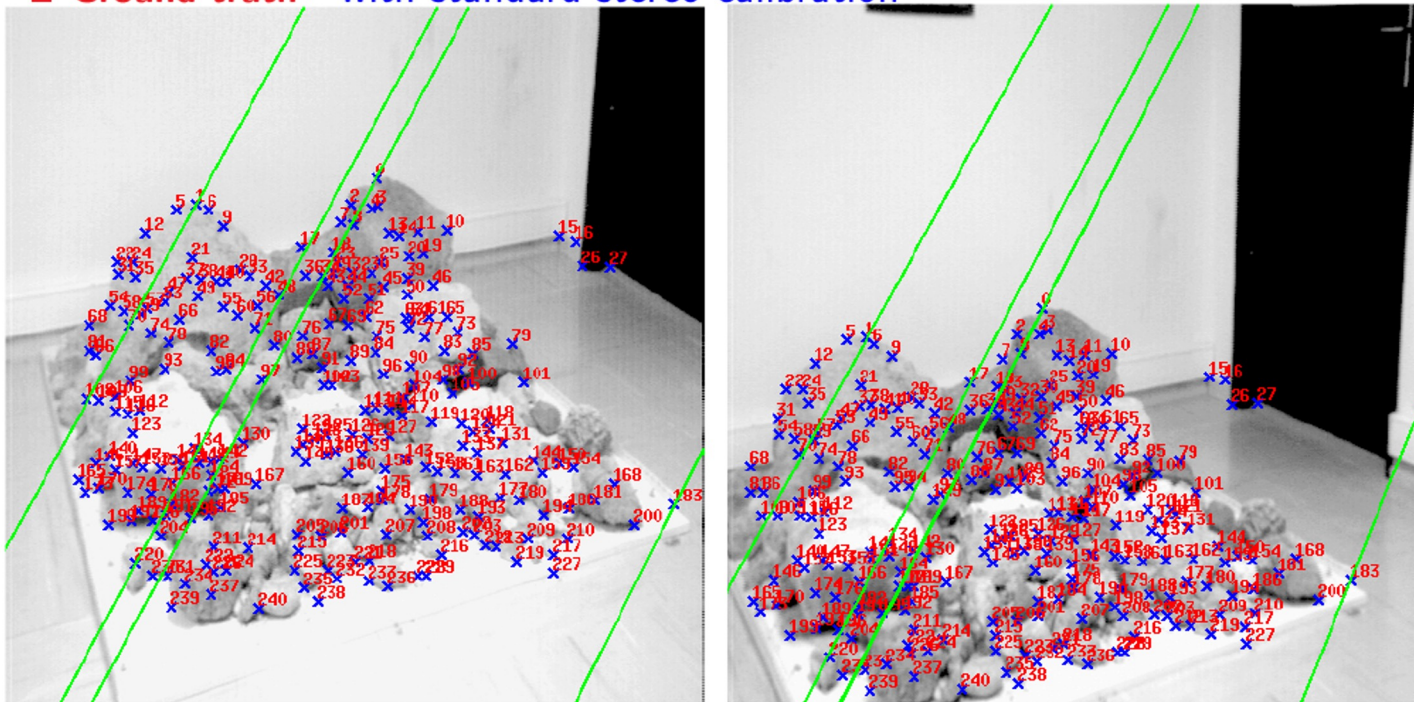
F = reshape(V(:,9),3,3)';

[U,D,V] = svd(F);
F = U*diag([D(1,1) D(2,2) 0])*V';

% Denormalise
F = T2'*F*T1;
```

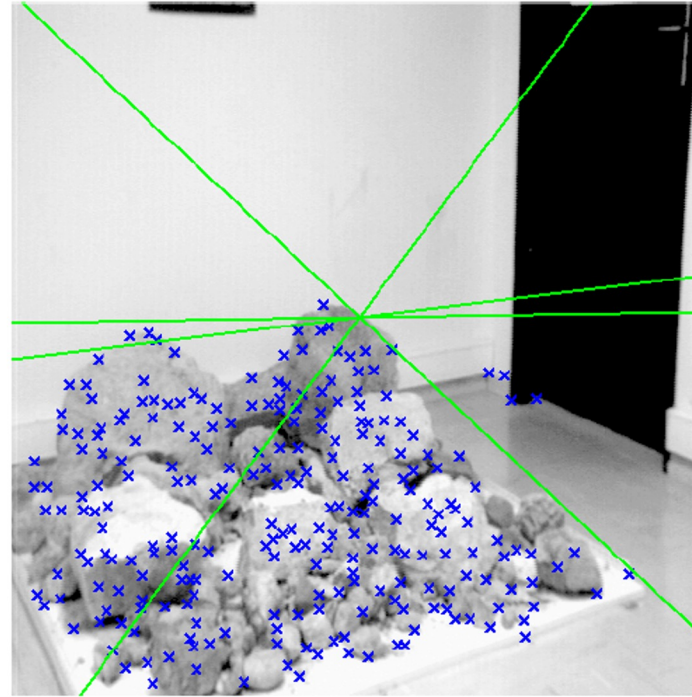
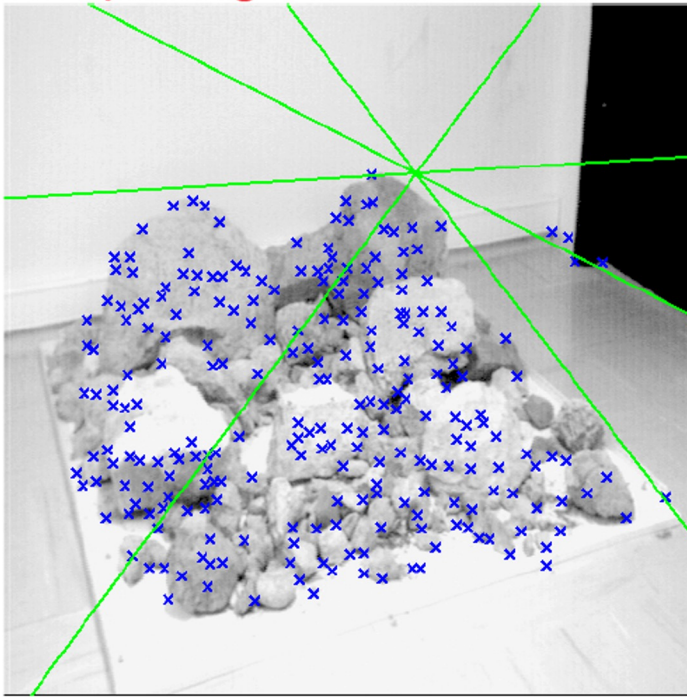
Results (ground truth)

■ Ground truth with standard stereo calibration



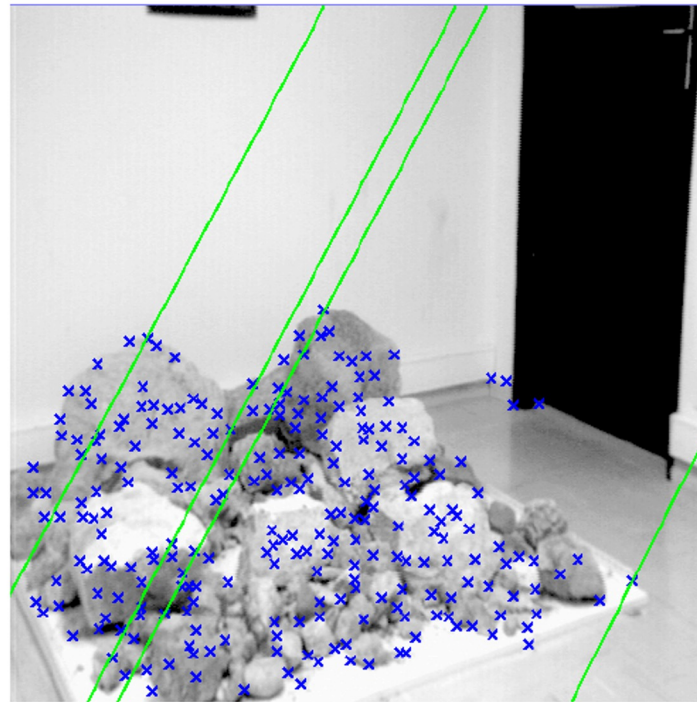
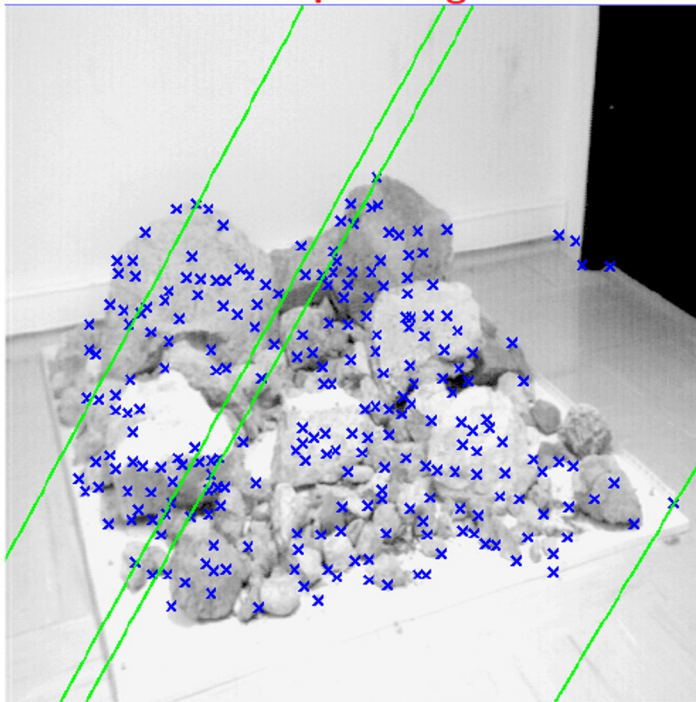
Results (8-point algorithm)

■ 8-point algorithm



Results (normalized 8-point algorithm)

■ Normalized 8-point algorithm



What about more than two views?

- The geometry of three views is described by a $3 \times 3 \times 3$ tensor called the *trifocal tensor*
- The geometry of four views is described by a $3 \times 3 \times 3 \times 3$ tensor called the *quadrifocal tensor*
- After this it starts to get complicated...

Next time: Large-scale structure from motion



Dubrovnik, Croatia. 4,619 images (out of an initial 57,845).

Total reconstruction time: 23 hours

Number of cores: 352

Fundamental matrix song

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

Questions?