

電腦視覺與應用

Computer Vision and Applications

Lecture-06-1 Two-views geometry

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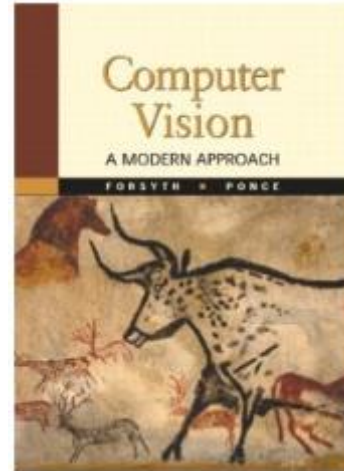
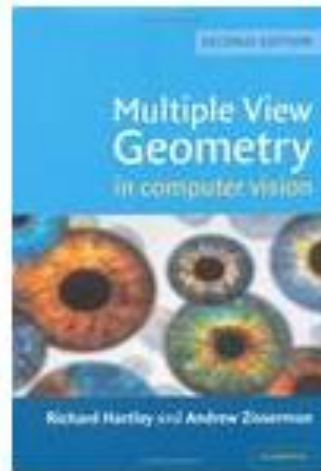
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Two-views geometry

- Description for *fundamental matrix*, \mathbf{F} , and *essential matrix*, \mathbf{E}
- Lecture Reference at:
 - Multiple View Geometry in Computer Vision, [Chapter 9, 11](#)
 - Computer Vision A Modern Approach, [Chapter 10](#).





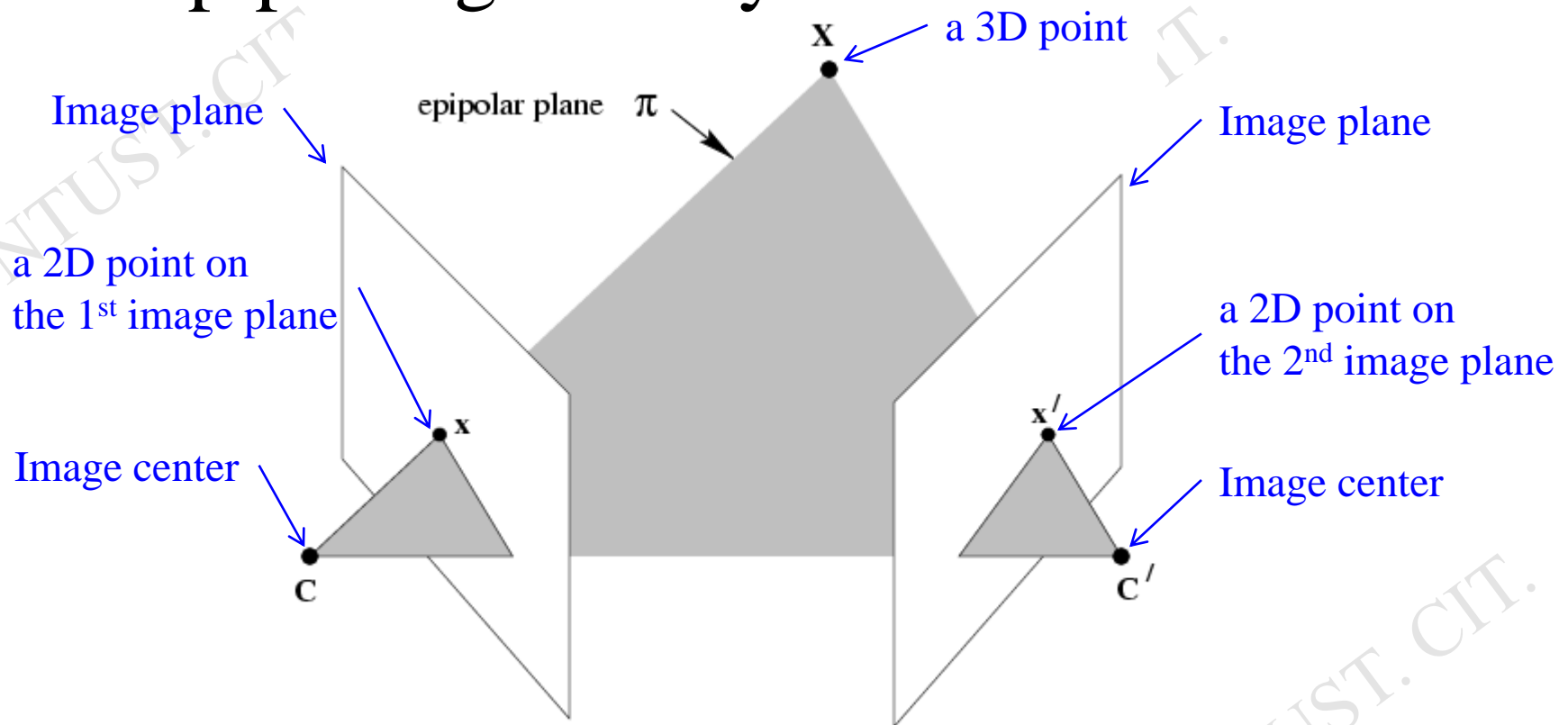
Two-views geometry – Outline

- epipole
- epipolar line
- epipolar plane

- Fundamental matrix \mathbf{F}
- Essential matrix $\mathbf{E} \rightarrow$ special case of \mathbf{F}
- Computation for *Fundamental Matrix* \mathbf{F}



The epipolar geometry



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

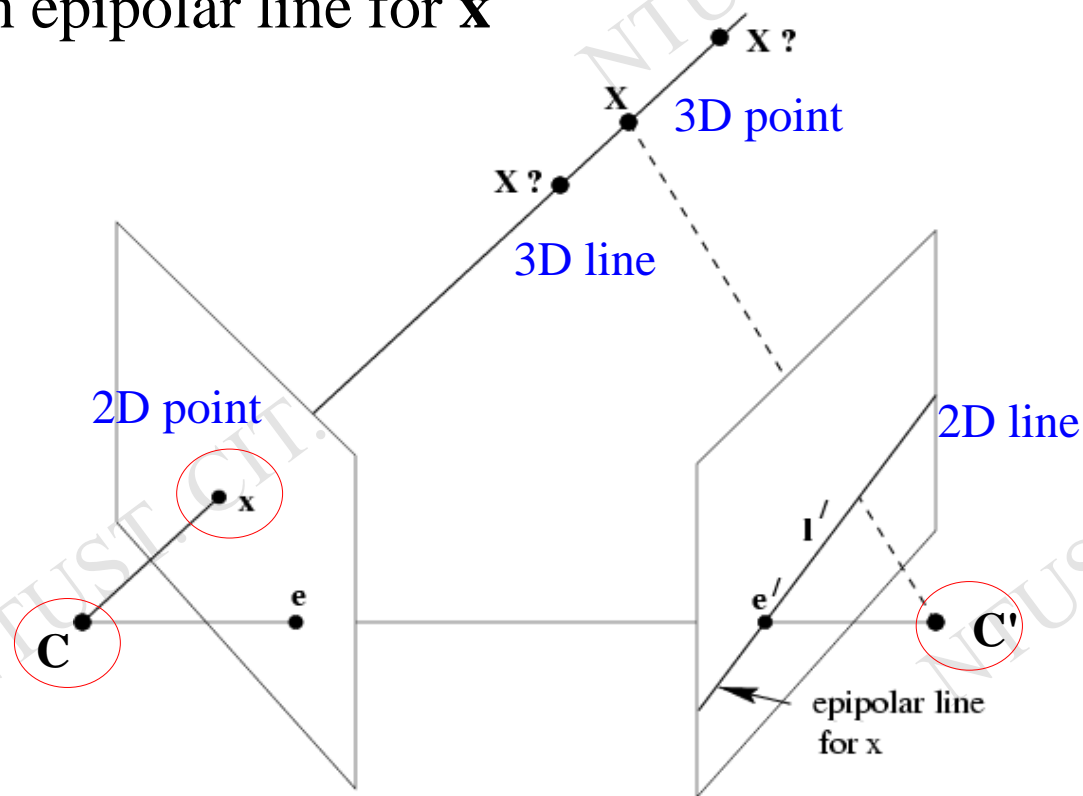
Note:

Two images may have different intrinsic parameter, be taken at either the same or different periods.



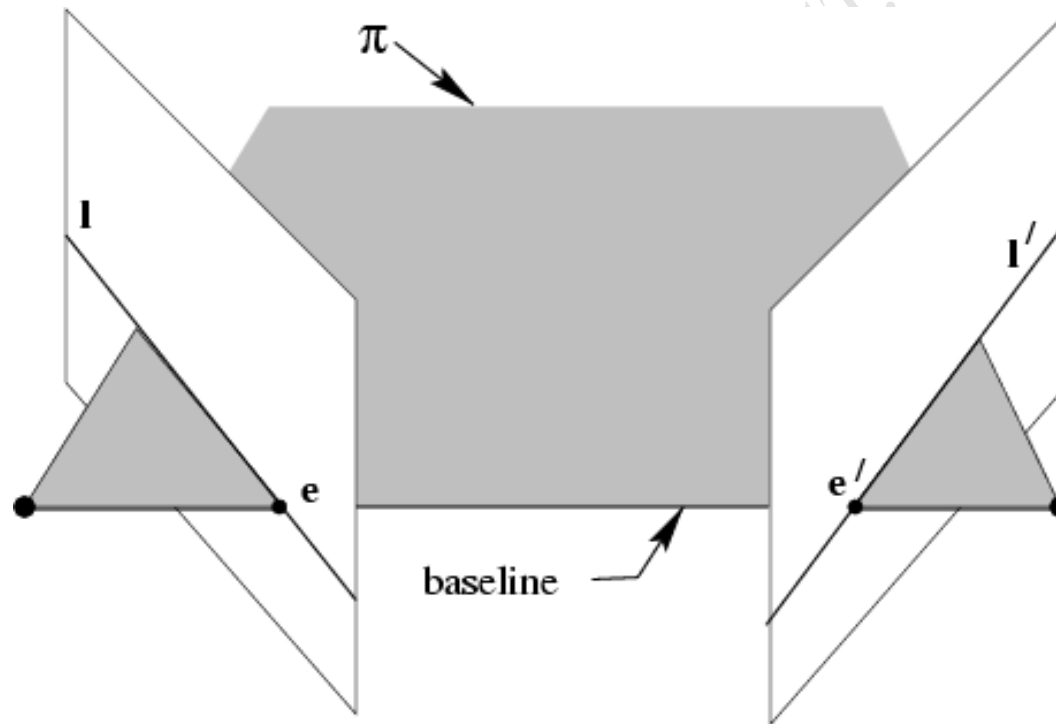
The epipolar geometry

- In case of given \mathbf{c} , \mathbf{c}' (says \mathbf{e} , \mathbf{e}' as well) and \mathbf{x}
→ define an epipolar line for \mathbf{x}





The epipolar geometry

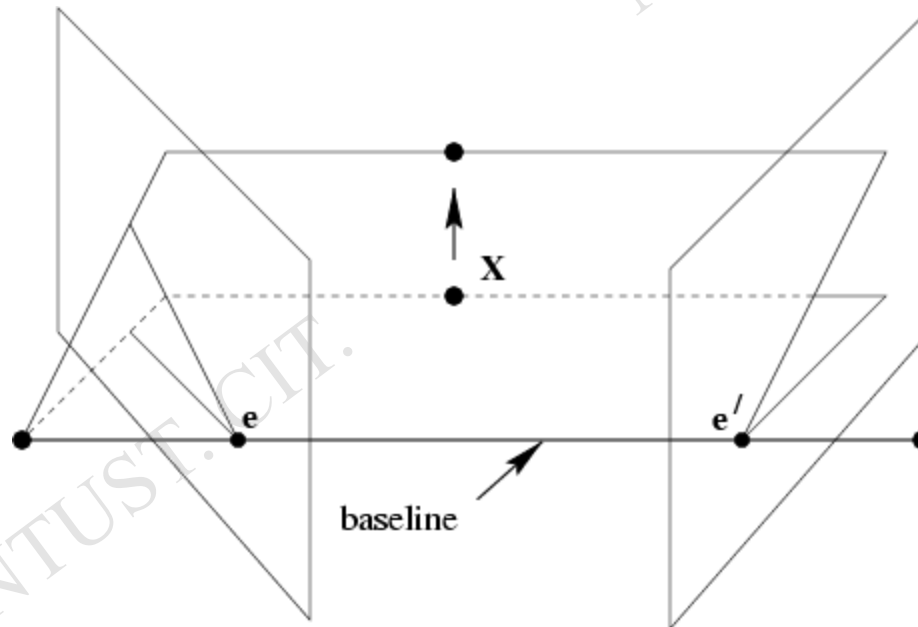


All points on π project on l and l'



The epipolar geometry

- Family of planes π and lines l and l' intersection in e and e'





The epipolar geometry

- Summary for definition

- **epipoles** e, e'

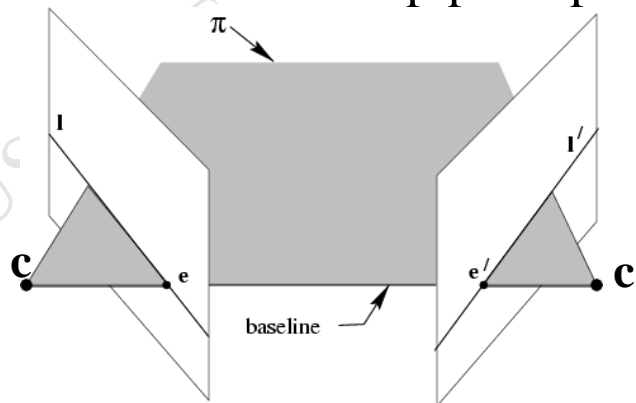
= intersection of baseline with image plane

= projection of projection center in other image

= vanishing point of camera motion direction

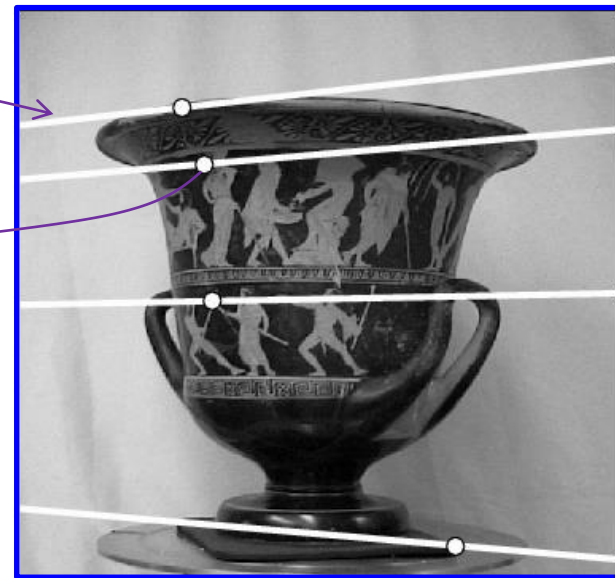
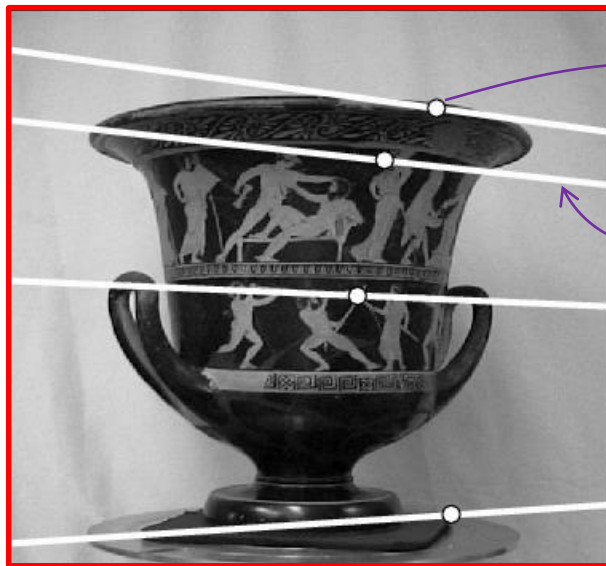
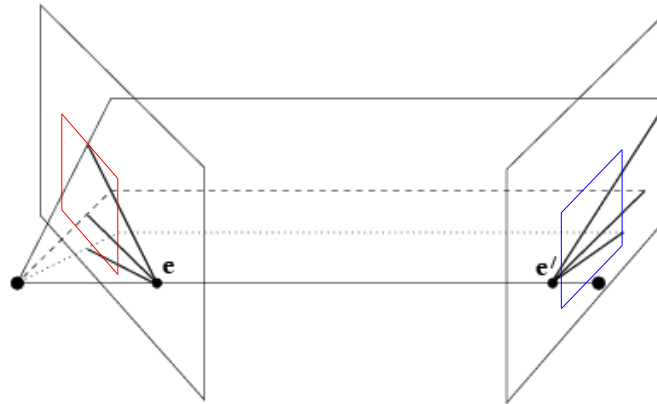
- **epipolar plane** = plane containing baseline

- **epipolar line** = intersection of epipolar plane with image



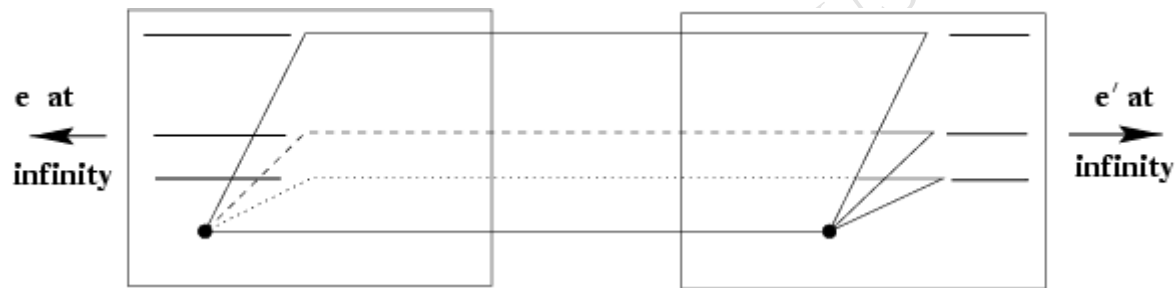


Example: converged stereo-camera



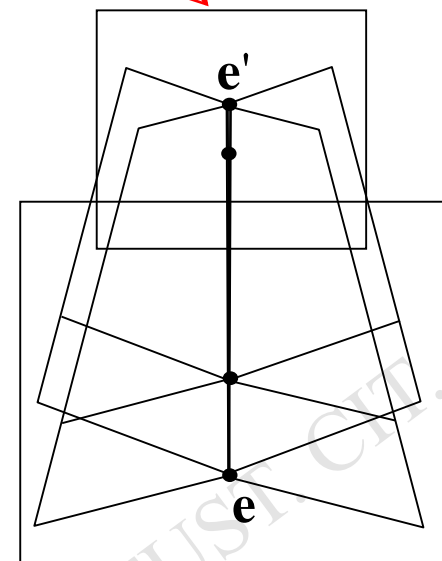
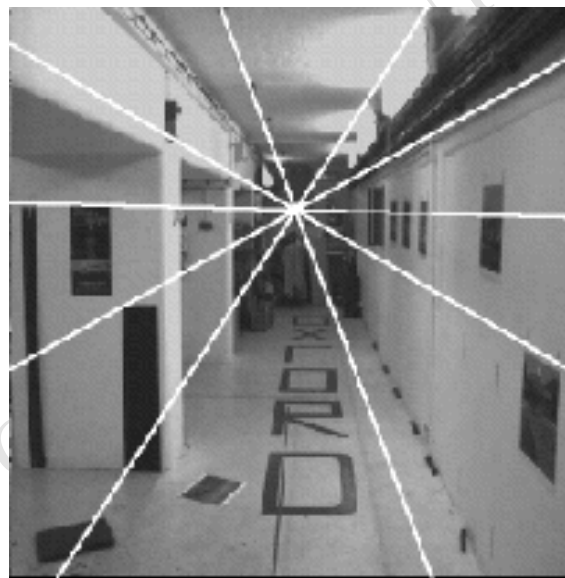
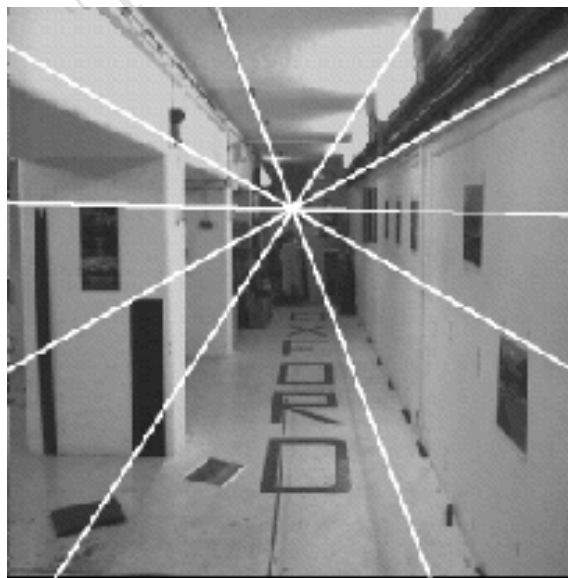


Example: motion parallel with image plane





Example: forward motion



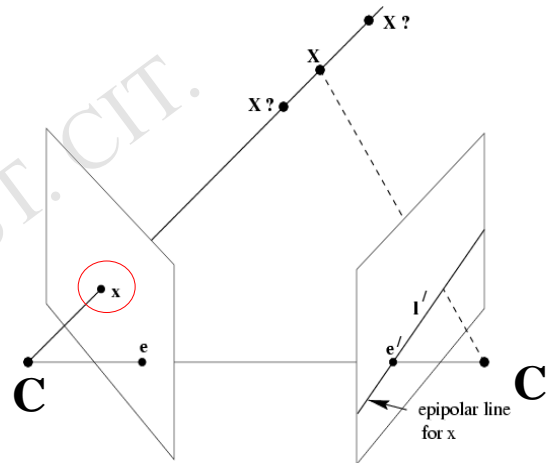


Fundamental matrix F

- Algebraic representation of epipolar geometry

$$\mathbf{x} \mapsto \mathbf{l}'$$

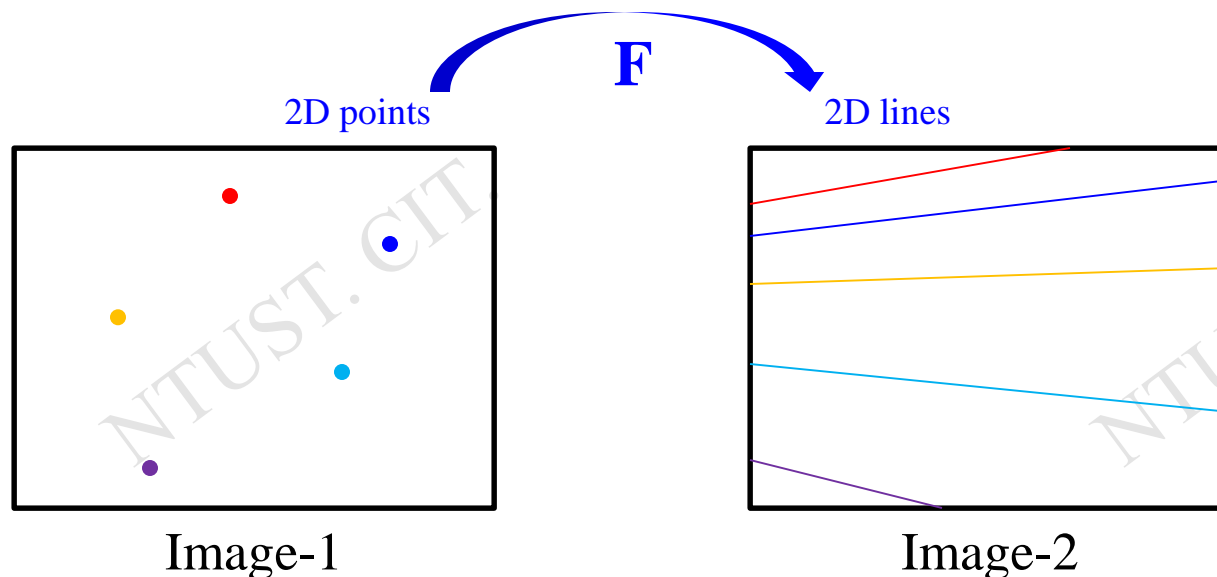
- We will see that mapping is (singular) correlation (i.e. projective mapping from points to lines) represented by the fundamental matrix F .
- 註：已知兩張照片的 F 轉換，可從一張影像的特徵點，可以預估這些特徵點會落在另一張影像上的線上(一個點產生一條線)





Fundamental matrix F

- Points(or features) in image-1 are mapped into lines in image-2 by applying a 3×3 matrix F .
- Note!!! all points in image-1 are NOT necessary to be co-planar in 3D space. (different from 3×3 homography)





Fundamental matrix F

•How to determine F from two images?(from textbook Hartley04)

- 1) Using known 3x3 Homography (3D points on one plane) and the epipole
- 2) Algebraic method
- 3) Using known correspondences (feature matching between two images)→most popular method in practice



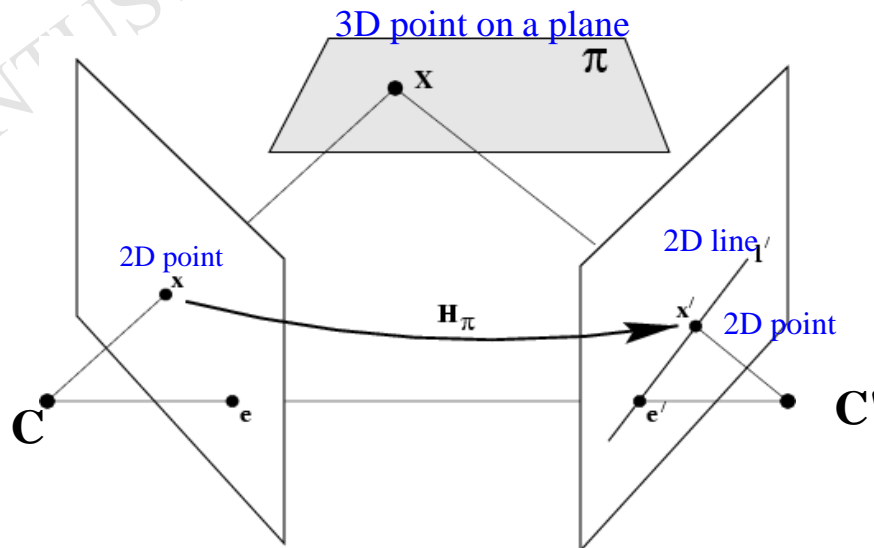
Determine fundamental matrix F

- 1) from 3×3 homography
- 2) from algebraic derivation
- 3) from correspondence from two-views



Determine fundamental matrix F

■ 1) from 3x3 homography



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

$$\mathbf{l}' = \mathbf{e}' \times \mathbf{x}' = \mathbf{e}' \times (\mathbf{H}_\pi \mathbf{x}) = ([\mathbf{e}']_\times \mathbf{H}_\pi) \mathbf{x} = \mathbf{F} \mathbf{x}$$

epipole (vector)

epipole (matrix)

Note! notation

vector

real (實數, 純量)

$$\mathbf{e}' = [e_1' \ e_2' \ e_3']^T$$

matrix (for calculation purpose)

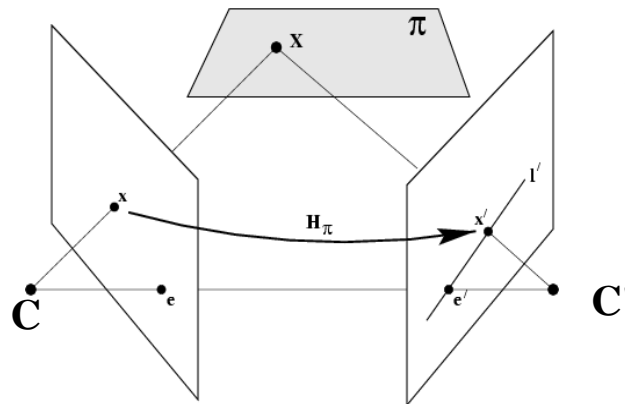
real (實數, 純量)

$$[\mathbf{e}']_\times = \begin{bmatrix} 0 & -e_3' & e_2' \\ e_3' & 0 & -e_1' \\ -e_2' & e_1' & 0 \end{bmatrix}$$



Determine fundamental matrix F

- 1) from 3x3 homography—cont.



$$\mathbf{x}' = \mathbf{H}_{\pi} \mathbf{x} \quad \rightarrow (3 \times 3) \text{ homography mapping} \\ \text{2D points mapping to 2D points}$$

$$\mathbf{l}' = \mathbf{F} \mathbf{x} \quad \rightarrow \text{2-Dimensional Mapping}$$



Determine fundamental matrix F

- 2) from algebraic derivation

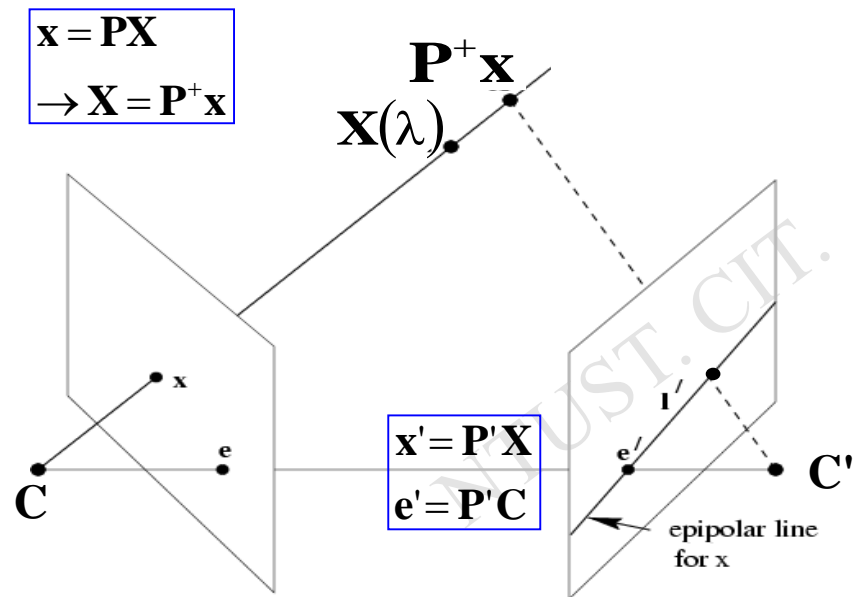
$$(\mathbf{P}^+ \mathbf{P} = \mathbf{I})$$

$$\mathbf{X}(\lambda) = \mathbf{P}^+ \mathbf{x} + \lambda \mathbf{C}$$

$$\mathbf{l}' = \mathbf{P}' \mathbf{C} \times \mathbf{P}' \mathbf{P}^+ \mathbf{x}$$

$$\mathbf{F} = [\mathbf{e}']_{\times} \mathbf{P}' \mathbf{P}^+$$

This method is the same formula with the previous method, by replace $\mathbf{P}' \mathbf{P}^+$ with \mathbf{H}_{π}





Determine fundamental matrix F

- 3) from correspondence from two-views
 - correspondence condition
 - The fundamental matrix satisfies the condition that for **any pair** of corresponding points $\mathbf{x} \leftrightarrow \mathbf{x}'$ in the two images
(one point on one line could be written as:)

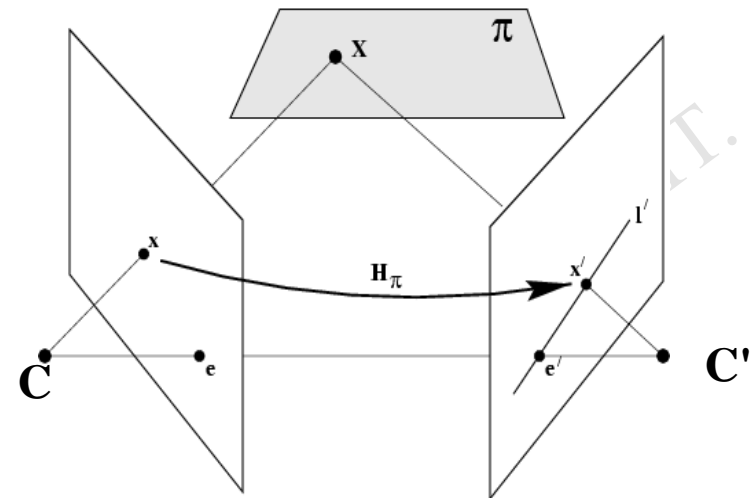
$$\mathbf{x}^T \mathbf{l} = 0 = \mathbf{l}^T \mathbf{x}$$

So, the governing equation will be

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

Since we have the following equation in image-2.

$$\because \mathbf{x}'^T \mathbf{l}' = 0$$





Determine fundamental matrix F

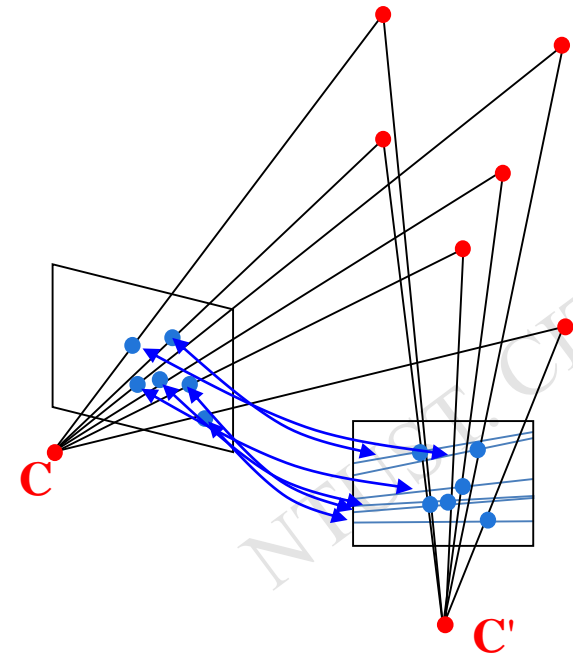
- 3) from correspondence from two-views—cont.
 - So called **Weak calibration** (for determining F in two views)

General form:

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

Written in matrix form:

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



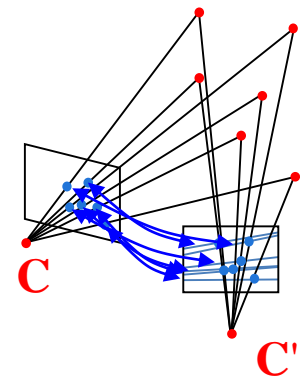


Determine fundamental matrix F

■ 3) from correspondence from two-views—cont.

■ Weak calibration

$$[u' \quad v' \quad 1] \begin{bmatrix} F_{11} & F_{12} & F_{13} \\ F_{21} & F_{22} & F_{23} \\ F_{31} & F_{32} & F_{33} \end{bmatrix} \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = 0$$



$$\rightarrow F_{11}u'u + F_{12}u'v + F_{13}u' + F_{21}uv' + F_{22}vv' + F_{23}v' + F_{31}u + F_{32}v + F_{33} = 0$$

Since F has 9-1 DOF, let $F_{33}=1$ and solving F .

In matrix form \rightarrow

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

8 unknowns, and one correspondence gives one constraint. It needs at least **8 correspondences**.

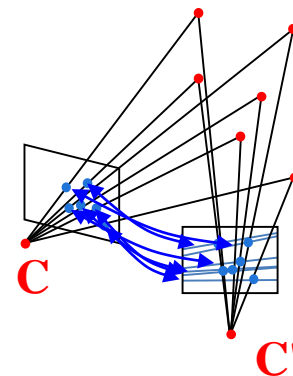


Determine fundamental matrix F

- 3) from correspondence from two-views—cont.
- Weak calibration

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

$$\begin{bmatrix} u_1'u_1 & u_1'v_1 & u_1' & u_1v_1' & v_1v_1' & v_1' & u_1 & v_1 \\ u_2'u_2 & u_2'v_2 & u_2' & u_2v_2' & v_2v_2' & v_2' & u_2 & v_2 \\ u_3'u_3 & u_3'v_3 & u_3' & u_3v_3' & v_3v_3' & v_3' & u_3 & v_3 \\ u_4'u_4 & u_4'v_4 & u_4' & u_4v_4' & v_4v_4' & v_4' & u_4 & v_4 \\ u_5'u_5 & u_5'v_5 & u_5' & u_5v_5' & v_5v_5' & v_5' & u_5 & v_5 \\ u_6'u_6 & u_6'v_6 & u_6' & u_6v_6' & v_6v_6' & v_6' & u_6 & v_6 \\ u_7'u_7 & u_7'v_7 & u_7' & u_7v_7' & v_7v_7' & v_7' & u_7 & v_7 \\ u_8'u_8 & u_8'v_8 & u_8' & u_8v_8' & v_8v_8' & v_8' & u_8 & v_8 \end{bmatrix} \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \end{bmatrix} = \begin{bmatrix} -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \end{bmatrix}$$



Solve F by taking an inverse operation to the above equation.

If you get more than 8 correspondences, least-square method or SVD may be used.

NOTE!! Since the order in every column is very different. The 1st column has values around $10^4 \sim 10^6$, but the 3th column is $10^2 \sim 10^3$. Without normalized, Least-Square-Method may yield poor results.



Property of the fundamental matrix F

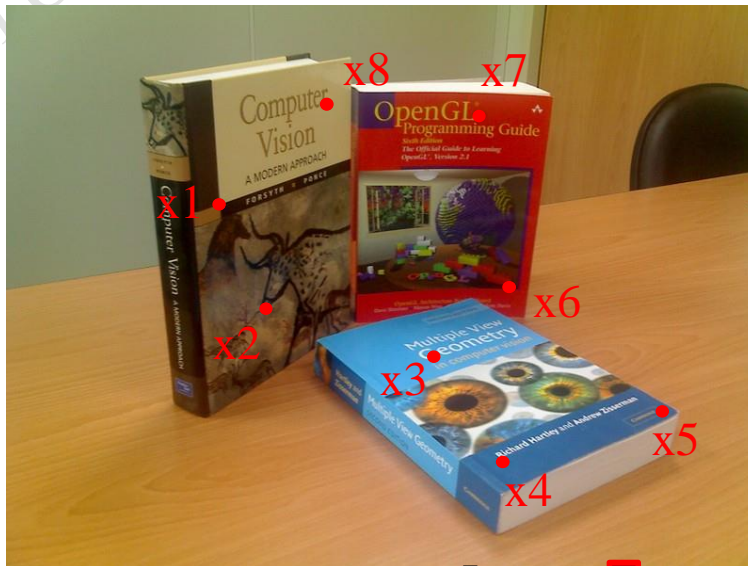
- F is the unique 3×3 rank 2 matrix that satisfies $\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0$ for all $\mathbf{x} \leftrightarrow \mathbf{x}'$

- 1) **Transpose:** if F is fundamental matrix for the pair of cameras (P, P') , then F^T is fundamental matrix for (P', P)
- 2) **Epipolar lines:** $\mathbf{l}' = \mathbf{F} \mathbf{x}$ & $\mathbf{l} = \mathbf{F}^T \mathbf{x}'$
- 3) **Epipoles:** on all epipolar lines, thus $\mathbf{e}'^T \mathbf{F} \mathbf{x} = 0, \forall \mathbf{x} \Rightarrow \mathbf{e}'^T \mathbf{F} = 0$, similarly $\mathbf{F} \mathbf{e} = 0$
- 4) F has 7 DOF, i.e. $3 \times 3 - 1$ (homogeneous) - 1 (rank 2)
- 5) F is a correlation, projective mapping from a point \mathbf{x} to a line $\mathbf{l}' = \mathbf{F} \mathbf{x}$ (not a proper correlation, i.e. not invertible)

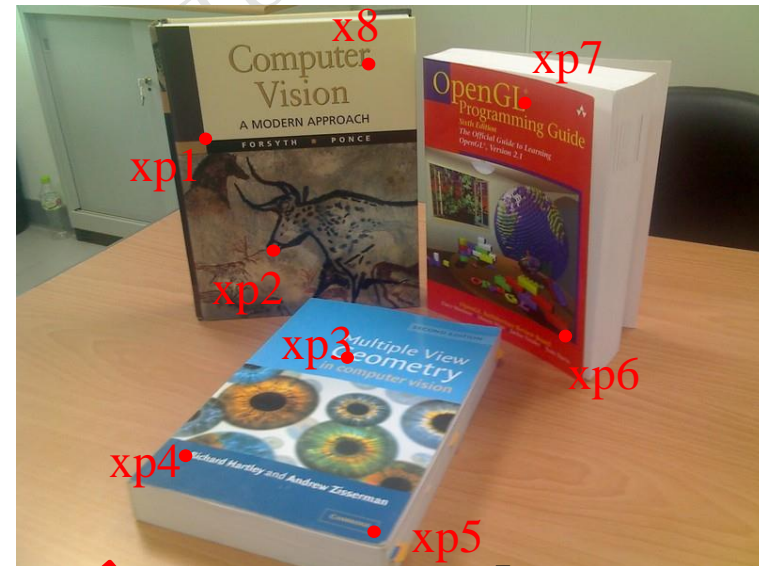


Determine fundamental matrix F

■ correspondence from two-views—example



$x_1 = [227, 212, 1]^T$
 $x_2 = [275, 322, 1]^T$
 $x_3 = [449, 370, 1]^T$
 $x_4 = [525, 481, 1]^T$
 $x_5 = [699, 432, 1]^T$
 $x_6 = [535, 298, 1]^T$
 $x_7 = [498, 118, 1]^T$
 $x_8 = [339, 106, 1]^T$



$x_{p1} = [201, 144, 1]^T$
 $x_{p2} = [275, 261, 1]^T$
 $x_{p3} = [349, 369, 1]^T$
 $x_{p4} = [182, 479, 1]^T$
 $x_{p5} = [380, 562, 1]^T$
 $x_{p6} = [584, 351, 1]^T$
 $x_{p7} = [542, 108, 1]^T$
 $x_{p8} = [373, 64, 1]^T$

F?

Note! This is **NOT** 2D
point to point mapping



Determine fundamental matrix F

■ correspondence from two-views—example

$$\begin{bmatrix} u_1' u_1 & u_1' v_1 & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 \\ u_2' u_2 & u_2' v_2 & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 \\ u_3' u_3 & u_3' v_3 & u_3' & u_3 v_3' & v_3 v_3' & v_3' & u_3 & v_3 \\ u_4' u_4 & u_4' v_4 & u_4' & u_4 v_4' & v_4 v_4' & v_4' & u_4 & v_4 \\ u_5' u_5 & u_5' v_5 & u_5' & u_5 v_5' & v_5 v_5' & v_5' & u_5 & v_5 \\ u_6' u_6 & u_6' v_6 & u_6' & u_6 v_6' & v_6 v_6' & v_6' & u_6 & v_6 \\ u_7' u_7 & u_7' v_7 & u_7' & u_7 v_7' & v_7 v_7' & v_7' & u_7 & v_7 \\ u_8' u_8 & u_8' v_8 & u_8' & u_8 v_8' & v_8 v_8' & v_8' & u_8 & v_8 \end{bmatrix} \begin{bmatrix} F_{11} \\ F_{12} \\ F_{13} \\ F_{21} \\ F_{22} \\ F_{23} \\ F_{31} \\ F_{32} \end{bmatrix} = \begin{bmatrix} -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \\ -1 \end{bmatrix}$$



x1=[227,212,1]^T
x2=[275,322,1]^T
x3=[449,370,1]^T
x4=[525,481,1]^T
x5=[699,432,1]^T
x6=[535,298,1]^T
x7=[498,118,1]^T
x8=[339,106,1]^T

xp1=[201,144,1]^T
xp2=[275,261,1]^T
xp3=[349,369,1]^T
xp4=[182,479,1]^T
xp5=[380,562,1]^T
xp6=[584,351,1]^T
xp7=[542,108,1]^T
xp8=[373,64,1]^T

A=[

xp1(1)*x1(1) xp1(1)*x1(2) xp1(1) x1(1)*xp1(2) x1(2)*xp1(2) xp1(2) x1(1) x1(2);
xp2(1)*x2(1) xp2(1)*x2(2) xp2(1) x2(1)*xp2(2) x2(2)*xp2(2) xp2(2) x2(1) x2(2);
xp3(1)*x3(1) xp3(1)*x3(2) xp3(1) x3(1)*xp3(2) x3(2)*xp3(2) xp3(2) x3(1) x3(2);
xp4(1)*x4(1) xp4(1)*x4(2) xp4(1) x4(1)*xp4(2) x4(2)*xp4(2) xp4(2) x4(1) x4(2);
xp5(1)*x5(1) xp5(1)*x5(2) xp5(1) x5(1)*xp5(2) x5(2)*xp5(2) xp5(2) x5(1) x5(2);
xp6(1)*x6(1) xp6(1)*x6(2) xp6(1) x6(1)*xp6(2) x6(2)*xp6(2) xp6(2) x6(1) x6(2);
xp7(1)*x7(1) xp7(1)*x7(2) xp7(1) x7(1)*xp7(2) x7(2)*xp7(2) xp7(2) x7(1) x7(2);
xp8(1)*x8(1) xp8(1)*x8(2) xp8(1) x8(1)*xp8(2) x8(2)*xp8(2) xp8(2) x8(1) x8(2)]

F =

0.0000 -0.0000 -0.0007
-0.0000 0.0000 0.0105
-0.0011 -0.0093 1.0000



Determine fundamental matrix F

■ correspondence from two-views—example, cont.

$$\mathbf{l}' = \mathbf{F}\mathbf{x}$$

F =

$$\begin{bmatrix} 0.0000 & -0.0000 & -0.0007 \\ -0.0000 & 0.0000 & 0.0105 \\ -0.0011 & -0.0093 & 1.0000 \end{bmatrix}$$

lp1 =	lp2 =	lp3 =	lp4 =	lp5 =	lp6 =	lp7 =	lp8 =
-0.0009	-0.0012	-0.0010	-0.0012	-0.0007	-0.0007	-0.0002	-0.0005
0.0098	0.0101	0.0089	0.0089	0.0073	0.0078	0.0071	0.0083
-1.2267	-2.3044	-2.9449	-4.0631	-3.8003	-2.3701	-0.6527	-0.3641





Determine fundamental matrix F

■ correspondence from two-views—example, cont.

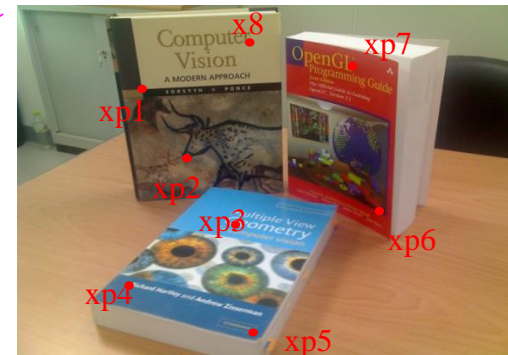
$$\mathbf{l} = \mathbf{F}^T \mathbf{x}'$$

>> F'

ans =

```
0.0000 -0.0000 -0.0011
-0.0000 0.0000 -0.0093
-0.0007 0.0105 1.0000
```

11 =	12 =	13 =	14 =	15 =	16 =	17 =	18 =
-0.0019	-0.0027	-0.0035	-0.0046	-0.0050	-0.0029	-0.0011	-0.0010
-0.0091	-0.0086	-0.0082	-0.0072	-0.0073	-0.0090	-0.0102	-0.0100
2.3599	3.5309	4.6076	5.8837	6.6067	4.2450	1.7302	1.3944





Determine fundamental matrix F

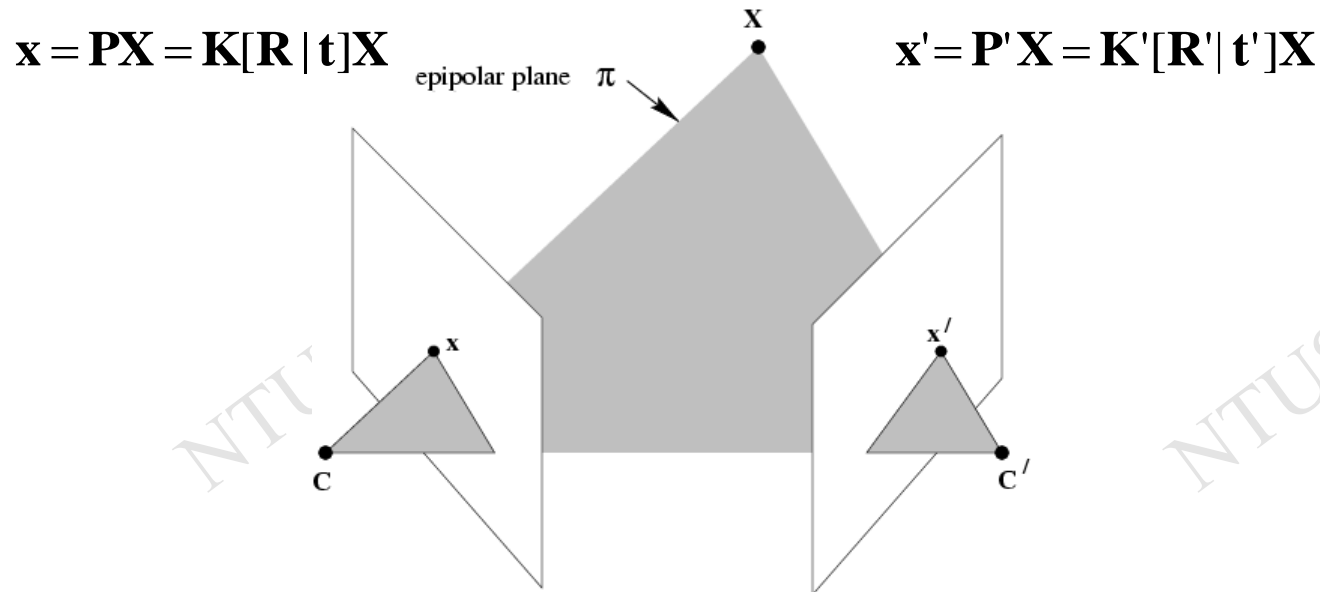
- correspondence from two-views—example, cont.
 - Evaluation for error, for example check $\mathbf{l}'^T \mathbf{x}'$
or $\mathbf{l}^T \mathbf{x}$ or $\mathbf{x}'^T \mathbf{F} \mathbf{x}$

	$\mathbf{l}'^T \mathbf{x}'$	$\mathbf{l}^T \mathbf{x}$	$\mathbf{x}'^T \mathbf{F} \mathbf{x}$
1)	-2.4425e-015	-2.6645e-015	-2.6645e-015
2)	4.5741e-014	-3.5527e-015	-3.5527e-015
3)	-1.2390e-013	-4.4409e-015	-4.4409e-015
4)	-5.3291e-015	-5.3291e-015	-5.3291e-015
5)	-3.5527e-015	-3.5527e-015	-3.5527e-015
6)	-3.5527e-015	-3.5527e-015	-3.5527e-015
7)	-8.8818e-016	-8.8818e-016	-8.8818e-016
8)	-1.6653e-015	-1.5543e-015	-1.5543e-015



Essential matrix E

- The *essential matrix* is the specialization of the *fundamental matrix* to the case of normalized image coordinate. Historically, the *essential matrix* was introduced before the *fundamental matrix*, and the *fundamental matrix* may be thought of as the generalization of the *essential matrix* in which the assumption of calibrated cameras is removed.





Essential matrix E

- Normalized coordinates:
- Consider the image without **K** effect.

2D points on an image

$$\mathbf{x} = \mathbf{P}\mathbf{X} = \mathbf{K}[\mathbf{R} \mid \mathbf{t}]\mathbf{X}$$

$$\mathbf{x}' = \mathbf{P}'\mathbf{X} = \mathbf{K}'[\mathbf{R}' \mid \mathbf{t}']\mathbf{X}$$



2D points on a
normalized image

$$\hat{\mathbf{x}} = \mathbf{K}^{-1}\mathbf{x} = \mathbf{K}^{-1}\mathbf{P}\mathbf{X} = [\mathbf{R} \mid \mathbf{t}]\mathbf{X}$$

$$\hat{\mathbf{x}}' = \mathbf{K}'^{-1}\mathbf{x}' = \mathbf{K}'^{-1}\mathbf{P}'\mathbf{X} = [\mathbf{R}' \mid \mathbf{t}']\mathbf{X}$$

$$\mathbf{P} = \mathbf{K}[\mathbf{R} \mid \mathbf{t}] \rightarrow \text{general camera matrix}$$

$$\mathbf{K}^{-1}\mathbf{P} = [\mathbf{R} \mid \mathbf{t}] \rightarrow \text{normalized camera matrix}$$

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

similar to fundamental matrix format

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

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

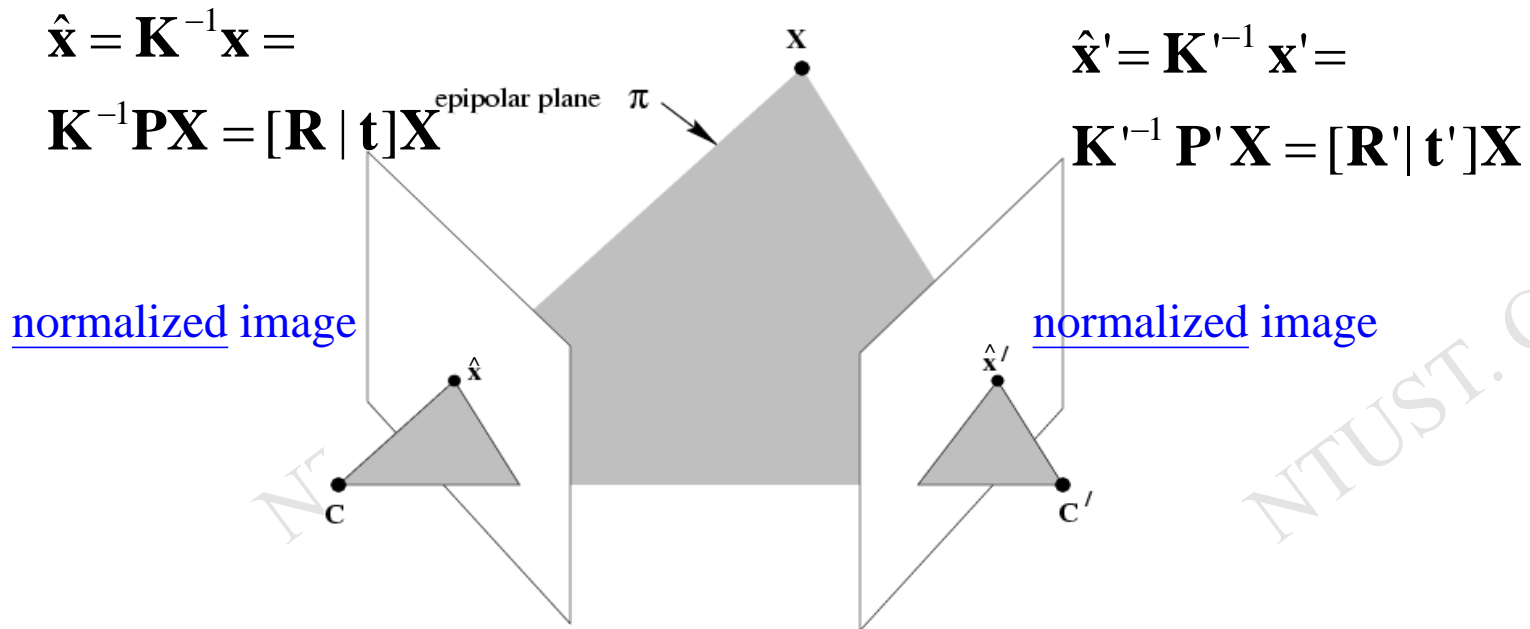
$$\hat{\mathbf{x}}' = \mathbf{K}'^{-1}\mathbf{x}'$$

$$\left. \begin{array}{l} \because \mathbf{x}'^T \mathbf{F} \mathbf{x} = 0 \\ \hat{\mathbf{x}} = \mathbf{K}^{-1}\mathbf{x} \\ \hat{\mathbf{x}}' = \mathbf{K}'^{-1}\mathbf{x}' \end{array} \right\} (\mathbf{K}'\hat{\mathbf{x}}')^T \mathbf{F} (\mathbf{K}\hat{\mathbf{x}}) = 0 \Rightarrow \hat{\mathbf{x}}'^T (\mathbf{K}'^T \mathbf{F} \mathbf{K}) \hat{\mathbf{x}} = 0 \Rightarrow \mathbf{E} = \mathbf{K}'^T \mathbf{F} \mathbf{K}$$



Essential matrix E

- Normalized coordinates:
- Consider the image without **K** effect.





Essential matrix E –example

- Continue the previous example:

$F =$

```
0.0000 -0.0000 -0.0007
-0.0000 0.0000 0.0105
-0.0011 -0.0093 1.0000
```

Assume we have intrinsic parameter of image 1&2:

```
K=[
857.249077 0.000000 402.813609
0.000000 866.660878 250.492920
0.000000 0.000000 1.000000]
```

Essential matrix can be determined by $E = K'^T F K$

```
>> E=K'*F*K
```

$E =$

```
1.2509 -2.0515 -0.6399
-5.9498 4.1481 7.4831
-2.0853 -7.8357 0.0815
```

Intrinsic parameter of **image-2**

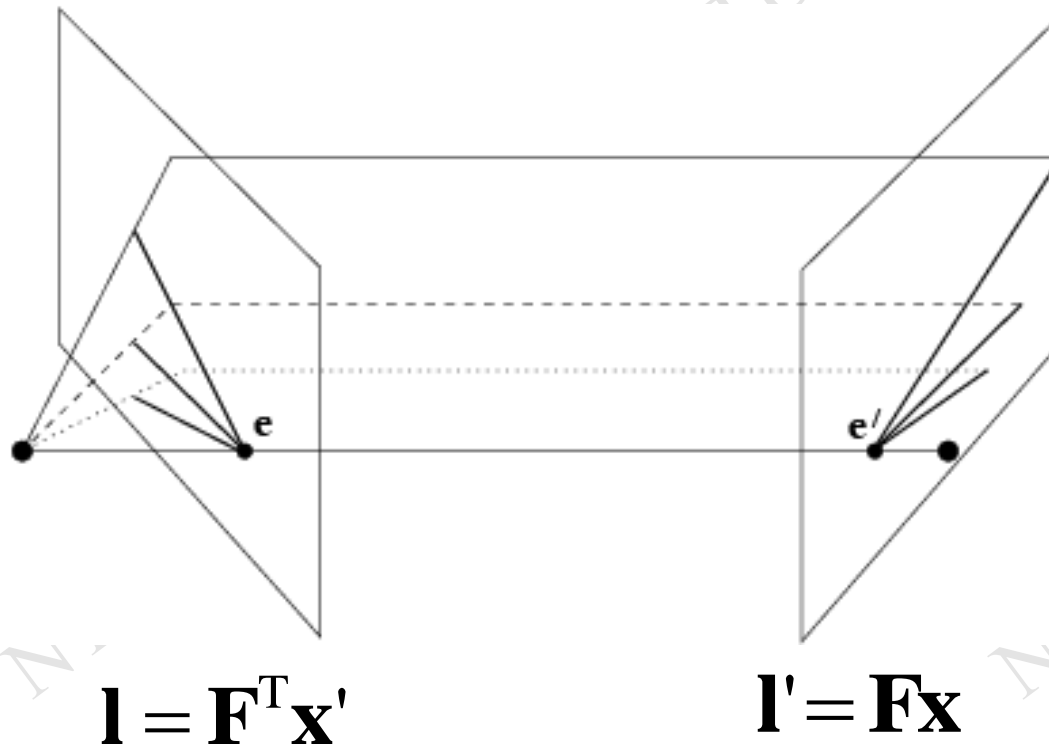
Intrinsic parameter of **image-1**

Fundamental matrix from
image-1 to image-2



Epipolar geometry

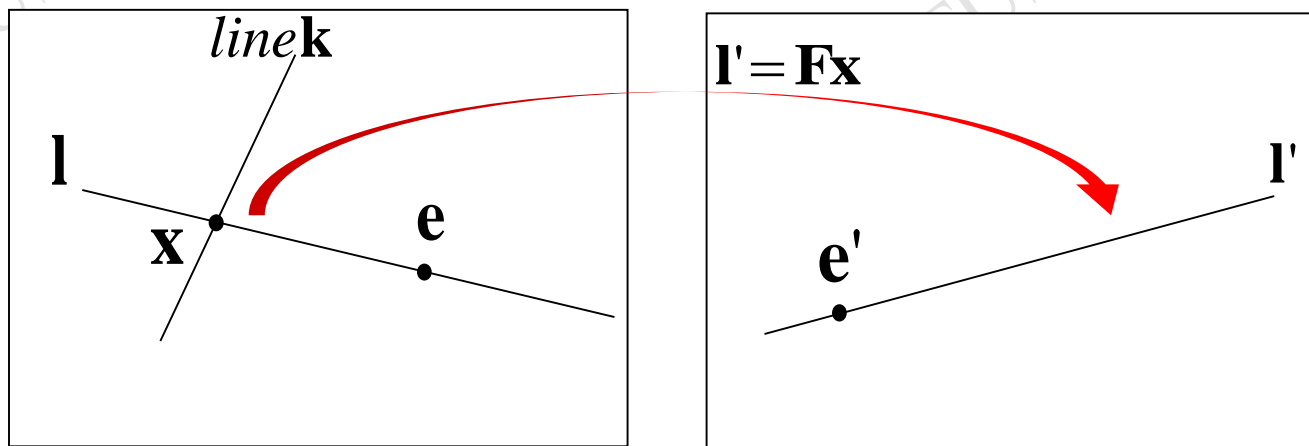
■ Review:





Epipolar geometry-epipolar line homography

- l, l' epipolar lines in left and right images.



Suppose l and l' are corresponding epipolar lines, and k is ANY "line" NOT passing through the epipole e , then l and l' are related by

$$l' = F[k]_{\times} l \quad \rightarrow \quad \because k^T e \neq 0, \quad e^T e \neq 0$$

$$l' = F[e]_{\times} l$$

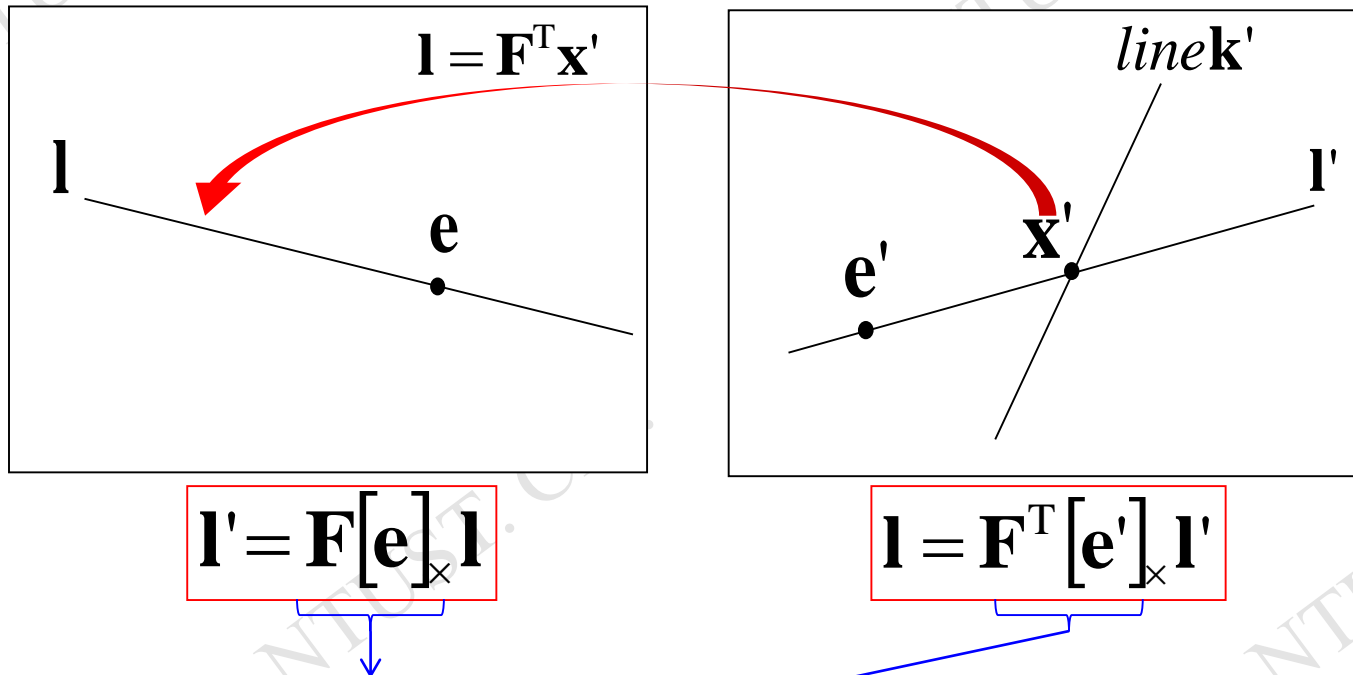
→Note: e , here, means the LINE for convenience not passing through the epipole e . So, we say e is one choice of line k .

Hartley04, sec.9.2.5



Epipolar geometry-epipolar line homography

- \mathbf{l}, \mathbf{l}' epipolar lines in left and right images.

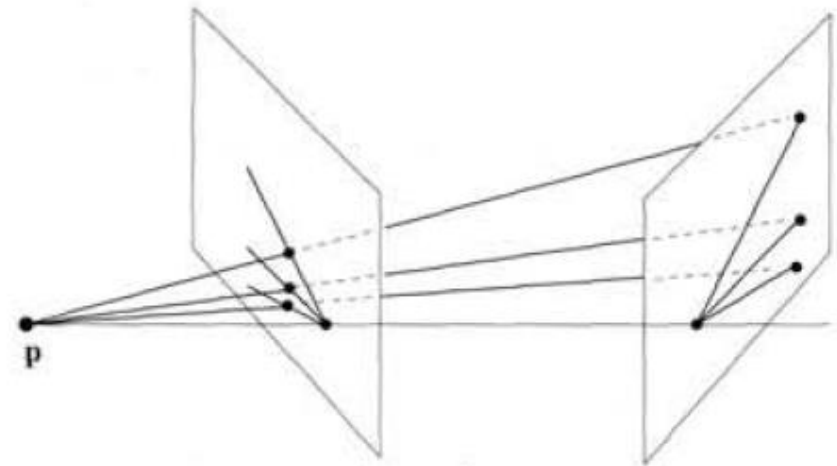
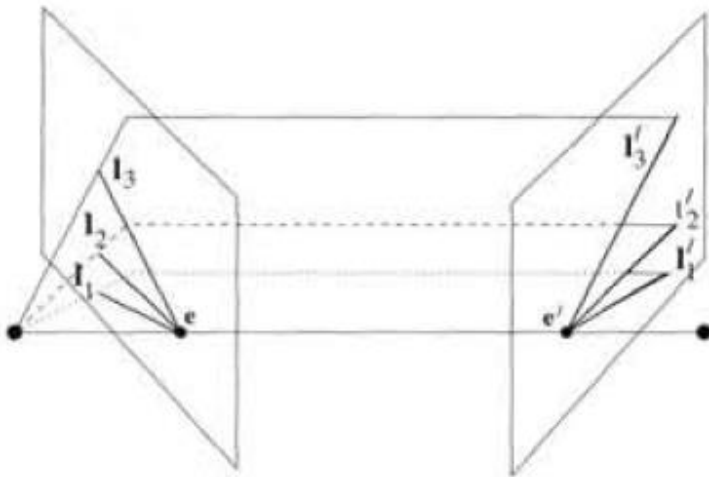


A **homography** between two lines

Hartley04, sec.9.2.5



Epipolar geometry-epipolar line homography

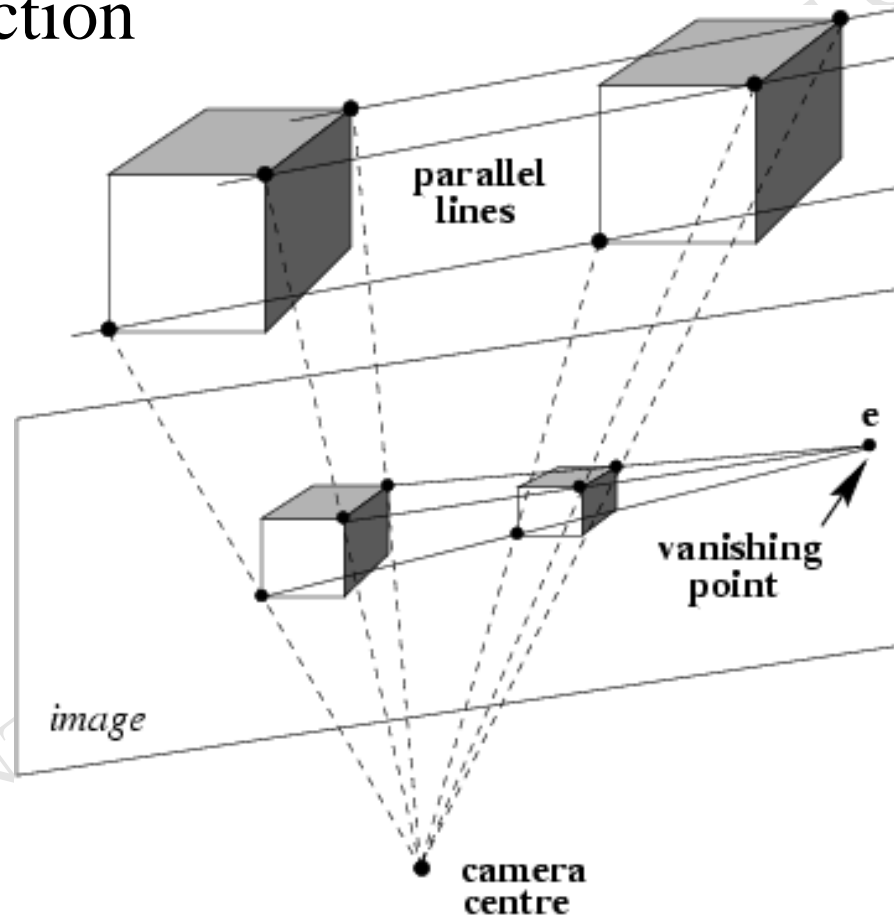


p is any point on the baseline



Fundamental matrix for pure translation

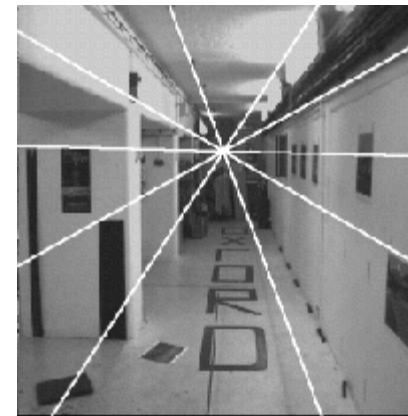
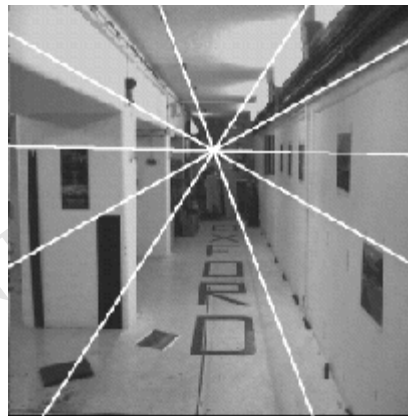
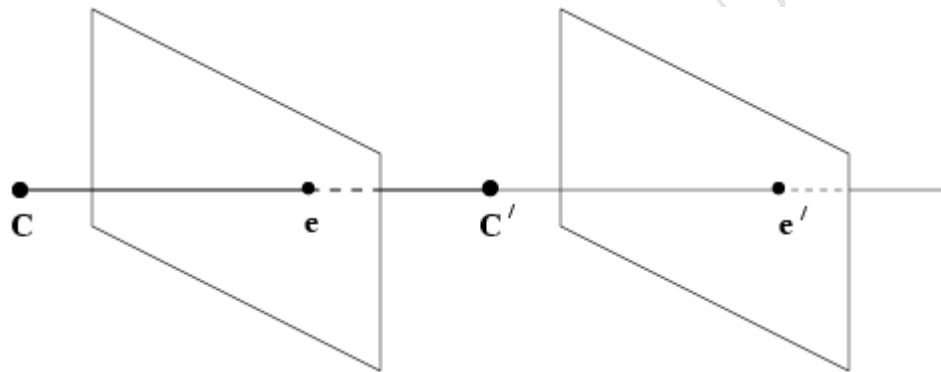
■ Side direction





Fundamental matrix for pure translation

■ Forward and backward





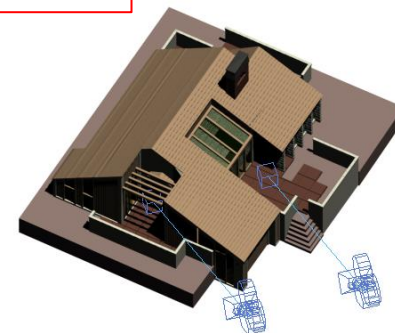
Fundamental matrix—example 1



$x_1=[375,219,1]^T$
 $x_2=[405,263,1]^T$
 $x_3=[433,560,1]^T$
 $x_4=[630,66,1]^T$
 $x_5=[678,96,1]^T$
 $x_6=[698,323,1]^T$
 $x_7=[696,367,1]^T$
 $x_8=[741,421,1]^T$



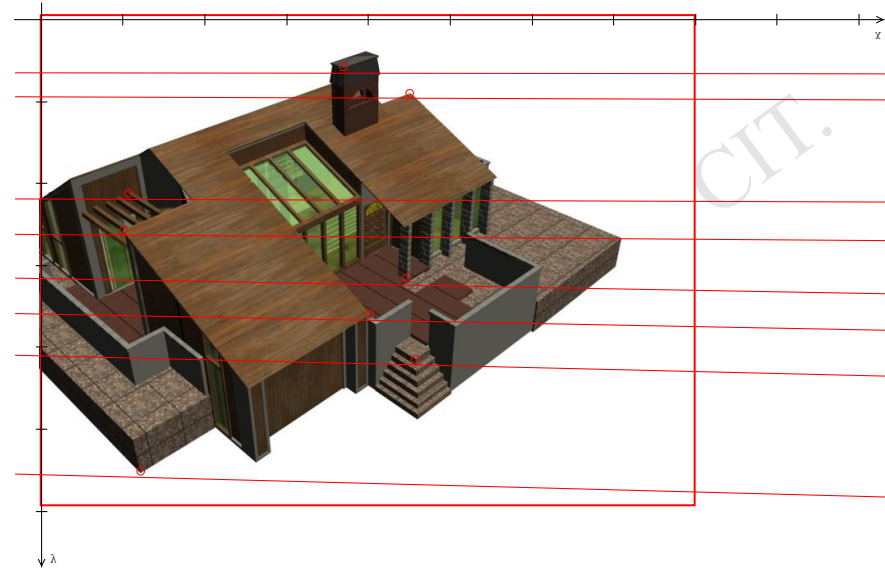
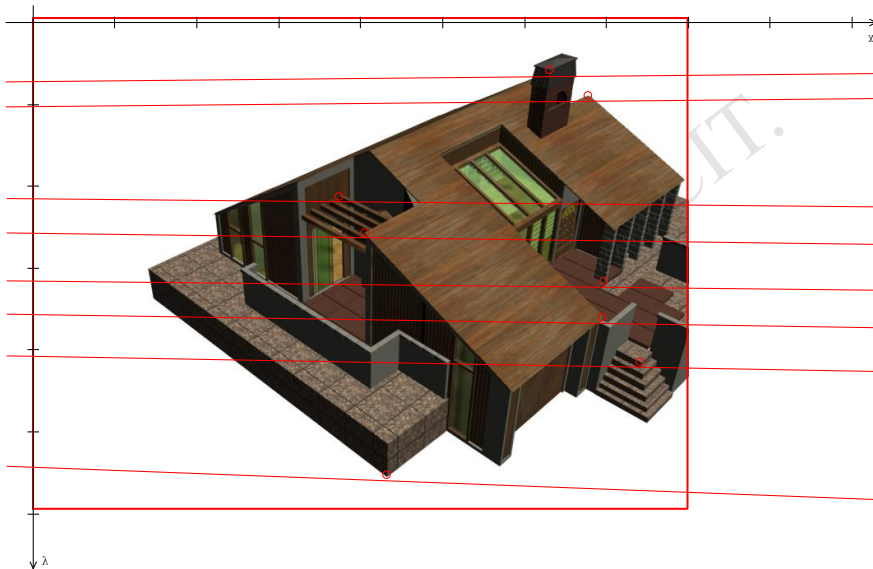
$x_{p1}=[108,219,1]^T$
 $x_{p2}=[100,263,1]^T$
 $x_{p3}=[123,559,1]^T$
 $x_{p4}=[370,65,1]^T$
 $x_{p5}=[452,96,1]^T$
 $x_{p6}=[448,324,1]^T$
 $x_{p7}=[403,367,1]^T$
 $x_{p8}=[458,421,1]^T$





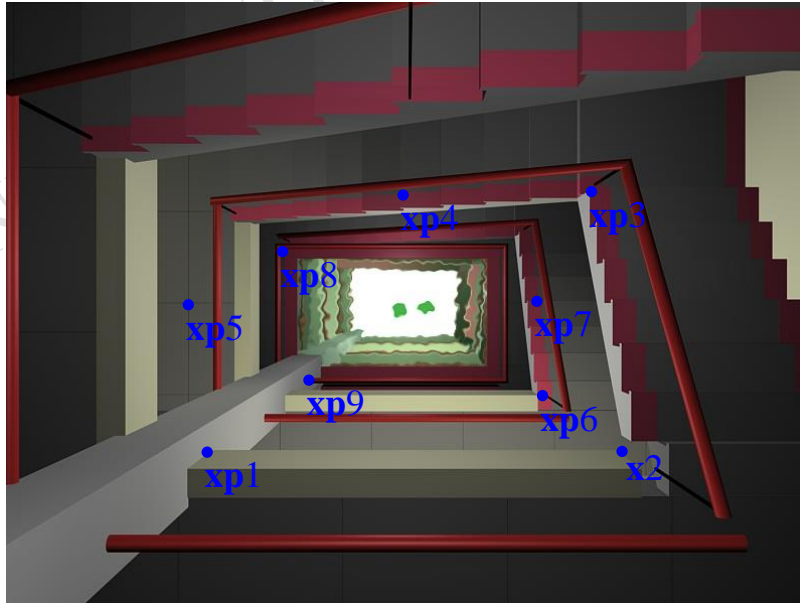
Fundamental matrix—example1, cont.

```
A=[
xp1(1)*x1(1) xp1(1)*x1(2) xp1(1) xp1(2)*x1(1) xp1(2)*x1(2) xp1(2) x1(1) x1(2) ;
xp2(1)*x2(1) xp2(1)*x2(2) xp2(1) xp2(2)*x2(1) xp2(2)*x2(2) xp2(2) x2(1) x2(2) ;
xp3(1)*x3(1) xp3(1)*x3(2) xp3(1) xp3(2)*x3(1) xp3(2)*x3(2) xp3(2) x3(1) x3(2) ;
xp4(1)*x4(1) xp4(1)*x4(2) xp4(1) xp4(2)*x4(1) xp4(2)*x4(2) xp4(2) x4(1) x4(2) ;
xp5(1)*x5(1) xp5(1)*x5(2) xp5(1) xp5(2)*x5(1) xp5(2)*x5(2) xp5(2) x5(1) x5(2) ;
xp6(1)*x6(1) xp6(1)*x6(2) xp6(1) xp6(2)*x6(1) xp6(2)*x6(2) xp6(2) x6(1) x6(2) ;
xp7(1)*x7(1) xp7(1)*x7(2) xp7(1) xp7(2)*x7(1) xp7(2)*x7(2) xp7(2) x7(1) x7(2) ;
xp8(1)*x8(1) xp8(1)*x8(2) xp8(1) xp8(2)*x8(1) xp8(2)*x8(2) xp8(2) x8(1) x8(2) ];
d=[-1 -1 -1 -1 -1 -1 -1 -1]';
f=inv(A)*d;
F=[f(1:3)';f(4:6)';f(7:8)' 1]
```

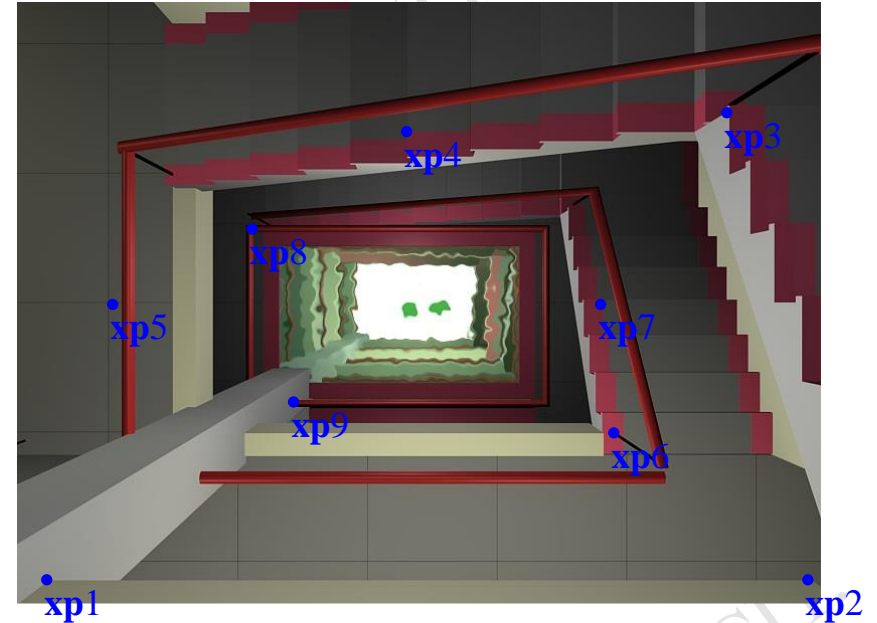




Fundamental matrix—example2



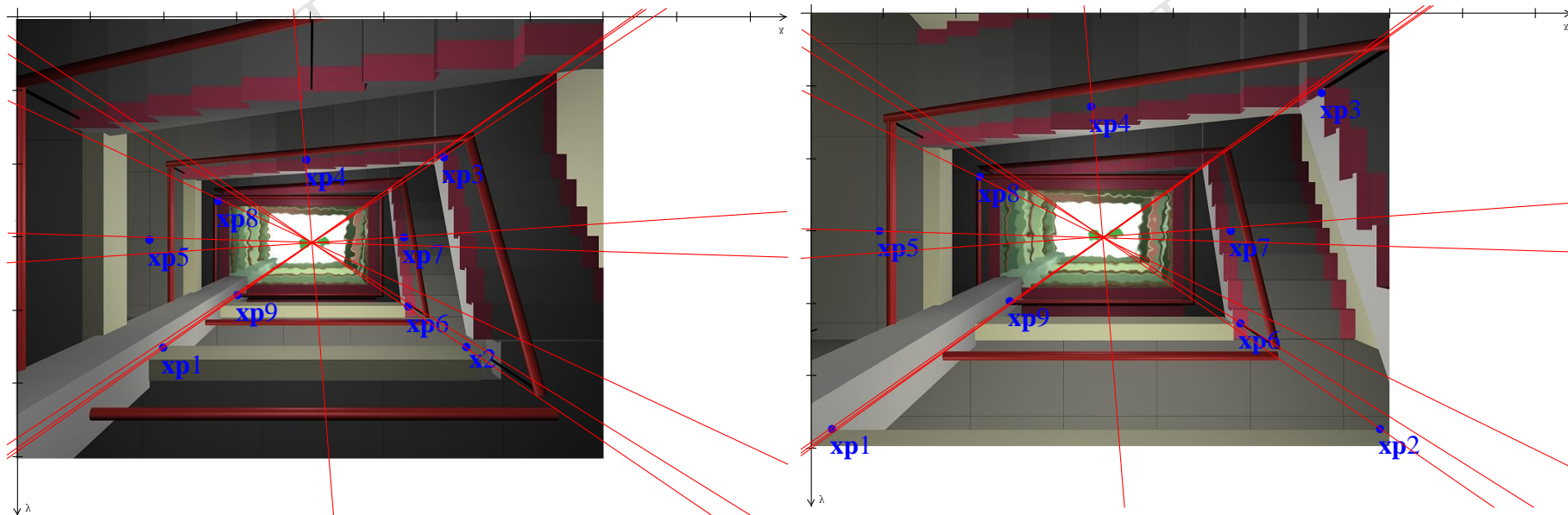
$x1=[207,446,1]^T$
 $x2=[605,446,1]^T$
 $x3=[586,182,1]^T$
 $x4=[393,191,1]^T$
 $x5=[182,301,1]^T$
 $x6=[535,390,1]^T$
 $x7=[532,299,1]^T$
 $x8=[274,246,1]^T$
 $x9=[303,377,1]^T$



$xp1=[34,577,1]^T$
 $xp2=[790,577,1]^T$
 $xp3=[705,105,1]^T$
 $xp4=[389,131,1]^T$
 $xp5=[92,300,1]^T$
 $xp6=[592,428,1]^T$
 $xp7=[581,297,1]^T$
 $xp8=[236,230,1]^T$
 $xp9=[275,401,1]^T$



Fundamental matrix—example2, cont.



Solve it by OpenCV

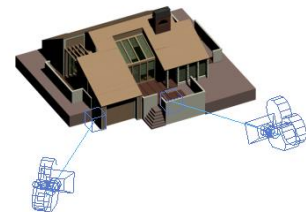
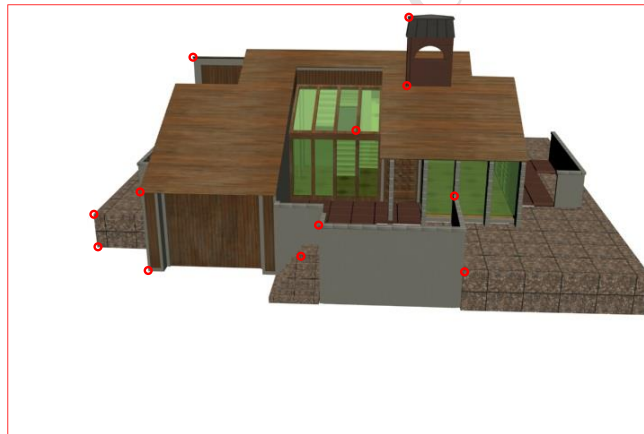
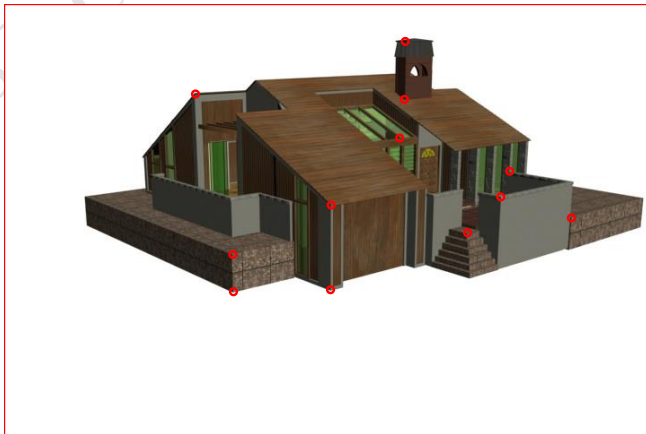
$F = [-0.000001 \ 0.000648 \ -0.199148$
 $-0.000636 \ -0.000002 \ 0.256521$
 $0.197009 \ -0.260813 \ 1.000000]$

$\mathbf{l}_1^T = [-0.1700 \ -0.2399 \ 142.2416]$
 $\mathbf{l}_2^T = [-0.1708 \ 0.2500 \ -8.3143]$
 \vdots
 $[0.1295 \ 0.1958 \ -112.4646]$
 $[0.1133 \ -0.0090 \ -42.8643]$
 $[0.0061 \ -0.2018 \ 59.6347]$
 $[-0.0758 \ 0.1219 \ -7.1046]$
 $[0.0075 \ 0.1151 \ -38.5183]$
 $[0.0505 \ -0.1083 \ 13.0009]$
 $\mathbf{l}_9^T = [-0.0583 \ -0.0834 \ 49.0992]$

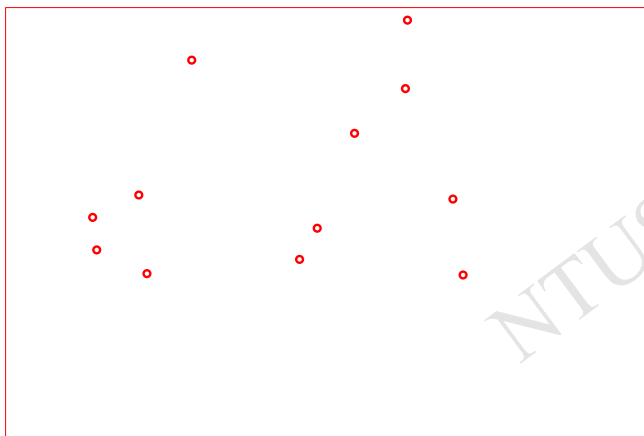
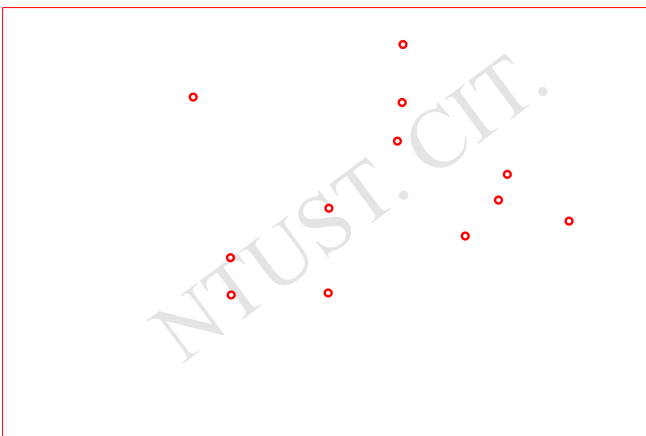
$\mathbf{l}'_1^T = [0.0897 \ 0.1240 \ -74.5417]$
 $\mathbf{l}'_2^T = [0.0893 \ -0.1292 \ 3.8678]$
 \vdots
 $[-0.0818 \ -0.1165 \ 68.9793]$
 $[-0.0758 \ 0.0062 \ 28.6093]$
 $[-0.0043 \ 0.1402 \ -41.6491]$
 $[0.0530 \ -0.0845 \ 4.6827]$
 $[-0.0059 \ -0.0824 \ 27.8257]$
 $[-0.0400 \ 0.0818 \ -9.1795]$
 $\mathbf{l}'_9^T = [0.0448 \ 0.0631 \ -37.6328]$



Fundamental matrix—example3



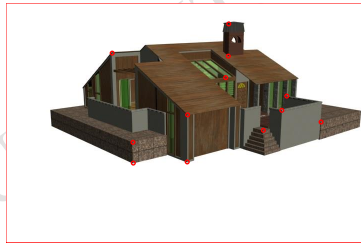
$x_1=[211,99,1]^T$
 $x_2=[252,278,1]^T$
 $x_3=[253,320,1]^T$
 $x_4=[362,318,1]^T$
 $x_5=[362,223,1]^T$
 $x_6=[514,255,1]^T$
 $x_7=[630,238,1]^T$
 $x_8=[551,214,1]^T$
 $x_9=[561,185,1]^T$
 $x_{10}=[437,148,1]^T$
 $x_{11}=[444,105,1]^T$
 $x_{12}=[445,39,1]^T$



$x_{p1}=[205,57,1]^T$
 $x_{p2}=[95,233,1]^T$
 $x_{p3}=[99,270,1]^T$
 $x_{p4}=[156,296,1]^T$
 $x_{p5}=[146,210,1]^T$
 $x_{p6}=[325,279,1]^T$
 $x_{p7}=[507,296,1]^T$
 $x_{p8}=[345,246,1]^T$
 $x_{p9}=[496,211,1]^T$
 $x_{p10}=[386,140,1]^T$
 $x_{p11}=[442,90,1]^T$
 $x_{p12}=[445,12,1]^T$



Fundamental matrix—example3, cont.



normalized

$x_1=[211,99,1]^T$
 $x_2=[252,278,1]^T$
 $x_3=[253,320,1]^T$
 $x_4=[362,318,1]^T$
 $x_5=[362,223,1]^T$
 $x_6=[514,255,1]^T$
 $x_7=[630,238,1]^T$
 $x_8=[551,214,1]^T$
 $x_9=[561,185,1]^T$
 $x_{10}=[437,148,1]^T$
 $x_{11}=[444,105,1]^T$
 $x_{12}=[445,39,1]^T$

	A	B	C	D	E	F	G	H	I	J
1	x						length		nx	
2	211	99		-207.5	-102.8333		231.5836		-2.03549	-1.00875
3	252	278		-166.5	76.16667		183.0945		-1.63329	0.747163
4	253	320		-165.5	118.1667		203.3559		-1.62348	1.159165
5	362	318		-56.5	116.1667		129.178		-0.55424	1.139545
6	362	223		-56.5	21.16667		60.33471		-0.55424	0.207636
7	514	255		95.5	53.16667		109.3021		0.936814	0.521542
8	630	238		211.5	36.16667		214.57		2.074725	0.35478
9	551	214		132.5	12.16667		133.0574		1.299769	0.11935
10	561	185		142.5	-16.83333		143.4908		1.397864	-0.16513
11	437	148		18.5	-53.83333		56.92344		0.181477	-0.52808
12	444	105		25.5	-96.83333		100.1346		0.250144	-0.94989
13	445	39		26.5	-162.8333		164.9756		0.259954	-1.59733
14	Average									
15	418.5	201.83333		0	3.27E-13		144.1667			

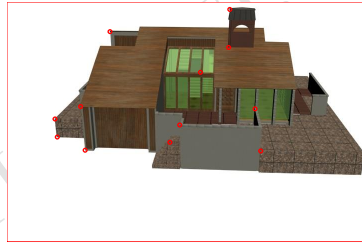
$$T = \begin{bmatrix} \frac{\sqrt{2}}{144.1667} & 0 & 0 \\ 0 & \frac{\sqrt{2}}{144.1667} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -418.5 \\ 0 & 1 & -201.8333 \\ 0 & 0 & 1 \end{bmatrix}$$

T =

$$\begin{bmatrix} 0.0098 & 0 & -4.1053 \\ 0 & 0.0098 & -1.9799 \\ 0 & 0 & 1.0000 \end{bmatrix}$$



Fundamental matrix—example3, cont.



normalized

$xp1=[205,57,1]^T$
 $xp2=[95,233,1]^T$
 $xp3=[99,270,1]^T$
 $xp4=[156,296,1]^T$
 $xp5=[146,210,1]^T$
 $xp6=[325,279,1]^T$
 $xp7=[507,296,1]^T$
 $xp8=[345,246,1]^T$
 $xp9=[496,211,1]^T$
 $xp10=[386,140,1]^T$
 $xp11=[442,90,1]^T$
 $xp12=[445,12,1]^T$

	A	B	C	D	E	F	G	H	I	J
1	xp						length		nxp	
2	205	57		-98.9167	-138		169.789596		-0.83388	-1.16336
3	95	233		-208.917	38		212.344469		-1.76119	0.320345
4	99	270		-204.917	75		218.210541		-1.72747	0.63226
5	156	296		-147.917	101		179.109855		-1.24696	0.851443
6	146	210		-157.917	15		158.627468		-1.33126	0.126452
7	325	279		21.08333	84		86.6054672		0.177735	0.708131
8	507	296		203.0833	101		226.812346		1.712019	0.851443
9	345	246		41.08333	51		65.4892379		0.346338	0.429937
10	496	211		192.0833	16		192.748559		1.619287	0.134882
11	386	140		82.08333	-55		98.8062428		0.691973	-0.46366
12	442	90		138.0833	-105		173.470479		1.16406	-0.88516
13	445	12		141.0833	-183		231.070351		1.189351	-1.54271
14	Average									
15	303.9167	195		6.44E-13	0		167.757051			

$$T' = \begin{bmatrix} \frac{\sqrt{2}}{167.757051} & 0 & 0 \\ 0 & \frac{\sqrt{2}}{167.757051} & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} 1 & 0 & -303.9167 \\ 0 & 1 & -195 \\ 0 & 0 & 1 \end{bmatrix}$$

TP =

0.0084 0 -2.5621
 0 0.0084 -1.6439
 0 0 1.0000



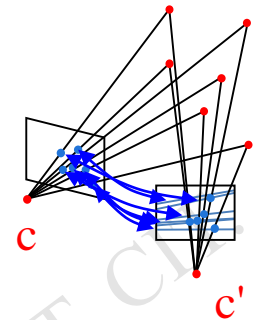
Fundamental matrix—example3, cont.

- In this example, we have 12 correspondences (over-determine than 8), solve it by SVD.

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

$$\rightarrow F_{11}u'u + F_{12}u'v + F_{13}u' + F_{21}uv' + F_{22}vv' + F_{23}v' + F_{31}u + F_{32}v + F_{33} = 0$$

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





Fundamental matrix—example3, cont.

- NOTE! Data is normalized! So far, we are determining $\hat{\mathbf{F}}$

A=[

```
nxp1(1)*nx1(1) nxp1(1)*nx1(2) nxp1(1) nxp1(2)*nx1(1) nxp1(2)*nx1(2) nxp1(2) nx1(1) nx1(2) 1;
nxp2(1)*nx2(1) nxp2(1)*nx2(2) nxp2(1) nxp2(2)*nx2(1) nxp2(2)*nx2(2) nxp2(2) nx2(1) nx2(2) 1;
nxp3(1)*nx3(1) nxp3(1)*nx3(2) nxp3(1) nxp3(2)*nx3(1) nxp3(2)*nx3(2) nxp3(2) nx3(1) nx3(2) 1;
nxp4(1)*nx4(1) nxp4(1)*nx4(2) nxp4(1) nxp4(2)*nx4(1) nxp4(2)*nx4(2) nxp4(2) nx4(1) nx4(2) 1;
nxp5(1)*nx5(1) nxp5(1)*nx5(2) nxp5(1) nxp5(2)*nx5(1) nxp5(2)*nx5(2) nxp5(2) nx5(1) nx5(2) 1;
nxp6(1)*nx6(1) nxp6(1)*nx6(2) nxp6(1) nxp6(2)*nx6(1) nxp6(2)*nx6(2) nxp6(2) nx6(1) nx6(2) 1;
nxp7(1)*nx7(1) nxp7(1)*nx7(2) nxp7(1) nxp7(2)*nx7(1) nxp7(2)*nx7(2) nxp7(2) nx7(1) nx7(2) 1;
nxp8(1)*nx8(1) nxp8(1)*nx8(2) nxp8(1) nxp8(2)*nx8(1) nxp8(2)*nx8(2) nxp8(2) nx8(1) nx8(2) 1;
nxp9(1)*nx9(1) nxp9(1)*nx9(2) nxp9(1) nxp9(2)*nx9(1) nxp9(2)*nx9(2) nxp9(2) nx9(1) nx9(2) 1;
nxp10(1)*nx10(1) nxp10(1)*nx10(2) nxp10(1) nxp10(2)*nx10(1) nxp10(2)*nx10(2) nxp10(2) nx10(1) nx10(2) 1;
nxp11(1)*nx11(1) nxp11(1)*nx11(2) nxp11(1) nxp11(2)*nx11(1) nxp11(2)*nx11(2) nxp11(2) nx11(1) nx11(2) 1;
nxp12(1)*nx12(1) nxp12(1)*nx12(2) nxp12(1) nxp12(2)*nx12(1) nxp12(2)*nx12(2) nxp12(2) nx12(1) nx12(2) 1]
```

[U,S,V]=svd(A)

>> Fh=[V(1:3,9)';V(4:6,9)';V(7:9,9)']

Denormalized for F

Fh =

$\hat{\mathbf{F}} =$

0.0058	0.0290	-0.0303
0.0353	-0.0197	-0.7377
0.1644	0.6520	0.0134

>> F=TP'*Fh*T

F =

$\mathbf{F} = \mathbf{T}^T \hat{\mathbf{F}} \mathbf{T} =$

0.0000	0.0000	-0.0009
0.0000	-0.0000	-0.0071
0.0009	0.0060	-0.2791

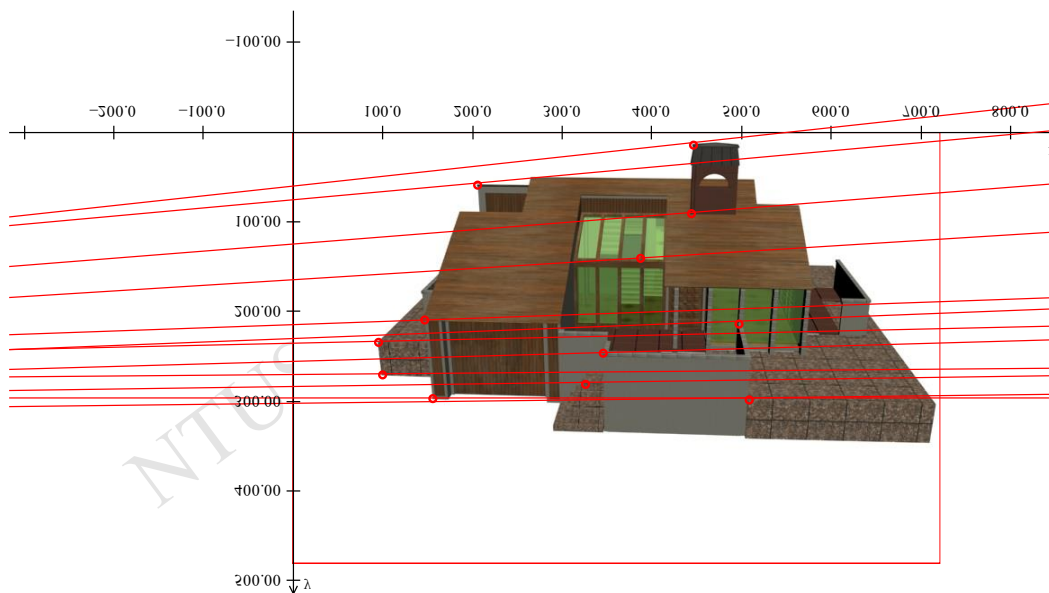


Fundamental matrix—example3, cont.

- Find epipolar lines in the 2nd image for points of 1st image

>> F*x1 >> F*x2 >> F*x3 >> F*x4 >> F*x5 >> F*x6 >> F*x7 >> F*x8 >> F*x9 >> F*x10 >> F*x11 >> F*x12

ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-0.0006	-0.0002	-0.0001	-0.0000	-0.0002	-0.0001	-0.0001	-0.0002	-0.0002	-0.0004	-0.0005	-0.0006
-0.0067	-0.0068	-0.0069	-0.0066	-0.0064	-0.0060	-0.0057	-0.0059	-0.0058	-0.0061	-0.0060	-0.0059
0.5025	1.6102	1.8624	1.9482	1.3798	1.7077	1.7100	1.4955	1.3310	0.9984	0.7474	0.3534



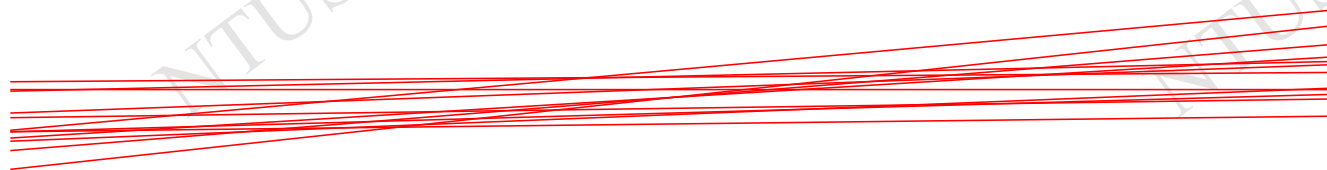
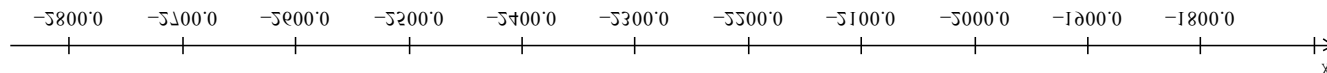


Fundamental matrix—example3, cont.

- Estimate the error, by $\mathbf{x}'^T \mathbf{F} \mathbf{x}$

>> xp1'*F*x1	>> xp2'*F*x2	>> xp3'*F*x3	>> xp4'*F*x4	>> xp5'*F*x5	>> xp6'*F*x6	>> xp7'*F*x7	>> xp8'*F*x8	>> xp9'*F*x9	>> xp10'*F*x10	>> xp11'*F*x11	>> xp12'*F*x12
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-5.3137e-004	0.0045	-0.0042	0.0020	-0.0020	-5.4760e-004	4.2649e-004	-2.6209e-004	-5.8426e-004	0.0023	-0.0018	7.5518e-004

Correspondences 2 has large error than others, let remove them then re-calculate (see next slide)





Fundamental matrix—example3, cont.

```
A=[
nxp1(1)*nx1(1) nxp1(1)*nx1(2) nxp1(1) nxp1(2)*nx1(1) nxp1(2)*nx1(2) nxp1(2) nx1(1) nx1(2) 1;
nxp3(1)*nx3(1) nxp3(1)*nx3(2) nxp3(1) nxp3(2)*nx3(1) nxp3(2)*nx3(2) nxp3(2) nx3(1) nx3(2) 1;
nxp4(1)*nx4(1) nxp4(1)*nx4(2) nxp4(1) nxp4(2)*nx4(1) nxp4(2)*nx4(2) nxp4(2) nx4(1) nx4(2) 1;
nxp5(1)*nx5(1) nxp5(1)*nx5(2) nxp5(1) nxp5(2)*nx5(1) nxp5(2)*nx5(2) nxp5(2) nx5(1) nx5(2) 1;
nxp6(1)*nx6(1) nxp6(1)*nx6(2) nxp6(1) nxp6(2)*nx6(1) nxp6(2)*nx6(2) nxp6(2) nx6(1) nx6(2) 1;
nxp7(1)*nx7(1) nxp7(1)*nx7(2) nxp7(1) nxp7(2)*nx7(1) nxp7(2)*nx7(2) nxp7(2) nx7(1) nx7(2) 1;
nxp8(1)*nx8(1) nxp8(1)*nx8(2) nxp8(1) nxp8(2)*nx8(1) nxp8(2)*nx8(2) nxp8(2) nx8(1) nx8(2) 1;
nxp9(1)*nx9(1) nxp9(1)*nx9(2) nxp9(1) nxp9(2)*nx9(1) nxp9(2)*nx9(2) nxp9(2) nx9(1) nx9(2) 1;
nxp10(1)*nx10(1) nxp10(1)*nx10(2) nxp10(1) nxp10(2)*nx10(1) nxp10(2)*nx10(2) nxp10(2) nx10(1) nx10(2) 1;
nxp11(1)*nx11(1) nxp11(1)*nx11(2) nxp11(1) nxp11(2)*nx11(1) nxp11(2)*nx11(2) nxp11(2) nx11(1) nx11(2) 1;
nxp12(1)*nx12(1) nxp12(1)*nx12(2) nxp12(1) nxp12(2)*nx12(1) nxp12(2)*nx12(2) nxp12(2) nx12(1) nx12(2) 1]
```

$[U, S, V] = \text{svd}(A)$

$F_h = [V(1:3,9)'; V(4:6,9)'; V(7:9,9)']$

$F = TP' * F_h * T$

>> xp1'*F*x1	>> xp3'*F*x3	>> xp4'*F*x4	>> xp5'*F*x5	>> xp6'*F*x6	>> xp7'*F*x7	>> xp8'*F*x8	>> xp9'*F*x9	>> xp10'*F*x10	>> xp11'*F*x11	>> xp12'*F*x12
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-9.0214e-005	9.6499e-004	-0.0019	2.3422e-004	0.0025	-4.8966e-004	-7.3015e-004	6.9723e-005	-0.0015	8.8603e-004	5.1497e-005



Fundamental matrix—example3, cont.

```
A=[
nxp1(1)*nx1(1) nxp1(1)*nx1(2) nxp1(1) nxp1(2)*nx1(1) nxp1(2)*nx1(2) nxp1(2) nx1(1) nx1(2) 1;
nxp3(1)*nx3(1) nxp3(1)*nx3(2) nxp3(1) nxp3(2)*nx3(1) nxp3(2)*nx3(2) nxp3(2) nx3(1) nx3(2) 1;
nxp4(1)*nx4(1) nxp4(1)*nx4(2) nxp4(1) nxp4(2)*nx4(1) nxp4(2)*nx4(2) nxp4(2) nx4(1) nx4(2) 1;
nxp5(1)*nx5(1) nxp5(1)*nx5(2) nxp5(1) nxp5(2)*nx5(1) nxp5(2)*nx5(2) nxp5(2) nx5(1) nx5(2) 1;
nxp7(1)*nx7(1) nxp7(1)*nx7(2) nxp7(1) nxp7(2)*nx7(1) nxp7(2)*nx7(2) nxp7(2) nx7(1) nx7(2) 1;
nxp8(1)*nx8(1) nxp8(1)*nx8(2) nxp8(1) nxp8(2)*nx8(1) nxp8(2)*nx8(2) nxp8(2) nx8(1) nx8(2) 1;
nxp9(1)*nx9(1) nxp9(1)*nx9(2) nxp9(1) nxp9(2)*nx9(1) nxp9(2)*nx9(2) nxp9(2) nx9(1) nx9(2) 1;
nxp10(1)*nx10(1) nxp10(1)*nx10(2) nxp10(1) nxp10(2)*nx10(1) nxp10(2)*nx10(2) nxp10(2) nx10(1) nx10(2) 1;
nxp11(1)*nx11(1) nxp11(1)*nx11(2) nxp11(1) nxp11(2)*nx11(1) nxp11(2)*nx11(2) nxp11(2) nx11(1) nx11(2) 1;
nxp12(1)*nx12(1) nxp12(1)*nx12(2) nxp12(1) nxp12(2)*nx12(1) nxp12(2)*nx12(2) nxp12(2) nx12(1) nx12(2) 1]
```

$[U, S, V] = \text{svd}(A)$

$F_h = [V(1:3, 9)'; V(4:6, 9)'; V(7:9, 9)']$

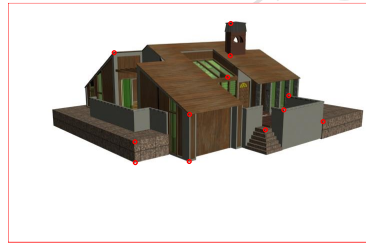
$F = TP' * F_h * T$

>> xp1'*F*x1	>> xp3'*F*x3	>> xp4'*F*x4	>> xp5'*F*x5	>> xp7'*F*x7	>> xp8'*F*x8	>> xp9'*F*x9	>> xp10'*F*x10	>> xp11'*F*x11	>> xp12'*F*x12
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-4.4279e-005	-1.5922e-004	1.1958e-004	2.4719e-004	1.0935e-004	-2.8128e-004	-1.6777e-005	-1.5967e-004	2.4016e-004	-5.5050e-005



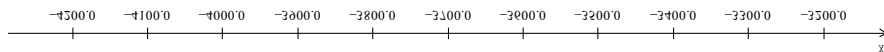
Fundamental matrix—example3, cont.

Find epipolar lines in the 2nd image for points of 1st image (10 correspondences)

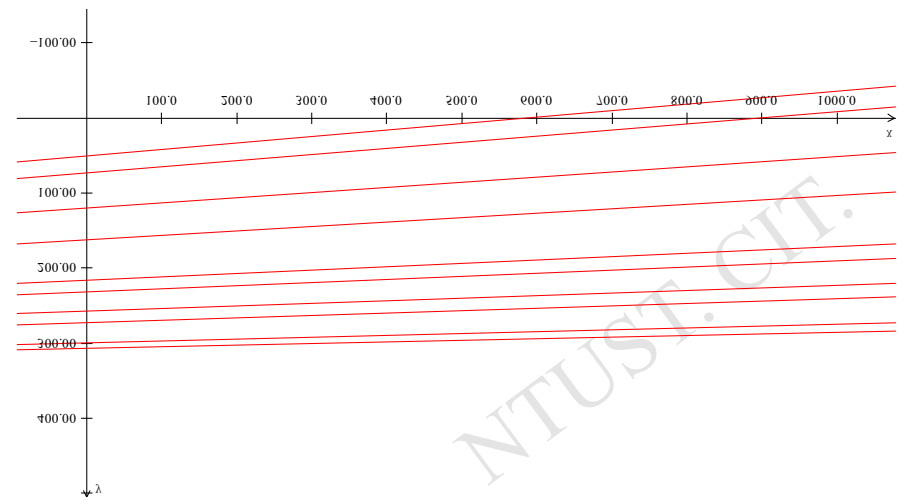


>> F*x1 >> F*x3 >> F*x4 >> F*x5 >> F*x7 >> F*x8 >> F*x9 >> F*x10 >> F*x11 >> F*x12

ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
0.0006	0.0002	0.0002	0.0003	0.0001	0.0002	0.0002	0.0004	0.0004	0.0005
0.0067	0.0071	0.0067	0.0065	0.0056	0.0058	0.0057	0.0060	0.0059	0.0058
-0.4978	-1.9467	-2.0165	-1.4073	-1.7067	-1.4929	-1.3145	-0.9833	-0.7129	-0.2904



e' (epipole)





Fundamental matrix—example3, cont.

```
A=[
nxp1(1)*nx1(1) nxp1(1)*nx1(2) nxp1(1) nxp1(2)*nx1(1) nxp1(2)*nx1(2) nxp1(2) nx1(1) nx1(2) 1;
nxp3(1)*nx3(1) nxp3(1)*nx3(2) nxp3(1) nxp3(2)*nx3(1) nxp3(2)*nx3(2) nxp3(2) nx3(1) nx3(2) 1;
nxp4(1)*nx4(1) nxp4(1)*nx4(2) nxp4(1) nxp4(2)*nx4(1) nxp4(2)*nx4(2) nxp4(2) nx4(1) nx4(2) 1;
nxp5(1)*nx5(1) nxp5(1)*nx5(2) nxp5(1) nxp5(2)*nx5(1) nxp5(2)*nx5(2) nxp5(2) nx5(1) nx5(2) 1;
nxp7(1)*nx7(1) nxp7(1)*nx7(2) nxp7(1) nxp7(2)*nx7(1) nxp7(2)*nx7(2) nxp7(2) nx7(1) nx7(2) 1;
nxp9(1)*nx9(1) nxp9(1)*nx9(2) nxp9(1) nxp9(2)*nx9(1) nxp9(2)*nx9(2) nxp9(2) nx9(1) nx9(2) 1;
nxp10(1)*nx10(1) nxp10(1)*nx10(2) nxp10(1) nxp10(2)*nx10(1) nxp10(2)*nx10(2) nxp10(2) nx10(1) nx10(2) 1;
nxp11(1)*nx11(1) nxp11(1)*nx11(2) nxp11(1) nxp11(2)*nx11(1) nxp11(2)*nx11(2) nxp11(2) nx11(1) nx11(2) 1;
nxp12(1)*nx12(1) nxp12(1)*nx12(2) nxp12(1) nxp12(2)*nx12(1) nxp12(2)*nx12(2) nxp12(2) nx12(1) nx12(2) 1]
```

$[U, S, V] = \text{svd}(A)$

$F_h = [V(1:3, 9)'; V(4:6, 9)'; V(7:9, 9)']$

$F = TP' * F_h * T$

<code>>> xp1'*F*x1</code>	<code>>> xp3'*F*x3</code>	<code>>> xp4'*F*x4</code>	<code>>> xp5'*F*x5</code>	<code>>> xp7'*F*x7</code>	<code>>> xp9'*F*x9</code>	<code>>> xp10'*F*x10</code>	<code>>> xp11'*F*x11</code>	<code>>> xp12'*F*x12</code>
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-1.2016e-005	1.7811e-005	-2.4047e-005	1.6801e-006	2.8201e-005	-5.3142e-005	3.7243e-005	3.0845e-006	1.1849e-006



Fundamental matrix—example3, cont.

ERROR Comparison: residual error (for equation or line)

```
A=[
npx1(1)*nx1(1) npx1(1)*nx1(2) npx1(1) npx1(2)*nx1(1) npx1(2)*nx1(2) npx1(2) nx1(1) nx1(2) 1;
npx2(1)*nx2(1) npx2(1)*nx2(2) npx2(1) npx2(2)*nx2(1) npx2(2)*nx2(2) npx2(2) nx2(1) nx2(2) 1;
npx3(1)*nx3(1) npx3(1)*nx3(2) npx3(1) npx3(2)*nx3(1) npx3(2)*nx3(2) npx3(2) nx3(1) nx3(2) 1;
npx4(1)*nx4(1) npx4(1)*nx4(2) npx4(1) npx4(2)*nx4(1) npx4(2)*nx4(2) npx4(2) nx4(1) nx4(2) 1;
npx5(1)*nx5(1) npx5(1)*nx5(2) npx5(1) npx5(2)*nx5(1) npx5(2)*nx5(2) npx5(2) nx5(1) nx5(2) 1;
npx6(1)*nx6(1) npx6(1)*nx6(2) npx6(1) npx6(2)*nx6(1) npx6(2)*nx6(2) npx6(2) nx6(1) nx6(2) 1;
npx7(1)*nx7(1) npx7(1)*nx7(2) npx7(1) npx7(2)*nx7(1) npx7(2)*nx7(2) npx7(2) nx7(1) nx7(2) 1;
npx8(1)*nx8(1) npx8(1)*nx8(2) npx8(1) npx8(2)*nx8(1) npx8(2)*nx8(2) npx8(2) nx8(1) nx8(2) 1;
npx9(1)*nx9(1) npx9(1)*nx9(2) npx9(1) npx9(2)*nx9(1) npx9(2)*nx9(2) npx9(2) nx9(1) nx9(2) 1;
npx10(1)*nx10(1) npx10(1)*nx10(2) npx10(1) npx10(2)*nx10(1) npx10(2)*nx10(2) npx10(2) nx10(1) nx10(2) 1;
npx11(1)*nx11(1) npx11(1)*nx11(2) npx11(1) npx11(2)*nx11(1) npx11(2)*nx11(2) npx11(2) nx11(1) nx11(2) 1;
npx12(1)*nx12(1) npx12(1)*nx12(2) npx12(1) npx12(2)*nx12(1) npx12(2)*nx12(2) npx12(2) nx12(1) nx12(2) 1]
```

[U,S,V]=svd(A)

Fh=[V(1:3,9)';V(4:6,9)';V(7:9,9)']

F=TP'*Fh*T

lp1=F*x1;lp1=lp1./sqrt(lp1(1)^2+lp1(2)^2);

Error estimation
function

ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-0.0795	0.6574	-0.6152	0.2976	-0.3051	-0.0908	0.0753	-0.0448	-0.1011	0.3848	-0.3072	0.1278
>> xp1'*F*x1	>> xp2'*F*x2	>> xp3'*F*x3	>> xp4'*F*x4	>> xp5'*F*x5	>> xp6'*F*x6	>> xp7'*F*x7	>> xp8'*F*x8	>> xp9'*F*x9	>> xp10'*F*x10	>> xp11'*F*x11	>> xp12'*F*x12
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-5.3137e-004	0.0045	-0.0042	0.0020	-0.0020	-5.4760e-004	4.2649e-004	-2.6209e-004	-5.8426e-004	0.0023	-0.0018	7.5518e-004

Euclidean
distance

$\mathbf{x}^T \mathbf{F} \mathbf{x}$



Fundamental matrix computation

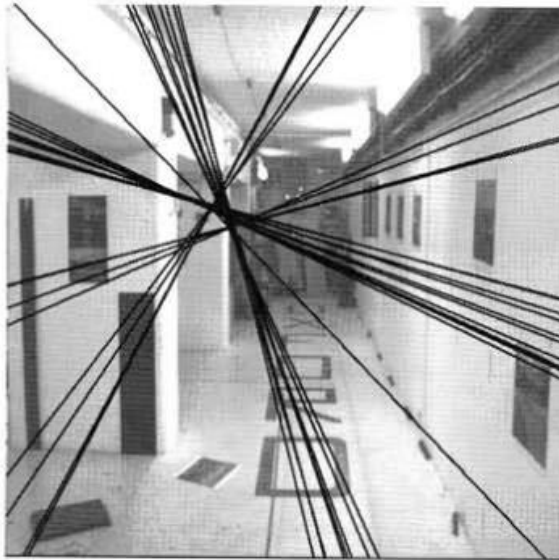
- Short summary
 - Why error occurs ?
 - Since the real camera is NOT the perfect pin-hole camera model
→undistort images or avoid lens distortion in practice.
 - The image has physical limits in resolution and capacity.
→earn more budget? Subpixel? Interpolation / super-resolution
 - Numerical issue. Currently, in computer vision field, less textbooks will teach you the *Analytical Solution*. Iteration error, round-off error, truncated error,
 - Matching error (correspondences) & measurement uncertainty



Fundamental matrix (enforcing singularity)

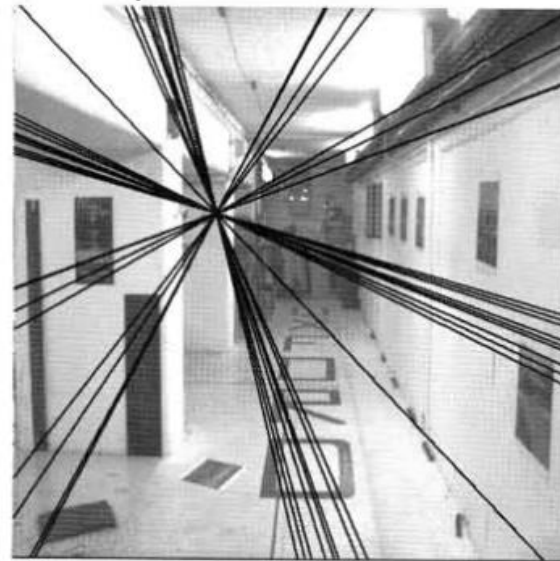
$$\mathbf{F} = \mathbf{U}\mathbf{S}\mathbf{V}^T = \mathbf{U} \begin{bmatrix} r & 0 & 0 \\ 0 & s & 0 \\ 0 & 0 & t \end{bmatrix} \mathbf{V}^T \quad \Rightarrow \quad \mathbf{F}' = \mathbf{U}\mathbf{S}'\mathbf{V}^T = \mathbf{U} \begin{bmatrix} r & 0 & 0 \\ 0 & s & 0 \\ 0 & 0 & 0 \end{bmatrix} \mathbf{V}^T$$

The effect of a non-singular
fundamental matrix



a

A singular fundamental matrix

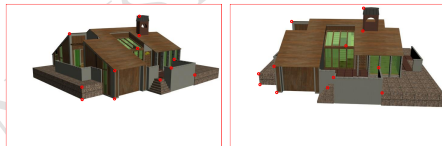


b



Fundamental matrix (enforcing singularity)

■ Example



Recall the previous example again.

Determine the normalized fundamental matrix $\hat{\mathbf{F}}$
Then, enforcing the singularity for $\hat{\mathbf{F}}$ to have $\hat{\mathbf{F}}'$
Denormalized by $\hat{\mathbf{F}}'$ instead of $\hat{\mathbf{E}}$

```
//SAMPLE CODE in MATLAB
A=[npx1(1)*nx1(1) npx1(1)*nx1(2) npx1(1) npx1(2)*nx1(1) npx1(2) npx1(2) nx1(1) nx1(2) 1;
.....
npx12(1)*nx12(1) npx12(1)*nx12(2) npx12(1) npx12(2)*nx12(1) npx12(2)*nx12(2) npx12(2) nx12(1) nx12(2) 1]
```

$[U, S, V] = \text{svd}(A)$

$f = [V(1:3,9); V(4:6,9); V(7:9,9)]$

$[Uf, Sf, Vf] = \text{svd}(f)$

$Sf(3,3) = 0;$

$FP = Uf * Sf * Vf'$

$F = TP' * FP * T$

$$\Rightarrow \begin{bmatrix} r & 0 & 0 \\ 0 & s & 0 \\ 0 & 0 & t \end{bmatrix} = \begin{bmatrix} 0.7413 & 0 & 0 \\ 0 & 0.6712 & 0 \\ 0 & 0 & 0.0031 \end{bmatrix}$$

replace it by 0.0

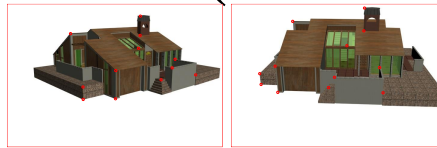
$$\mathbf{F} = \mathbf{T}^T \hat{\mathbf{F}}' \mathbf{T} = \begin{bmatrix} 0.0000 & 0.0000 & -0.0010 \\ 0.0000 & -0.0000 & -0.0071 \\ 0.0008 & 0.0060 & -0.2523 \end{bmatrix}$$

(let's redraw epipolar lines for image2, next slide)

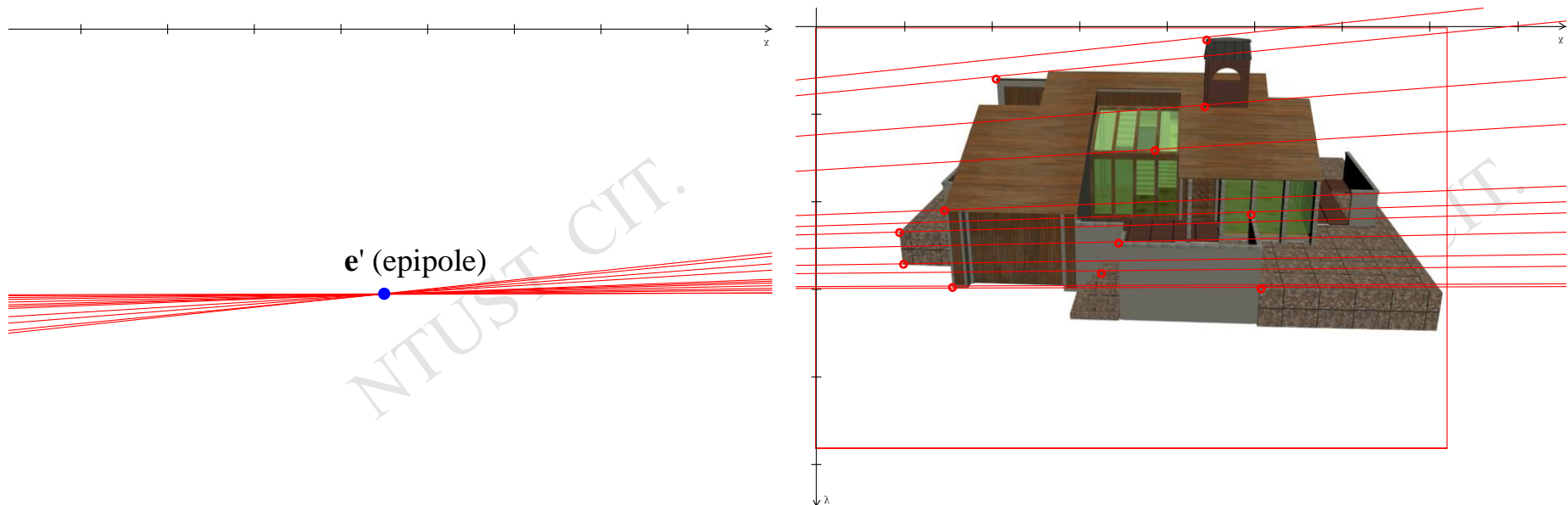


Fundamental matrix (enforcing singularity)

■ Example—cont.



>> F*x1	>> F*x2	>> F*x3	>> F*x4	>> F*x5	>> F*x6	>> F*x7	>> F*x8	>> F*x9	>> F*x10	>> F*x11	>> F*x12
ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =	ans =
-0.0006	-0.0002	-0.0001	-0.0000	-0.0002	-0.0001	-0.0000	-0.0001	-0.0002	-0.0004	-0.0005	-0.0006
-0.0067	-0.0068	-0.0069	-0.0066	-0.0064	-0.0060	-0.0057	-0.0059	-0.0058	-0.0061	-0.0060	-0.0059
0.5155	1.6236	1.8765	1.9542	1.3840	1.7012	1.6946	1.4855	1.3197	0.9956	0.7433	0.3480





Auto Fundamental matrix algorithm

Objective Compute the fundamental matrix 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 proximity and similarity of their intensity neighbourhood.
- (iii) **RANSAC robust estimation:** Repeat for N samples, where N is determined adaptively as in algorithm 4.5(p121):
 - (a) Select a random sample of 7 correspondences and compute the fundamental matrix F as described in section 11.1.2. There will be one or three real solutions.
 - (b) Calculate the distance d_{\perp} for each putative correspondence.
 - (c) Compute the number of inliers consistent with F by the number of correspondences for which $d_{\perp} < t$ pixels.
 - (d) If there are three real solutions for F the number of inliers is computed for each solution, and the solution with most inliers retained.

Choose the F with the largest number of inliers. In the case of ties choose the solution that has the lowest standard deviation of inliers.

- (iv) **Non-linear estimation:** re-estimate F from all correspondences classified as inliers by minimizing a cost function, e.g. (11.6), using the Levenberg–Marquardt algorithm of section A6.2(p600).
- (v) **Guided matching:** Further interest point correspondences are now determined using the estimated F to define a search strip about the epipolar line.

The last two steps can be iterated until the number of correspondences is stable.



Enforce singularity Fundamental matrix algorithm

Objective

Find the fundamental matrix F that minimizes the algebraic error $\|Af\|$ subject to $\|f\| = 1$ and $\det F = 0$.

Algorithm

- (i) Find a first approximation F_0 for the fundamental matrix using the normalized 8-point algorithm 11.1. Then find the right null-vector e_0 of F_0 .
- (ii) Starting with the estimate $e_i = e_0$ for the epipole, compute the matrix E_i according to (11.4), then find the vector $f_i = E_i m_i$ that minimizes $\|Af_i\|$ subject to $\|f_i\| = 1$. This is done using algorithm A5.6(p595).
- (iii) Compute the algebraic error $\epsilon_i = Af_i$. Since f_i and hence ϵ_i is defined only up to sign, correct the sign of ϵ_i (multiplying by minus 1 if necessary) so that $e_i^T e_{i-1} > 0$ for $i > 0$. This is done to ensure that ϵ_i varies smoothly as a function of e_i .
- (iv) The previous two steps define a mapping $\mathbb{R}^3 \rightarrow \mathbb{R}^9$ mapping $e_i \mapsto \epsilon_i$. Now use the Levenberg–Marquardt algorithm (section A6.2(p600)) to vary e_i iteratively so as to minimize $\|\epsilon_i\|$.
- (v) Upon convergence, f_i represents the desired fundamental matrix.



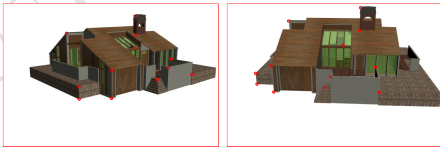
Fundamental matrix (enforcing singularity)

- Of course, openCV provides *findFundamentalMat* function
- Parameters
 - points1 – Array of N points from the first image. The point coordinates should be floating-point (single or double precision).
 - points2 – Array of the second image points of the same size and format as points1 .
 - method – Method for computing a fundamental matrix.
 - – CV_FM_7POINT for a 7-point algorithm. $N = 7$
 - – CV_FM_8POINT for an 8-point algorithm. $N \geq 8$
 - – CV_FM_RANSAC for the RANSAC algorithm. $N \geq 8$
 - – CV_FM_LMEDS for the LMedS algorithm. $N \geq 8$



Fundamental matrix using openCV

■ *findFundamentalMat*



(RANSAC)

F=

-0.000219 -0.000913 0.292220
0.000103 -0.000245 0.737529
-0.142952 -0.450960 1.000000

(LMEDS, Levenberg-Marquardt)

F=

-0.000219 -0.000913 0.292220
0.000103 -0.000245 0.737529
-0.142952 -0.450960 1.000000

$$\mathbf{F} = \mathbf{U}\mathbf{S}\mathbf{V}^T$$

↓

1.331905 0.000000 0.000000
0.000000 0.281374 0.000000
0.000000 0.000000 0.000000

$$\mathbf{e}' = \mathbf{l}_1' \times \mathbf{l}_2' = [\mathbf{F}\mathbf{x}_1] \times [\mathbf{F}\mathbf{x}_2] =$$

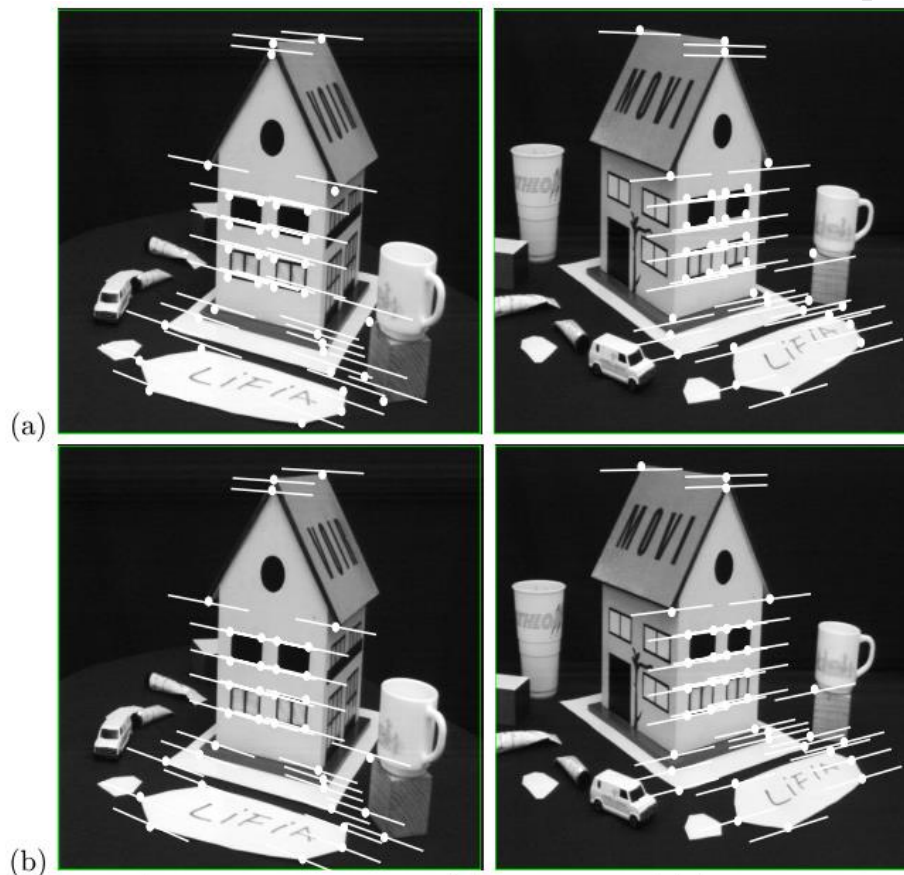
-552.206970
217.436905
1.000000

$$\mathbf{e} = \mathbf{l}_1 \times \mathbf{l}_2 = [\mathbf{F}^T \mathbf{x}_1'] \times [\mathbf{F}^T \mathbf{x}_2'] =$$

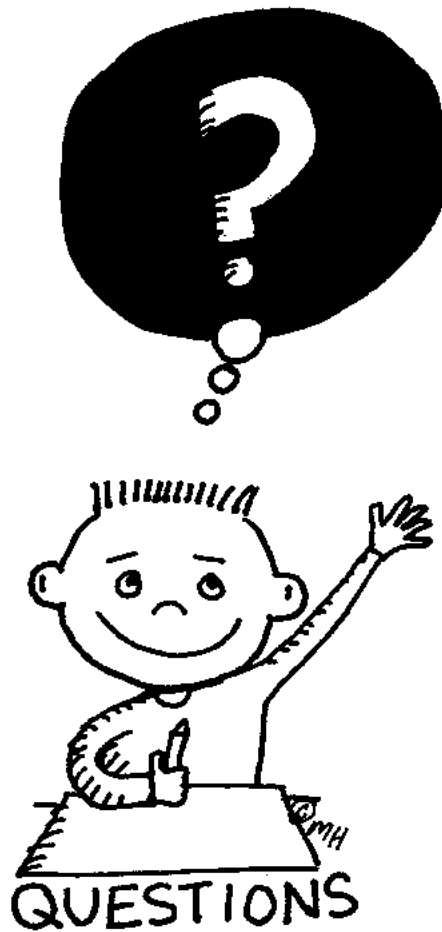
-4089.085693
1298.432373
1.000000



Comparison of different methods



	Linear Least Squares	[Hartley, 1995]	[Luong <i>et al.</i> , 1993]
Av. Dist. 1	2.33 pixels	0.92 pixel	0.86 pixel
Av. Dist. 2	2.18 pixels	0.85 pixel	0.80 pixel



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