

Fundamental matrix & Trifocal tensor

- Computation of the Fundamental Matrix F
- Introduction into the Trifocal tensor

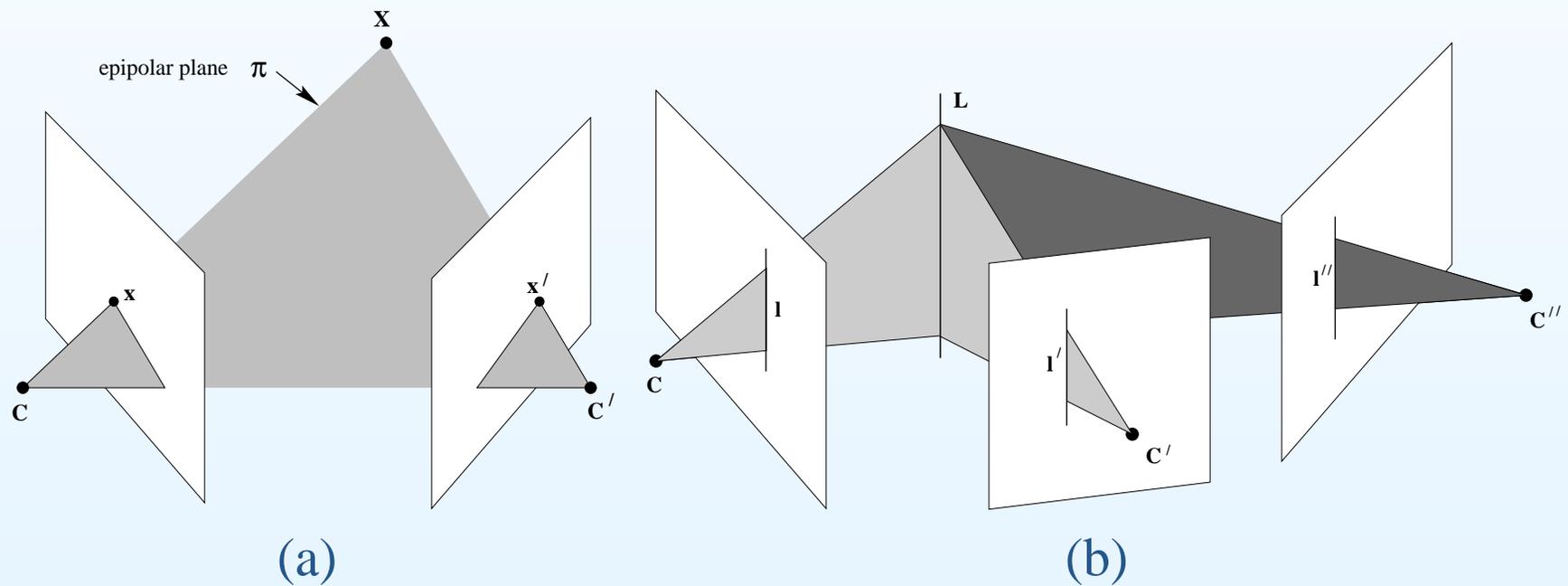


Figure 1: Two-view geometry(a), Tri-view geometry(b).

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- Normalized 8-point algorithm

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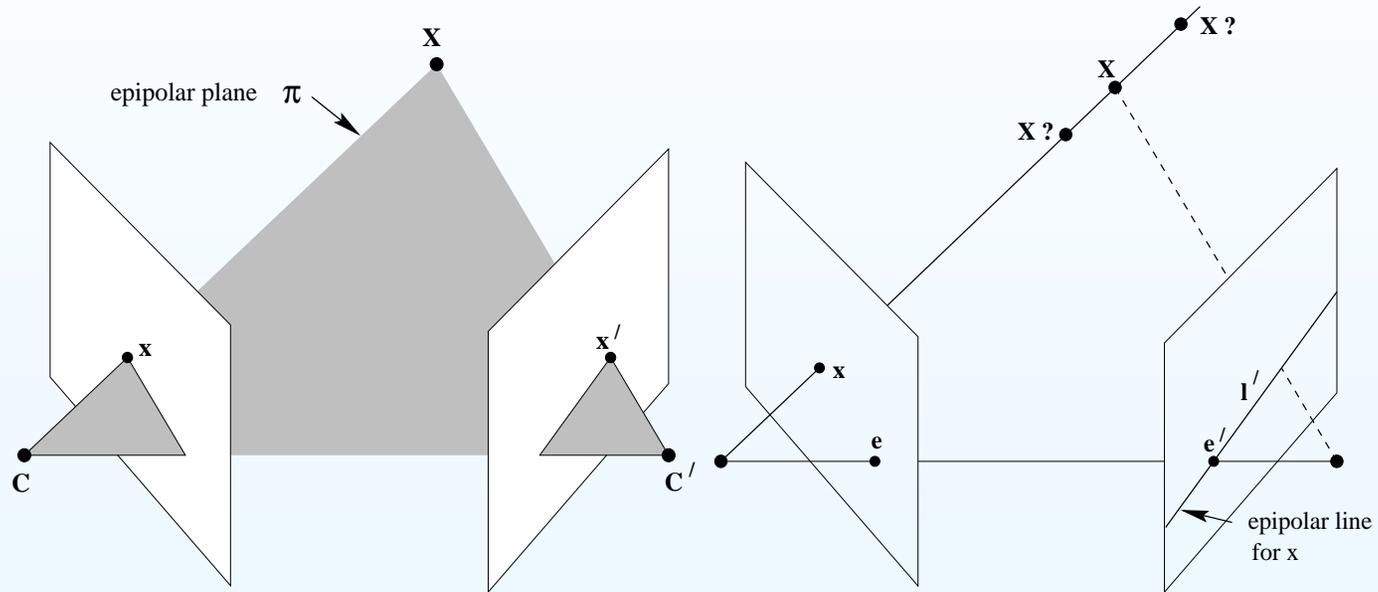
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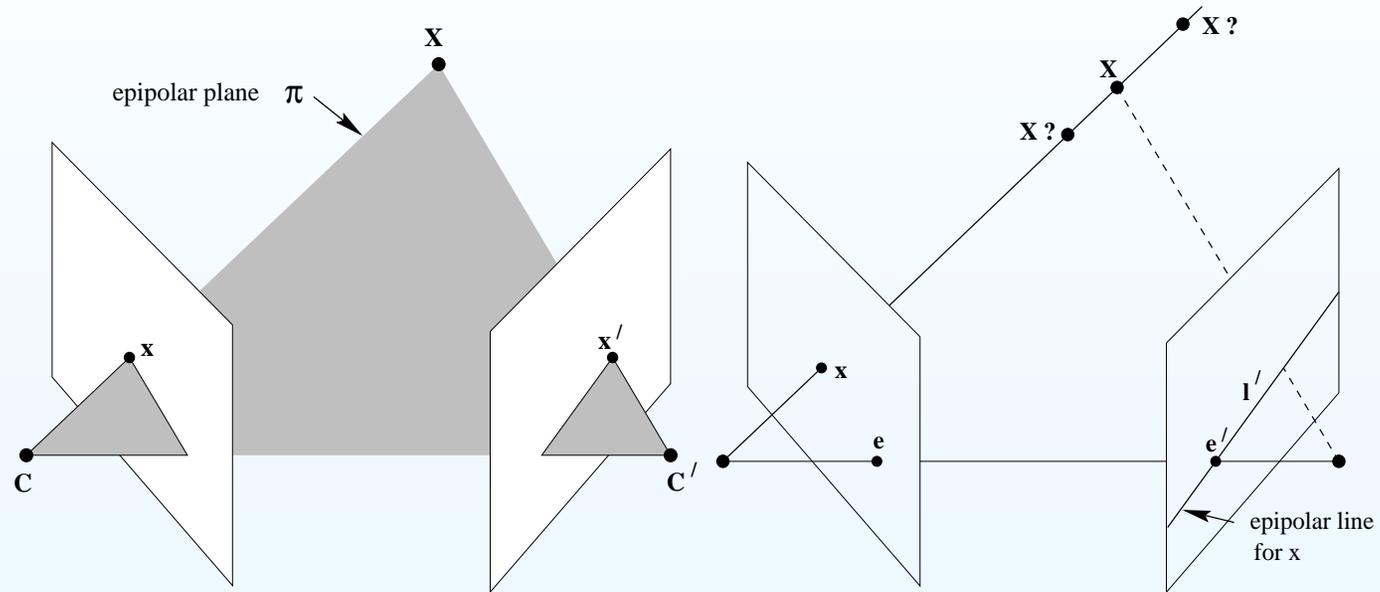
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The fundamental matrix



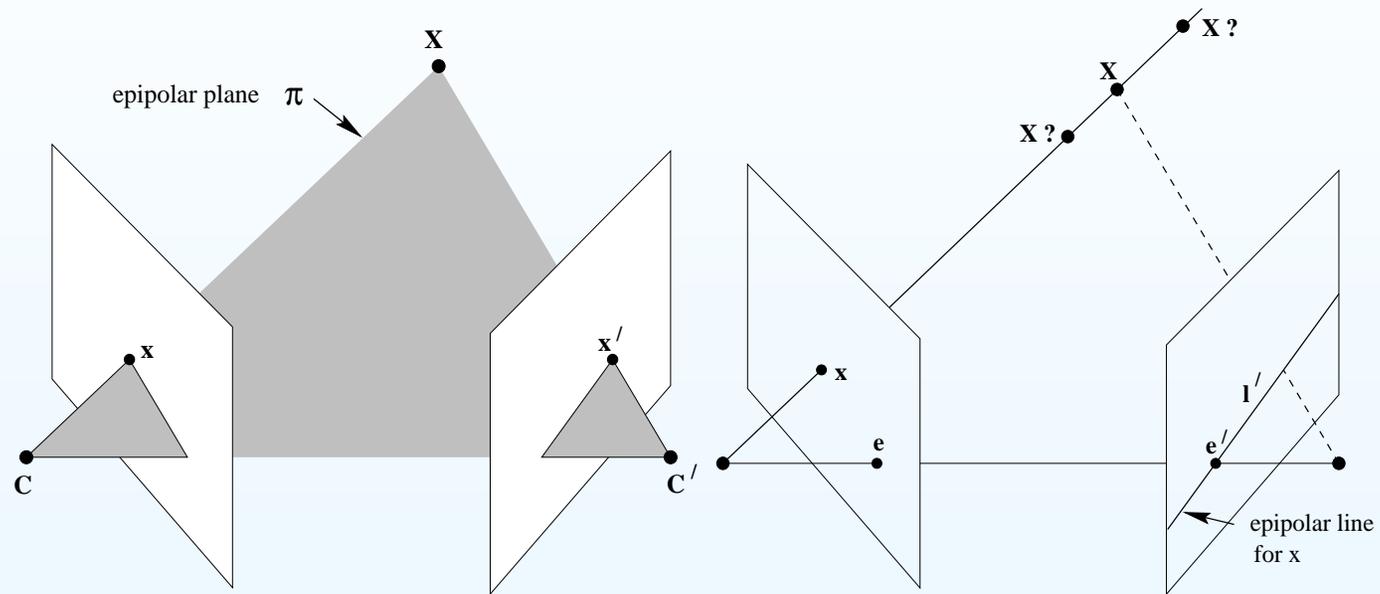
- F relates x to its epipolar line $l' = Fx$

The fundamental matrix



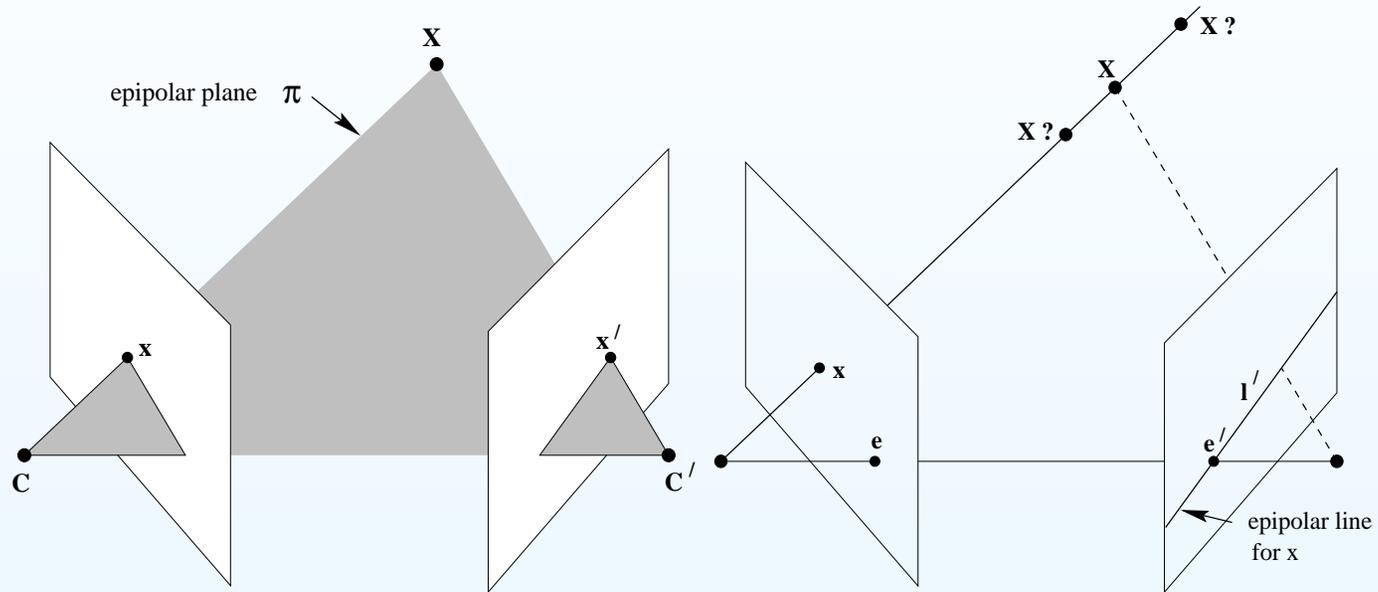
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- Since x' must be on l' we have $x'^T l' = 0$
- Thus $x'^T Fx = 0$
- F is singular, of rank 2, $\det F = 0$ and F has seven degrees of freedom.

8-point algorithm

$$x = (x, y, 1) \quad x' = (x', y', 1)$$

Let f be the vector representation (row-major) of F then

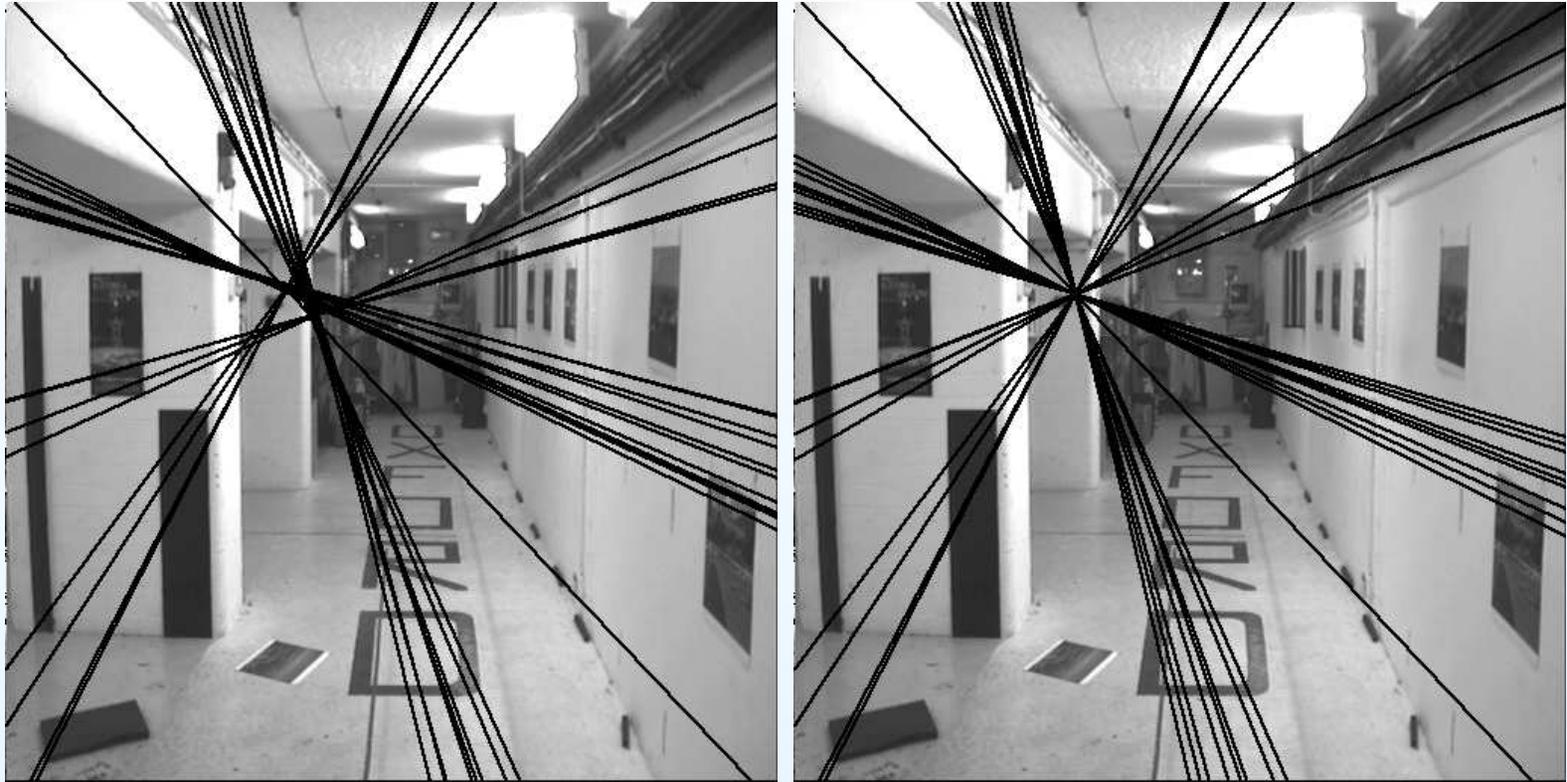
$$x'^T F x = 0 \text{ becomes } (x'x, x'y, x', y'x, y'y, y', x, y, 1)^T f = 0.$$

For n corresponding points we get the set of homogeneous equations:

$$Af = \begin{bmatrix} x'_1x_1 & x'_1y_1 & x'_1 & y'_1x_1 & y'_1y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots \\ x'_nx_n & x'_ny_n & x'_n & y'_nx_n & y'_ny_n & y'_n & x_n & y_n & 1 \end{bmatrix} f = \mathbf{0}.$$

The least-squares solution can be found using the SVD of A i.e. f is the singular vector of A with the smallest singular value.

Enforcing the singularity constraint



F found by solving the set of linear equations does not guarantee that F has rank 2 and thus is singular.

Enforcing the singularity constraint

To enforce rank 2 on F , replace F with F' where F' minimizes the Frobenius norm $\|F - F'\|_{Frobenius}$.

$$\|M\|_{Frobenius}^2 = \sum_1^{\min\{m,n\}} \sigma_i^2$$

with σ_n being the singular values of M .

This can be solved with the SVD of F .

Given $F = UDV^T$ and $\sigma_1 > \sigma_2$ are the two largest singular values of F then:

$$F' = U \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix} V^T.$$

7-point algorithm

- Using the singularity constraint we can also compute F when A has rank seven and is made of seven point correspondences.
- In this case the solution to $Af = 0$ becomes two-dimensional. The solution is in the form:

$$F = \alpha F_1 + (1 - \alpha)F_2$$

where F_1 and F_2 are the matrices corresponding to the generators of the right null-space f_1 and f_2 .

- Note that the singularity constraint enforces $\det F = 0$ thus $\det(F = \alpha F_1 + (1 - \alpha)F_2) = 0$. This gives a cubic polynomial in α from which we can solve for α .
- From this we get one or three real solutions for α . Given these solutions, we can put them in $F = \alpha F_1 + (1 - \alpha)F_2$ to retrieve the F 's.

Normalization

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- let T and T' be these appropriate normalization (translation and scaling) matrices. Then estimate F on the points $x_i = Tx_i$ and $x'_i = T'x'_i$.

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- Transform the solution for F back to the unnormalized frame with $F = T'^T FT$.

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- From the correspondences and F estimate the 3D positions of the real-world points relating to the imaged points.
- Given this 3D points project them back to both image planes using the estimate of the camera projection matrices (that were based on F).
- The difference in the real points and the backprojected points is what we want to minimize by varying the camera matrices P and P' and the coordinates of the 3D points (and thus also implicitly by varying F).

The Gold standard method

- Minimize a geometric distance (cost):

where d is differentiable in parameters relating to F , x_i and x'_i are the correspondence points and \hat{x}_i and \hat{x}'_i are their reprojections given the current F .

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

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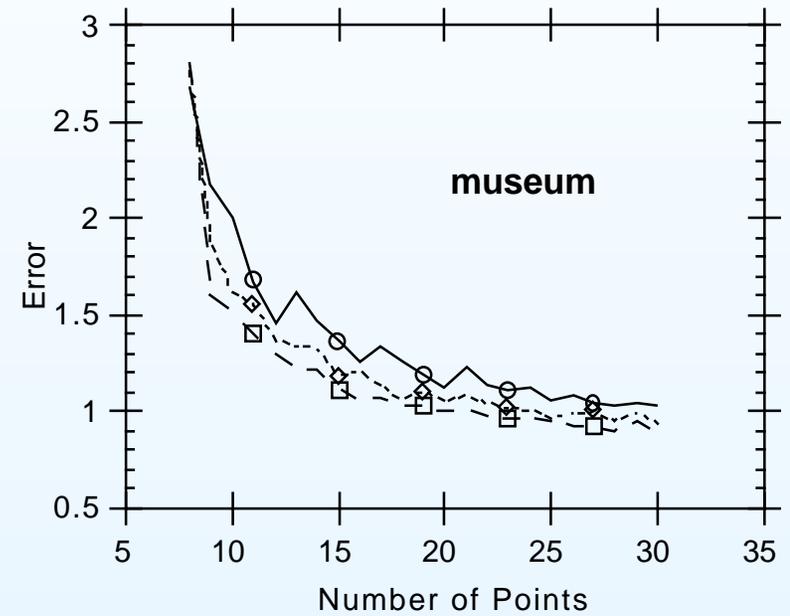
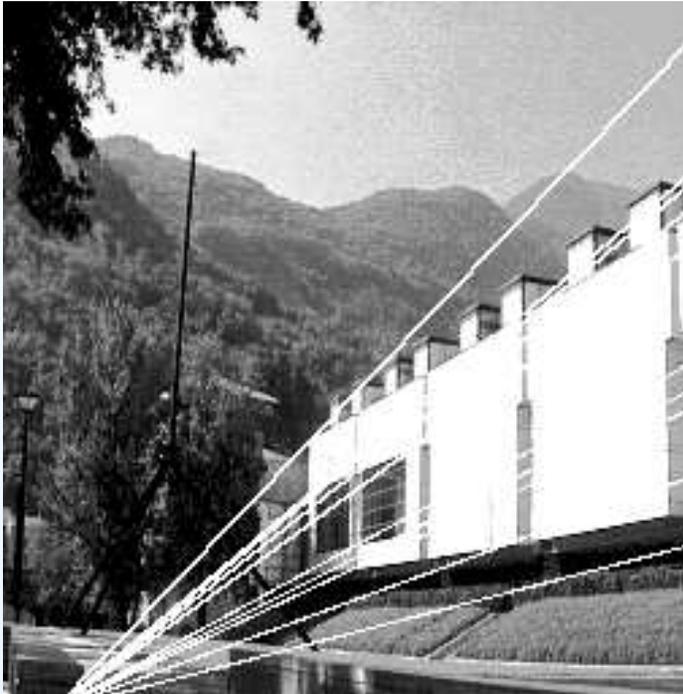
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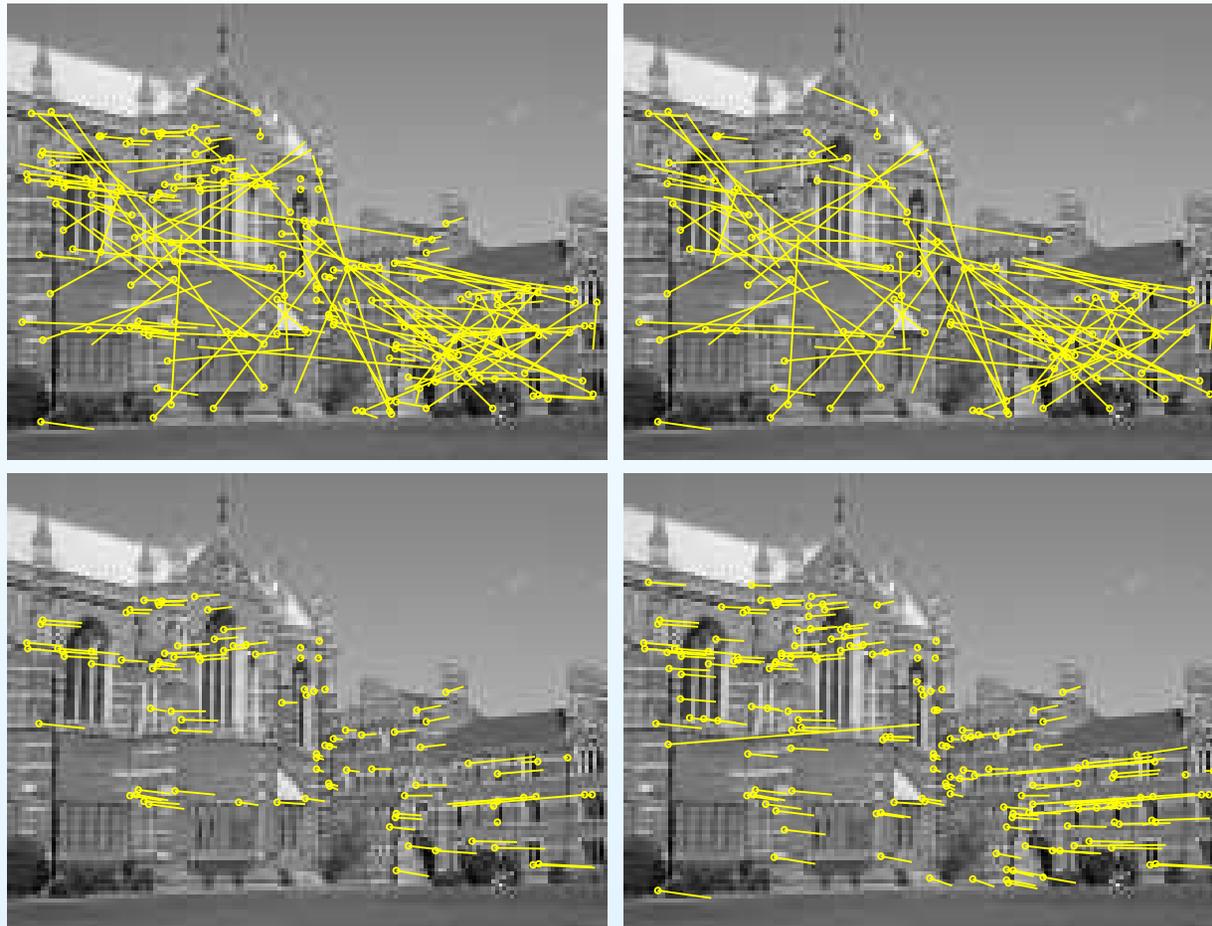
A comparison



$$\frac{1}{N} \sum_i d(x'_i, F x_i)^2 + d(x_i, F^T x'_i)^2$$

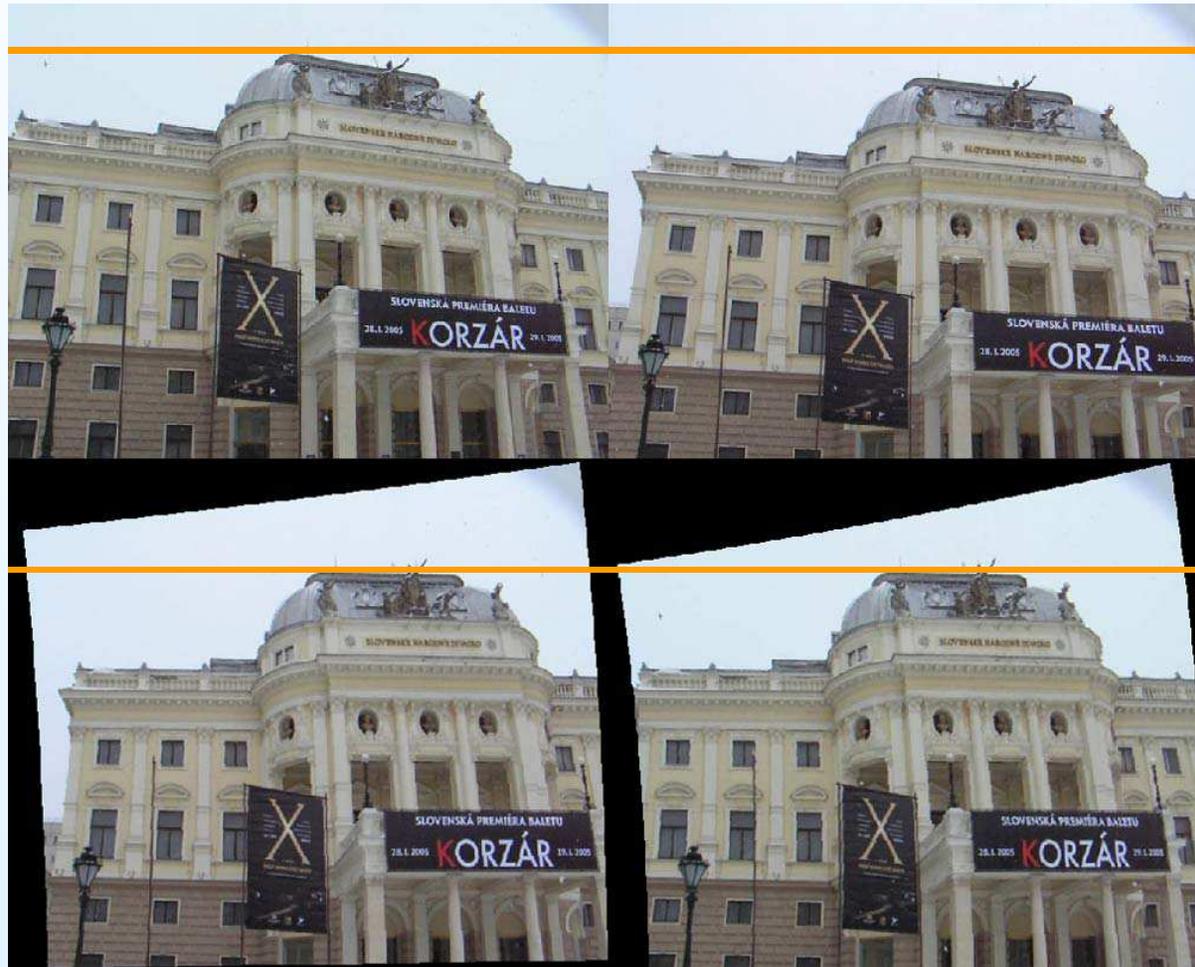
Automatic computation of F

Look at Hartley and Zisserman page 291 Algorithm 11.4.

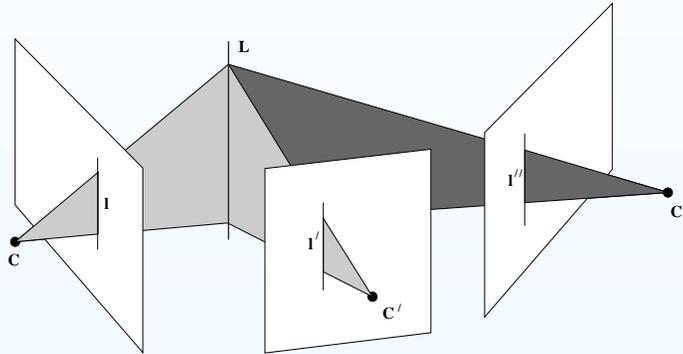


Using F for image rectification

Look at Hartley and Zisserman page 307 Algorithm 11.12.3

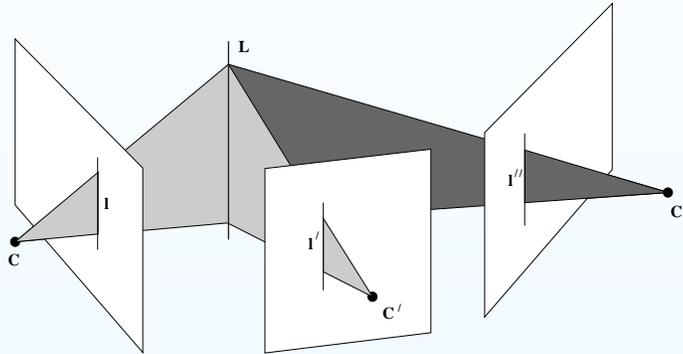


The Trifocal tensor



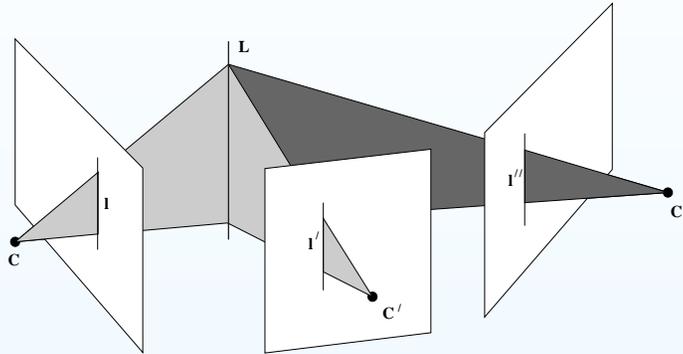
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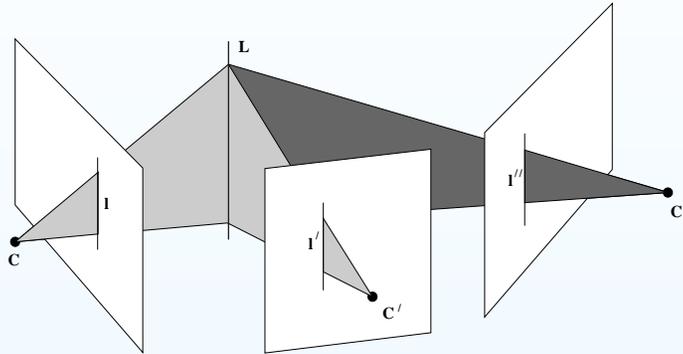
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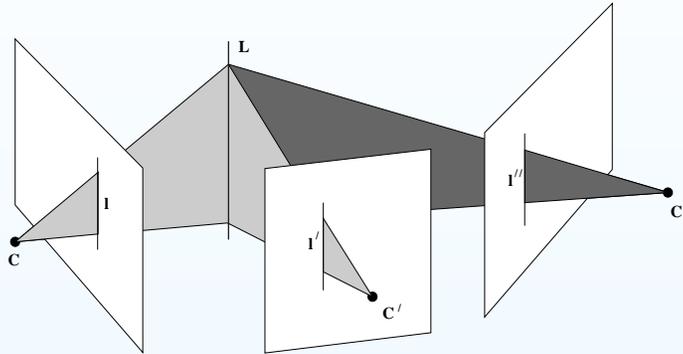
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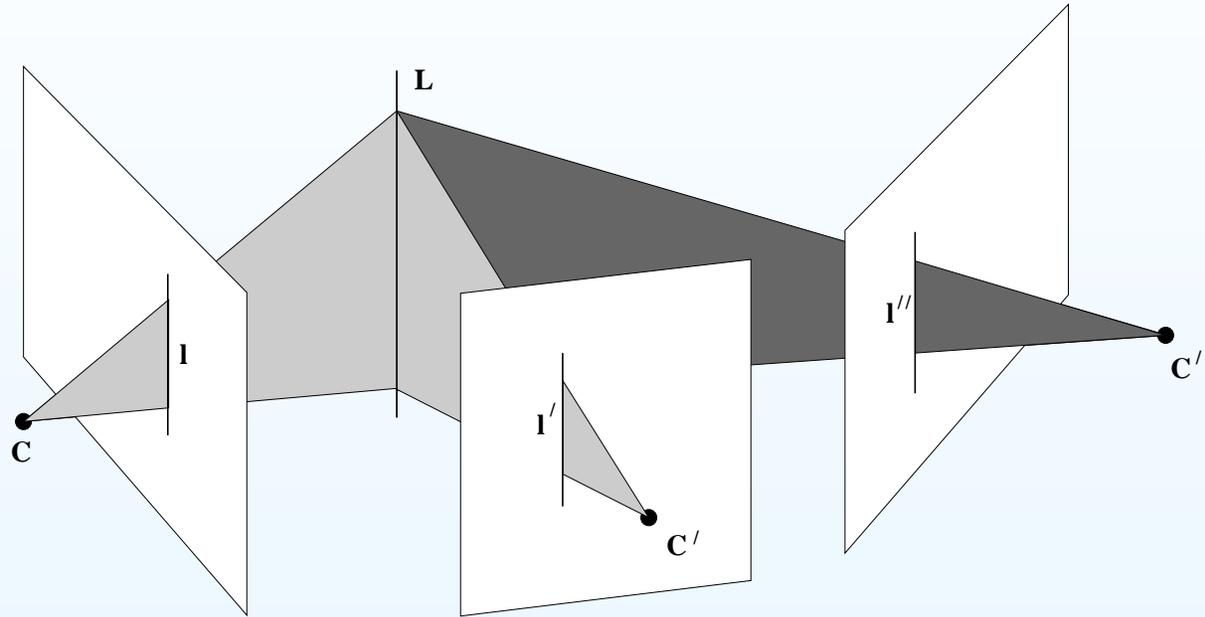
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- However, it can be computed directly from image correspondence without knowledge of the internal and external camera matrices.

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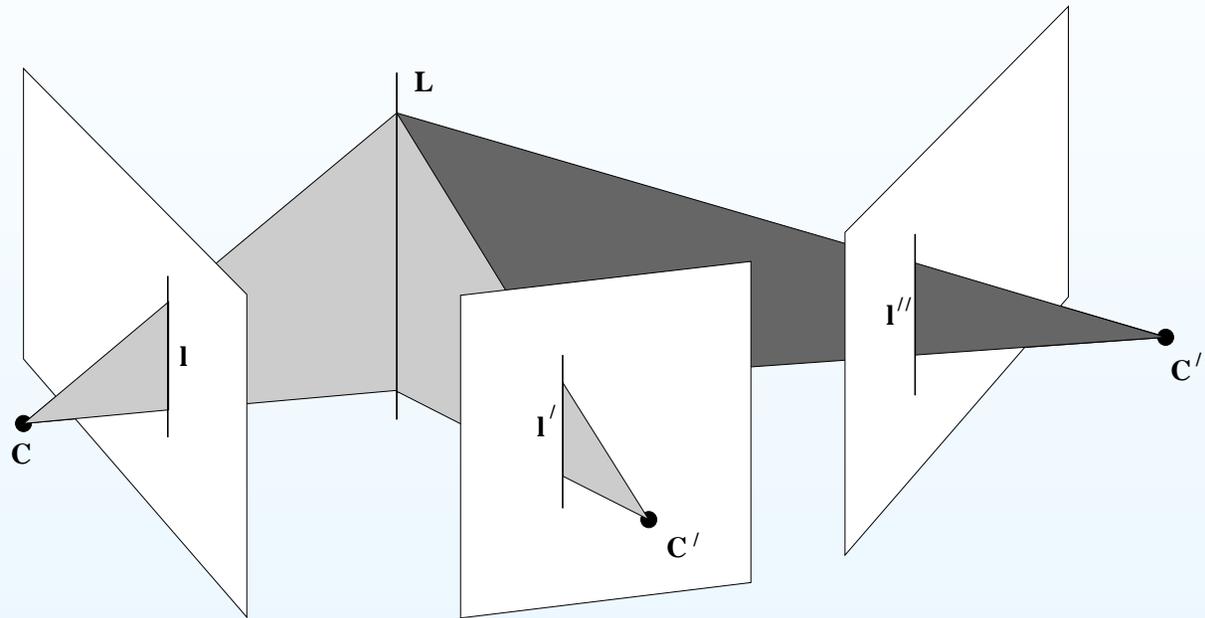
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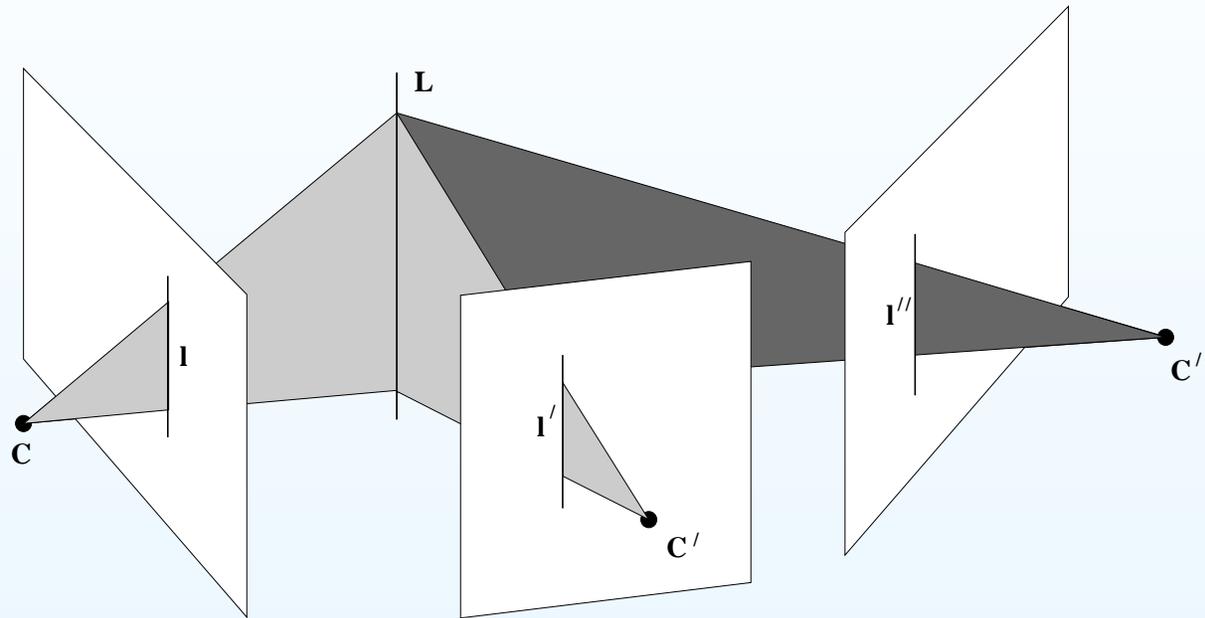
- Image lines back project to scene planes.

The Trifocal tensor



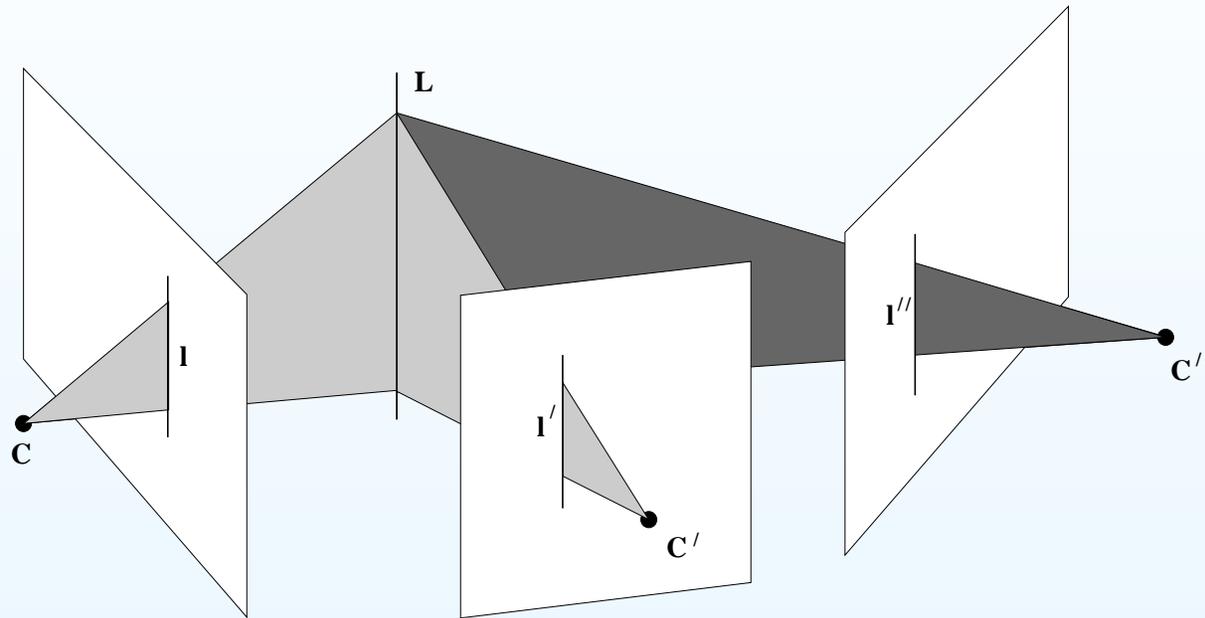
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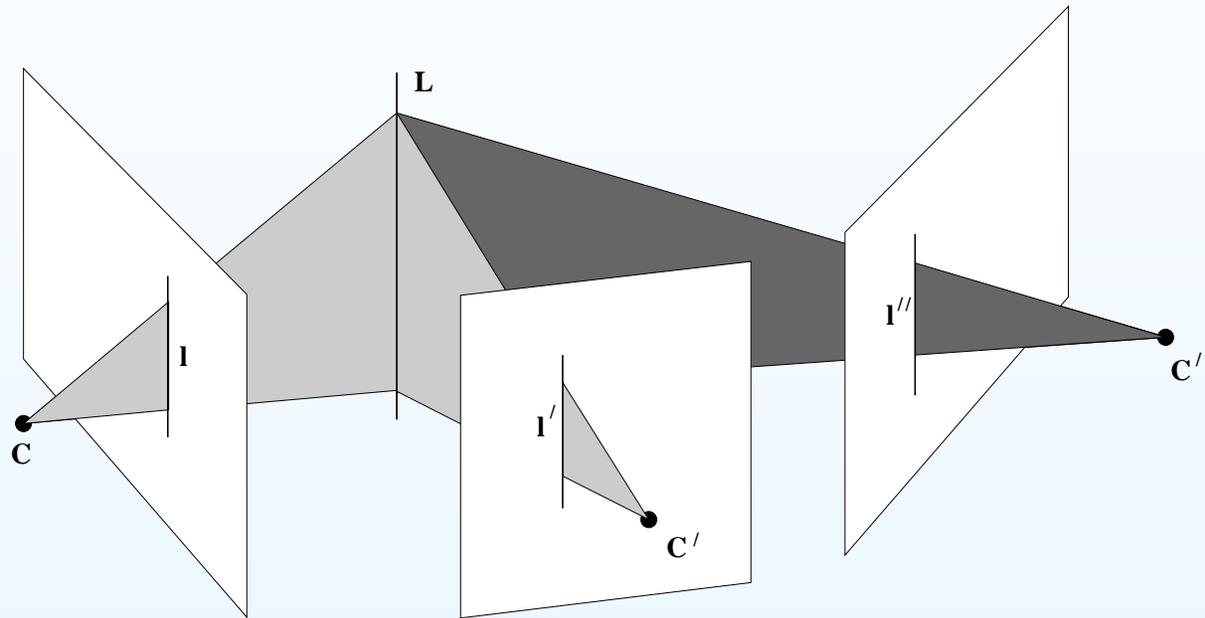
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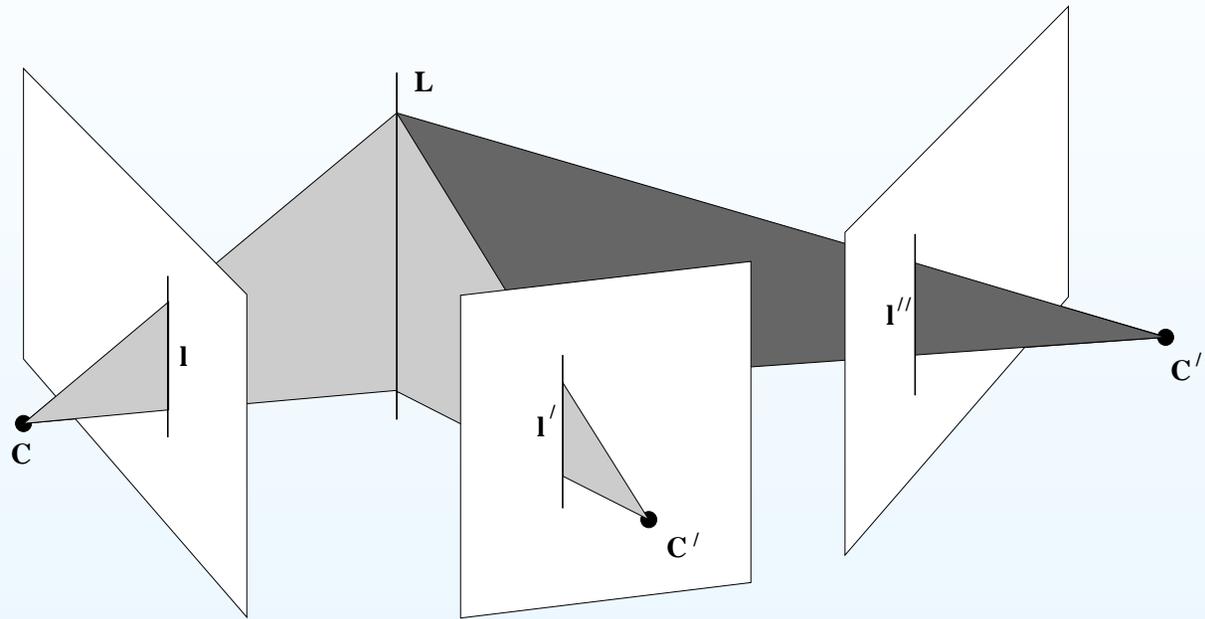
Three corresponding image lines: $l \leftrightarrow l' \leftrightarrow l''$

Camera matrices (3x4) for the three views:

$$P = [I | 0], \quad P' = [A | a_4], \quad P'' = [B | b_4]$$

$a_4 = e'$ and $b_4 = e''$ are the epipoles arising from the first camera center C thus: $e' = P'C$ and $e'' = P''C$

The Trifocal tensor

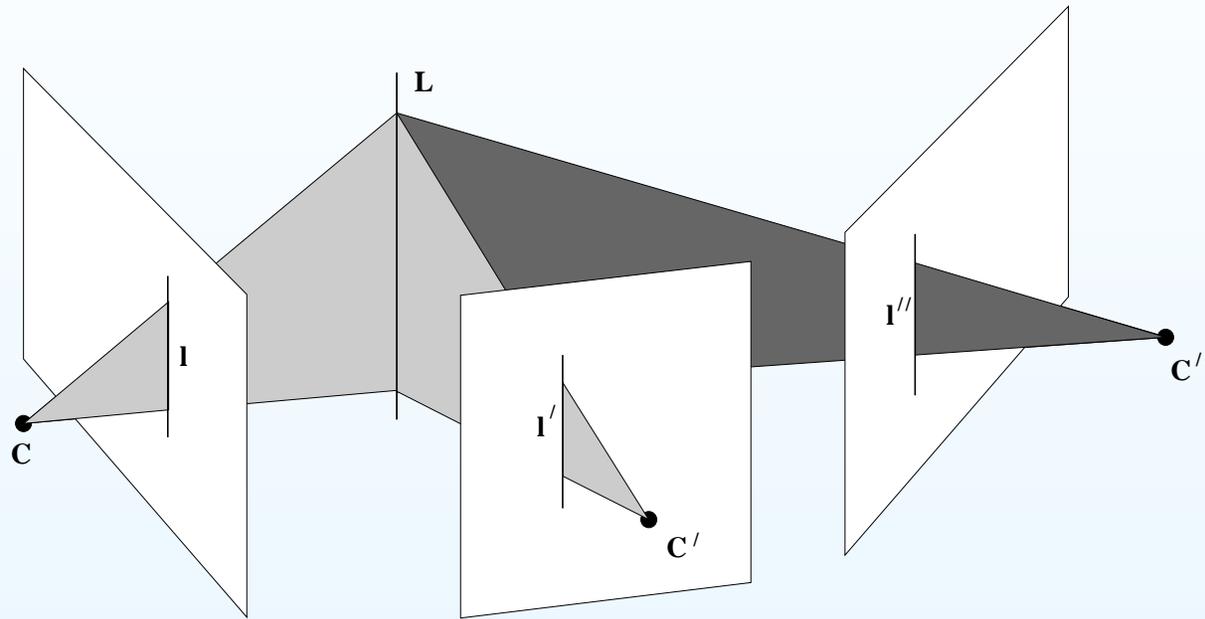


The lines: $l \leftrightarrow l' \leftrightarrow l''$ back project to the planes:

$$\pi = P^\top l = \begin{pmatrix} 1 \\ 0 \end{pmatrix}, \quad \pi' = P'^\top l' = \begin{pmatrix} A^\top l' \\ a_4^\top l' \end{pmatrix},$$

$$\pi'' = P''^\top l'' = \begin{pmatrix} B^\top l'' \\ b_4^\top l'' \end{pmatrix}.$$

The Trifocal tensor

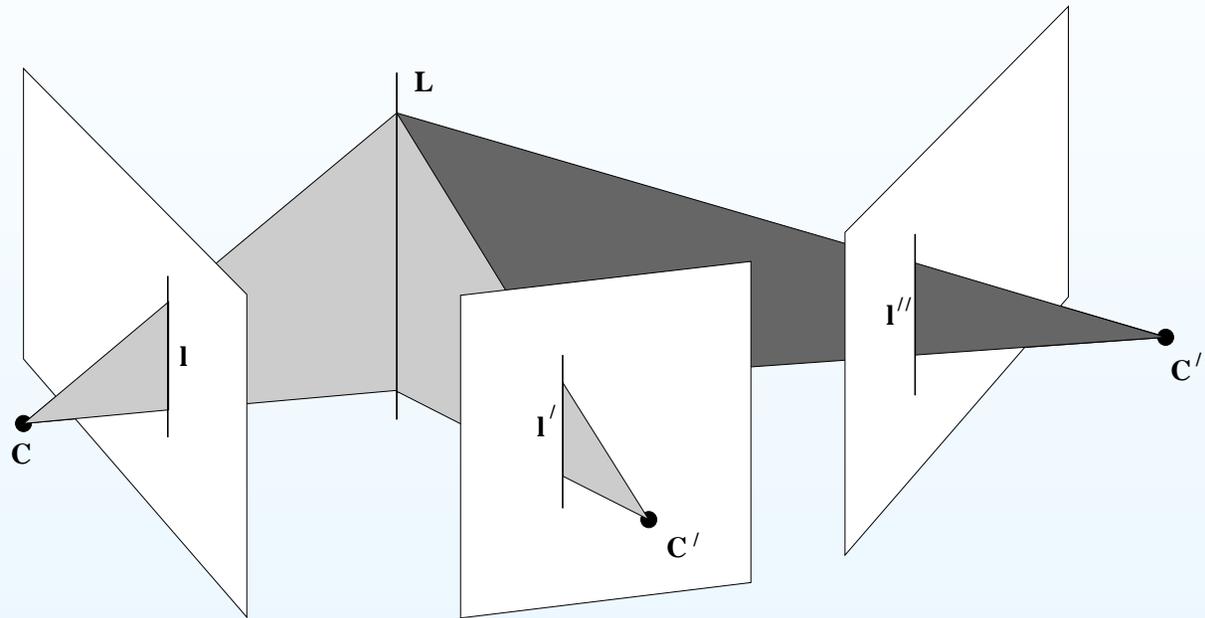


The planes π, π' and π'' coincide in the line L

This can be expressed algebraically with:

$$M = [\pi, \pi', \pi''], \quad \det(M) = 0$$

The Trifocal tensor

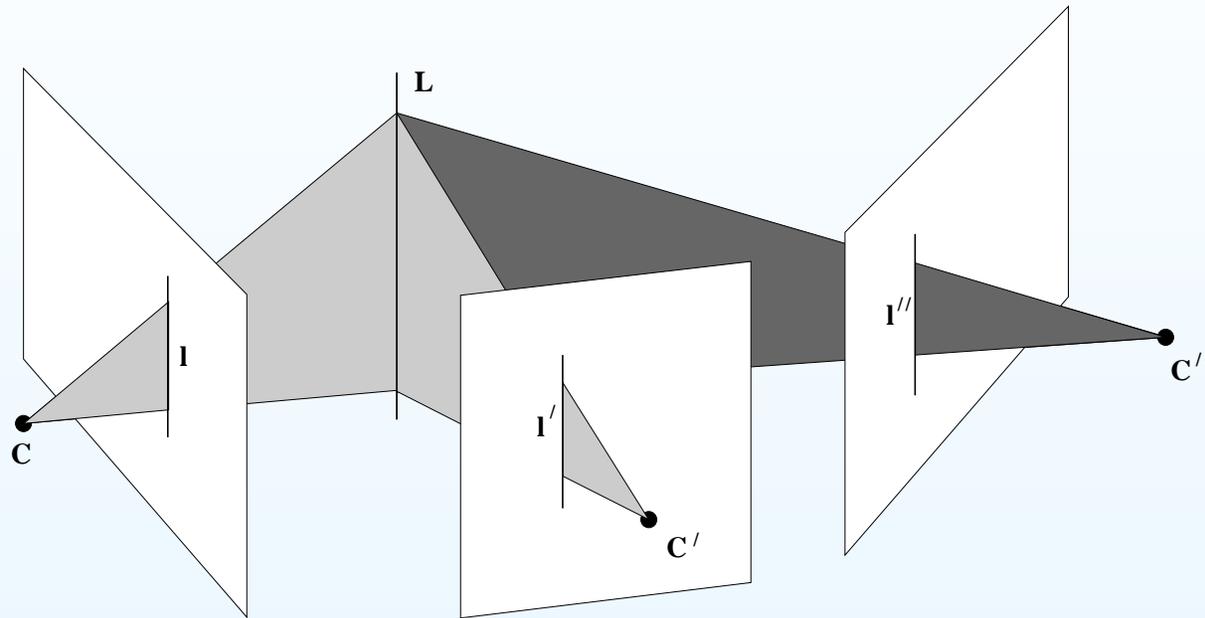


$$M = [m_1, m_2, m_3] = \begin{bmatrix} 1 & A^T l' & B^T l'' \\ 0 & a_4^T l' & b_4^T l'' \end{bmatrix}$$

Since $\det(M) = 0$ The columns must be linearly dependent.

$$\text{Thus, } m_1 = \alpha m_2 + \beta m_3$$

The Trifocal tensor

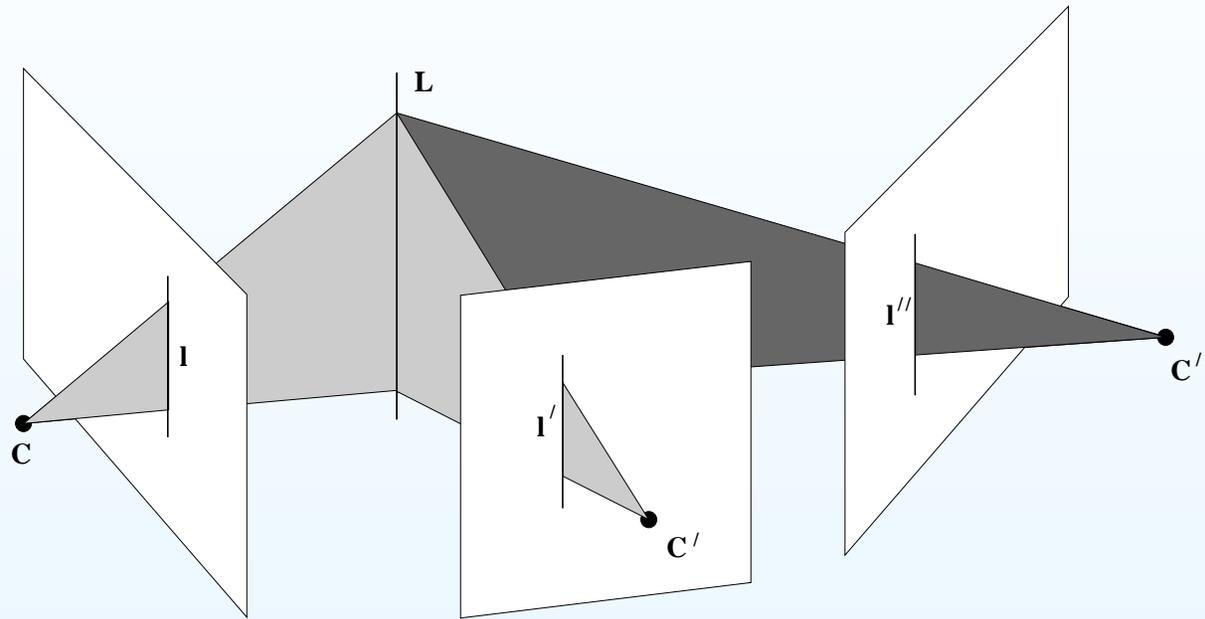


$$M = [m_1, m_2, m_3] = \begin{bmatrix} 1 & A^\top l' & B^\top l'' \\ 0 & a_4^\top l' & b_4^\top l'' \end{bmatrix}$$

Since the bottom left element of $M = 0$ it follows that:

$$\alpha = k(b_4^\top l'') \text{ and } \beta = -k(a_4^\top l')$$

The Trifocal tensor

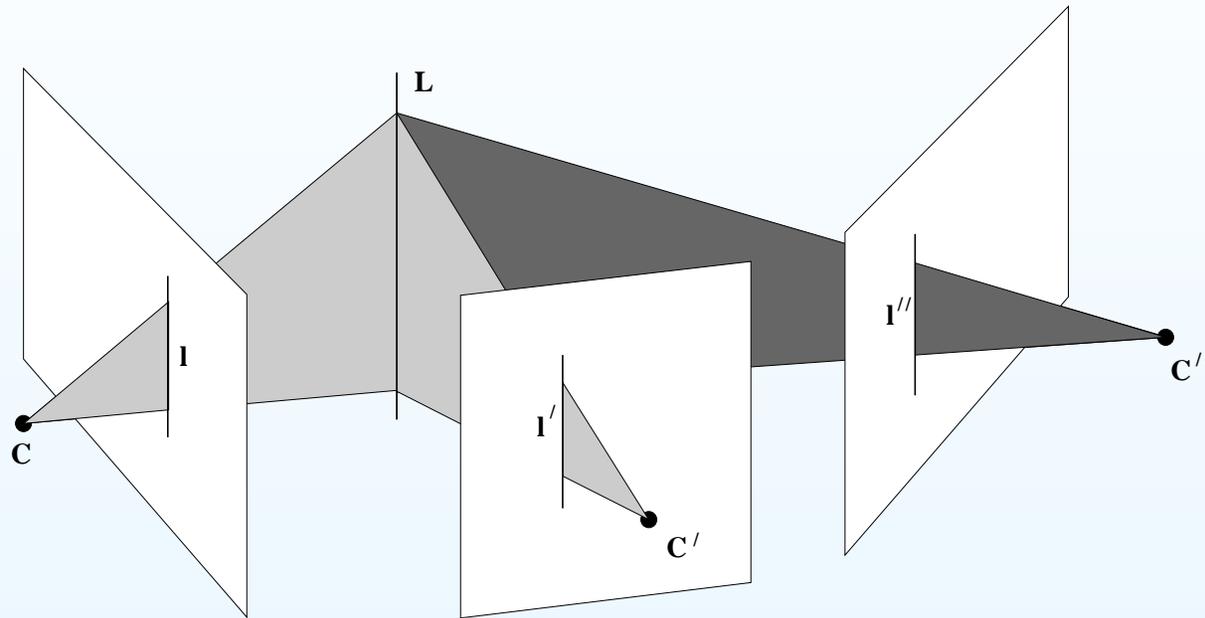


$$M = [m_1, m_2, m_3] = \begin{bmatrix} 1 & A^\top l' & B^\top l'' \\ 0 & a_4^\top l' & b_4^\top l'' \end{bmatrix}$$

For the top three vectors of M this gives:

$$l = (b_4^\top l'') A^\top l' - (a_4^\top l') B^\top l'' = (l''^\top b_4) A^\top l' - (l'^\top a_4) B^\top l''$$

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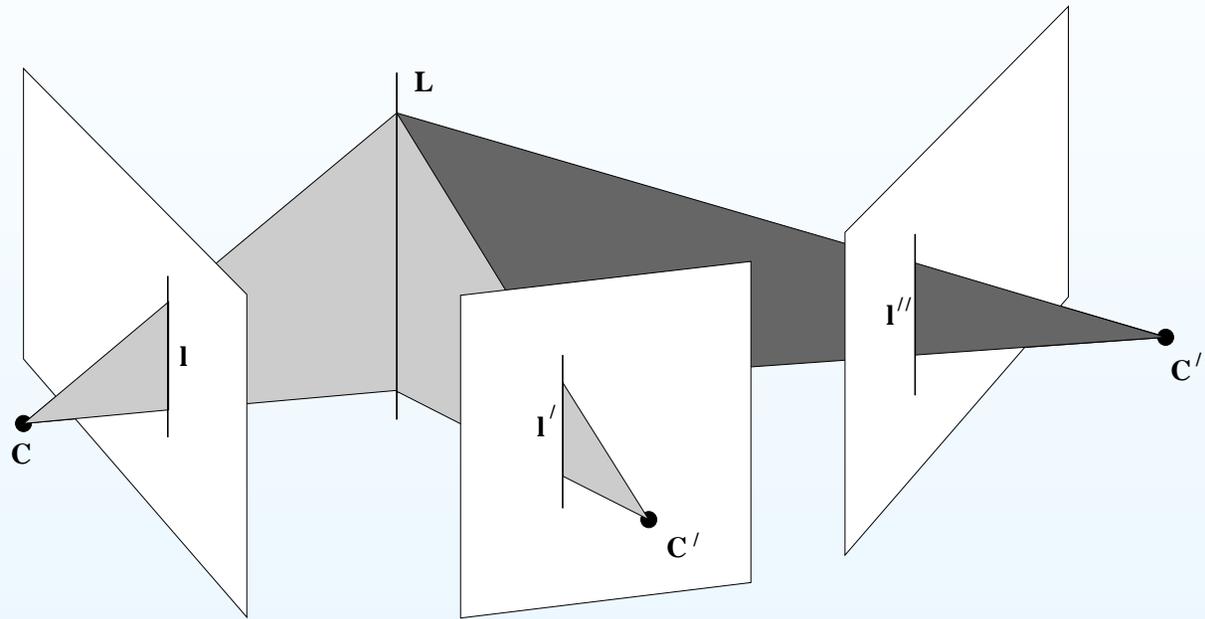


For the i -th element of we have:

$$l_i = l''^\top (b_4 a_i^\top) l' - l'^\top (a_4 b_i^\top) l''$$

$$l_i = l'^\top (a_i b_4^\top) l'' - l''^\top (a_4 b_i^\top) l'$$

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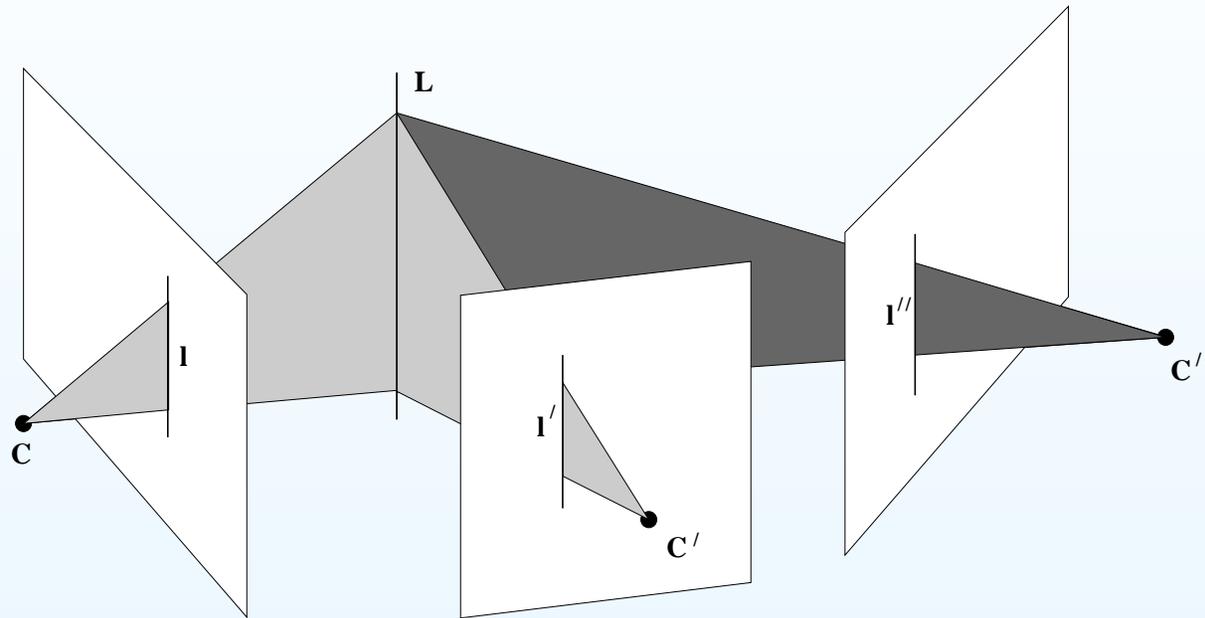


$$l_i = l'^T (a_i b_4^T) l'' - l'^T (a_4 b_i^T) l''$$

$$T_i = a_i b_4^T - a_4 b_i^T$$

$$l_i = l'^T T_i l''$$

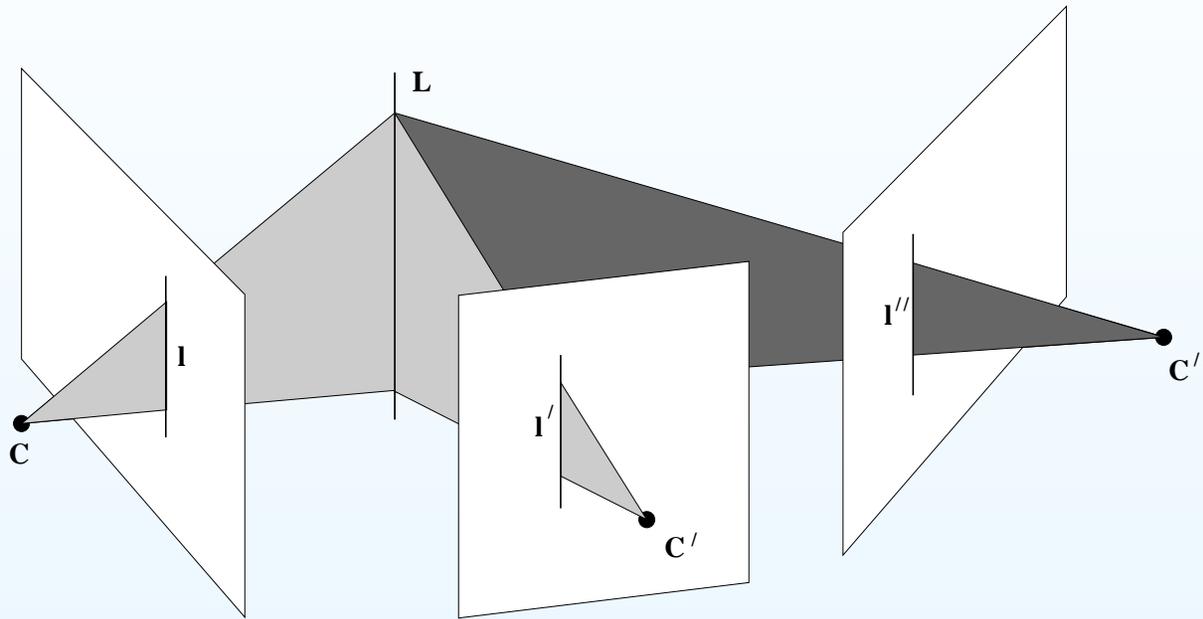
The Trifocal tensor



The set of the three matrices T_1, T_2, T_3 constitute the trifocal tensor in matrix notation.

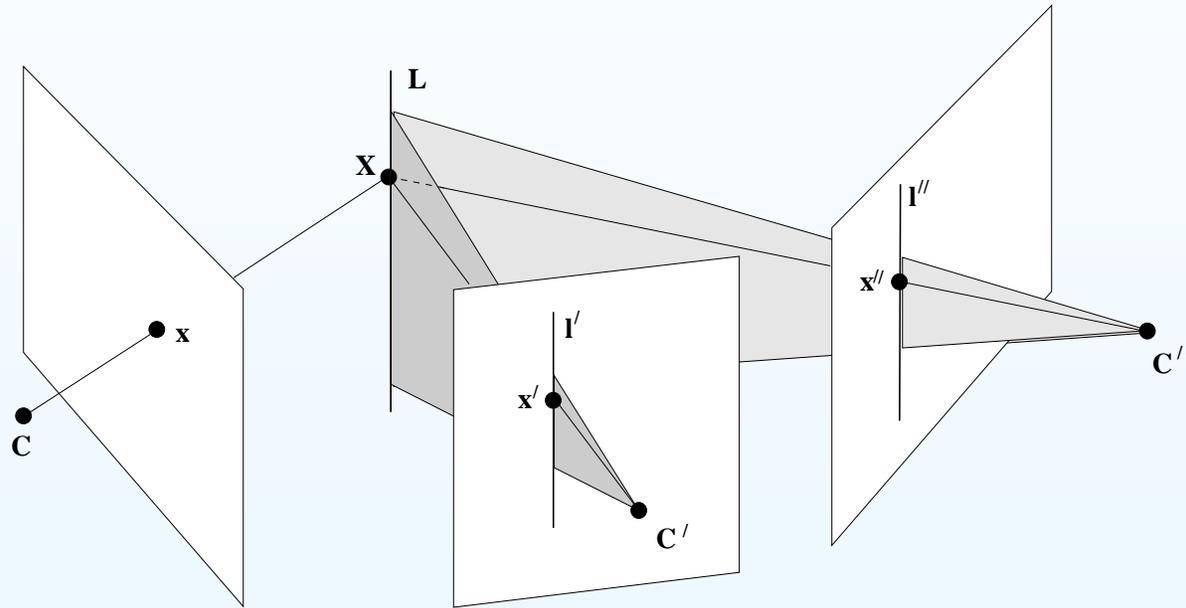
$$l^T = (l_i = l'^T T_1 l'', l_i = l'^T T_2 l'', l_i = l'^T T_3 l'') = l'^T \begin{bmatrix} T_1 & T_2 & T_3 \end{bmatrix} l''$$

Line-Line-Line correspondence



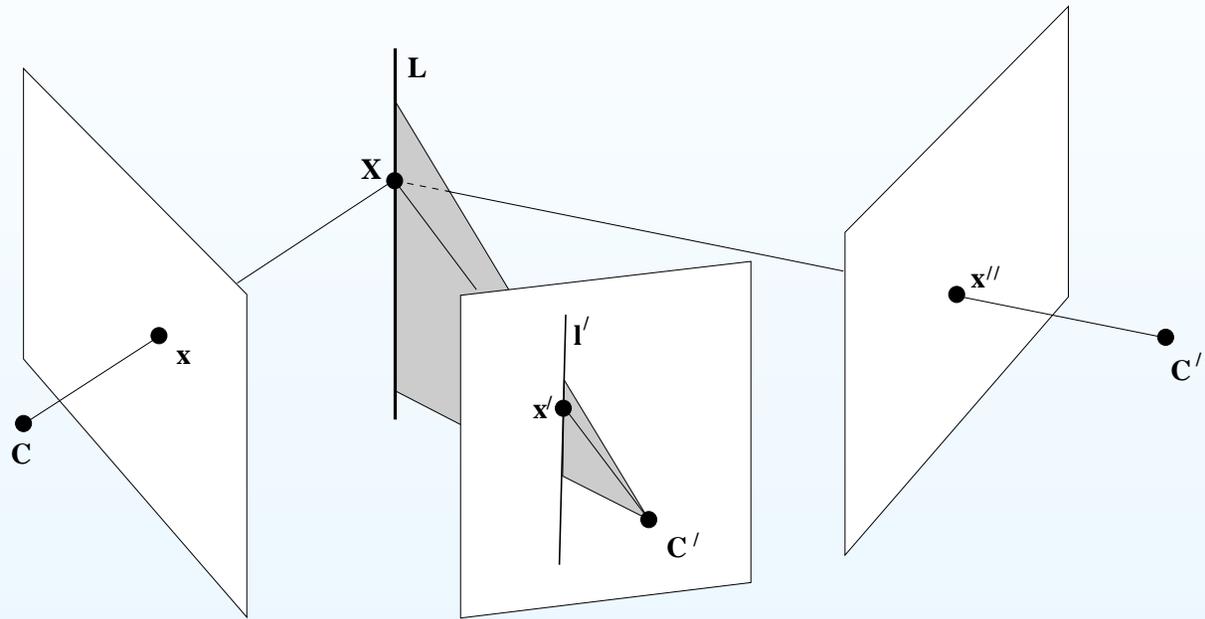
$$l^T = l'^T \begin{bmatrix} T_1 & T_2 & T_3 \end{bmatrix} l''$$

Point-Line-Line correspondence



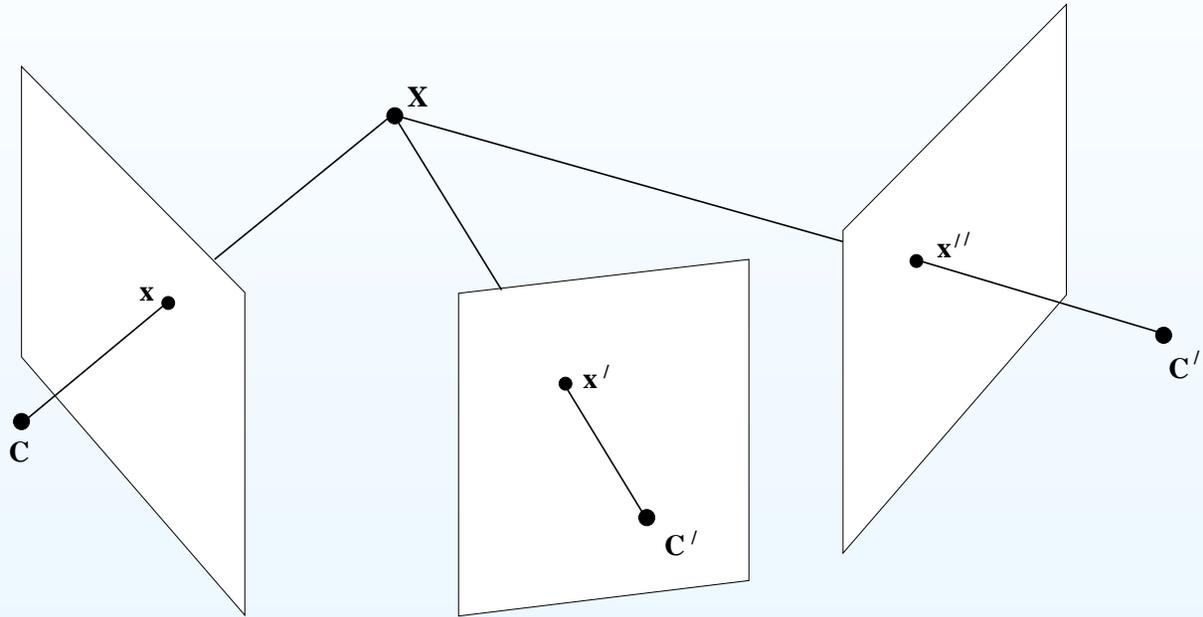
$$l'^T \left(\sum_i x^i T_i \right) l'' = 0$$

Point-Line-Point correspondence



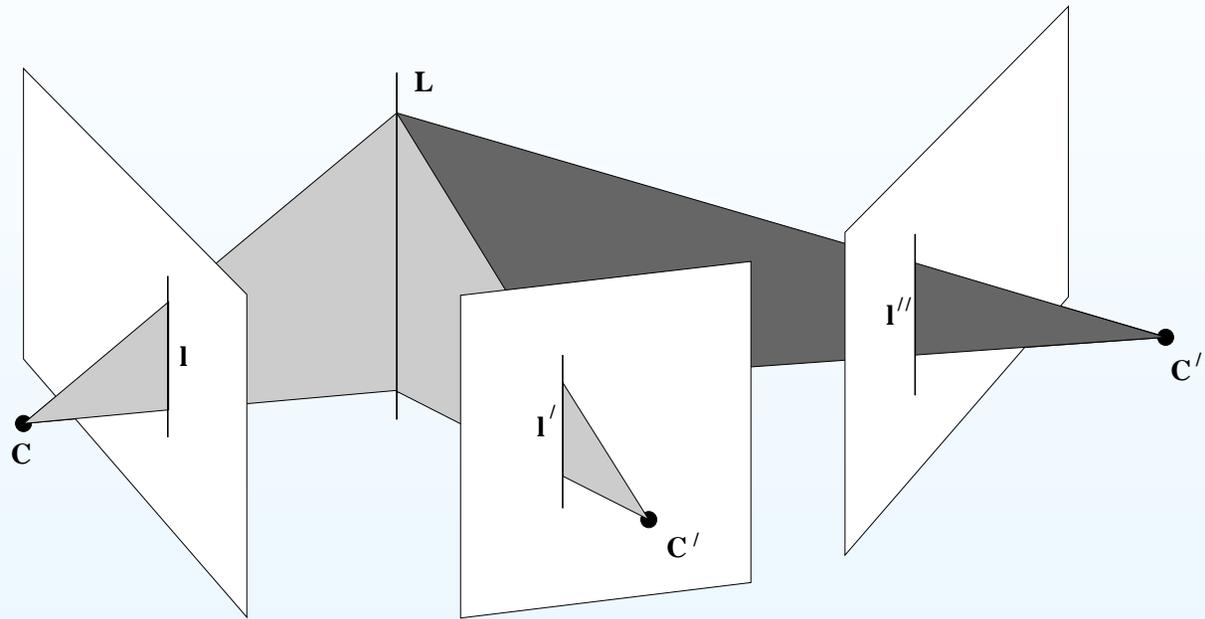
$$l'^T \left(\sum_i x^i T_i \right) [x'']_x = \mathbf{0}^T$$

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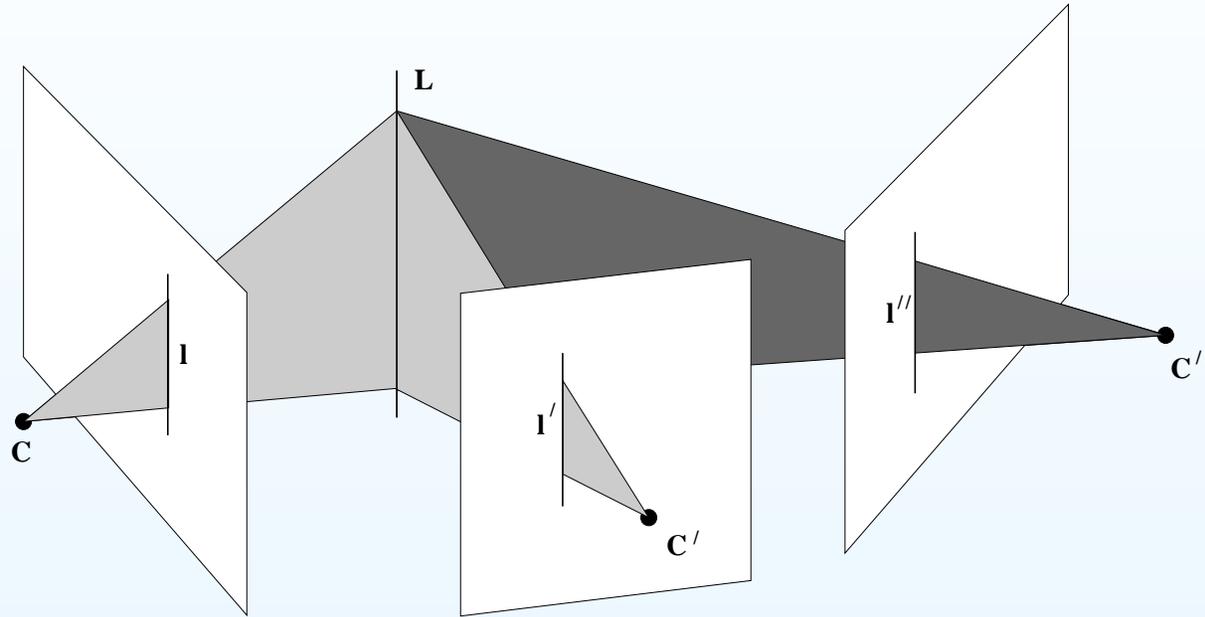
$$[x']_{\times} \left(\sum_i x^i T_i \right) [x'']_{\times} = 0_{3 \times 3}$$

Extracting the fundamental matrix



$$F_{21} = [e']_{\times} [T_1, T_2, T_3]e''$$

Retrieving the camera matrices



$$P' = [[T_1, T_2, T_3]e'' | e']$$

Retrieving food

