

Camera calibration - 3D calibration rig

consider simpler case first (no distortion)

$$\underline{\mathbf{X}} = \mathbf{K} [\mathbf{R} \quad \mathbf{t}] \underline{\mathbf{X}}$$

$$p_i = \begin{bmatrix} u_i \\ v_i \end{bmatrix} = \underline{\mathbf{M}} \underline{\mathbf{P}}_i = \begin{bmatrix} \frac{m_1 P_i}{m_3 P_i} \\ \frac{m_3 P_i}{m_3 P_i} \\ \frac{m_2 P_i}{m_3 P_i} \end{bmatrix}$$

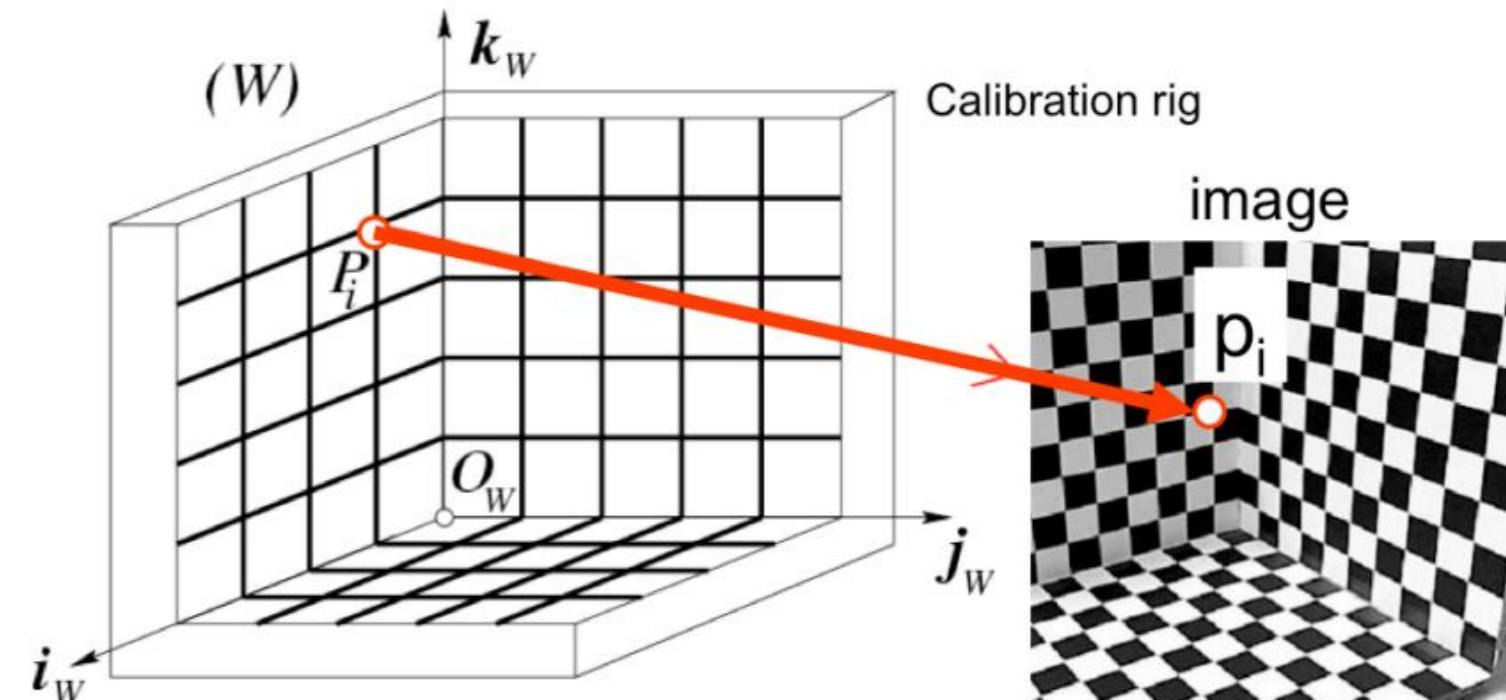
known from
calibration rig

(m_1, m_2, m_3 are rows of \mathbf{M})

$$u_i(m_3 P_i) - m_1 P_i = 0$$

$$v_i(m_3 P_i) - m_2 P_i = 0$$

each correspondence gives
2 equations, while \mathbf{M} has 11 DoF



$$u_1(m_3 P_1) - m_1 P_1 = 0$$

$$v_1(m_3 P_1) - m_2 P_1 = 0$$

:

$$u_n(m_3 P_n) - m_1 P_n = 0$$

$$v_n(m_3 P_n) - m_2 P_n = 0$$

we need at least 6 correspondences, but often
we use more as measurement are often noisy

Camera calibration - 3D calibration rig

$$\begin{bmatrix} P_1^T & 0^T & -u_1 P_1^T \\ 0^T & P_1^T & -v_1 P_1^T \\ \vdots & & \\ P_n^T & 0^T & -u_n P_n^T \\ 0^T & P_n^T & -v_n P_n^T \end{bmatrix} \begin{bmatrix} m_1^T \\ m_2^T \\ m_3^T \end{bmatrix} = \mathbf{P}m = 0$$



$$\underset{m}{\text{minimize}} \quad \|\mathbf{P}m\|^2$$

subject to $\|m\|^2 = 1$ **to avoid trivial solution $m=0$**
 $\forall k \in \mathbb{R}, km$ **is also a solution**

can be solved by singular value decomposition (SVD)



$$P = UDV^T$$

set m equal to the last column of V



$$M = K [R \mid t] = [KR \mid KRT] = \begin{array}{c|c} \text{3x3} & \text{3x1} \\ [C \mid CT] \end{array}$$

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$$\begin{bmatrix} P_1^T & 0^T & -u_1 P_1^T \\ 0^T & P_1^T & -v_1 P_1^T \\ \vdots & & \\ P_n^T & 0^T & -u_n P_n^T \\ 0^T & P_n^T & -v_n P_n^T \end{bmatrix} \begin{bmatrix} m_1^T \\ m_2^T \\ m_3^T \end{bmatrix} = \mathbf{P}m = 0$$

minimize m $\|\mathbf{P}m\|^2$

subject to $\|m\|^2 = 1$

$C = KR$
where K is upper triangular matrix
 R is orthogonal matrix ($R^T R = 1$)
we can use QR decomposition to
get K (intrinsic) and R (rotation)
to get T (translation), simply multiply
 C^{-1} to CT

can be solved by singular value decomposition (SVD)

$$P = UDV^T$$

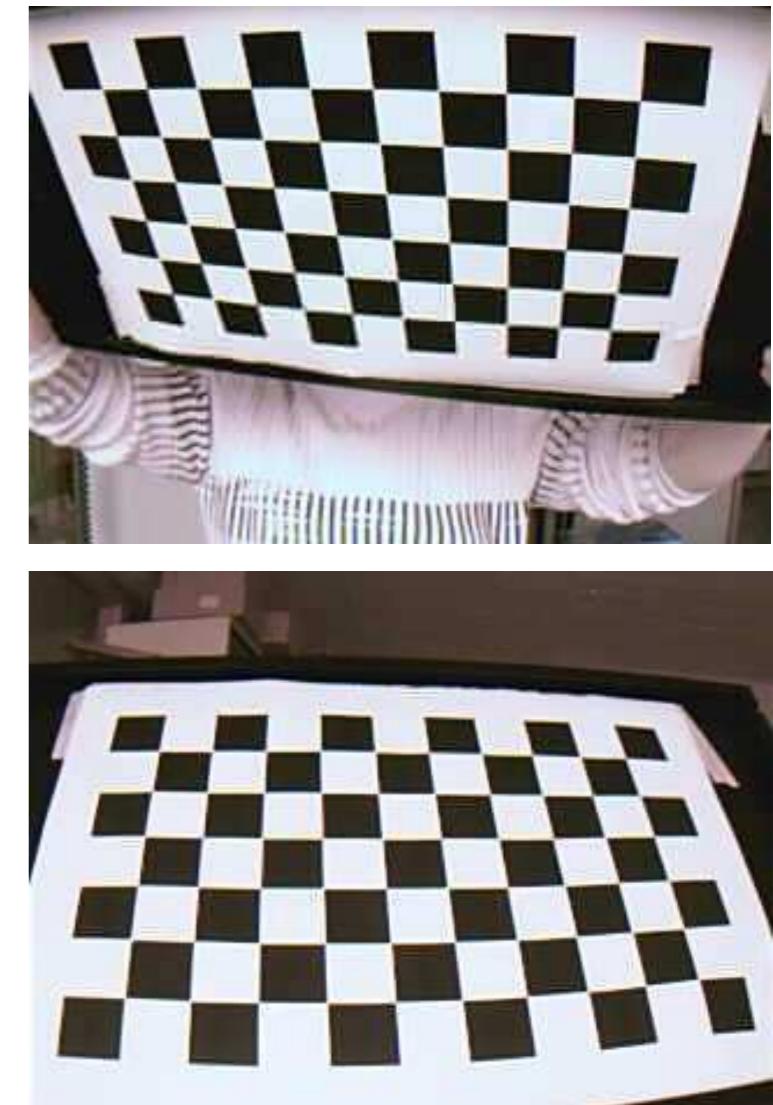
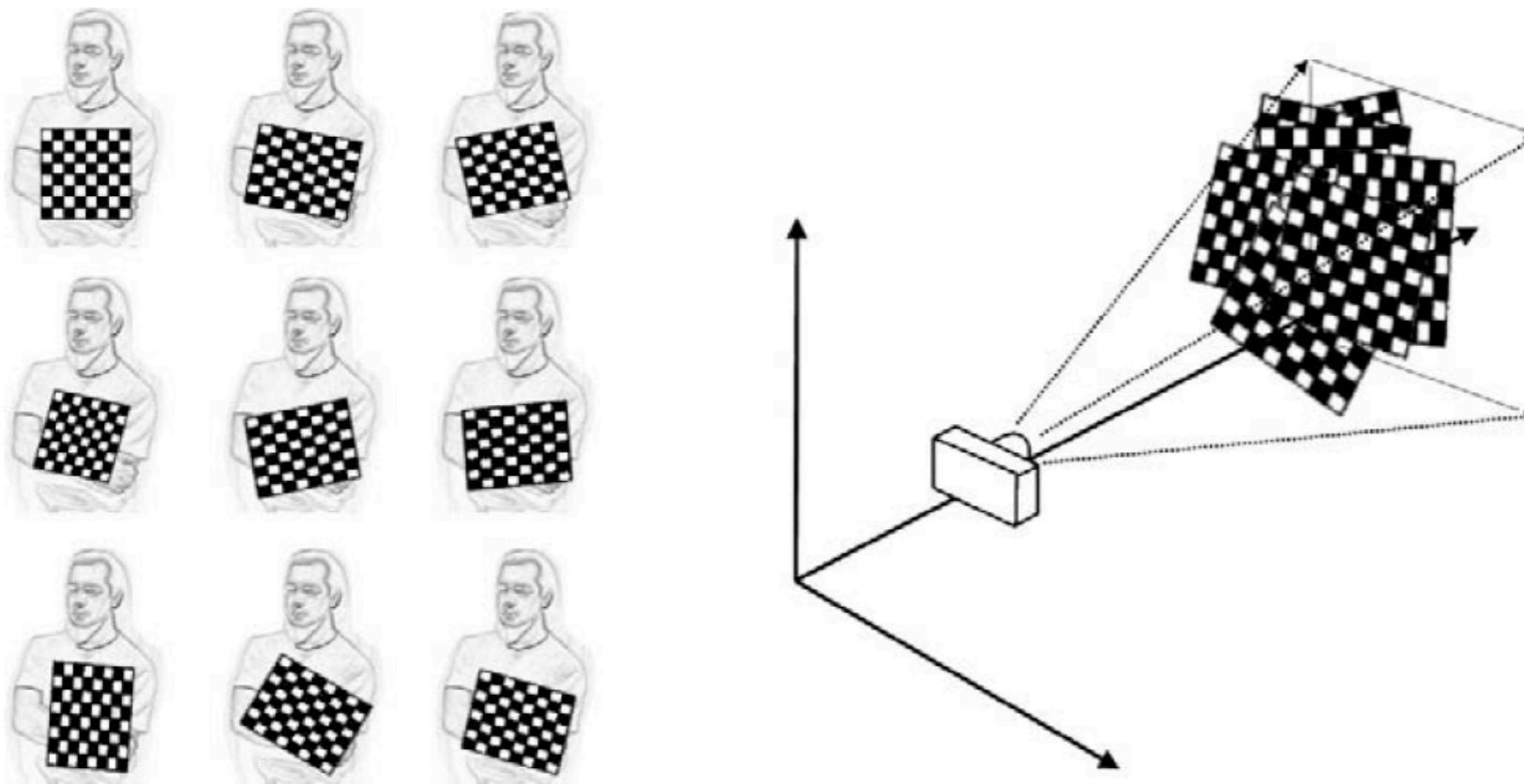
set m equal to the last column of V

$$M = K [R \mid t] = [KR \mid KRT] = [C \mid CT]$$

many other
calibration methods
and also we need to
consider distortion!

Camera calibration - 2D calibration chessboard

- 3D calibration rig hard to make (perpendicularity across 3 planes)
- Use a 2D pattern (e.g. a chessboard)
- Trick: set the world coordinate system to the corner of chessboard



Camera calibration - 2D calibration chessboard

- Trick: set the world coordinate system to the corner of chessboard
- Now: all points on the chessboard lie in one plane!

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \sim \begin{bmatrix} f/s_x & 0 & o_x \\ 0 & f/s_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & r_{13} \\ r_{21} & r_{22} & r_{23} \\ r_{31} & r_{32} & r_{33} \end{bmatrix} \begin{bmatrix} t_1 \\ t_2 \\ t_3 \end{bmatrix} \begin{bmatrix} U \\ V \\ W \\ 1 \end{bmatrix}$$

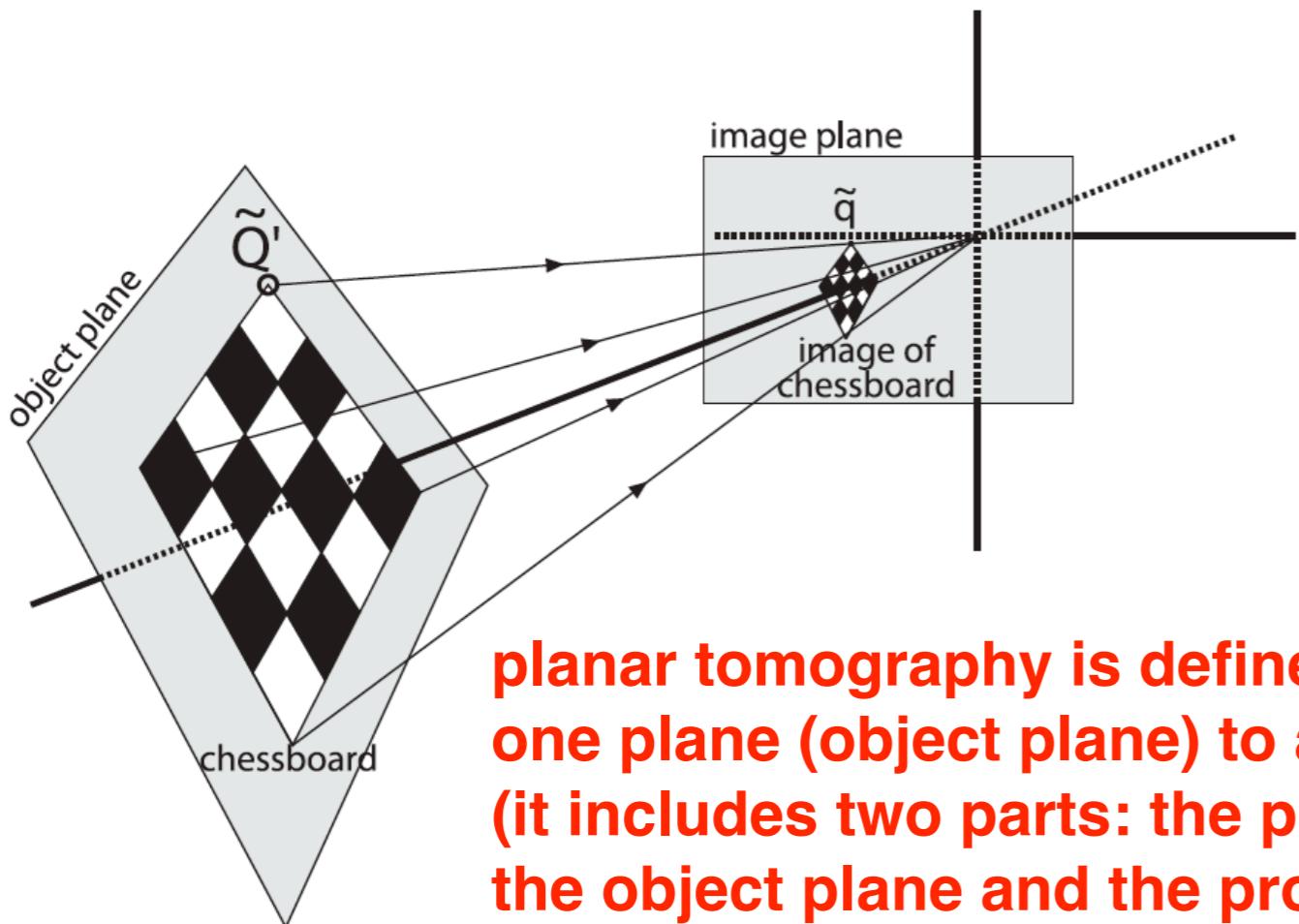
since all points lie in a plane, their W component is 0 in world coordinates

we can thus delete 3rd column
of extrinsic matrix

Camera calibration - 2D calibration chessboard

$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} \sim \begin{bmatrix} f/s_x & 0 & o_x \\ 0 & f/s_y & o_y \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix} \begin{bmatrix} U \\ V \\ 1 \end{bmatrix}$$

Homography H



$$\begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \rho H \begin{bmatrix} U \\ V \\ 1 \end{bmatrix}$$

up to a scale

planar tomography is defined as a perspective mapping from one plane (object plane) to another (image plane)
(it includes two parts: the physical transformation that locates the object plane and the projection that has camera intrinsic matrix)

Camera calibration - 2D calibration chessboard

$$H = (h_1, h_2, h_3) = \underbrace{\begin{bmatrix} f/s_x & 0 & o_x \\ 0 & f/s_y & o_y \\ 0 & 0 & 1 \end{bmatrix}}_{\mathbf{K}} \underbrace{\begin{bmatrix} r_{11} & r_{12} & t_1 \\ r_{21} & r_{22} & t_2 \\ r_{31} & r_{32} & t_3 \end{bmatrix}}_{(\mathbf{r}_1, \mathbf{r}_2, \mathbf{t})}$$

$$H = (h_1, h_2, h_3) = \mathbf{K}(\mathbf{r}_1, \mathbf{r}_2, \mathbf{t})$$

$$\mathbf{r}_1 = \mathbf{K}^{-1} \mathbf{h}_1 \text{ and } \mathbf{r}_2 = \mathbf{K}^{-1} \mathbf{h}_2$$

→ note that $(\mathbf{r}_1, \mathbf{r}_2, \mathbf{r}_3)$ form an orthonormal basis

thus $\mathbf{r}_1^\top \mathbf{r}_2 = 0$, $\|\mathbf{r}_1\| = \|\mathbf{r}_2\| = 1$

$$\rightarrow \mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_1 = \mathbf{h}_2^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2$$

Camera calibration - 2D calibration chessboard

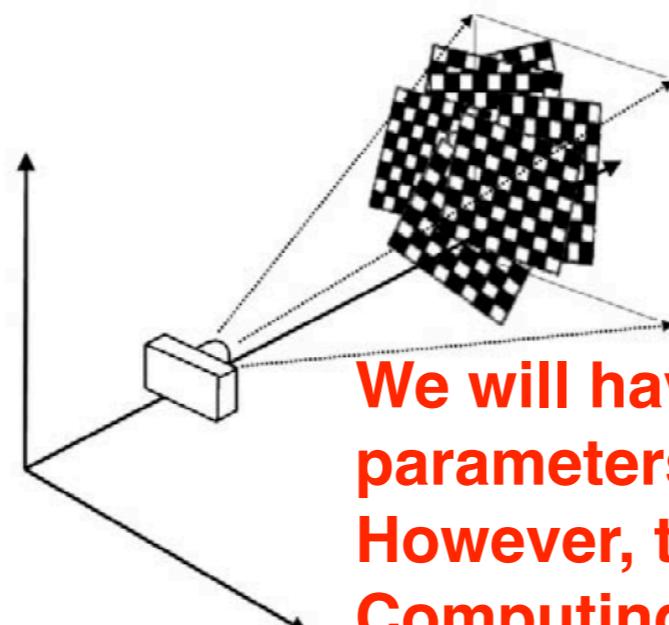
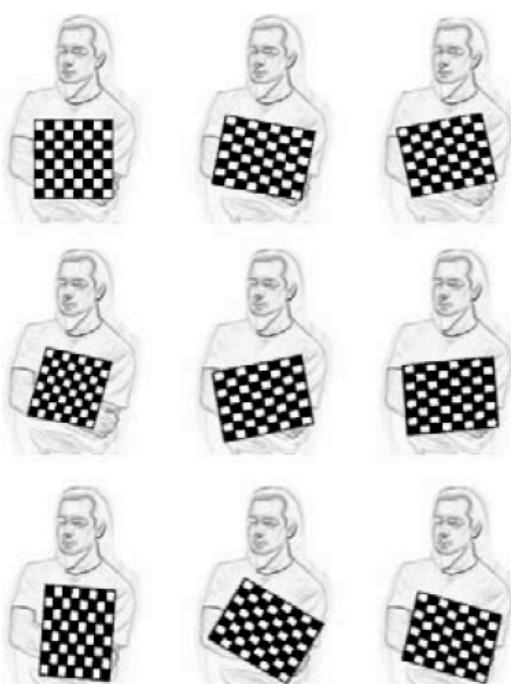
$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_1 = \mathbf{h}_2^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2$$

$\mathbf{B} := \mathbf{K}^{-\top} \mathbf{K}^{-1}$ is symmetric and positive definite

$$\mathbf{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

Note: \mathbf{K} can be calculated from \mathbf{B} using Cholesky factorization



We will have one set of new extrinsic parameters (define homography) for each view. However, the intrinsic parameters stay the same. Computing multiple H 's from multiple views can lead us to a unique set of intrinsic parameters.

Camera calibration - 2D calibration chessboard

$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

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$$\mathbf{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

→ define $\mathbf{b} = (b_{11}, b_{12}, b_{13}, b_{22}, b_{23}, b_{33})$

leads to the system of $\mathbf{Vb} = 0$

- Each plane gives 2 equations, \mathbf{B} has 6 DoF, we need at least 3 planes from different views

→ real measurements might be corrupted with noise, find solution that minimize least-squares error

$$\mathbf{b} = \underset{\mathbf{b}}{\operatorname{argmin}} \mathbf{Vb}$$

$$H = [\mathbf{h}_1 \quad \mathbf{h}_2 \quad \mathbf{h}_3] = \rho [\mathbf{r}_1 \quad \mathbf{r}_2 \quad \mathbf{t}] \rightarrow \lambda = 1/\|\mathbf{K}^{-1}\mathbf{h}_1\|$$

$$\mathbf{r}_1 = \lambda \mathbf{K}^{-1} \mathbf{h}_1$$

$$\mathbf{r}_2 = \lambda \mathbf{K}^{-1} \mathbf{h}_2$$

$$\mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2$$

$$\mathbf{t} = \lambda \mathbf{K}^{-1} \mathbf{h}_3$$

Camera calibration - 2D calibration chessboard

$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_1 = \mathbf{h}_2^\top \mathbf{K}^{-\top} \mathbf{K}^{-1} \mathbf{h}_2$$

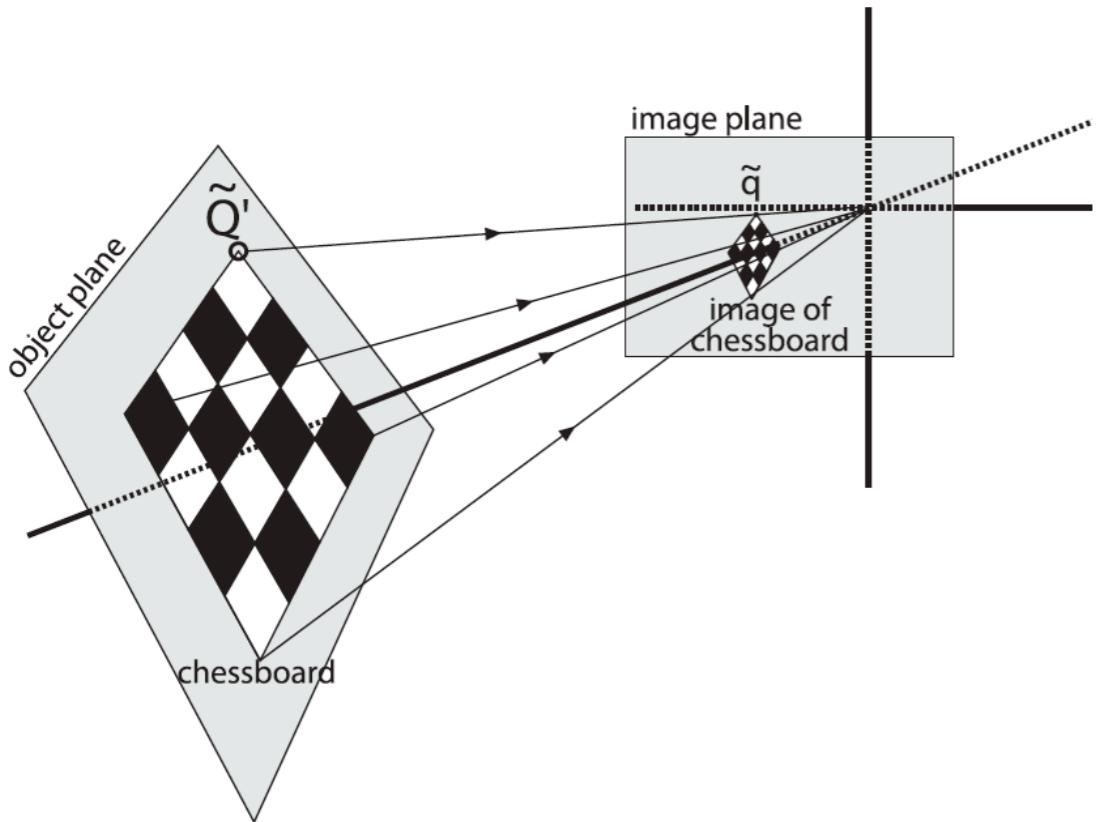
$$\mathbf{B} = \begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{12} & b_{22} & b_{23} \\ b_{13} & b_{23} & b_{33} \end{pmatrix}$$

→ define $\mathbf{b} = (b_{11}, b_{12}, b_{13}, b_{22}, b_{23}, b_{33})$

leads to the system of $\mathbf{Vb} = 0$

- Each plane gives 2 equations, \mathbf{B} has 6 DoF, we need at least 3 planes from different views
- N corners and M images of the chessboard (in different positions)
- M images of the chessboard provide $2NM$ constraints (x, y axes)
- Need to solve for 4 intrinsic parameters (ignore skew and distortion) and $6M$ extrinsic parameters (intrinsic parameters stay the same)
- $2NM$ must be \geq to $6M+4$ to solve for these parameters (or equivalently $(N-3)M \geq 2$)
- If $N = 5$ then we need only $M = 1$ image!?

Camera calibration - 2D calibration chessboard



- Only 4 points are needed to express that a planar perspective view can do
- A homography can yield at most 8 paras from 4 (x, y) pairs
- Per chessboard view, then, the equations can give us only 4 corners of information $(N-3)M \geq 2 \rightarrow (4-3)M \geq 2 \rightarrow M \geq 2$

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(or equivalently $(N-3)M \geq 2$)
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in practice we need more images of larger chessboard to achieve better stability!