## The Projection "Chain"



## Projection Geometry: Standard Camera Coordinates

- By convention, we place the image in front of the optical center
  - typically we approximate by saying it lies one focal distance from the center
  - in reality this can't be true for a finite size chip!
- Optical axis is z axis pointing outward
- X axis is parallel to the scanlines (rows) pointing to the right!
- By the right hand rule, the Y axis must point downward
- Note this corresponds with indexing an image from the upper left to the lower right, where the X coordinate is the column index and the Y coordinate is the row index.

#### Intrinsic Parameters

Intrinsic Parameters describe the conversion from unit focal length metric to pixel coordinates (and the reverse)

$$x_{mm} = -(x_{pix} - o_x) s_x --> -1/s_x x_{mm} + o_x = x_{pix}$$
  
 $y_{mm} = -(y_{pix} - o_y) s_y --> -1/s_y y_{mm} + o_y = y_{pix}$ 

or

$$\begin{pmatrix} x \\ y \\ w \end{pmatrix}_{pix} = \begin{pmatrix} -1/s_x & 0 & o_x \\ 0 & -1/s_y & o_y \\ 0 & 0 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \\ w \end{pmatrix}_{mm} = K_{int} p$$

It is common to combine scale and focal length together as the are both scaling factors; note projection is unitless in this case!

#### Putting it All Together

Now, using the idea of *homogeneous transforms*, we can write:

$$p' = \begin{pmatrix} R & T \\ 0 & 0 & 0 & 1 \end{pmatrix} p$$

R and T both require 3 parameters. These correspond to the 6 *extrinsic parameters* needed for camera calibration

Then we can write

 $q = \Pi p'$  for some projection model  $\Pi$ 

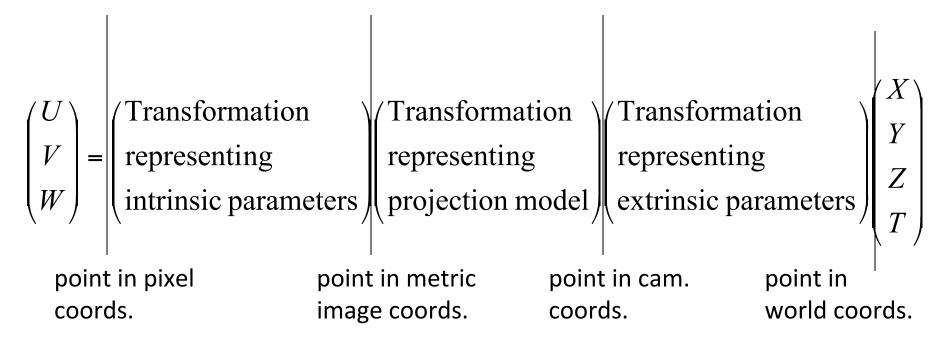
Finally, we can write

u = K q for intrinsic parameters K

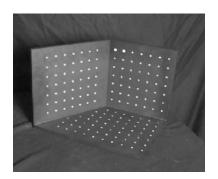
#### Camera parameters

#### Summary:

- points expressed in external frame
- points are converted to canonical camera coordinates
- points are projected
- points are converted to pixel units



## Calibration using a 3D target



R.Y. Tsai, An Efficient and Accurate Camera Calibration Technique for 3D Machine Vision.

Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Miami Beach, FL, pp. 364-374, 1986

#### Camera Calibration

Calibration = the computation of the camera intrinsic and extrinsic parameters

- General strategy:
  - view calibration object
  - identify image points
  - obtain camera matrix by minimizing error
  - obtain intrinsic parameters from camera matrix
- Most modern systems employ the multi-plane method
  - avoids knowing absolute coordinates of calibration points

- Error minimization:
  - Linear least squares
    - easy problem numerically
    - solution can be rather bad
  - Minimize image distance
    - more difficult numerical problem
    - solution usually rather good, but can be hard to find
      - start with linear least squares
  - Numerical scaling is an issue

#### Calibration Procedure

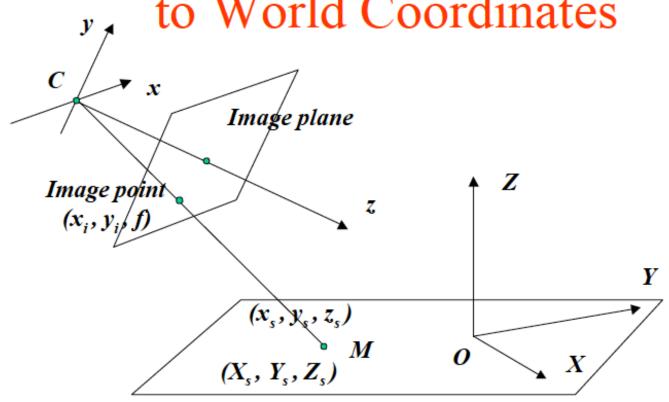
- Calibration target: 2 planes at right angle with checkerboard patterns (Tsai grid)
  - We know positions of pattern corners only with respect to a coordinate system of the target
  - We position camera in front of target and find images of corners
  - We obtain equations that describe imaging and contain internal parameters of camera
    - As a side benefit, we find position and orientation of camera with respect to target (camera *pose*)

# Image Processing of Image of Target

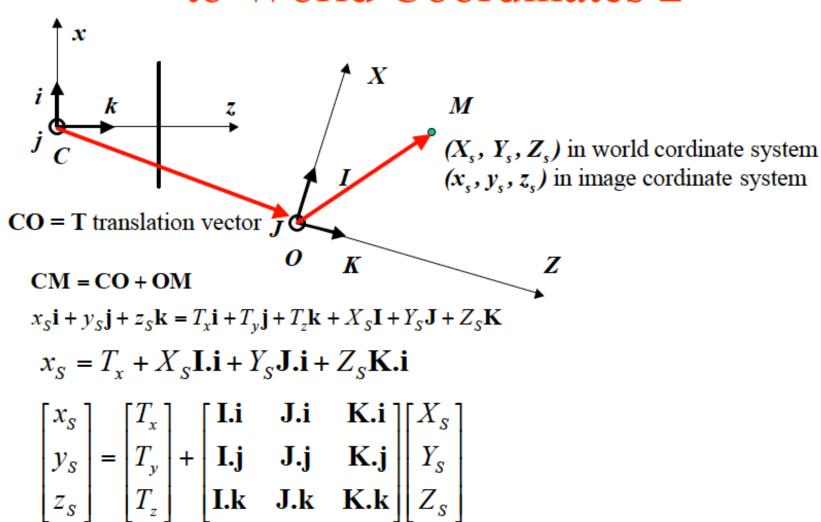
- Canny edge detection
- Straight line fitting to detected linked edges
- Intersecting the lines to obtain the image corners
- Matching image corners and 3D target checkerboard corners
  - By counting if whole target is visible in image
- We get pairs (image point)--(world point)

$$(x_i, y_i) \rightarrow (X_i, Y_i, Z_i)$$

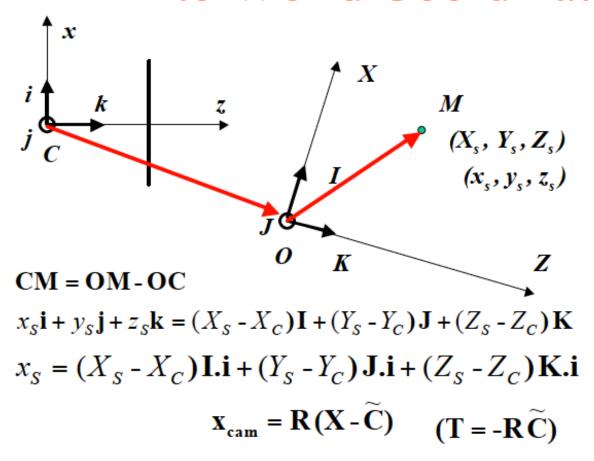
## From Camera Coordinates to World Coordinates



## From Camera Coordinates to World Coordinates 2



## From Camera Coordinates to World Coordinates 3



C is vector OC expressed in world coordinate system

#### Homogeneous Coordinates 2

• Here we use  $-\mathbf{R}\widetilde{\mathbf{C}}$  instead of  $\mathbf{T}$ 

$$\begin{bmatrix} x_S \\ y_S \\ z_S \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \\ \mathbf{0}_3^{\mathsf{T}} & 1 \end{bmatrix} \begin{bmatrix} X_S \\ Y_S \\ Z_S \\ 1 \end{bmatrix}$$

## Linear Transformation from World Coordinates to Pixels

 Combine camera projection and coordinate transformation matrices into a single matrix P

$$\begin{bmatrix} u' \\ v' \\ w' \end{bmatrix} = \mathbf{K} \begin{bmatrix} \mathbf{I}_3 & | & \mathbf{0}_3 \end{bmatrix} \begin{bmatrix} x_s \\ y_s \\ z_s \\ 1 \end{bmatrix}$$

$$\begin{bmatrix} x_s \\ y_s \\ z_s \\ 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \\ \mathbf{0}_3^{\mathsf{T}} & 1 \end{bmatrix} \begin{bmatrix} X_s \\ Y_s \\ Z_s \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} u' \\ v' \\ w' \end{bmatrix} = \mathbf{K} \begin{bmatrix} \mathbf{I}_3 & | & \mathbf{0}_3 \end{bmatrix} \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \\ \mathbf{0}_3^{\mathsf{T}} & 1 \end{bmatrix} \begin{bmatrix} X_s \\ Y_s \\ Z_s \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} u' \\ v' \\ w' \end{bmatrix} = \mathbf{P} \begin{bmatrix} X_s \\ Y_s \\ Z_s \\ 1 \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} \mathbf{X}_s \\ Y_s \\ Z_s \\ 1 \end{bmatrix}$$

#### Properties of Matrix P

• Further simplification of **P**:

$$\mathbf{x} = \mathbf{K} \begin{bmatrix} \mathbf{I}_{3} & | & \mathbf{0}_{3} \end{bmatrix} \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \\ \mathbf{0}_{3}^{\mathsf{T}} & 1 \end{bmatrix} \mathbf{X}$$

$$\begin{bmatrix} \mathbf{I}_{3} & | & \mathbf{0}_{3} \end{bmatrix} \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \\ \mathbf{0}_{3}^{\mathsf{T}} & 1 \end{bmatrix} = \begin{bmatrix} \mathbf{R} & -\mathbf{R} \widetilde{\mathbf{C}} \end{bmatrix} = \mathbf{R} \begin{bmatrix} \mathbf{I}_{3} & | & -\widetilde{\mathbf{C}} \end{bmatrix}$$

$$\mathbf{x} = \mathbf{K} \mathbf{R} \begin{bmatrix} \mathbf{I}_{3} & | & -\widetilde{\mathbf{C}} \end{bmatrix} \mathbf{X}$$

$$\mathbf{P} = \mathbf{K} \mathbf{R} \begin{bmatrix} \mathbf{I}_{3} & | & -\widetilde{\mathbf{C}} \end{bmatrix}$$

- P has 11 degrees of freedom:
  - 5 from triangular calibration matrix K, 3 from R and 3 from C
- P is a fairly general 3 x 4 matrix
  - •left 3x3 submatrix **KR** is non-singular

#### **Calibration**

- 1. Estimate matrix **P** using scene points and their images
- 2. Estimate the interior parameters and the exterior parameters

$$P = KR \left[ I_3 \mid -\widetilde{C} \right]$$

■ Left 3x3 submatrix of **P** is product of upper-triangular matrix and orthogonal matrix

#### Finding Camera Translation

- Find homogeneous coordinates of C in the scene
- C is the null vector of matrix P
  - $\mathbf{P} \mathbf{C} = 0$ :  $\mathbf{P} = \mathbf{K} \mathbf{R} \begin{bmatrix} \mathbf{I}_{3} & | & -\widetilde{\mathbf{C}} \end{bmatrix}$   $\begin{bmatrix} 1 & 0 & 0 & -X_{c} \\ 0 & 1 & 0 & -Y_{c} \\ 0 & 0 & 1 & -Z_{c} \end{bmatrix} \begin{bmatrix} X_{c} \\ Y_{c} \\ Z_{c} \\ 1 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 0 \end{bmatrix}$
- Find null vector **C** of **P** using SVD
  - C is the unit singular vector of P corresponding to the smallest singular value (the last column of V, where P = U D V<sup>T</sup> is the SVD of P)

## Finding Camera Orientation and Internal Parameters

- Left 3x3 submatrix M of P is of form M=K R
  - **K** is an upper triangular matrix
  - **R** is an orthogonal matrix
- Any non-singular square matrix M can be decomposed into the product of an uppertriangular matrix K and an orthogonal matrix R using the RQ factorization
  - Similar to QR factorization but order of 2 matrices is reversed

#### RQ Factorization of M

$$\mathbf{R}_{\mathbf{x}} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & c & -s \\ 0 & s & c \end{bmatrix}, \ \mathbf{R}_{\mathbf{y}} = \begin{bmatrix} c' & 0 & s' \\ 0 & 1 & 0 \\ -s' & 0 & c' \end{bmatrix}, \ \mathbf{R}_{\mathbf{z}} = \begin{bmatrix} c'' & -s'' & 0 \\ s'' & c'' & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

• Compute 
$$c = -\frac{m_{33}}{(m_{32}^2 + m_{33}^2)^{1/2}}$$
,  $s = \frac{m_{32}}{(m_{32}^2 + m_{33}^2)^{1/2}}$ 

- Multiply M by R<sub>x</sub>. The resulting term at (3,2) is zero because of the values selected for c and s
- Multiply the resulting matrix by  $\mathbf{R}_{y}$ , after selecting c' and s' so that the resulting term at position (3,1) is set to zero
- Multiply the resulting matrix by  $\mathbf{R}_z$ , after selecting c' and s' so that the resulting term at position (2,1) is set to zero

$$\mathbf{M} \mathbf{R}_{\mathbf{x}} \mathbf{R}_{\mathbf{y}} \mathbf{R}_{\mathbf{z}} = \mathbf{K} \Rightarrow \mathbf{M} = \mathbf{K} \mathbf{R}_{\mathbf{z}}^{\mathsf{T}} \mathbf{R}_{\mathbf{y}}^{\mathsf{T}} \mathbf{R}_{\mathbf{x}}^{\mathsf{T}} = \mathbf{K} \mathbf{R}$$

#### Computing Matrix P

- Use corresponding image and scene points
  - $\blacksquare$  3D points  $X_i$  in world coordinate system
  - Images  $x_i$  of  $X_i$  in image
- Write  $\mathbf{x_i} = \mathbf{P} \mathbf{X_i}$  for all i
- Similar problem to finding projectivity matrix **H** (i.e. homography)

### Computation of P

- $\mathbf{x_i} = \mathbf{P} \mathbf{X_i}$  involves homogeneous coordinates, thus  $\mathbf{x_i}$  and  $\mathbf{P} \mathbf{X_i}$  just have to be proportional:  $\mathbf{x_i} \times \mathbf{P} \mathbf{X_i} = 0$
- Let  $\mathbf{p}_1^T$ ,  $\mathbf{p}_2^T$ ,  $\mathbf{p}_3^T$  be the 3 row vectors of **P**

$$\mathbf{P} \mathbf{X}_{i} = \begin{bmatrix} \mathbf{p}_{1}^{\mathsf{T}} \mathbf{X}_{i} \\ \mathbf{p}_{2}^{\mathsf{T}} \mathbf{X}_{i} \\ \mathbf{p}_{3}^{\mathsf{T}} \mathbf{X}_{i} \end{bmatrix} \qquad \mathbf{x}_{i} \times \mathbf{P} \mathbf{X}_{i} = \begin{bmatrix} v'_{i} \mathbf{p}_{3}^{\mathsf{T}} \mathbf{X}_{i} - w'_{i} \mathbf{p}_{2}^{\mathsf{T}} \mathbf{X}_{i} \\ w'_{i} \mathbf{p}_{1}^{\mathsf{T}} \mathbf{X}_{i} - u'_{i} \mathbf{p}_{3}^{\mathsf{T}} \mathbf{X}_{i} \\ u'_{i} \mathbf{p}_{2}^{\mathsf{T}} \mathbf{X}_{i} - v'_{i} \mathbf{p}_{1}^{\mathsf{T}} \mathbf{X}_{i} \end{bmatrix}$$

$$\Rightarrow \begin{bmatrix} \mathbf{0}_{4}^{T} & -w'_{i} \mathbf{X}_{i}^{T} & v'_{i} \mathbf{X}_{i}^{T} \\ w'_{i} \mathbf{X}_{i}^{T} & \mathbf{0}_{4}^{T} & -u'_{i} \mathbf{X}_{i}^{T} \\ -v'_{i} \mathbf{X}_{i}^{T} & u'_{i} \mathbf{X}_{i}^{T} & \mathbf{0}_{4}^{T} \end{bmatrix} \begin{bmatrix} \mathbf{p}_{1} \\ \mathbf{p}_{2} \\ \mathbf{p}_{3} \end{bmatrix} = 0 \qquad \begin{bmatrix} \mathbf{p}_{1} \\ \mathbf{p}_{2} \\ \mathbf{p}_{3} \end{bmatrix} \text{ is a } 12 \times 1 \text{ vector}$$

#### Computation of P

• Third row can be obtained from sum of  $u'_i$  times first row -  $v'_i$  times second row

$$\begin{bmatrix} \mathbf{0}_{4}^{T} & -w_{i}^{T} \mathbf{X}_{i}^{T} & v_{i}^{T} \mathbf{X}_{i}^{T} \\ w_{i}^{T} \mathbf{X}_{i}^{T} & \mathbf{0}_{4}^{T} & -u_{i}^{T} \mathbf{X}_{i}^{T} \\ -v_{i}^{T} \mathbf{X}_{i}^{T} & u_{i}^{T} \mathbf{X}_{i}^{T} & \mathbf{0}_{4}^{T} \end{bmatrix} \begin{bmatrix} \mathbf{p}_{1} \\ \mathbf{p}_{2} \\ \mathbf{p}_{3} \end{bmatrix} = 0$$

- So we get 2 independent equations in 11 unknowns (ignoring scale)
- With 6 point correspondences, we get enough equations to compute matrix **P**

$$\mathbf{A} \mathbf{p} = 0$$

### Solving $\mathbf{A} \mathbf{p} = 0$

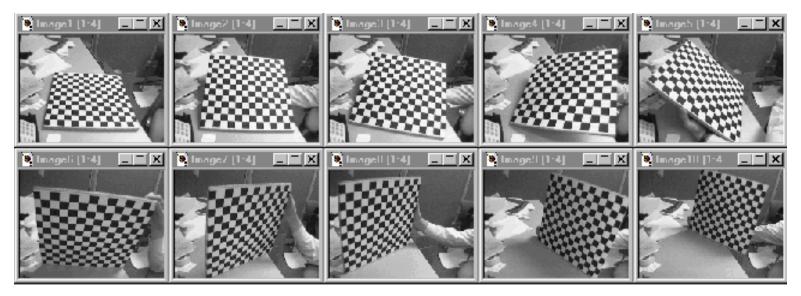
- Linear system  $\mathbf{A} \mathbf{p} = 0$
- When possible, have at least 5 times as many equations as unknowns (28 points)
- Minimize  $|| \mathbf{A} \mathbf{p} ||$  with the constraint  $|| \mathbf{p} || = 1$ 
  - P is the unit singular vector of A corresponding to the smallest singular value (the last column of V, where  $A = U D V^T$  is the SVD of A)
- Called Direct Linear Transformation (DLT)

## Improving **P** Solution with Nonlinear Minimization

- Find **p** using DLT
- Use as initialization for nonlinear minimization of  $\sum d(\mathbf{x_i}, \mathbf{PX_i})^2$ 
  - Use Levenberg-Marquardt iterative minimization

### Multi-planar calibration

#### Alternative: multi-plane calibration



Images courtesy Jean-Yves Bouguet, Intel Corp.

#### Advantage

- Only requires a plane
- Don't have to know positions/orientations
- Good code available online!
  - Intel's OpenCV library: <a href="http://www.intel.com/research/mrl/research/opencv/">http://www.intel.com/research/mrl/research/opencv/</a>
  - Matlab version by Jean-Yves Bouget:
     <a href="http://www.vision.caltech.edu/bouguetj/calib\_doc/index.html">http://www.vision.caltech.edu/bouguetj/calib\_doc/index.html</a>

#### **Parameters**

 (same model as before - just different notations)

Projection equation: 
$$s\widetilde{\mathbf{m}} = \mathbf{A} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \widetilde{\mathtt{M}}$$

Intrinsic parameters:

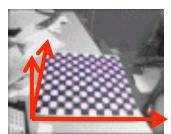
$$\mathbf{A} = egin{bmatrix} lpha & \gamma & u_0 \ 0 & eta & v_0 \ 0 & 0 & 1 \end{bmatrix}$$

### Planar homography

Assume world coordinate system is such that
 Z=0 on the calibration pattern

Projected pattern point:

$$s\widetilde{\mathbf{m}} = \mathbf{A} \begin{bmatrix} \mathbf{R} & \mathbf{t} \end{bmatrix} \widetilde{\mathbf{M}}$$
  $s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix}$ 



$$s \begin{bmatrix} u \\ v \\ 1 \end{bmatrix} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{r}_3 & \mathbf{t} \end{bmatrix} \begin{bmatrix} A \\ Y \\ 0 \\ 1 \end{bmatrix}$$

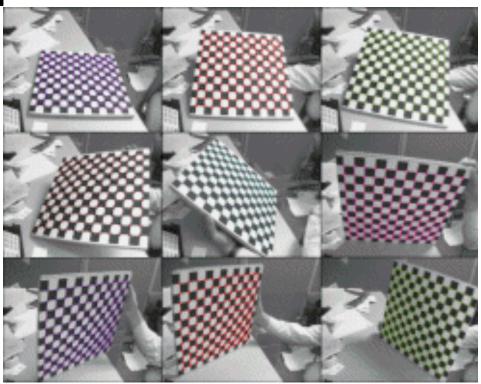
$$= \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix} \begin{bmatrix} X \\ Y \\ 1 \end{bmatrix}.$$

Pattern and its image are related by homography:

$$s\widetilde{\mathbf{m}} = \mathbf{H}\widetilde{\mathbf{M}}$$
 with  $\mathbf{H} = \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix}$ 

### Homography H

Compute H for each image using known correspondences



#### Constraints on internal parameters

Noting

$$\mathbf{H} = \begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3 \end{bmatrix}$$

And using the equation

$$\begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3 \end{bmatrix} = \lambda \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix}$$

One derives two equations on internal parameters only:

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2 = 0$$

$$\mathbf{h}_1^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_1 = \mathbf{h}_2^T \mathbf{A}^{-T} \mathbf{A}^{-1} \mathbf{h}_2$$

### **Computing Intrinsics**

Rotation Matrix is orthogonal....

$$r_i^T r_j = 0$$
$$r_i^T r_i = r_j^T r_j$$

Write the homography in terms of its columns...

$$h_1 = sAr_1$$

$$h_2 = sAr_2$$

$$h_3 = sAt$$

### **Computing Intrinsics**

• Derive t

$$h_1 = sAr_1$$

$$\frac{1}{s}A^{-1}h_1 = r_1$$

$$\frac{1}{s}A^{-1}h_2 = r_2$$

$$r_1^T r_2 = 0 
 h_1^T A^{-T} A^{-1} h_2 = 0$$

$$r_1^T r_1 = r_2^T r_2$$
  
 $h_1^T A^{-T} A^{-1} h_1 = h_2^T A^{-T} A^{-1} h_2$ 

#### Closed-Form Solution

$$\operatorname{Let} B = A^{-T} A^{-1} = \begin{bmatrix} \frac{1}{\alpha^2} & -\frac{\gamma}{\alpha^2 \beta} & \frac{v_0 \gamma - u_0 \beta}{\alpha^2 \beta} \\ -\frac{\gamma}{\alpha^2 \beta} & \frac{\gamma^2}{\alpha^2 \beta^2} + \frac{1}{\beta^2} & -\frac{\gamma(v_0 \gamma - u_0 \beta))}{\alpha^2 \beta^2} - \frac{v_0}{\beta^2} \\ \frac{v_0 \gamma - u_0 \beta}{\alpha^2 \beta} & -\frac{\gamma(v_0 \gamma - u_0 \beta))}{\alpha^2 \beta^2} - \frac{v_0}{\beta^2} & \frac{(v_0 \gamma - u_0 \beta)^2}{\alpha^2 \beta^2} + \frac{v_0^2}{\beta^2} + 1 \end{bmatrix}$$

- Notice B is symmetric, 6 parameters can be written as a vector b.
- From the two constraints, we have  $h_1^T B h_2 = v_{12} b$

$$\left[\begin{array}{c} v_{ij}^{T} \\ (v_{11} - v_{22})^{T} \end{array}\right] b = 0;$$

- Stack up n of these for n images and build a 2n\*6 system.
- Solve with SVD.
- Intrinsic parameters "fall-out" of the result easily using algebra

### Solve for extrinsic parameters

Using equation (A is known)

$$\begin{bmatrix} \mathbf{h}_1 & \mathbf{h}_2 & \mathbf{h}_3 \end{bmatrix} = \lambda \mathbf{A} \begin{bmatrix} \mathbf{r}_1 & \mathbf{r}_2 & \mathbf{t} \end{bmatrix}$$

One obtains

$$\lambda = 1/\|\mathbf{A}^{-1}\mathbf{h}_1\| = 1/\|\mathbf{A}^{-1}\mathbf{h}_2\|$$

Issue: due to noise r1 and r2 may not be orthogonal

$$\mathbf{r}_1 = \lambda \mathbf{A}^{-1} \mathbf{h}_1$$
 $\mathbf{r}_2 = \lambda \mathbf{A}^{-1} \mathbf{h}_2$ 
 $\mathbf{r}_3 = \mathbf{r}_1 \times \mathbf{r}_2$ 
 $\mathbf{t} = \lambda \mathbf{A}^{-1} \mathbf{h}_3$ 

(-> board)

#### Non-linear Refinement

- Closed-form solution minimized algebraic distance.
- Since full-perspective is a non-linear model

- Can in 
$$\sum_{i=1}^{n} \sum_{j=1}^{m} ||m_{ij} - \hat{m}(A, R_k, T_k, M_j)||^2$$
 tanger  $\sum_{i=1}^{n} \sum_{j=1}^{m} ||m_{ij} - \hat{m}(A, R_k, T_k, M_j)||^2$ 

Use maximum likelihood inference for our estimated parameters.

#### Notes

- Improvement (like for previous method)
  - use non-linear optimization to refine the results
  - compute radial distortion

- Degenerate configurations?
  - Pure translation
  - Parallel planes