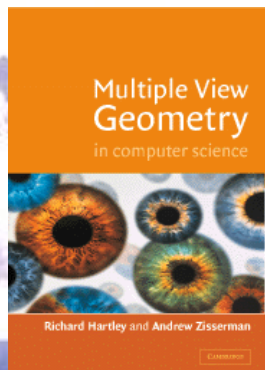


Computer Vision

The 2D projective plane and its applications



Hartley Zisserman Ch 2. In particular: Ch 2.1-4, 2.7,
Estimation: HZ: Ch 4.1-4.2.5, 4.4.4-4.8 cursorly
(Szelisky: Ch 2.1.1, 2.1.2)

Richard Hartley and Andrew Zisserman, Multiple View Geometry,
Cambridge University Publishers, 2nd ed. 2004

Homogeneous coordinates

Homogeneous representation of 2D points and lines

$$ax + by + c = 0 \qquad (a, b, c)^T (x, y, 1) = 0$$

The point x lies on the line l if and only if

$$l^T x = 0$$

Note that scale is unimportant for incidence relation

$$(a, b, c)^T \sim k(a, b, c)^T, \forall k \neq 0 \qquad (x, y, 1)^T \sim k(x, y, 1)^T, \forall k \neq 0$$

equivalence class of vectors, any vector is representative

Set of all equivalence classes in $\mathbf{R}^3 - (0, 0, 0)^T$ forms \mathbf{P}^2

Homogeneous coordinates $(x_1, x_2, x_3)^T$ but only 2DOF
Inhomogeneous coordinates $(x, y)^T$

Points from lines and vice-versa

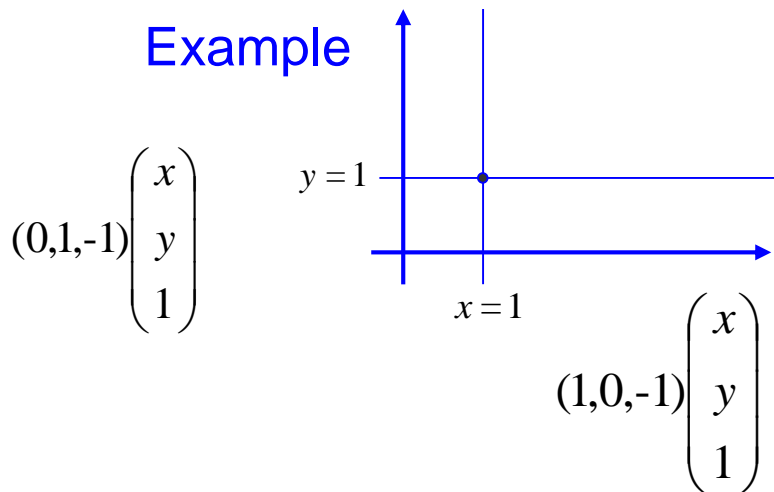
Intersections of lines

The intersection of two lines l and l' is $x = l \times l'$

Line joining two points

The line through two points x and x' is $l = x \times x'$

Example



Note:

$$x \times x' = [x]_{\times} x'$$

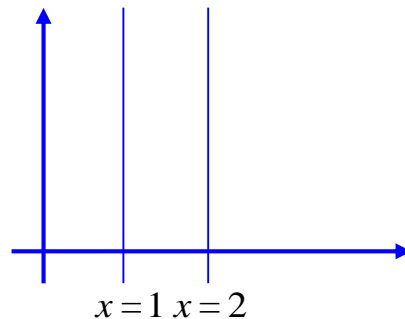
with $[x]_{\times} = \begin{bmatrix} 0 & z & -y \\ -z & 0 & x \\ y & -x & 0 \end{bmatrix}$

Ideal points and the line at infinity

Intersections of parallel lines

$$l = (a, b, c)^T \text{ and } l' = (a, b, c')^T \quad l \times l' = (b, -a, 0)^T$$

Example



$(b, -a)$ tangent vector
 (a, b) normal direction

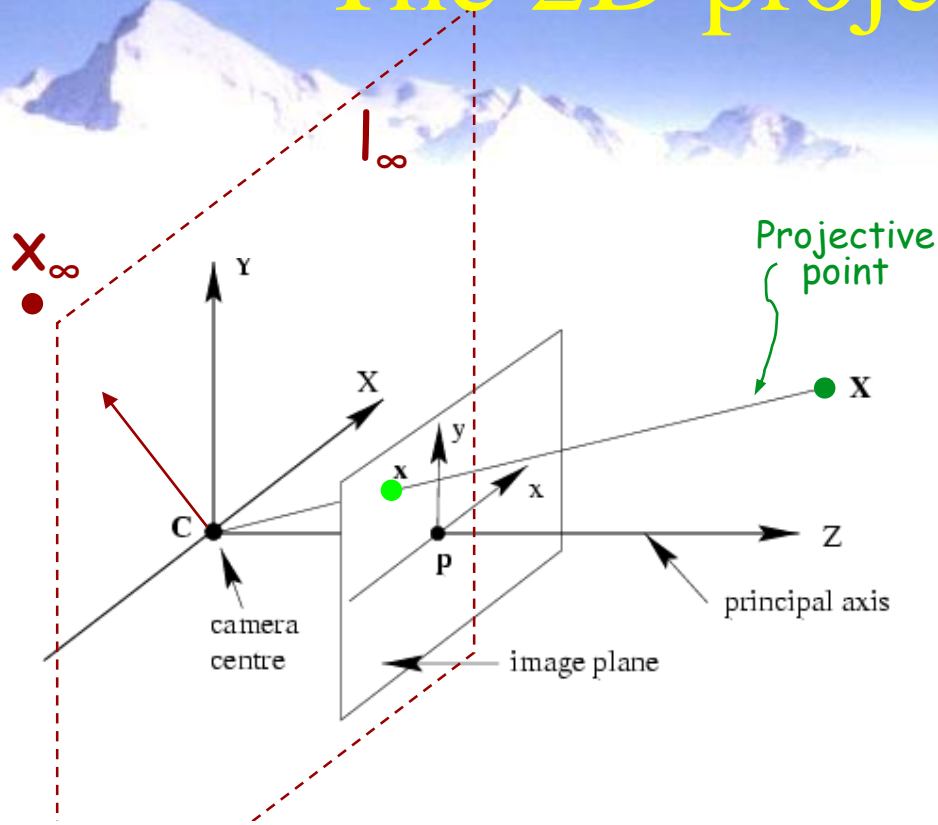
Ideal points $(x_1, x_2, 0)^T$

Line at infinity $l_\infty = (0, 0, 1)^T$

$$\mathbf{P}^2 = \mathbf{R}^2 \cup l_\infty$$

Note that in \mathbf{P}^2 there is no distinction between ideal points and others

The 2D projective plane



Homogeneous coordinates

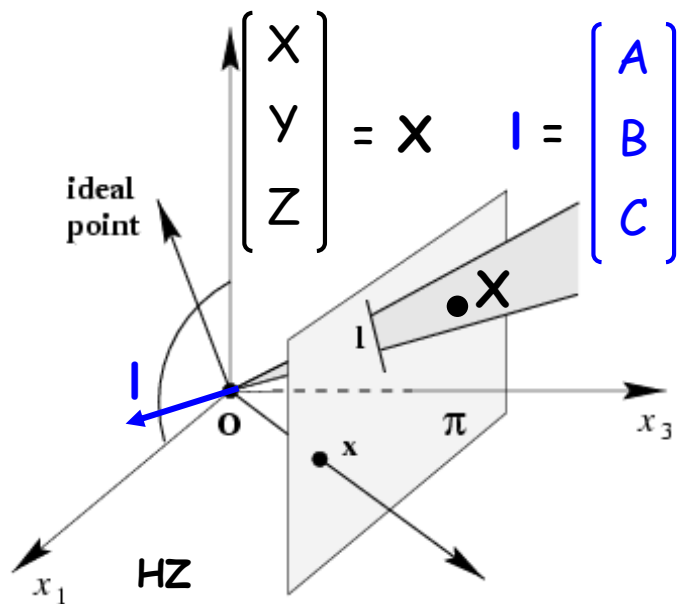
$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \equiv s \begin{bmatrix} X \\ Y \\ Z \end{bmatrix} \quad s \neq 0$$

$$\begin{bmatrix} x \\ y \end{bmatrix} = \frac{1}{Z} \begin{bmatrix} X \\ Y \end{bmatrix} \quad \text{Inhomogeneous equivalent}$$

- Perspective imaging models 2d projective space
- Each 3D ray is a point in P^2 : homogeneous coords.
- Ideal points
- P^2 is R^2 plus a “line at infinity” l_∞

$$X_\infty = \begin{bmatrix} X \\ Y \\ 0 \end{bmatrix}$$

Lines



- Projective line ~ a plane through the origin

$$l^T X = X^T l = AX + BY + CZ = 0$$

$$X_\infty = \begin{bmatrix} X \\ Y \\ 0 \end{bmatrix}$$

$$l_\infty = \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} \text{ "line at infinity"}$$

- Ideal line ~ the plane parallel to the image

Duality: For any 2d projective property, a dual property holds when the role of points and lines are interchanged.

$$l = X_1 \times X_2$$

The line joining two points

$$X = l_1 \times l_2$$

The point joining two lines

Conics

Curve described by 2nd-degree equation in the plane

$$ax^2 + bxy + cy^2 + dx + ey + f = 0$$

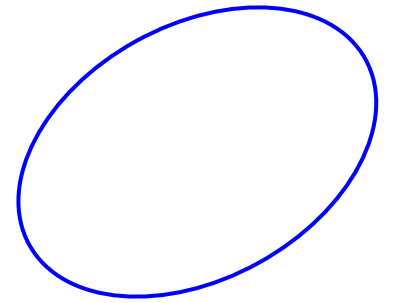
or homogenized $x \mapsto x_1/x_3, y \mapsto x_2/x_3$

$$ax_1^2 + bx_1x_2 + cx_2^2 + dx_1x_3 + ex_2x_3 + fx_3^2 = 0$$

or in matrix form

$$\mathbf{x}^T \mathbf{C} \mathbf{x} = 0 \quad \text{with} \quad \mathbf{C} = \begin{bmatrix} a & b/2 & d/2 \\ b/2 & c & e/2 \\ d/2 & e/2 & f \end{bmatrix}$$

5DOF: $\{a:b:c:d:e:f\}$



Five points define a conic

For each point the conic passes through

$$ax_i^2 + bx_iy_i + cy_i^2 + dx_i + ey_i + f = 0$$

or

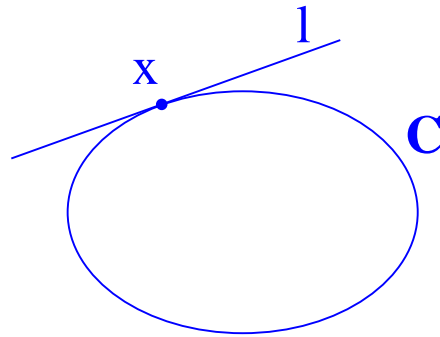
$$(x_i^2, x_iy_i, y_i^2, x_i, y_i, 1)\mathbf{c} = 0 \quad \mathbf{c} = (a, b, c, d, e, f)^T$$

stacking constraints yields

$$\begin{bmatrix} x_1^2 & x_1y_1 & y_1^2 & x_1 & y_1 & 1 \\ x_2^2 & x_2y_2 & y_2^2 & x_2 & y_2 & 1 \\ x_3^2 & x_3y_3 & y_3^2 & x_3 & y_3 & 1 \\ x_4^2 & x_4y_4 & y_4^2 & x_4 & y_4 & 1 \\ x_5^2 & x_5y_5 & y_5^2 & x_5 & y_5 & 1 \end{bmatrix} \mathbf{c} = 0$$

Tangent lines to conics

The line l tangent to C at point x on C is given by $l=Cx$

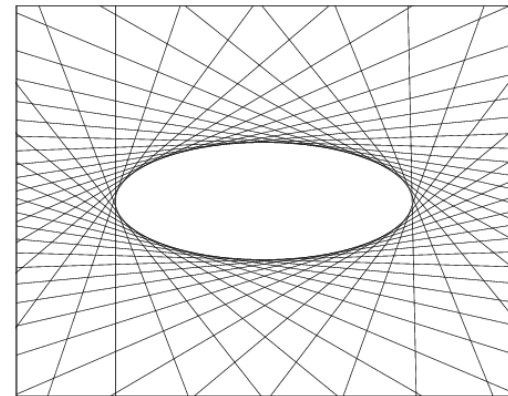
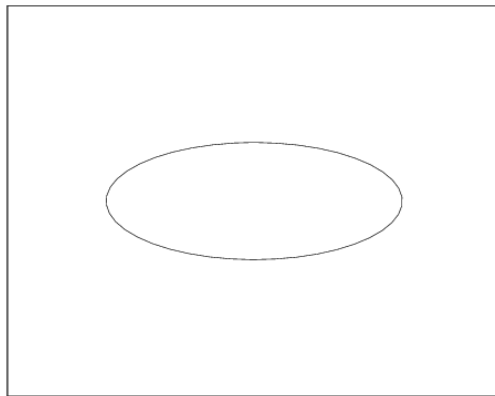


Dual conics

A line tangent to the conic \mathbf{C} satisfies $\mathbf{1}^T \mathbf{C}^* \mathbf{1} = 0$

In general (\mathbf{C} full rank): $\mathbf{C}^* = \mathbf{C}^{-1}$

Dual conics = line conics = conic envelopes

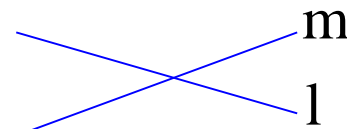


Degenerate conics

A conic is degenerate if matrix \mathbf{C} is not of full rank

e.g. two lines (rank 2)

$$\mathbf{C} = \mathbf{l}\mathbf{m}^T + \mathbf{m}\mathbf{l}^T$$



e.g. repeated line (rank 1)

$$\mathbf{C} = \mathbf{l}\mathbf{l}^T$$



Degenerate line conics: 2 points (rank 2), double point (rank 1)

Note that for degenerate conics $(\mathbf{C}^*)^* \neq \mathbf{C}$

Conics: summary

- Conic:

- Euclidean geometry: hyperbola, ellipse, parabola & degenerate
- Projective geometry: equivalent under projective transform
- Defined by 5 points

$$ax^2 + bxy + cy^2 + dx + ey + f = 0$$

inhomogeneous

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

homogeneous

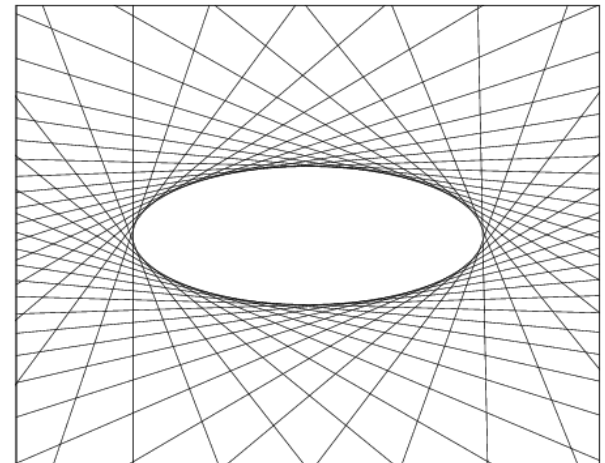
$$C = \begin{bmatrix} a & b/2 & d/2 \\ b/2 & c & e/2 \\ d/2 & e/2 & f \end{bmatrix}$$

- Tangent line

$$\mathbf{l} = C\mathbf{x}$$

- Dual conic C^*

$$\mathbf{l}^T C^* \mathbf{l} = 0$$



Projective transformations

Definition:

A *projectivity* (=homography) is an invertible mapping h from P^2 to itself such that three points x_1, x_2, x_3 lie on the same line if and only if $h(x_1), h(x_2), h(x_3)$ do.

Theorem:

A mapping $h: P^2 \rightarrow P^2$ is a projectivity if and only if there exist a non-singular 3×3 matrix \mathbf{H} such that for any point in P^2 represented by a vector x it is true that $h(x) = \mathbf{H}x$

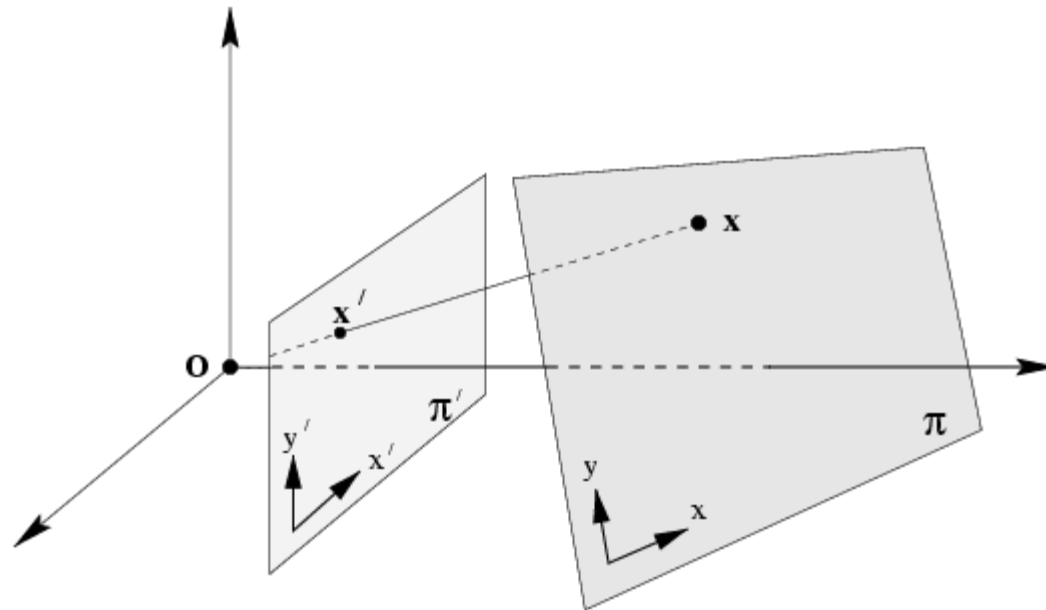
Definition: Projective transformation

$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix} \quad \text{or} \quad x' = \mathbf{H}x$$

8DOF

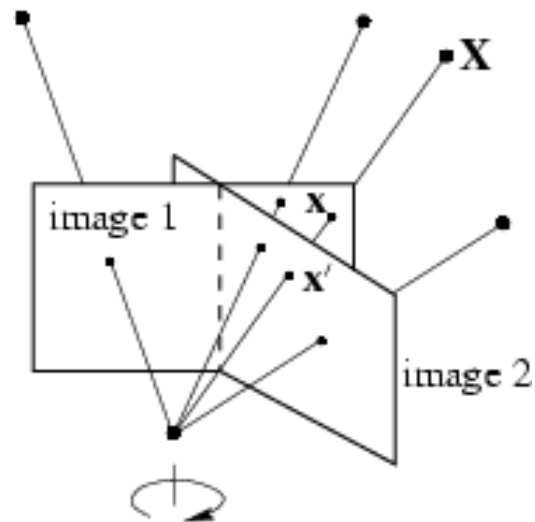
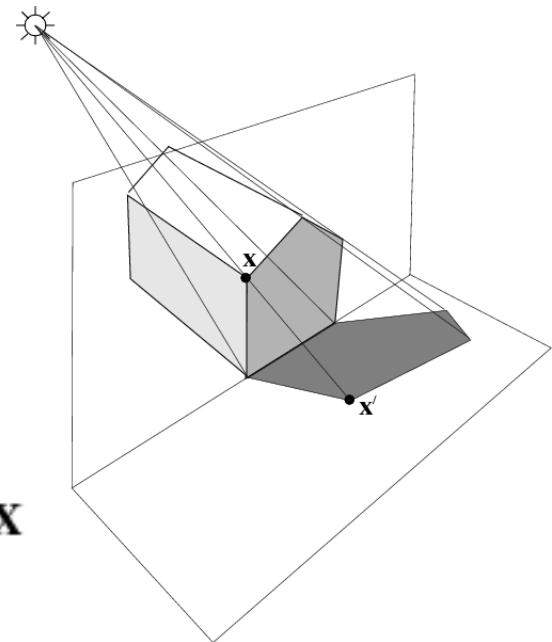
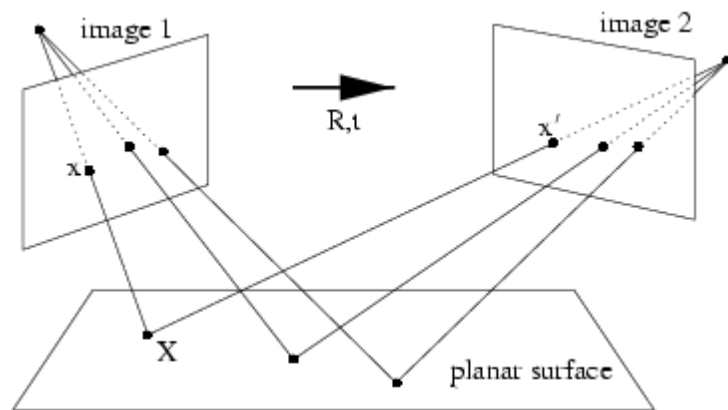
projectivity=collineation=projective transformation=homography

Mapping between planes



central projection may be expressed by $x' = Hx$
(application of theorem)

More examples



Projective transformations

- Homographies, collineations, projectivities

- 3x3 nonsingular H

maps P^2 to P^2

8 degrees of freedom

determined by 4 corresponding points

$$\begin{pmatrix} x'_1 \\ x'_2 \\ x'_3 \end{pmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ x_3 \end{pmatrix}$$

- Transforming Lines?

$$x' = Hx$$

subspaces preserved

$$x^T \mathbf{1} = 0 \quad x'^T \mathbf{1}' = 0$$





substitution

$$x^T H^T \mathbf{1}' = 0$$

dual transformation

$$\mathbf{1}' = H^{-T} \mathbf{1}$$

Homographies a generalization of affine and Euclidean transforms

Group	Transformation	Invariants	Distortion
Projective 8 DOF	$H_P = \begin{bmatrix} A & \mathbf{t} \\ \mathbf{v}^T & v \end{bmatrix}$	<ul style="list-style-type: none"> • Cross ratio • Intersection • Tangency 	
Affine 6 DOF	$H_A = \begin{bmatrix} A & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$	<ul style="list-style-type: none"> • Parallelism • Relative dist in 1d • Line at infinity \mathbf{l}_∞ 	
Metric 4 DOF	$H_S = \begin{bmatrix} sR & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$	<ul style="list-style-type: none"> • Relative distances • Angles • Dual conic C_∞^* 	
Euclidean 3 DOF	$H_E = \begin{bmatrix} R & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$	<ul style="list-style-type: none"> • Lengths • Areas 	

2 dof
 \mathbf{l}_∞

2 dof
 C_∞^*

Planar Projective Warping



HZ

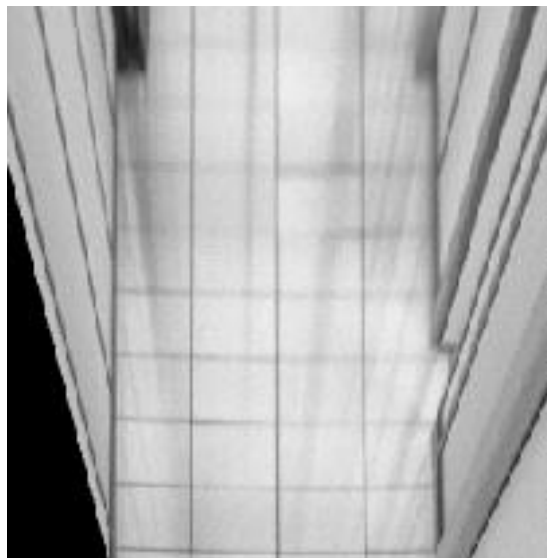
$$x_i' = Hx_i$$
$$i = 1 \dots 4$$

A novel view rendered via four points with known structure

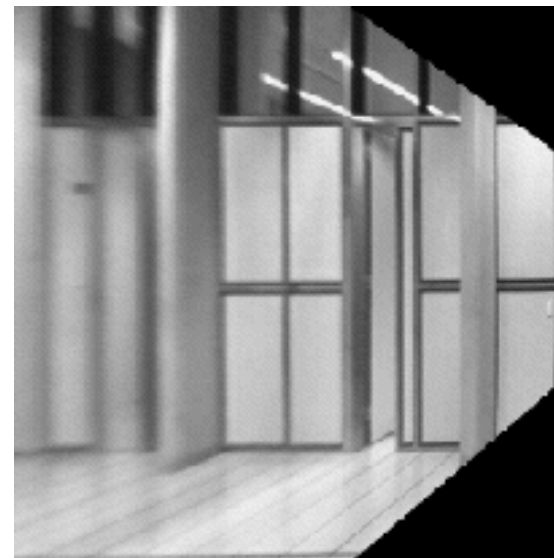
Planar Projective Warping



Original



Top-down



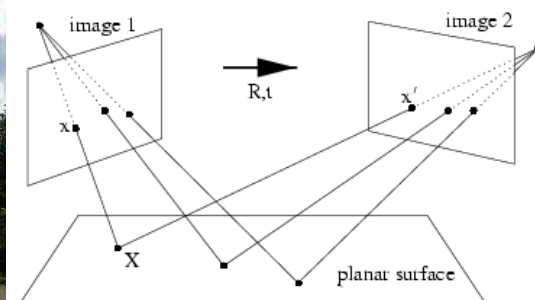
Facing right

HZ

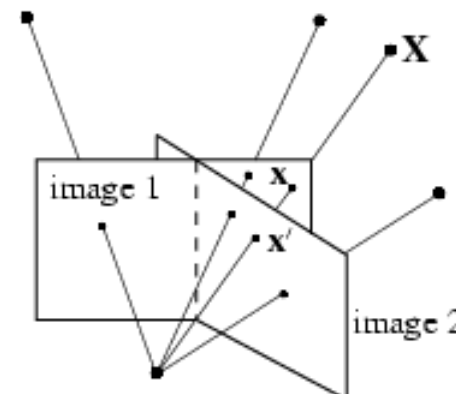
Artifacts are apparent where planarity is violated...

2d Homographies

2 images of a plane



2 images from the same viewpoint (Perspectivity)



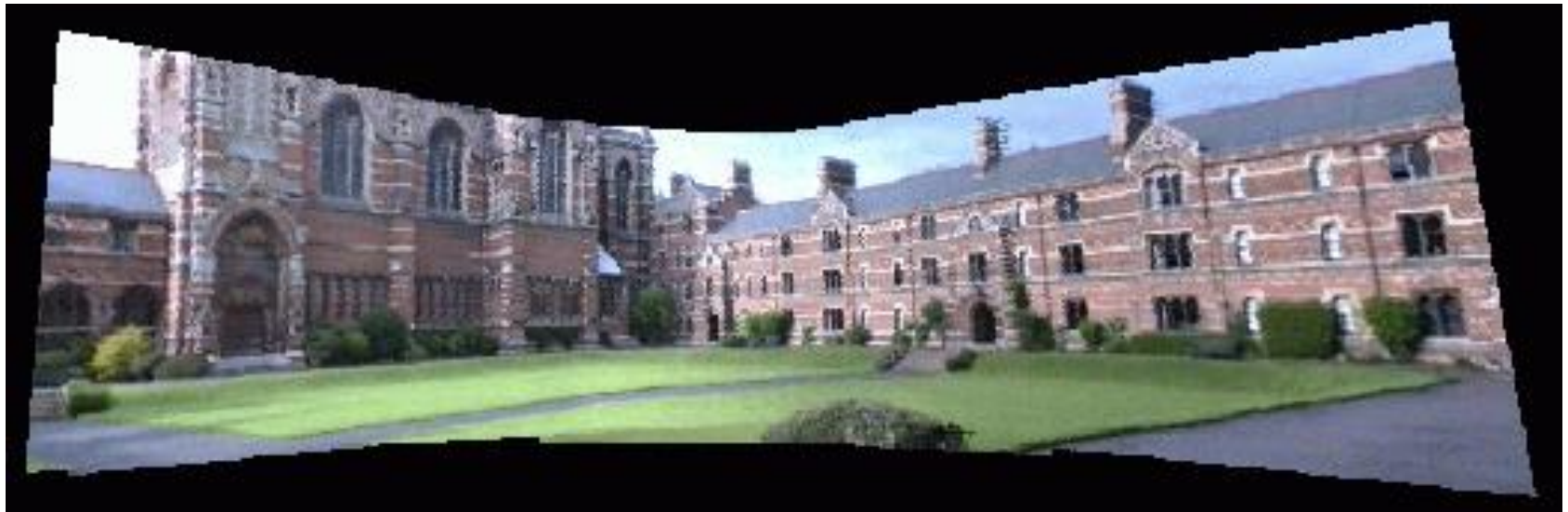
Panoramic imaging

Appl: Quicktime VR, robot navigation etc.



Homographies of the world, unite!

Image mosaics are stitched by homographies



Action of affinities and projectivities on line at infinity

$$\begin{bmatrix} \mathbf{A} & \mathbf{t} \\ 0^\top & v \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 0 \end{pmatrix} = \begin{pmatrix} \mathbf{A} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\ 0 \end{pmatrix}$$

Line at infinity stays at infinity,
but points move along line

$$\begin{bmatrix} \mathbf{A} & \mathbf{t} \\ \mathbf{v}^\top & v \end{bmatrix} \begin{pmatrix} x_1 \\ x_2 \\ 0 \end{pmatrix} = \begin{pmatrix} \mathbf{A} \begin{pmatrix} x_1 \\ x_2 \end{pmatrix} \\ v_1 x_1 + v_2 x_2 \end{pmatrix}$$

Line at infinity becomes finite,
allows to observe vanishing points, horizon,

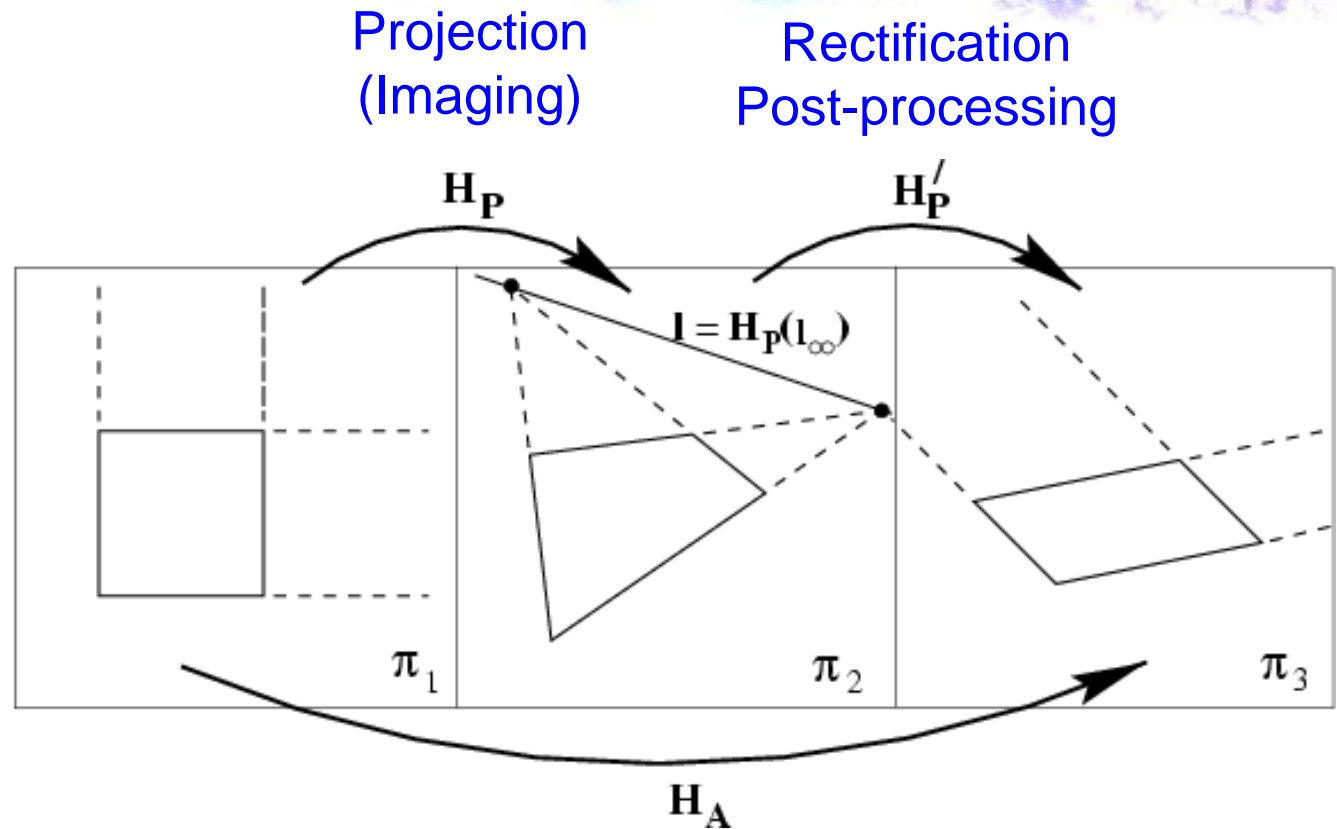
The line at infinity

The line at infinity l_∞ is a fixed line under a projective transformation H if and only if H is an affinity

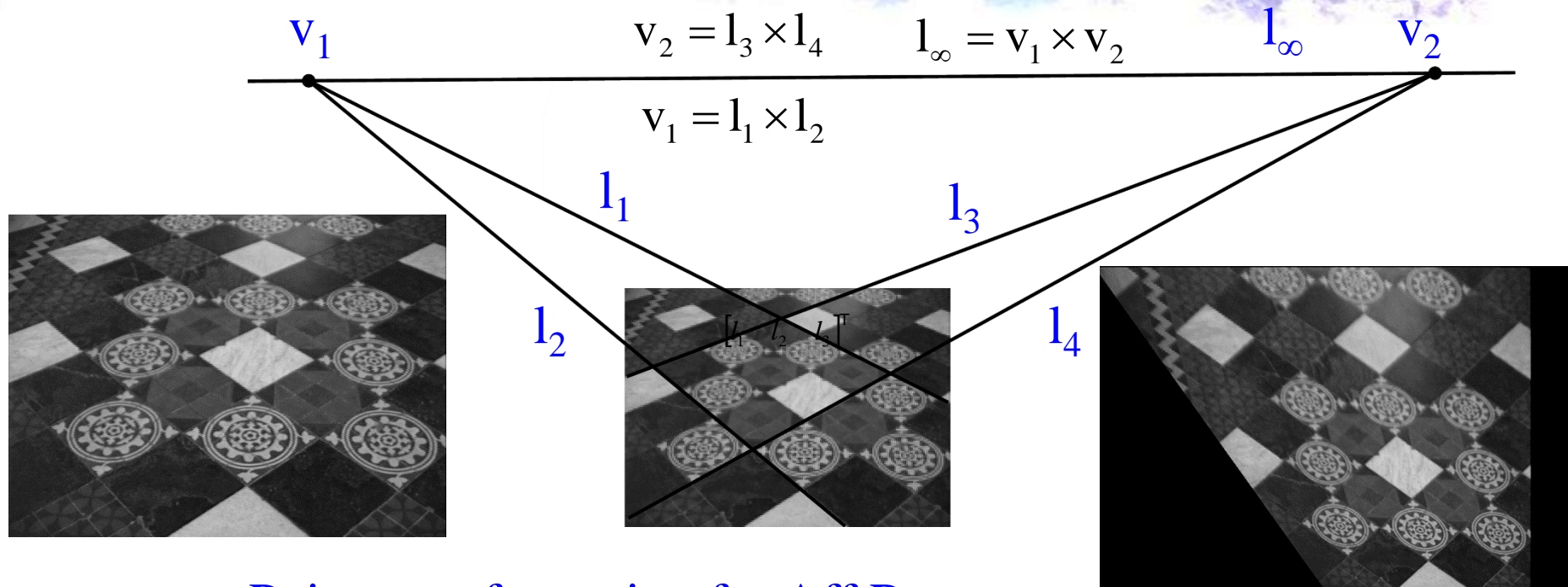
$$l'_\infty = \mathbf{H}_A^{-T} l_\infty = \begin{bmatrix} \mathbf{A}^{-T} & 0 \\ -\mathbf{t}^T \mathbf{A}^{-T} & 1 \end{bmatrix} \begin{pmatrix} 0 \\ 0 \\ 1 \end{pmatrix} = l_\infty$$

Note: But points on l_∞ can be rearranged to new points on l_∞

Affine properties from images



Affine rectification







Point transformation for Aff Rect:

$$l_\infty = [l_1 \ l_2 \ l_3]^T, l_3 \neq 0$$

$$\mathbf{H}_{PA} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ l_1 & l_2 & l_3 \end{bmatrix} \mathbf{H}_A$$

Exercise: Verify $\mathbf{H}_{PA} [l_1 \ l_2 \ l_3]^T = [0, 0, 1]^T$

Geometric strata: 2d overview

Group	Transformation	Invariants	Distortion
Projective 8 DOF	$H_P = \begin{bmatrix} A & \mathbf{t} \\ \mathbf{v}^T & v \end{bmatrix}$	<ul style="list-style-type: none"> • Cross ratio • Intersection • Tangency 	
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Euclidean 3 DOF	$H_E = \begin{bmatrix} R & \mathbf{t} \\ \mathbf{0}^T & 1 \end{bmatrix}$	<ul style="list-style-type: none"> • Lengths • Areas 	

2 dof
 \mathbf{l}_∞

2 dof
 C_∞^*

Parameter estimation in geometric transforms

- 2D homography

Given a set of (x_i, x_i') , compute H ($x_i' = Hx_i$)

cs428

- 3D to 2D camera projection

Given a set of (X_i, x_i) , compute P ($x_i = PX_i$)

- Fundamental matrix

Given a set of (x_i, x_i') , compute F ($x_i'^T F x_i = 0$)

Useful in • Trifocal tensor

Grad research Given a set of (x_i, x_i', x_i'') , compute T

Math tools 1:

Solving Linear Systems

- If $m = n$ (\mathbf{A} is a square matrix), then we can obtain the solution by simple inversion:

$$\mathbf{x} = \mathbf{A}^{-1}\mathbf{b}$$

- If $m > n$, then the system is **over-constrained** and \mathbf{A} is not invertible
 - Use Matlab “\” to obtain **least-squares solution** $\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$ to $\mathbf{Ax} = \mathbf{b}$ internally Matlab uses QR-factorization (cput418/340) to solve this.
 - Can also write this using pseudoinverse $\mathbf{A}^+ = (\mathbf{A}^T \mathbf{A})^{-1} \mathbf{A}^T$ to obtain **least-squares solution** $\mathbf{x} = \mathbf{A}^+ \mathbf{b}$

Fitting Lines

- A 2-D point $\mathbf{X} = (x, y)$ is on a line with slope m and intercept b if and only if $y = mx + b$

- Equivalently,

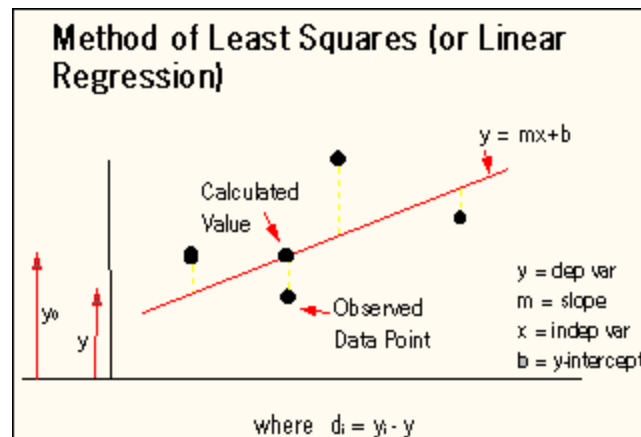
$$\begin{pmatrix} x & 1 \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix} = y$$

- So the line defined by two points $\mathbf{X}_1, \mathbf{X}_2$ is the solution to the following system of equations:

$$\begin{pmatrix} x_1 & 1 \\ x_2 & 1 \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \end{pmatrix}$$

Fitting Lines

- With more than two points, there is no guarantee that they will all be on the same line
- Least-squares solution obtained from pseudoinverse is line that is “closest” to all of the points



courtesy of
Vanderbilt U.

Example: Fitting a Line

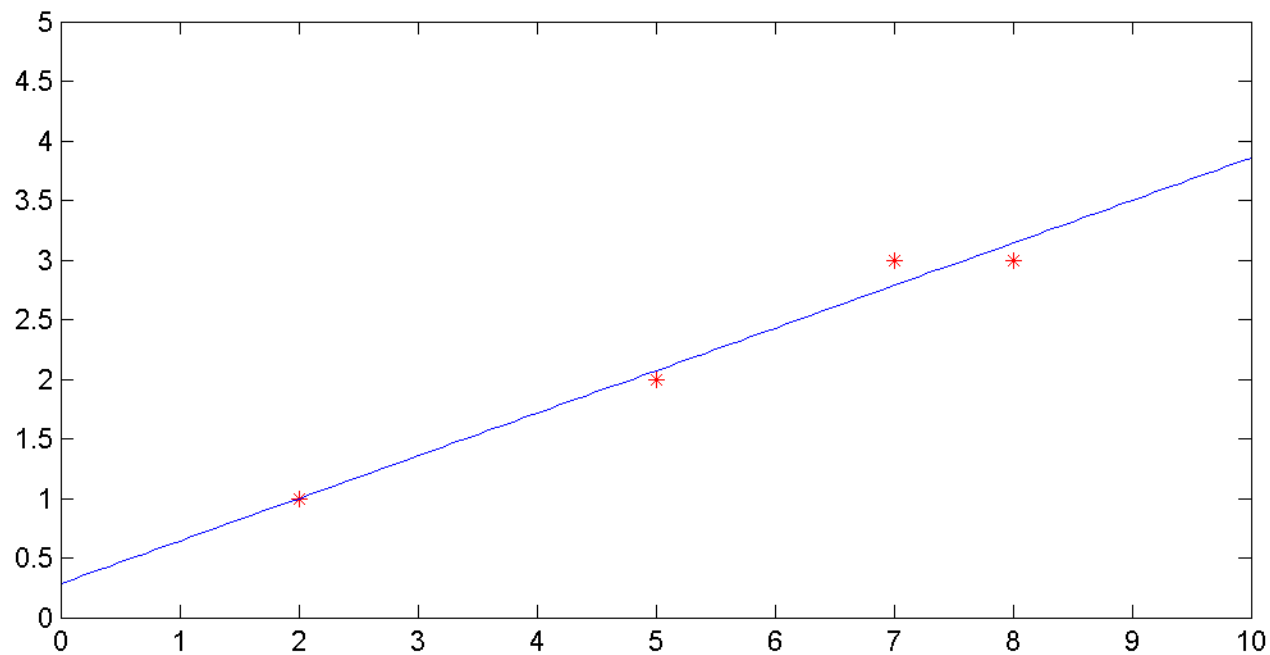
- Suppose we have points (2, 1), (5, 2), (7, 3), and (8, 3)
- Then

$$\begin{pmatrix} 2 & 1 \\ 5 & 1 \\ 7 & 1 \\ 8 & 1 \end{pmatrix} \begin{pmatrix} m \\ b \end{pmatrix} = \begin{pmatrix} 1 \\ 2 \\ 3 \\ 3 \end{pmatrix} \rightarrow \mathbf{A}^+ = \begin{pmatrix} -0.1667 & -0.0238 & 0.0714 & 0.1190 \\ 1.1667 & 0.3810 & -0.1429 & -0.4048 \end{pmatrix}$$

$$\text{and } \mathbf{x} = \mathbf{A}^+ \mathbf{b} = (0.3571, 0.2857)^T$$

Matlab: $\mathbf{x} = \mathbf{A} \backslash \mathbf{b}$

Example: Fitting a Line



Homogeneous Systems of Equations

- Suppose we want to solve $\mathbf{Ax} = \mathbf{0}$
- There is a trivial solution $\mathbf{x} = \mathbf{0}$, but we don't want this. For what other values of \mathbf{x} is \mathbf{Ax} close to $\mathbf{0}$?
- This is satisfied by computing the **singular value decomposition** (SVD) $\mathbf{A} = \mathbf{UDV}^T$ (a non-negative diagonal matrix between two orthogonal matrices) and taking \mathbf{x} as the last column of \mathbf{V}
 - Note that Matlab returns $[\mathbf{U}, \mathbf{D}, \mathbf{V}] = \text{svd}(\mathbf{A})$

Line-Fitting as a Homogeneous System

- A 2-D homogeneous point $\mathbf{x} = (x, y, 1)^T$ is on the line $\mathbf{l} = (a, b, c)^T$ only when

$$ax + by + c = 0$$

- We can write this equation with a dot product:

$\mathbf{x} \bullet \mathbf{l} = 0$, and hence the following system is implied for multiple points $\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n$:

$$\begin{pmatrix} \mathbf{x}_1^T \\ \vdots \\ \mathbf{x}_n^T \end{pmatrix} \mathbf{l} = 0$$

340/418

Heath example 3.21

Example: Homogeneous Line-Fitting

- Again we have 4 points, but now in homogeneous form:

$(2, 1, 1), (5, 2, 1), (7, 3, 1),$ and $(8, 3, 1)$

- Our system is:

$$\mathbf{A}\mathbf{x} = \begin{pmatrix} 2 & 1 & 1 \\ 5 & 2 & 1 \\ 7 & 3 & 1 \\ 8 & 3 & 1 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \end{pmatrix} = \mathbf{0}$$

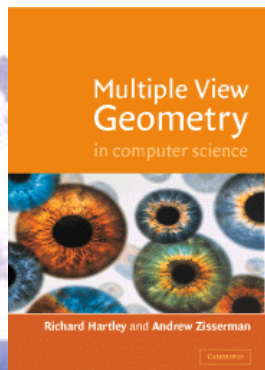
- Taking the SVD of \mathbf{A} , we get:

compare to $\mathbf{x} = (0.3571, 0.2857)^T$

$$\mathbf{V} = \begin{pmatrix} -0.9183 & 0.2334 & 0.31197 \\ -0.3690 & -0.2128 & -0.9047 \\ -0.1431 & -0.9488 & 0.2816 \end{pmatrix} \quad \begin{array}{l} a/-b=0.3534 \\ c/-b=0.3113 \end{array}$$

Computer Vision

The 2D projective plane and its applications



Hartley Zisserman Ch 2. In particular: Ch 2.1-4, 2.7,
Estimation: HZ: Ch 4.1-4.2.5, 4.4.4-4.8 cursorly
(Szelisky: Ch 2.1.1, 2.1.2)

Richard Hartley and Andrew Zisserman, Multiple View Geometry,
Cambridge University Publishers, 2nd ed. 2004

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Useful in

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Grad research

Given a set of (x_i, x_i', x_i'') , compute T

Estimating Homography H given image points x

HZ Ch 4



HZ

$$x_i' = Hx_i$$
$$i = 1 \dots 4$$

A novel view rendered via four
points with known structure

Number of measurements required

- At least as many independent equations as degrees of freedom required
- Example:

$$\lambda \begin{bmatrix} x' \\ y' \\ w' \end{bmatrix} = \begin{bmatrix} h_{11} & h_{12} & h_{13} \\ h_{21} & h_{22} & h_{23} \\ h_{31} & h_{32} & h_{33} \end{bmatrix} \begin{bmatrix} x \\ y \\ 1 \end{bmatrix}$$

2 independent equations / point

8 degrees of freedom

$$4 \times 2 \geq 8$$

Approximate solutions

- Minimal solution

 - 4 points yield an exact solution for H

- More points

 - No exact solution, because measurements are inexact (“noise”)
 - Search for “best” according to some cost function
 - Algebraic or geometric/statistical cost

Estimating **H**: The Direct Linear Transformation (DLT) Algorithm

HZ Ch 4.1

- $\mathbf{x}_i = \mathbf{H}\mathbf{X}_i$ is an equation involving homogeneous vectors, so $\mathbf{H}\mathbf{X}_i$ and \mathbf{x}_i need only be in the same direction, not strictly equal

$$\begin{pmatrix} \mathbf{x} \\ 1 \end{pmatrix} \equiv \begin{pmatrix} \lambda \mathbf{x} \\ \lambda \end{pmatrix}$$

- We can specify “same directionality” by using a cross product formulation:

$$\mathbf{x}'_i \times \mathbf{H}\mathbf{x}_i = 0$$

Direct Linear Transformation (DLT)

$$\lambda \mathbf{x}'_i \times \mathbf{Hx}_i = 0 \quad \mathbf{x}'_i = (x'_i, y'_i, w'_i)^\top \quad \mathbf{Hx}_i = \begin{pmatrix} \mathbf{h}^{1^\top} \mathbf{x}_i \\ \mathbf{h}^{2^\top} \mathbf{x}_i \\ \mathbf{h}^{3^\top} \mathbf{x}_i \end{pmatrix}$$

$$\mathbf{x}'_i \times \mathbf{Hx}_i = \begin{pmatrix} y'_i \mathbf{h}^{3^\top} \mathbf{x}_i - w'_i \mathbf{h}^{2^\top} \mathbf{x}_i \\ w'_i \mathbf{h}^{1^\top} \mathbf{x}_i - x'_i \mathbf{h}^{3^\top} \mathbf{x}_i \\ x'_i \mathbf{h}^{2^\top} \mathbf{x}_i - y'_i \mathbf{h}^{1^\top} \mathbf{x}_i \end{pmatrix}$$

$$\begin{bmatrix} 0^\top & -w'_i \mathbf{x}_i^\top & y'_i \mathbf{x}_i^\top \\ w'_i \mathbf{x}_i^\top & 0^\top & -x'_i \mathbf{x}_i^\top \\ -y'_i \mathbf{x}_i^\top & x'_i \mathbf{x}_i^\top & 0^\top \end{bmatrix} \begin{pmatrix} \mathbf{h}^1 \\ \mathbf{h}^2 \\ \mathbf{h}^3 \end{pmatrix} = 0$$

$$\mathbf{A}_i \mathbf{h} = 0$$

Direct Linear Transformation (DLT)

- Equations are linear in \mathbf{h}

$$\mathbf{A}_i \mathbf{h} = 0$$

- Only 2 out of 3 are linearly independent
(indeed, 2 eq/pt)

$$\begin{bmatrix} 0^\top & -w'_i \mathbf{x}_i^\top & y'_i \mathbf{x}_i^\top \\ w'_i \mathbf{x}_i^\top & 0^\top & -x'_i \mathbf{x}_i^\top \end{bmatrix} \begin{pmatrix} h^1 \\ h^2 \\ h^3 \end{pmatrix} = 0$$

$$x'_i \mathbf{A}_i^1 + y'_i \mathbf{A}_i^2 + w'_i \mathbf{A}_i^3 = 0$$

(only drop third row if $w'_i \neq 0$)

- Holds for any homogeneous representation,
e.g. $(x_i', y_i', 1)$

Direct Linear Transformation (DLT)

- Solving for H

$$\begin{bmatrix} A_1 \\ A_2 \\ A_3 \\ A_4 \end{bmatrix} h = 0$$

$$Ah = 0$$

size A is 8x9 or 12x9, but rank 8

Trivial solution is $h=0_9^T$ is not interesting

1-D null-space yields solution of interest

pick for example the one with $\|h\| = 1$

Obtain SVD of A. Solution for h
is last column of V

Direct Linear Transformation (DLT)

- Over-determined solution: more than 4 p-p corresp

$$\begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_n \end{bmatrix} \mathbf{h} = 0$$

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

No exact solution because of inexact measurement
i.e. "noise"

Find approximate solution

- Additional constraint needed to avoid 0, e.g. $\|\mathbf{h}\| = 1$
- $A\mathbf{h} = 0$ not possible, so minimize $\|A\mathbf{h}\|$

DLT algorithm

Objective

Given $n \geq 4$ 2D to 2D point correspondences $\{x_i \leftrightarrow x'_i\}$, determine the 2D homography matrix H such that $x'_i = Hx_i$

Algorithm

- (i) For each correspondence $x_i \leftrightarrow x'_i$ compute A_i . Usually only two first rows needed.
- (ii) Assemble n 2×9 matrices A_i into a single $2n \times 9$ matrix A
- (iii) Obtain SVD of A . Solution for h is last column of V
- (iv) Determine H from h (reshape)

Inhomogeneous solution

Since h can only be computed up to scale,
pick $h_j=1$, e.g. $h_9=1$, and solve for 8-vector \tilde{h}

$$\begin{bmatrix} 0 & 0 & 0 & -x_i w_i' & -y_i w_i' & -w_i w_i' & x_i y_i' & y_i y_i' \\ x_i w_i' & y_i w_i' & w_i w_i' & 0 & 0 & 0 & x_i x_i' & y_i x_i' \end{bmatrix} \tilde{h} = \begin{pmatrix} -w_i y_i' \\ w_i x_i' \end{pmatrix}$$

Solve using Gaussian elimination (4 points) or
using linear least-squares (more than 4 points)

However, if $h_9=0$ this approach fails
also poor results if h_9 close to zero

Therefore, not recommended for general
homographies

Note $h_9=H_{33}=0$ if origin is mapped to infinity

$$1_{\infty}^T H x_0 = \begin{bmatrix} 0 & 0 & 1 \end{bmatrix} H \begin{bmatrix} 0 \\ 0 \\ 1 \end{bmatrix} = 0$$

Algebraic distance

DLT minimizes $\|Ah\|$

$e = Ah$ residual vector

e_i partial vector for each $(x_i \leftrightarrow x_i')$
algebraic error vector

$$d_{\text{alg}}(x'_i, Hx_i)^2 = \|e_i\|^2 = \left\| \begin{bmatrix} 0^\top & -w'_i x_i^\top & -y'_i x_i^\top \\ -w'_i x_i^\top & 0^\top & -x'_i x_i^\top \end{bmatrix} h \right\|^2$$

algebraic distance

$$d_{\text{alg}}(x_1, x_2)^2 = a_1^2 + a_2^2 \text{ where } a = (a_1, a_2, a_3)^\top = x_1 \times x_2$$

$$\sum_i d_{\text{alg}}(x'_i, Hx_i)^2 = \sum_i \|e_i\|^2 = \|Ah\|^2 = \|e\|^2$$

Not geometrically/statistically meaningful, but given good normalization it works fine and is very fast (use for

DLT: Importance of normalization

$$\begin{bmatrix} 0 & 0 & 0 & -x'_i & -y'_i & -1 & y'_i x_i & y'_i y_i & y'_i \\ x_i & y_i & 1 & 0 & 0 & 0 & -x'_i x_i & -x'_i y_i & -x'_i \end{bmatrix} \begin{pmatrix} h^1 \\ h^2 \\ h^3 \end{pmatrix} = 0$$

$\sim 10^2 \quad \sim 10^2 \quad 1 \quad \sim 10^2 \quad \sim 10^2 \quad 1 \quad \sim 10^4 \quad \sim 10^4 \quad \sim 10^2$

orders of magnitude difference!



Un-normalized



normalized

Normalizing transformations

- Since DLT is not invariant to coordinate transforms, what is a good choice of coordinates?

e.g.

- Translate centroid to origin
- Scale to a $\sqrt{2}$ average distance to the origin
- Independently on both images

Or

$$\mathbf{T}_{\text{norm}} = \begin{bmatrix} w+h & 0 & w/2 \\ 0 & w+h & h/2 \\ 0 & 0 & 1 \end{bmatrix}^{-1}$$

Normalized DLT algorithm

Objective

Given $n \geq 4$ 2D to 2D point correspondences $\{x_i \leftrightarrow x'_i\}$, determine the 2D homography matrix H such that $x'_i = Hx_i$

Algorithm

- (i) Normalize points $\tilde{x}_i = T_{\text{norm}} x_i, \tilde{x}'_i = T'_{\text{norm}} x'_i$
- (ii) Apply DLT algorithm to $\tilde{x}_i \leftrightarrow \tilde{x}'_i$,
- (iii) Denormalize solution $H = T'^{-1}_{\text{norm}} \tilde{H} T_{\text{norm}}$

DLT: Importance of normalization

$$\begin{bmatrix} 0 & 0 & 0 & -x'_i & -y'_i & -1 & y'_i x_i & y'_i y_i & y'_i \\ x_i & y_i & 1 & 0 & 0 & 0 & -x'_i x_i & -x'_i y_i & -x'_i \end{bmatrix} \begin{pmatrix} h^1 \\ h^2 \\ h^3 \end{pmatrix} = 0$$

Un-normalized $10^2 \sim 10^2 \quad 1 \quad \sim 10^2 \quad \sim 10^2 \quad 1 \quad \sim 10^4 \quad \sim 10^4 \quad \sim 10^2$

normalized $\sim 1 \quad \sim 1 \quad 1 \quad \sim 1 \quad \sim 1 \quad 1 \quad \sim 1 \quad \sim 1 \quad \sim 1$

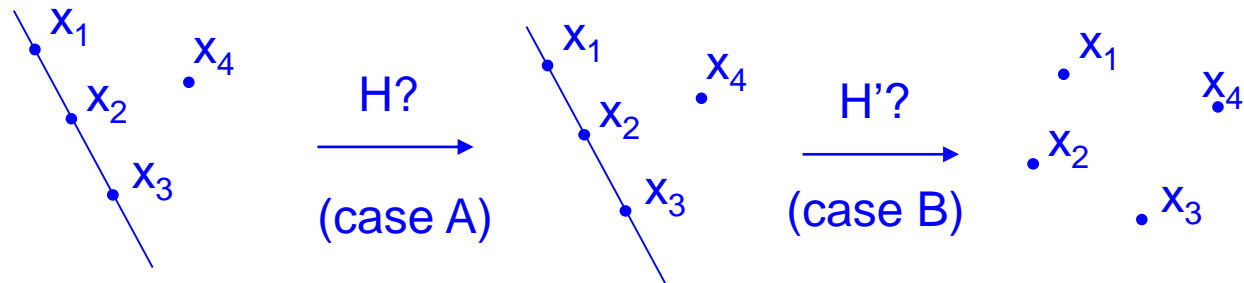


Un-normalized



normalized

Degenerate configurations



Constraints: $\mathbf{x}'_i \times \mathbf{H}\mathbf{x}_i = 0 \quad i=1,2,3,4$

Define: $\mathbf{H}^* = \mathbf{x}'_4 \mathbf{1}^\top$

Then, $\mathbf{H}^* \mathbf{x}_i = \mathbf{x}'_4 (\mathbf{1}^\top \mathbf{x}_i) = 0, \quad i = 1, 2, 3$

$$\mathbf{H}^* \mathbf{x}_4 = \mathbf{x}'_4 (\mathbf{1}^\top \mathbf{x}_4) = k \mathbf{x}'_4$$

\mathbf{H}^* is rank-1 matrix and thus not a homography

If \mathbf{H}^* is unique solution, then no homography mapping $\mathbf{x}_i \rightarrow \mathbf{x}'_i$ (case B)

If further solution \mathbf{H} exist, then also $\alpha \mathbf{H}^* + \beta \mathbf{H}$ (case A)

(2-D null-space instead of 1-D null-space)

Solutions from lines, etc.

2D homographies from 2D lines

$$l'_i = H^T l_i \quad Ah = 0$$

Minimum of 4 lines

3D Homographies (15 dof)

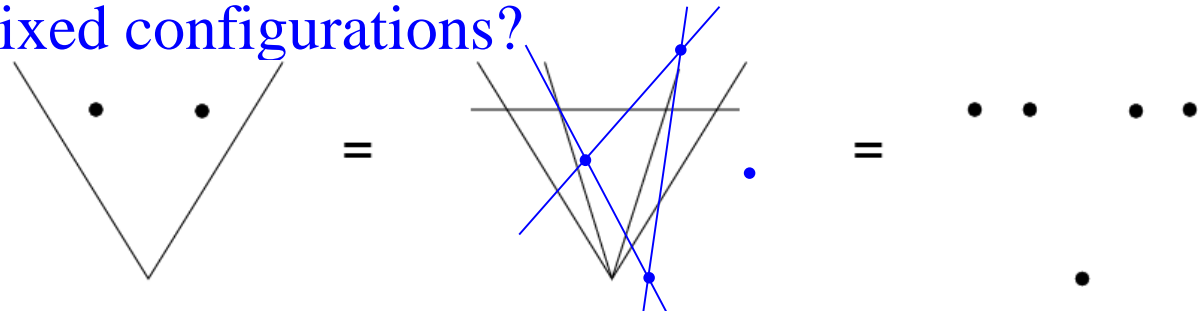
Minimum of 5 points or 5 planes

2D affinities (6 dof)

Minimum of 3 points or lines

Conic provides 5 constraints

Mixed configurations?



Homography: Summary

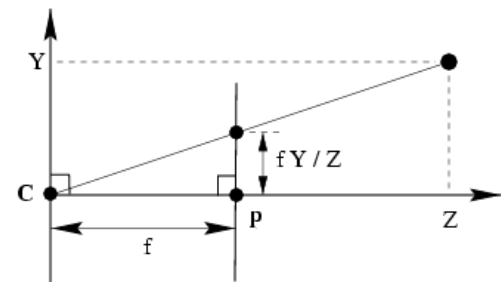
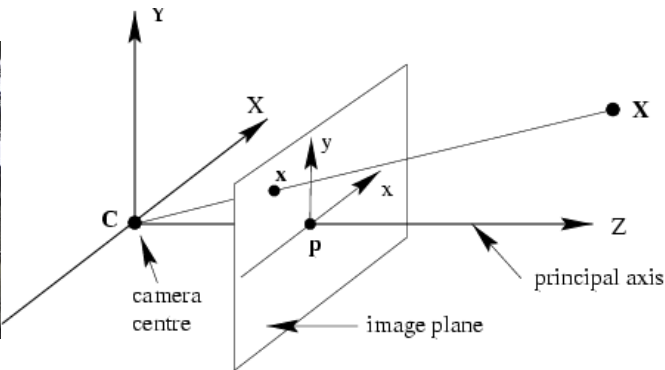
- Direct Linear Transform
- Inhomogenous solution
- Projective – Affine (- Metric) upgrade
- Non-linear computation (Tracking)



- First 3D proj geom
- Then review and more on camera models
- Then following P estimation

Camera Models

Mostly pinhole camera model



$$\lambda \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} f & p_x \\ & f & p_y \\ & & 1 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

or $\lambda \mathbf{x} = \mathbf{P} \cdot \mathbf{X}$

$$\begin{pmatrix} U \\ V \\ W \end{pmatrix} = \begin{pmatrix} \text{Transformation} \\ \text{representing} \\ \text{intrinsic parameters} \end{pmatrix} \begin{pmatrix} \text{Transformation} \\ \text{representing} \\ \text{projection model} \end{pmatrix} \begin{pmatrix} \text{Transformation} \\ \text{representing} \\ \text{extrinsic parameters} \end{pmatrix} \begin{pmatrix} X \\ Y \\ Z \\ T \end{pmatrix}$$

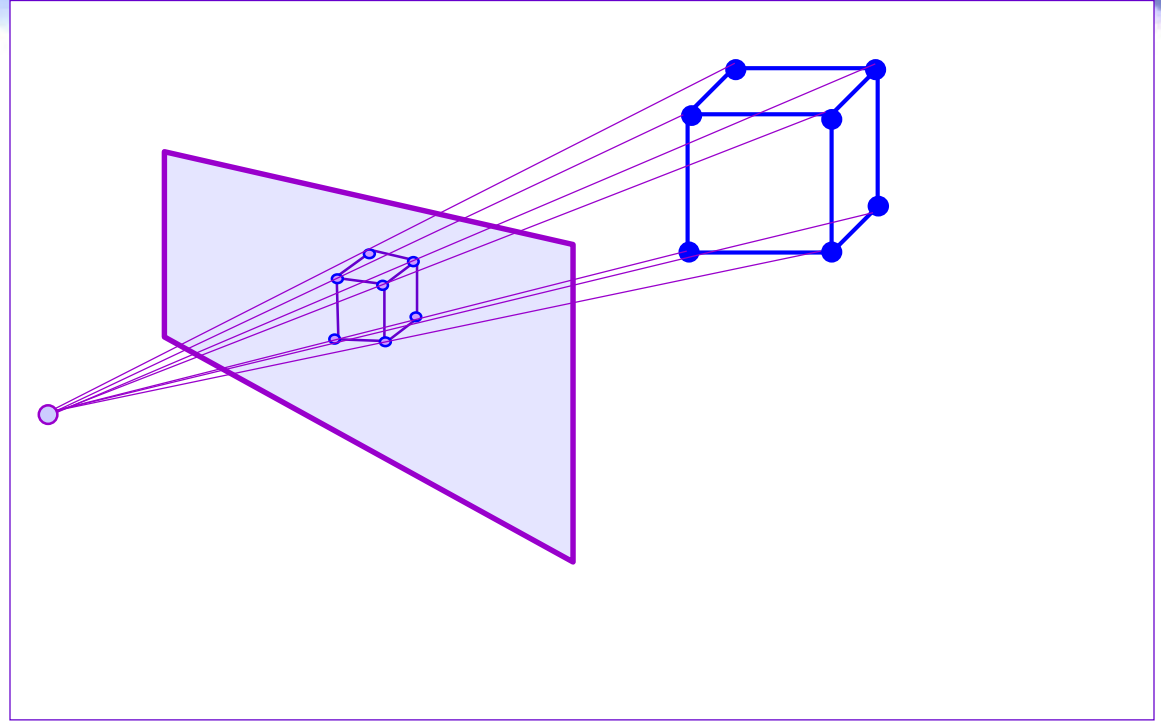
A 3D Vision Problem: Multi-view geometry - resection

- Projection equation

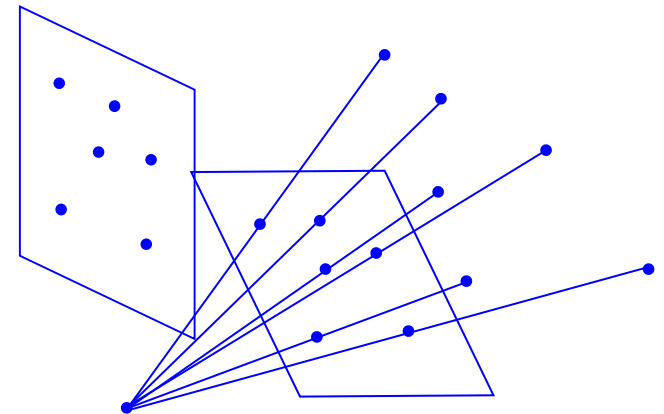
$$\mathbf{x}_i = \mathbf{P}_i \mathbf{X}$$

- Resection:

$$- \mathbf{x}_i, \mathbf{X} \longrightarrow \mathbf{P}_i$$



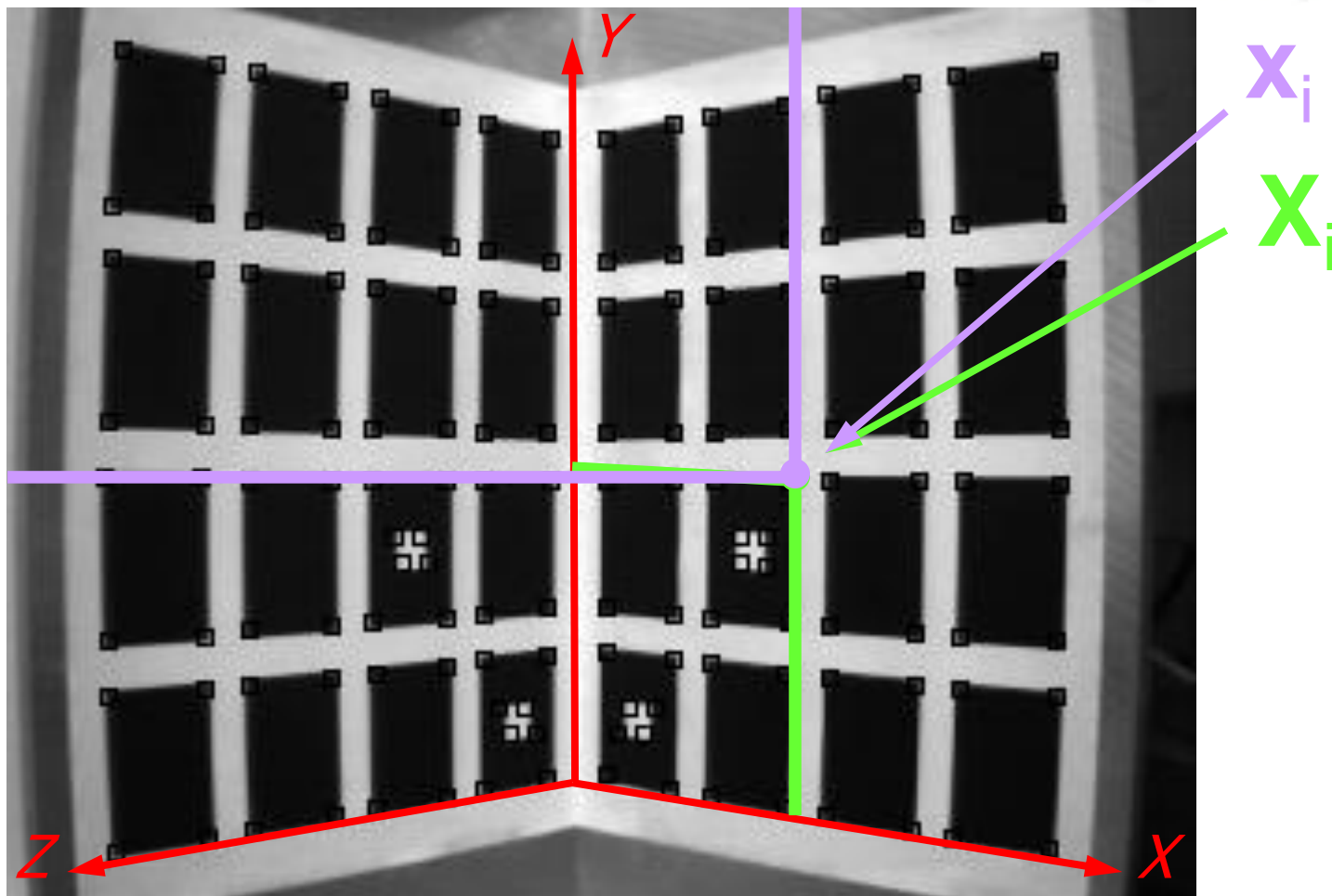
Given image points and 3D points
calculate camera projection matrix.



Estimating camera matrix **P**

- Given a number of correspondences between 3-D points and their 2-D image projections $\mathbf{X}_i \leftrightarrow \mathbf{x}_i$, we would like to determine the **camera projection matrix \mathbf{P}** such that $\mathbf{x}_i = \mathbf{P}\mathbf{X}_i$ for all i

A Calibration Target



courtesy of B. Wilburn

Estimating **P**: The Direct Linear Transformation (DLT) Algorithm

- $\mathbf{x}_i = \mathbf{P}\mathbf{X}_i$ is an equation involving homogeneous vectors, so $\mathbf{P}\mathbf{X}_i$ and \mathbf{x}_i need only be in the same direction, not strictly equal

$$\begin{pmatrix} \mathbf{x} \\ 1 \end{pmatrix} \equiv \begin{pmatrix} \lambda \mathbf{x} \\ \lambda \end{pmatrix}$$

- We can specify “same directionality” by using a cross product formulation:

$$\mathbf{x}_i \times \mathbf{P}\mathbf{X}_i = \mathbf{0}$$

DLT Camera Matrix Estimation: Preliminaries

- Let the image point $\mathbf{x}_i = (x_i, y_i, w_i)^T$
(remember that \mathbf{X}_i has 4 elements)
- Denoting the j th row of \mathbf{P} by $\mathbf{p}^j{}^T$ (a 4-element row vector), we have:

$$\mathbf{P}\mathbf{X}_i = \begin{pmatrix} \mathbf{p}^{1T} \\ \mathbf{p}^{2T} \\ \mathbf{p}^{3T} \end{pmatrix} \mathbf{X}_i = \begin{pmatrix} \mathbf{p}^{1T}\mathbf{X}_i \\ \mathbf{p}^{2T}\mathbf{X}_i \\ \mathbf{p}^{3T}\mathbf{X}_i \end{pmatrix}$$

DLT Camera Matrix Estimation: Step 1

- Then by the definition of the cross product,

$\mathbf{x}_i \times \mathbf{P}\mathbf{X}_i$ is:

$$\begin{pmatrix} y_i \mathbf{p}^{3T} \mathbf{X}_i - w_i \mathbf{p}^{2T} \mathbf{X}_i \\ w_i \mathbf{p}^{1T} \mathbf{X}_i - x_i \mathbf{p}^{3T} \mathbf{X}_i \\ x_i \mathbf{p}^{2T} \mathbf{X}_i - y_i \mathbf{p}^{1T} \mathbf{X}_i \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix} = \mathbf{0}$$

DLT Camera Matrix Estimation: Step 2

- The dot product commutes, so $\mathbf{p}^j{}^T \mathbf{X}_i = \mathbf{X}_i^T \mathbf{p}^j$, and we can rewrite the preceding as:

$$\begin{pmatrix} y_i \mathbf{X}_i^T \mathbf{p}^3 - w_i \mathbf{X}_i^T \mathbf{p}^2 \\ w_i \mathbf{X}_i^T \mathbf{p}^1 - x_i \mathbf{X}_i^T \mathbf{p}^3 \\ x_i \mathbf{X}_i^T \mathbf{p}^2 - y_i \mathbf{X}_i^T \mathbf{p}^1 \end{pmatrix} = 0$$

DLT Camera Matrix Estimation: Step 3

- Collecting terms, this can be rewritten as a matrix product:

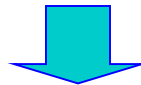
$$\begin{pmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & \mathbf{0}^T \end{pmatrix} \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix}$$

where $\mathbf{0}^T = (0, 0, 0, 0)$. This is a 3 x 12 matrix times a 12-element column vector

$$\mathbf{p} = (\mathbf{p}^{1T}, \mathbf{p}^{2T}, \mathbf{p}^{3T})^T$$

What We Just Did

$$\begin{pmatrix} y_i \mathbf{X}_i^T \mathbf{p}^3 - w_i \mathbf{X}_i^T \mathbf{p}^2 \\ w_i \mathbf{X}_i^T \mathbf{p}^1 - x_i \mathbf{X}_i^T \mathbf{p}^3 \\ x_i \mathbf{X}_i^T \mathbf{p}^2 - y_i \mathbf{X}_i^T \mathbf{p}^1 \end{pmatrix}$$



$$\begin{pmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & \mathbf{0}^T \end{pmatrix} \begin{pmatrix} \mathbf{p}^1 \\ \mathbf{p}^2 \\ \mathbf{p}^3 \end{pmatrix}$$

DLT Camera Matrix Estimation: Step 4

$$\begin{pmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \\ -y_i \mathbf{X}_i^T & x_i \mathbf{X}_i^T & \mathbf{0}^T \end{pmatrix} \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix}$$

- There are only two linearly independent rows here
 - The third row is obtained by adding \mathbf{X}_i times the first row to y_i times the second and scaling the sum by $-1/w_i$

DLT Camera Matrix Estimation: Step 4

- So we can eliminate one row to obtain the following linear matrix equation for the i th pair of corresponding points:

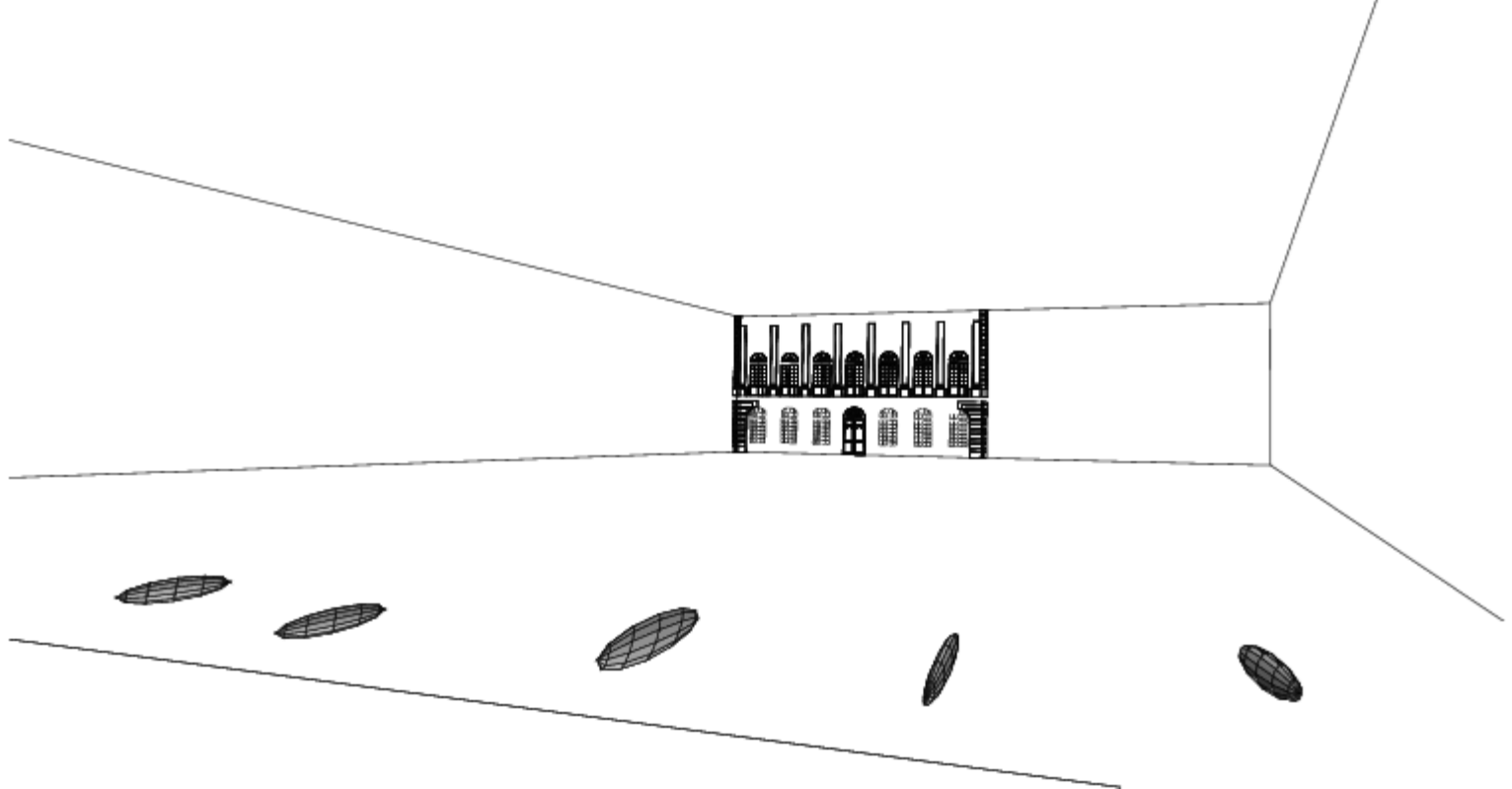
$$\begin{pmatrix} \mathbf{0}^T & -w_i \mathbf{X}_i^T & y_i \mathbf{X}_i^T \\ w_i \mathbf{X}_i^T & \mathbf{0}^T & -x_i \mathbf{X}_i^T \end{pmatrix} \begin{pmatrix} p^1 \\ p^2 \\ p^3 \end{pmatrix} = \mathbf{0}$$

- Write this as **$\mathbf{A}_i \mathbf{p} = \mathbf{0}$**

DLT Camera Matrix Estimation: Step 5

- Remember that there are 11 unknowns which generate the 3×4 homogeneous matrix \mathbf{P} (represented in vector form by \mathbf{p})
- Each point correspondence yields 2 equations (the two rows of \mathbf{A}_i)
 - We need at least $5 \frac{1}{2}$ point correspondences to solve for \mathbf{p}
- Stack \mathbf{A}_i to get homogeneous linear system $\mathbf{A}\mathbf{p} = \mathbf{0}$

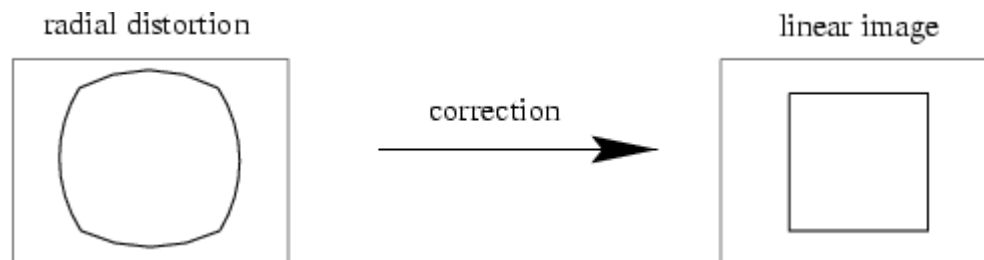
Experiment:



Radial Distortion



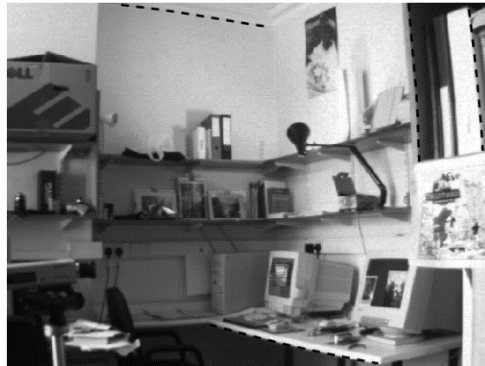
short and long focal length



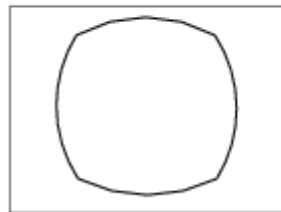
Radial Distortion



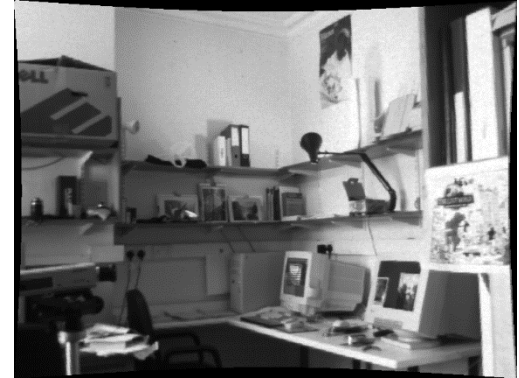
Radial Distortion



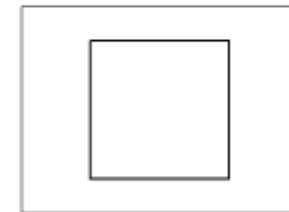
radial distortion



correction →



linear image



$$(\tilde{x}, \tilde{y}, 1)^T = [\mathbf{I} \mid \mathbf{0}] \mathbf{X}_{\text{cam}}$$

$$\begin{pmatrix} x_d \\ y_d \end{pmatrix} = L(\tilde{r}) \begin{pmatrix} \tilde{x} \\ \tilde{y} \end{pmatrix}$$

Radial Distortion

Correction of distortion

$$\hat{x} = x_c + L(r)(x - x_c) \quad \hat{y} = y_c + L(r)(y - y_c)$$

Choice of the distortion function and center

$$\begin{aligned} x &= x_o + (x_o - c_x)(K_1 r^2 + K_2 r^4 + \dots) \\ y &= y_o + (y_o - c_y)(K_1 r^2 + K_2 r^4 + \dots) \end{aligned}$$

$$r = (x_o - c_x)^2 + (y_o - c_y)^2 \ .$$

Computing the parameters of the distortion function

- (i) Minimize with additional unknowns
- (ii) Straigten lines
- (iii) ...