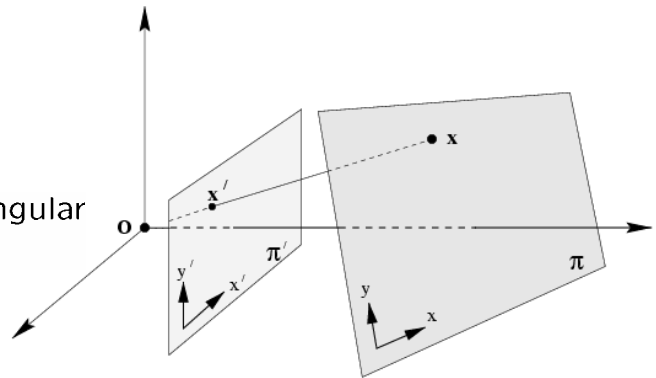


## Reminder: Plane Projective transformation

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

or  $\mathbf{x}' = \mathbf{H}\mathbf{x}$ , where  $\mathbf{H}$  is a  $3 \times 3$  non-singular homogeneous matrix.

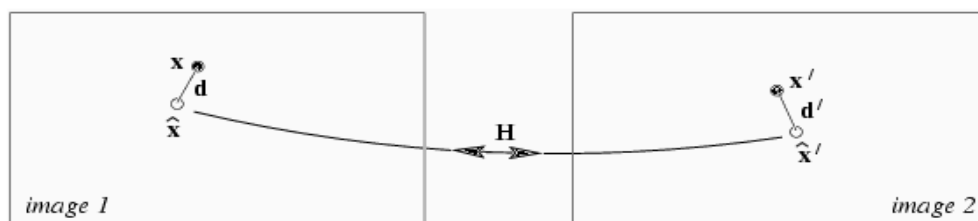


- A projective transformation is also called a "homography" and a "collineation".
- $\mathbf{H}$  has 8 degrees of freedom.
- It can be estimated from 4 or more point correspondences

## Maximum Likelihood estimation of homography $\mathbf{H}$

If the measurement error is Gaussian, then the ML estimate of  $\mathbf{H}$  **and** the corrected correspondences  $\{\hat{\mathbf{x}}_i \leftrightarrow \hat{\mathbf{x}}'_i\}$  is given by minimizing

$$\mathcal{C} = \sum_i d^2(\hat{\mathbf{x}}_i, \mathbf{x}_i) + d^2(\hat{\mathbf{x}}'_i, \mathbf{x}'_i) \quad \text{subject to} \quad \hat{\mathbf{x}}_i = \hat{\mathbf{H}}\hat{\mathbf{x}}'_i, \forall i$$

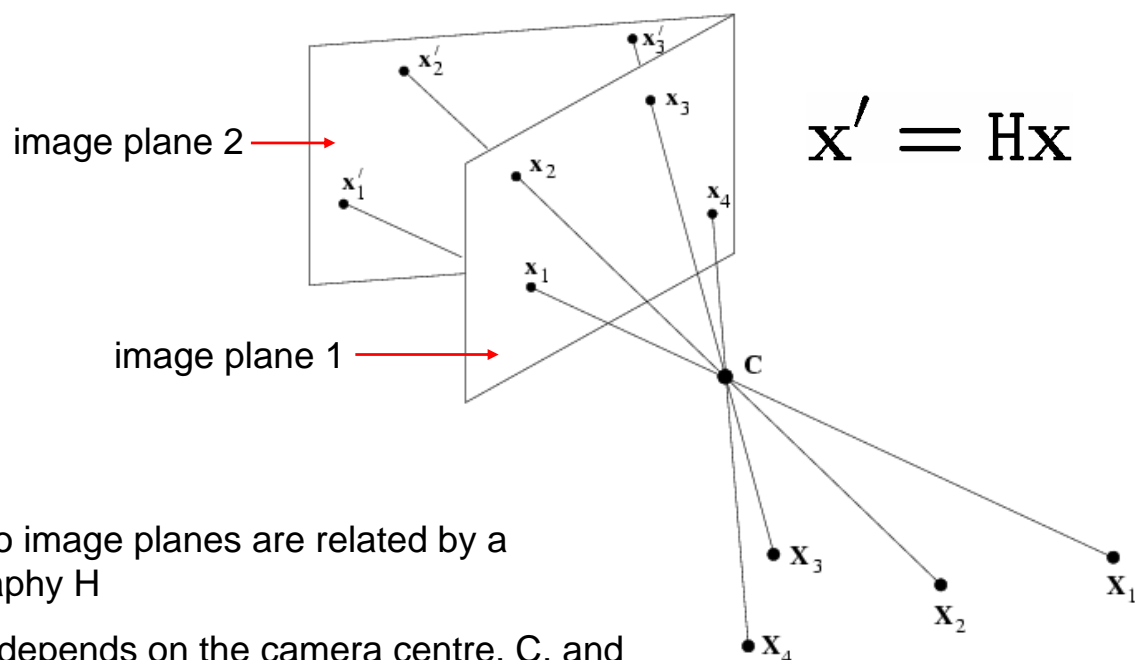


Cost function minimization:

- for 2D affine transformations there is a matrix solution (**non-examinable**)
- for 2D projective transformation, minimize numerically using e.g. non-linear gradient descent

e.g. Camera rotating about its centre

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- The two image planes are related by a homography  $H$
- $H$  only depends on the camera centre,  $C$ , and the planes, **not** on the 3D structure

## Example : Building panoramic mosaics

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4 frames from a sequence of 30



The camera rotates (and zooms) with fixed centre

## Example : Building panoramic mosaics

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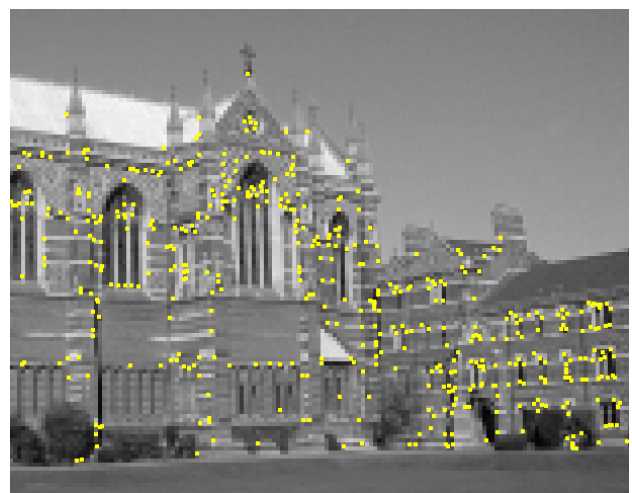
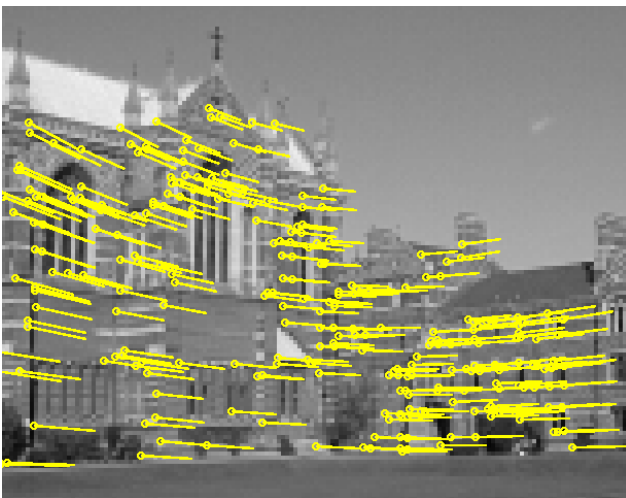
30 frames



The camera rotates (and zooms) with fixed centre

## Homography between two frames

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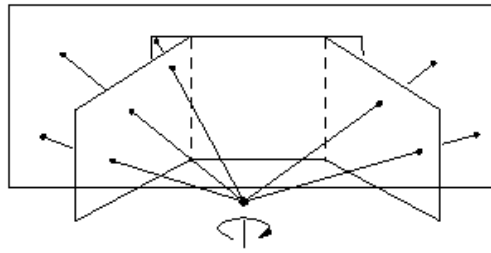


ML estimate of homography from these 100s of point correspondences

## Choice of mosaic frame

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Choose central image as reference



This produces the classic "bow-tie" mosaic.



# General Linear Least Squares

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$$\min_{a,b} \sum_i (y_i - ax_i - b)^2$$

Write the residuals as an  $n$ -vector

$$\begin{pmatrix} w_1 \\ w_2 \\ \vdots \\ w_n \end{pmatrix} = \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} - \begin{bmatrix} x_1 & 1 \\ x_2 & 1 \\ \vdots & \vdots \\ x_n & 1 \end{bmatrix} \begin{pmatrix} a \\ b \end{pmatrix}$$

$$\mathbf{w} = \mathbf{y} - H\theta$$

$H$  is a  $n \times 2$  matrix

Then the sum of squared residuals becomes

$$\mathbf{w}^\top \mathbf{w} = (\mathbf{y} - H\theta)^\top (\mathbf{y} - H\theta)$$

We want to minimize this w.r.t.  $\theta$

$$\frac{d}{d\theta} (\mathbf{y} - H\theta)^\top (\mathbf{y} - H\theta) = 2H^\top (\mathbf{y} - H\theta) = 0$$

$$H^\top H\theta = H^\top \mathbf{y}$$

$$\theta = (H^\top H)^{-1} H^\top \mathbf{y} = H^+ \mathbf{y}$$

$$\begin{pmatrix} \end{pmatrix} = \begin{pmatrix} \end{pmatrix} \begin{pmatrix} \end{pmatrix} \begin{pmatrix} \end{pmatrix}$$

## Summary

- If the generative model is linear  $\mathbf{y} = H\theta$
- then the ML solution for Gaussian noise is  $\theta = H^+ \mathbf{y}$
- where the matrix  $H^+ = (H^\top H)^{-1} H^\top$  is the **pseudo-inverse** of  $H$