

Reconstruct

- Scene geometry
- Camera motion

## The story so far ... stereo reconstruction from 2 views

Given cameras  $P = K[I \mid 0]$   $P' = K'[R \mid t]$

- Epipolar geometry: compute fundamental matrix  $F = K'^{-T}[t]_xRK^{-1}$
- Correspondence search: 1D search for corresponding points  $x \leftrightarrow x'$  along epipolar line  $l' = Fx$
- Triangulation: compute 3D point  $X$  from  $x \leftrightarrow x'$ , and  $P, P'$

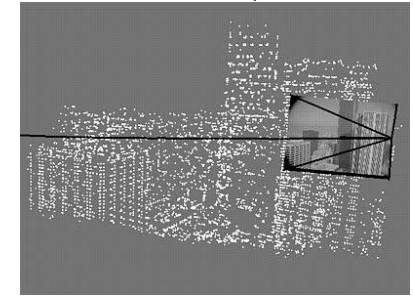
Now, structure and motion ...

# Example

image sequence



cameras and points



## Structure and Motion: Problem statement

Given 2 (or more) images of a scene, compute the scene structure and the camera motion



- Assume internal calibration ( $K, K'$ ) is known
- Assume scene is rigid
- Start with 2 views only
- NB epipolar geometry is not known

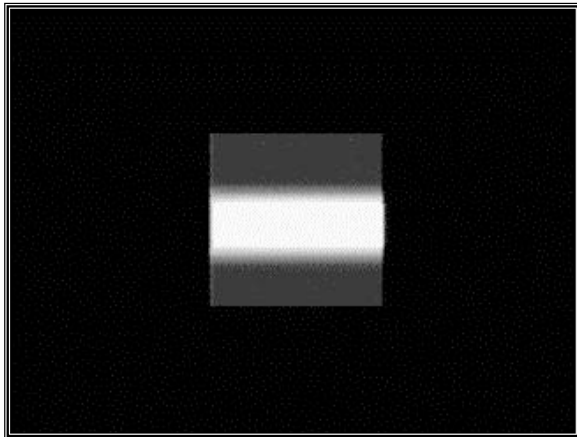
## Outline

---

- Image point motion
- Computing the fundamental matrix
  - 8-point algorithm
  - automation
  - motion from the fundamental matrix
- More than two views
  - matching
  - estimation
- Applications

## The aperture problem

---



Only the component of motion perpendicular to the line can be determined from local image measurements

## Why use interest points ?

---

Compute points to avoid the aperture problem

2D feature



1D feature (edge)



uniform



## interest points computed for each frame

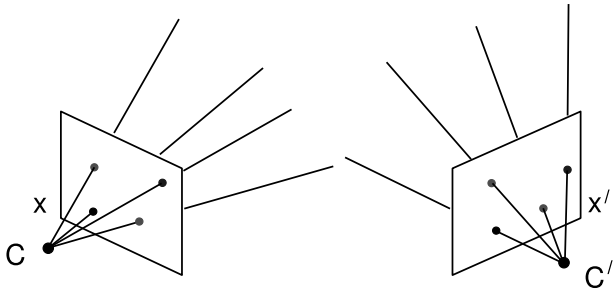
---

- Harris corner detector



## The geometric motion problem

Given image point correspondences,  $x_i \leftrightarrow x'_i$ , determine  $R$  and  $t$



Rotate and translate camera until stars of rays intersect

## Outline of structure and motion computation

1. Compute the fundamental matrix  $F$  from point correspondences  $x_i \leftrightarrow x'_i$
2. Compute the cameras (motion) from the fundamental matrix (recall  $F = K'^{-T}[t]_{\times}RK^{-1}$ ).  
Obtain
$$P = K[I \mid 0], \quad P' = K'[R \mid t]$$
3. Compute the 3D structure  $X_i$  from the cameras  $P, P'$  and point correspondences  $x_i \leftrightarrow x'_i$  (triangulation)

## What can be computed from point correspondences?

Suppose we have computed  $F = K'^{-T}[t]_{\times}RK^{-1}$  can the motion be computed?  $F$  is a homogeneous matrix, so

$$F = K'^{-T}[t]_{\times}RK^{-1} = K'^{-T}[\lambda t]_{\times}RK^{-1}$$

i.e. the translation can only be determined up to scale. This is a consequence of the depth / speed ambiguity: only the ratio of  $t$  and  $Z$  can be computed since if

$$t \rightarrow \lambda t \quad \text{and} \quad Z \rightarrow \lambda Z$$

the images are unchanged.

- a large motion of a distant object, and
- a small motion of a nearby object

are indistinguishable (from point motion alone)

Summary: the rotation  $R$  (3 dof) can be determined completely, but only the translation direction (2 dof) can be determined, not its magnitude

## How many point correspondences are required ?

- for  $n$  points there are  $3n$  unknowns (the 3D position of each point)
- for 2 views there are 5 unknowns (that are recoverable)
- each point correspondence gives 4 measurements
- for  $n$  points expect a solution if  $4n \geq (3n + 5)$ , i.e.  $n \geq 5$
- we will give solutions for  $n = 7$  and  $n = 8$  correspondences

# Computing the fundamental matrix

## Problem statement

Given:  $n$  corresponding points  $\{\mathbf{x}_i \leftrightarrow \mathbf{x}'_i, i = 1, \dots, n\}$   
compute the fundamental matrix  $F$  such that

$$\mathbf{x}'_i{}^T F \mathbf{x}_i = 0 \quad 1 \leq i \leq n$$

## Solution

Each point correspondence  $\mathbf{x}_i \leftrightarrow \mathbf{x}'_i$  generates one constraint on  $F$

$$(x'_i \ y'_i \ 1) \begin{bmatrix} f_1 & f_2 & f_3 \\ f_4 & f_5 & f_6 \\ f_7 & f_8 & f_9 \end{bmatrix} \begin{pmatrix} x_i \\ y_i \\ 1 \end{pmatrix} = 0$$

which may be written

$$x'x f_1 + x'y f_2 + x' f_3 + y'x f_4 + y'y f_5 + y' f_6 + x f_7 + y f_8 + f_9 = 0$$

$$(x'x, x'y, x', y'x, y'y, y', x, y, 1) \begin{pmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \\ f_8 \\ f_9 \end{pmatrix} = 0$$

For  $n$  points

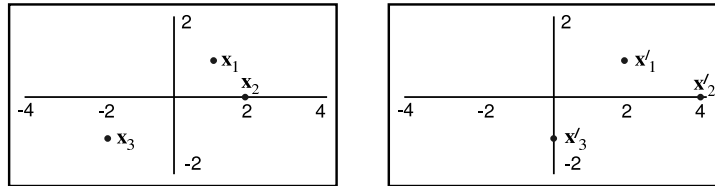
$$A\mathbf{f} = \begin{bmatrix} x'_1x_1 & x'_1y_1 & x'_1 & y'_1x_1 & y'_1y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x'_nx_n & x'_ny_n & x'_n & y'_nx_n & y'_ny_n & y'_n & x_n & y_n & 1 \end{bmatrix} \begin{pmatrix} f_1 \\ f_2 \\ f_3 \\ f_4 \\ f_5 \\ f_6 \\ f_7 \\ f_8 \\ f_9 \end{pmatrix} = 0$$

$A$  is an  $n \times 9$  measurement matrix, and  $\mathbf{f}$  is the fundamental matrix written as a 9-vector

- For 8 points,  $A$  is an  $8 \times 9$  matrix and  $\mathbf{f}$  can be computed as the null-vector of  $A$ , i.e.  $\mathbf{f}$  is determined up to scale
- Note, this solution (and those following) does not require  $(K, K')$

Example: compute F from 8 point correspondences

Images from a parallel camera stereo rig – epipolar lines  $y = y'$



just consider first three points  $\begin{pmatrix} x_1 \\ y_1 \end{pmatrix}$   $\begin{pmatrix} x'_1 \\ y'_1 \end{pmatrix}$   $\begin{pmatrix} x_2 \\ y_2 \end{pmatrix}$   $\begin{pmatrix} x'_2 \\ y'_2 \end{pmatrix}$   $\begin{pmatrix} x_3 \\ y_3 \end{pmatrix}$   $\begin{pmatrix} x'_3 \\ y'_3 \end{pmatrix}$   
 $\begin{pmatrix} 1 \\ 1 \end{pmatrix} \leftrightarrow \begin{pmatrix} 2 \\ 1 \end{pmatrix}$   $\begin{pmatrix} 2 \\ 0 \end{pmatrix} \leftrightarrow \begin{pmatrix} 4 \\ 0 \end{pmatrix}$   $\begin{pmatrix} -2 \\ -1 \end{pmatrix} \leftrightarrow \begin{pmatrix} 0 \\ -1 \end{pmatrix}$

$$A = \begin{bmatrix} x'_1 x_1 & x'_1 y_1 & x'_1 & y'_1 x_1 & y'_1 y_1 & y'_1 & x_1 & y_1 & 1 \\ 2 & 2 & 2 & 1 & 1 & 1 & 1 & 1 & 1 \\ 8 & 0 & 4 & 0 & 0 & 0 & 2 & 0 & 1 \\ 0 & 0 & 0 & 2 & 1 & 0 & -2 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$A = \begin{bmatrix} x'_i x_i & x'_i y_i & x'_i & y'_i x_i & y'_i y_i & y'_i & x_i & y_i & 1 \\ 2 & 2 & 2 & 1 & 1 & 1 & 1 & 1 & 1 \\ 8 & 0 & 4 & 0 & 0 & 0 & 2 & 0 & 1 \\ 0 & 0 & 0 & 2 & 1 & 0 & -2 & 0 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \end{bmatrix}$$

$$\mathbf{f} = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & -1 & 0 & 1 & 0 \end{pmatrix}^T$$

satisfies  $A\mathbf{f} = \mathbf{0}$

write  $\mathbf{f}$  in matrix form

$$F = \begin{bmatrix} 0 & 0 & 0 \\ 0 & 0 & -1 \\ 0 & 1 & 0 \end{bmatrix}$$

## The “8-point” algorithm – Least squares solution

Given  $n$  corresponding points ( $n$  is typically hundreds) with noise on their measured positions

For  $n > 8$  point correspondences,  $A$  is a  $n \times 9$  matrix,

$$\begin{bmatrix} x'_1 x_1 & x'_1 y_1 & x'_1 & y'_1 x_1 & y'_1 y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x'_n x_n & x'_n y_n & x'_n & y'_n x_n & y'_n y_n & y'_n & x_n & y_n & 1 \end{bmatrix} \mathbf{f} = \mathbf{0}$$

and in general there will not be an exact solution to  $A\mathbf{f} = \mathbf{0}$ .

A (linear) solution which minimises  $\|A\mathbf{f}\|$ , subject to  $\|\mathbf{f}\| = 1$  is obtained from the eigenvector with least eigenvalue of  $A^T A$ .

## Solution for 7 points

1. Form the  $7 \times 9$  set of equations  $A\mathbf{f} = \mathbf{0}$
2. The system has a 2-dimensional solution set
3. General solution (use SVD) has the form

$$\mathbf{f} = \lambda \mathbf{f}_0 + \mu \mathbf{f}_1$$

4. In matrix terms

$$F = \lambda F_0 + \mu F_1$$

5. Condition  $\det F = 0$  gives cubic equation in  $\lambda$  and  $\mu$
6. Either one or three real solutions for ratio  $\lambda : \mu$

## A note on minimizing residuals

We have seen two examples of needing to minimize residuals of the form  $\|A\mathbf{x}\|$  over  $\mathbf{x}$

1. In computing the fundamental matrix from point correspondences over two views

For  $n > 8$  point correspondences,  $A$  is a  $n \times 9$  matrix,

$$\begin{bmatrix} x'_1 x_1 & x'_1 y_1 & x'_1 & y'_1 x_1 & y'_1 y_1 & y'_1 & x_1 & y_1 & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ x'_n x_n & x'_n y_n & x'_n & y'_n x_n & y'_n y_n & y'_n & x_n & y_n & 1 \end{bmatrix} \mathbf{f} = \mathbf{0}$$

2. In triangulating the 3D position of a point from its image in two or more views

$$\mathbf{x} = P\mathbf{X} \quad \mathbf{x}' = P'\mathbf{X} \quad \begin{bmatrix} x\mathbf{p}^{3T} - \mathbf{p}^{1T} \\ y\mathbf{p}^{3T} - \mathbf{p}^{2T} \\ x'\mathbf{p}'^{3T} - \mathbf{p}'^{1T} \\ y'\mathbf{p}'^{3T} - \mathbf{p}'^{2T} \end{bmatrix} \mathbf{X} = \mathbf{0}$$

For  $m$  views  $A$  is a  $2m \times 4$  matrix

We want to avoid the trivial solution  $\mathbf{x} = \mathbf{0}$ , so add the constraint that  $\|\mathbf{x}\| = 1$

$$\min_{\mathbf{x}} \|A\mathbf{x}\| \quad \text{subject to} \quad \|\mathbf{x}\| = 1$$

For a  $m \times n$  matrix (with  $m > n$ ) the vector  $\mathbf{x}$  that minimizes  $\|A\mathbf{x}\|$  subject to  $\|\mathbf{x}\| = 1$  is given by the eigenvector of  $A^T A$  corresponding to the least eigenvalue

## Proof

Write the residuals as a  $m$ -vector  $\mathbf{r} = A\mathbf{x}$

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

Then  $\|\mathbf{r}\|^2 = \mathbf{r}^T \mathbf{r} = \mathbf{x}^T A^T A \mathbf{x}$

Write  $M = A^T A$ . This is a  $n \times n$  (i.e. square) positive semi-definite symmetric matrix:

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

- The eigenvalues  $\lambda_i$  are real, and the eigenvectors  $\mathbf{e}_i$  are orthonormal,  $\mathbf{e}_i \cdot \mathbf{e}_j = \delta_{ij}$
- Let  $\mathbf{x} = \mathbf{e}_i$  then  $\mathbf{e}_i^T M \mathbf{e}_i = \lambda_i$ , and since  $\mathbf{x}^T M \mathbf{x} \geq 0 \forall \mathbf{x}$  it follows that  $\lambda_i \geq 0$

Eigenvector decomposition

$$M = \begin{bmatrix} \mathbf{e}_1 & \mathbf{e}_2 & \mathbf{e}_3 & \dots & \mathbf{e}_n \\ \vdots & \vdots & \vdots & & \vdots \end{bmatrix} \begin{bmatrix} \lambda_1 & & & & \\ & \lambda_2 & & & \\ & & \lambda_3 & & \\ & & & \dots & \\ & & & & \lambda_n \end{bmatrix} \begin{bmatrix} \mathbf{e}_1^T \dots \\ \mathbf{e}_2^T \dots \\ \mathbf{e}_3^T \dots \\ \vdots \\ \mathbf{e}_n^T \dots \end{bmatrix} = \sum_i \lambda_i \mathbf{e}_i \mathbf{e}_i^T$$

where  $0 \leq \lambda_1 < \lambda_2 < \dots < \lambda_n$

Then

$$\mathbf{x}^T M \mathbf{x} = \lambda_1 (\mathbf{x} \cdot \mathbf{e}_1)^2 + \lambda_2 (\mathbf{x} \cdot \mathbf{e}_2)^2 \dots + \lambda_n (\mathbf{x} \cdot \mathbf{e}_n)^2$$

This is minimized if  $\mathbf{x} = \mathbf{e}_1$ .

# Automatic Computation of the fundamental matrix

Given Image pair



Find The fundamental matrix  $F$  and correspondences  $x_i \leftrightarrow x'_i$ .

- Compute image points
- Compute correspondences
- Compute epipolar geometry

Step 1: interest points



Harris corner detector  
100's of points per image

Step 2a: match points – proximity



- proximity - search within disparity window

## Step 2b: match points – cross-correlate



- cross-correlate on intensity neighbourhoods

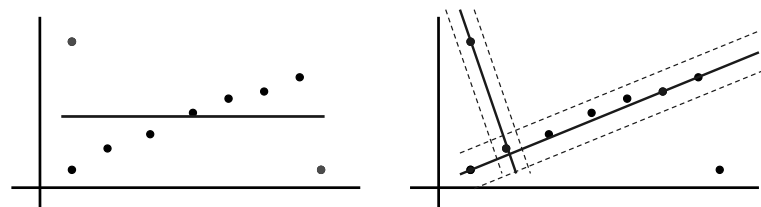
## Correlation matching results



- Many wrong matches (10-50%), but enough to compute F

## Robust line estimation - RANSAC

Fit a line to 2D data containing outliers



There are two problems

1. a line fit which minimizes perpendicular distance
2. a classification into inliers (valid points) and outliers

Solution: use robust statistical estimation algorithm RANSAC (RANdom Sample Consensus) [Fishler & Bolles, 1981]

## RANSAC robust line estimation

Repeat

1. Select random sample of 2 points
2. Compute the line through these points
3. Measure support (number of points within threshold distance of the line)

Choose the line with the largest number of inliers

- Compute least squares fit of line to inliers (regression)



## Algorithm summary – RANSAC robust F estimation

---

Repeat

1. Select random sample of 7 correspondences
2. Compute F (1 or 3 solutions)
3. Measure support (number of inliers within threshold distance of epipolar line)

Choose the F with the largest number of inliers

## Correspondences consistent with epipolar geometry

---



- Use RANSAC robust estimation algorithm
- Obtain correspondences  $x_i \leftrightarrow x'_i$  and F

## Computed epipolar geometry

---



# Determining cameras from the fundamental matrix

## Decomposing the fundamental matrix

$$F = K'^{-T} [t]_{\times} R K^{-1}$$

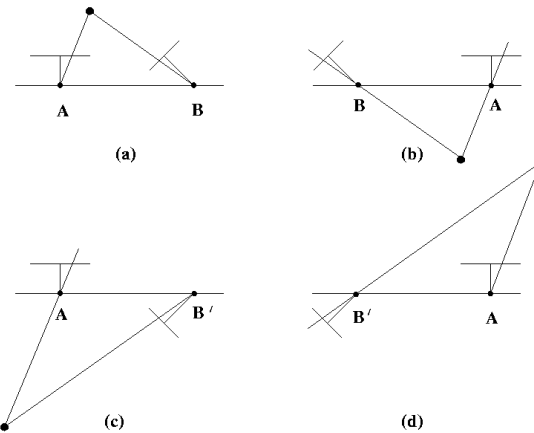
Form the Essential matrix  $E = [t]_{\times} R = K'^T F K$

1. Compute  $t$  as left null-vector of  $E$ , i.e.  $E^T t = 0$   
This determines  $t$  up to scale.
2. Compute  $R$  from  $E$  (see below)  
There are two solutions  $R_1$  and  $R_2$ .
3. Set  $P = K[I \mid 0]$  for the first camera

The four solutions for the second camera are

$$\begin{aligned} P' &= K'[R_1 \mid \mu t] & P' &= K'[R_1 \mid -\mu t] \\ P' &= K'[R_2 \mid \mu t] & P' &= K'[R_2 \mid -\mu t] \end{aligned} \quad \mu > 0$$

## The four camera solutions



The 3D point is only in front of both cameras in one case

Computing the rotation matrix from the Essential matrix (non-examinable)

- Compute the SVD of  $E = U \text{diag}(1, 1, 0) V^T$

- Set  $W = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

- Solutions are  $R_1 = U W V^T$   $R_2 = U W^T V^T$

# Structure and Motion for more than 2 views

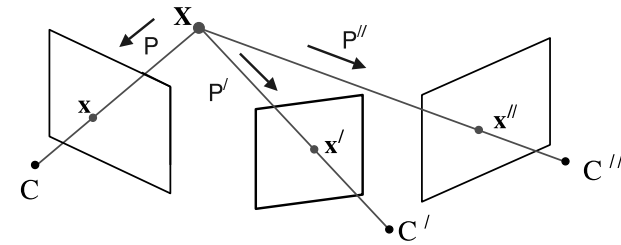
## What is gained by having more than 2 views?

1. The two view ambiguities do not get worse
  - there is an overall scale ambiguity
2. Matching:
  - matches can be verified
3. Estimation:
  - accuracy increased by using more measurements

## Notation for three or more views

For 3 views the cameras are  $P$ ,  $P'$  and  $P''$ , and a 3D point is imaged as

$$\mathbf{x} = P\mathbf{X} \quad \mathbf{x}' = P'\mathbf{X} \quad \mathbf{x}'' = P''\mathbf{X}$$



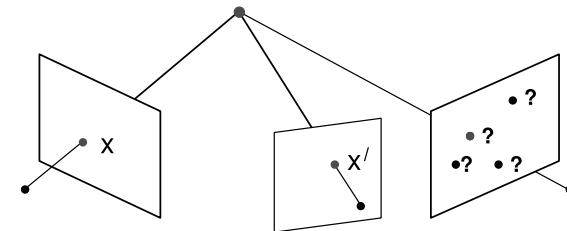
For  $m$  views, a point  $\mathbf{X}_j$  is imaged in the “ $i$ ” th view as

$$\mathbf{x}_j^i = P^i \mathbf{X}_j$$

## Point correspondence over 3 views

Given: the cameras  $P$ ,  $P'$  and  $P''$ , and matching points  $\mathbf{x}$  and  $\mathbf{x}'$

Find: the matching point in the third view



Algorithm:

- compute the 3D point from  $\mathbf{x}$  and  $\mathbf{x}'$  and project it into the third view
- the matching point coincides with the projected point

## Problem statement: structure and motion

Given:  $n$  matching image points  $\mathbf{x}_j^i$  over  $m$  views

Find: the cameras  $P^i$  and the 3D points  $\mathbf{X}_j$  such that  $\mathbf{x}_j^i = P^i \mathbf{X}_j$

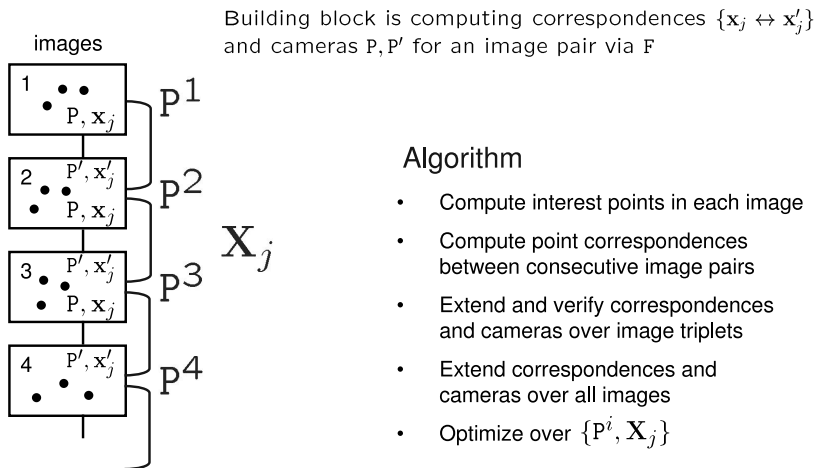
$$\min_{P^i, \mathbf{X}_j} \sum_{j \in \text{points}} \sum_{i \in \text{views}} d(\mathbf{x}_j^i, P^i \mathbf{X}_j)^2$$

number of parameters

- for each camera there are 6 parameters
- for each 3D point there are 3 parameters

a total of  $6m + 3n$  parameters must be estimated

## Algorithm for structure and motion



### Algorithm

- Compute interest points in each image
- Compute point correspondences between consecutive image pairs
- Extend and verify correspondences and cameras over image triplets
- Extend correspondences and cameras over all images
- Optimize over  $\{P^i, \mathbf{X}_j\}$

## Application: Augmented reality

original sequence



## Augmentation

