

Structure from motion

Digital Visual Effects, Spring 2007

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with slides by Richard Szeliski, Steve Seitz, Zhengyou Zhang and Marc Pollefeys

Announcements

- Project #2 is due today. Same submission mechanism. Please hand it in before Sunday if possible.
- The class of 5/8 will begin at 2:30pm.

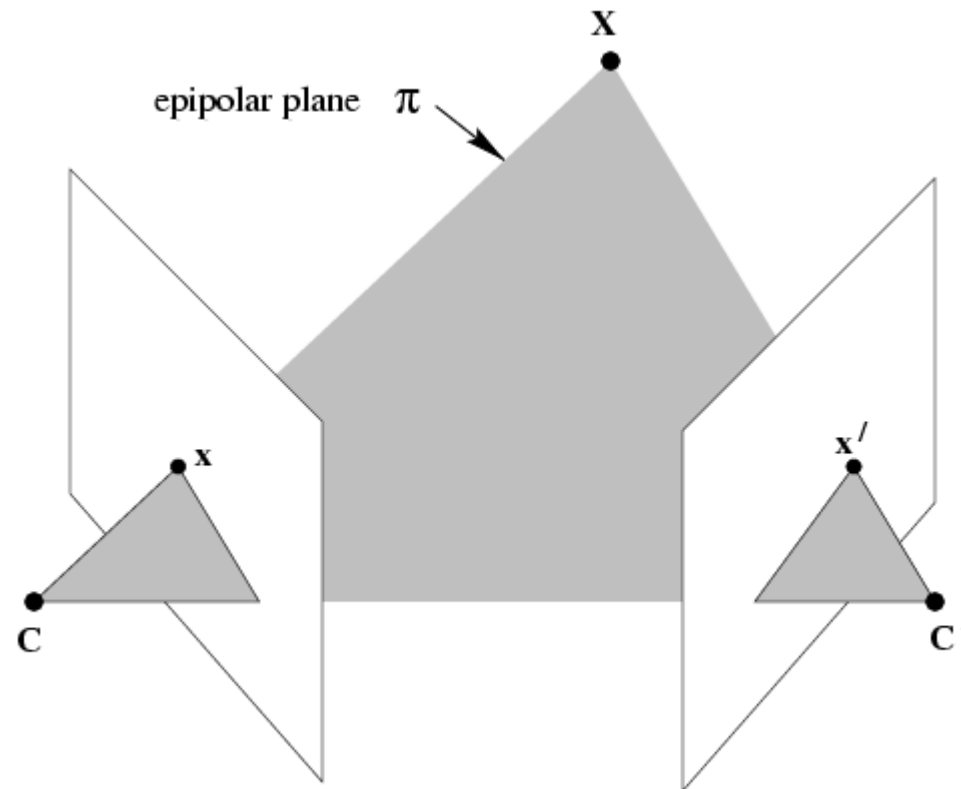
Outline

- Epipolar geometry and fundamental matrix
- Structure from motion
- Factorization method
- Bundle adjustment
- Applications

Epipolar geometry & fundamental matrix

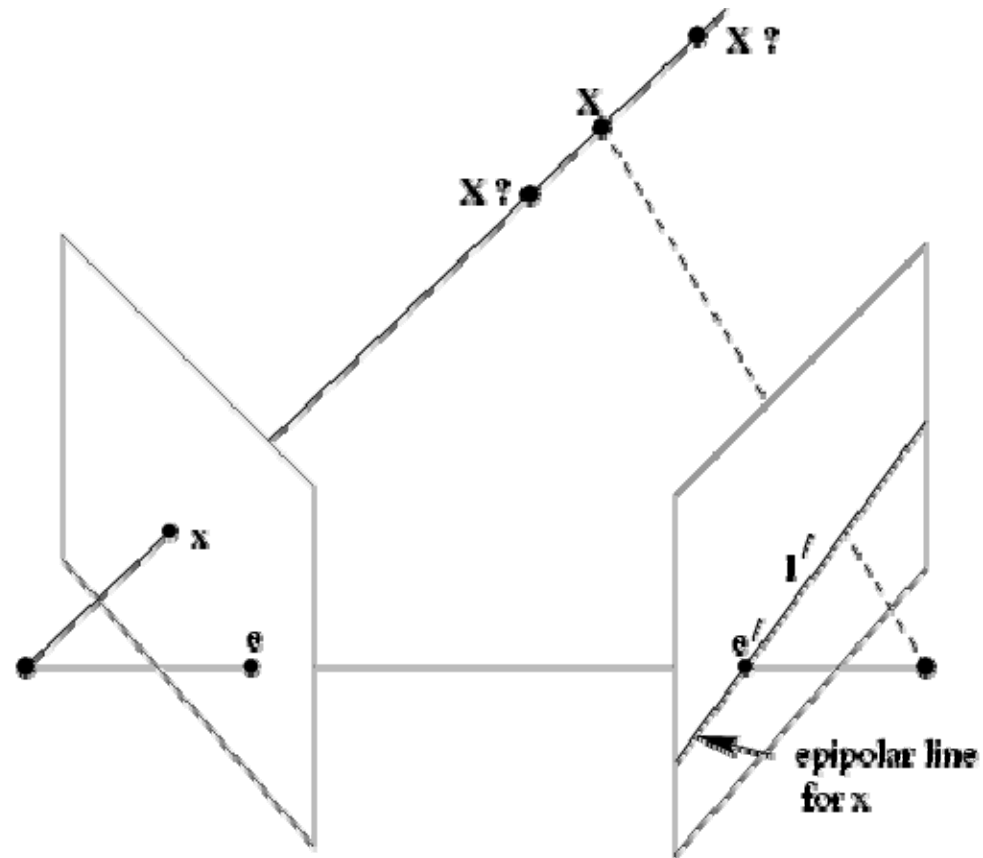
The epipolar geometry

[epipolar geometry demo](#)



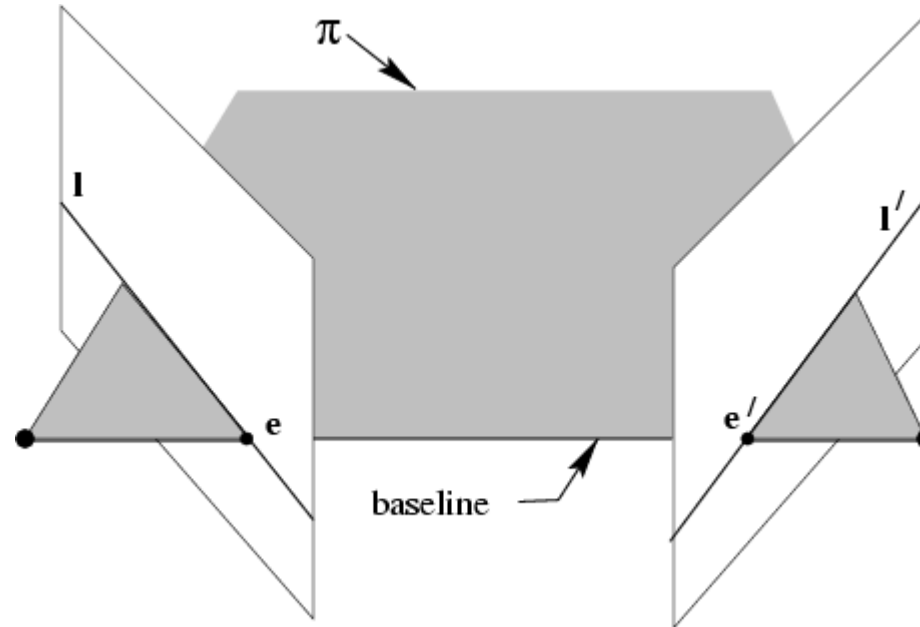
C, C', x, x' and X are coplanar

The epipolar geometry



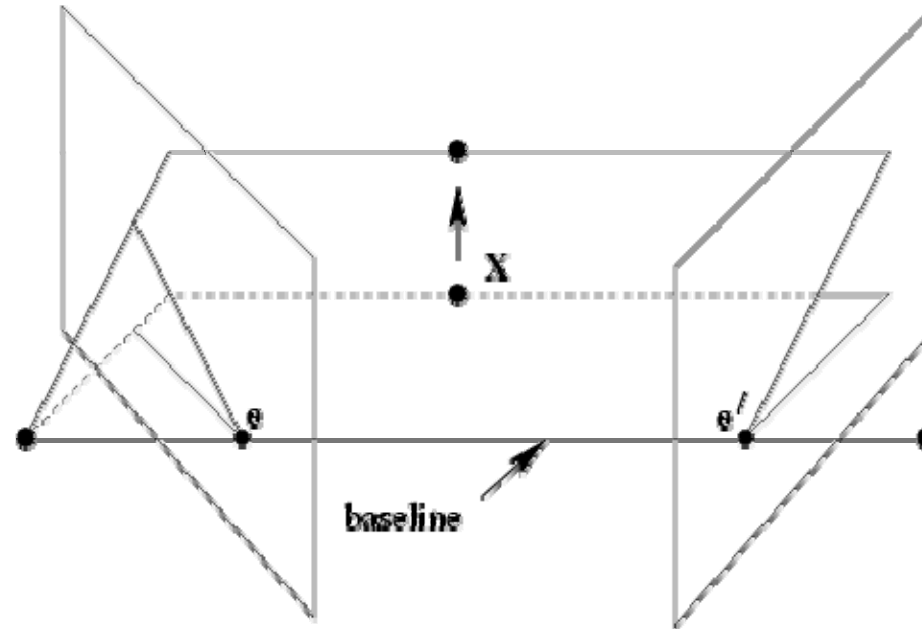
What if only C, C', x are known?

The epipolar geometry



All points on π project on l and l'

The epipolar geometry



Family of planes π and lines l and l' intersect at e and e'

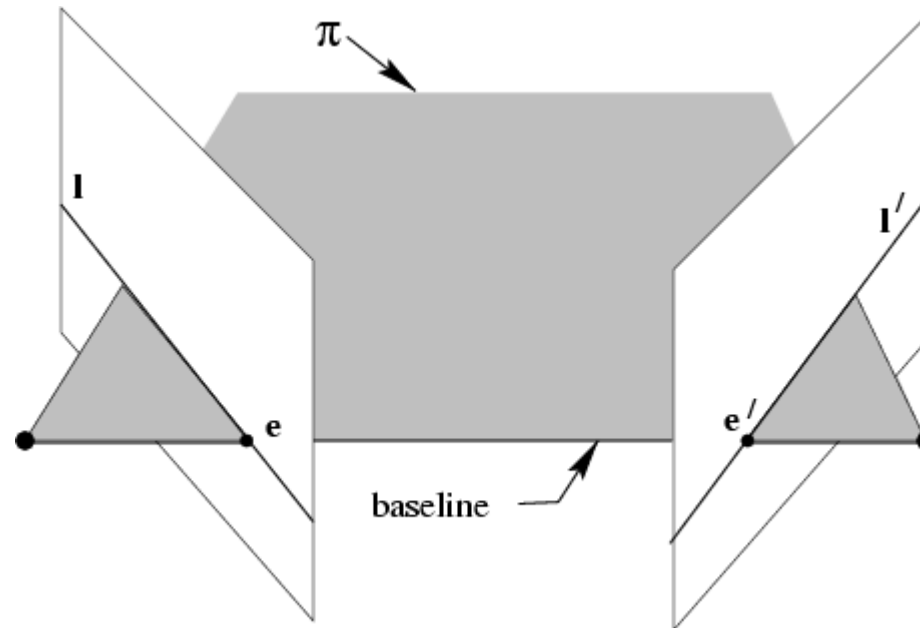
The epipolar geometry

epipolar pole

[epipolar geometry demo](#)

= intersection of baseline with image plane

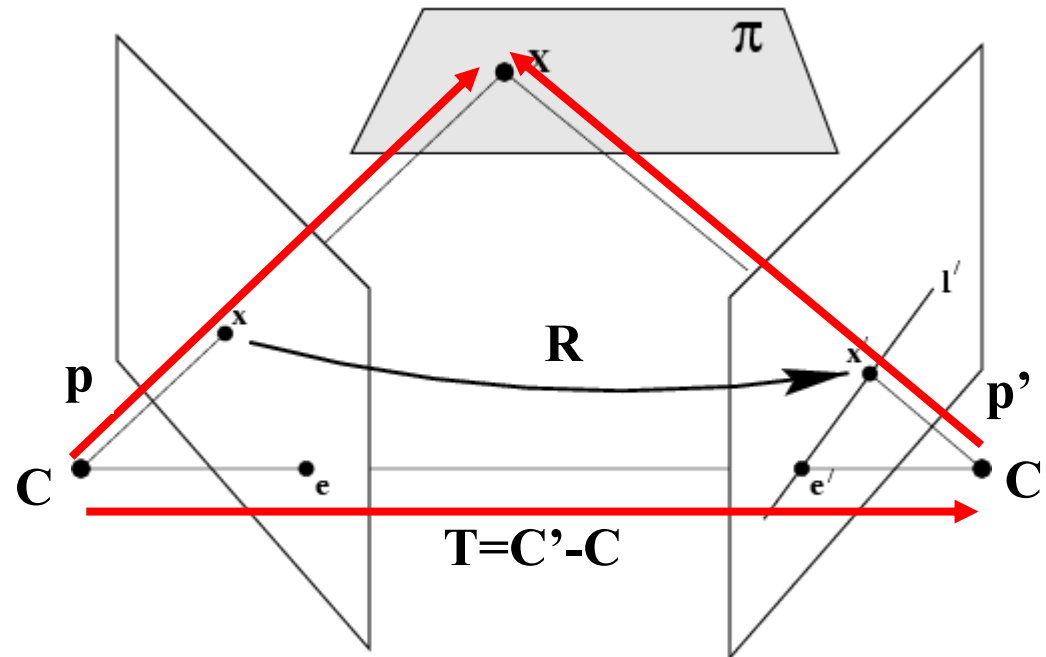
= projection of projection center in other image



epipolar plane = plane containing baseline

epipolar line = intersection of epipolar plane with image

The fundamental matrix F



Two reference frames are related via the extrinsic parameters

$$p' = R(p - T)$$

The equation of the epipolar plane through X is

$$(p - T)^T (T \times p) = 0 \quad \rightarrow \quad (R^T p')^T (T \times p) = 0$$

The fundamental matrix F

$$(\mathbf{R}^T \mathbf{p}')^T (\mathbf{T} \times \mathbf{p}) = 0$$

$$\mathbf{T} \times \mathbf{p} = \mathbf{S} \mathbf{p}$$

$$\mathbf{S} = \begin{bmatrix} 0 & -T_z & T_y \\ T_z & 0 & -T_x \\ -T_y & T_x & 0 \end{bmatrix}$$

$$\rightarrow (\mathbf{R}^T \mathbf{p}')^T (\mathbf{S} \mathbf{p}) = 0$$

$$\rightarrow (\mathbf{p}'^T \mathbf{R}) (\mathbf{S} \mathbf{p}) = 0$$

$$\rightarrow \mathbf{p}'^T \mathbf{E} \mathbf{p} = 0 \quad \text{essential matrix}$$

The fundamental matrix F

$$\mathbf{p}'^T \mathbf{E} \mathbf{p} = 0$$

Let \mathbf{M} and \mathbf{M}' be the intrinsic matrices, then

$$\mathbf{p} = \mathbf{M}^{-1} \mathbf{x} \quad \mathbf{p}' = \mathbf{M}'^{-1} \mathbf{x}'$$

$$\rightarrow (\mathbf{M}'^{-1} \mathbf{x}')^T \mathbf{E} (\mathbf{M}^{-1} \mathbf{x}) = 0$$

$$\rightarrow \mathbf{x}'^T \mathbf{M}'^{-T} \mathbf{E} \mathbf{M}^{-1} \mathbf{x} = 0$$

$$\rightarrow \mathbf{x}'^T \mathbf{F} \mathbf{x} = 0 \quad \text{fundamental matrix}$$

The fundamental matrix F

- The fundamental matrix is the algebraic representation of epipolar geometry
- The fundamental matrix satisfies the condition that for any pair of corresponding points $x \leftrightarrow x'$ in the two images

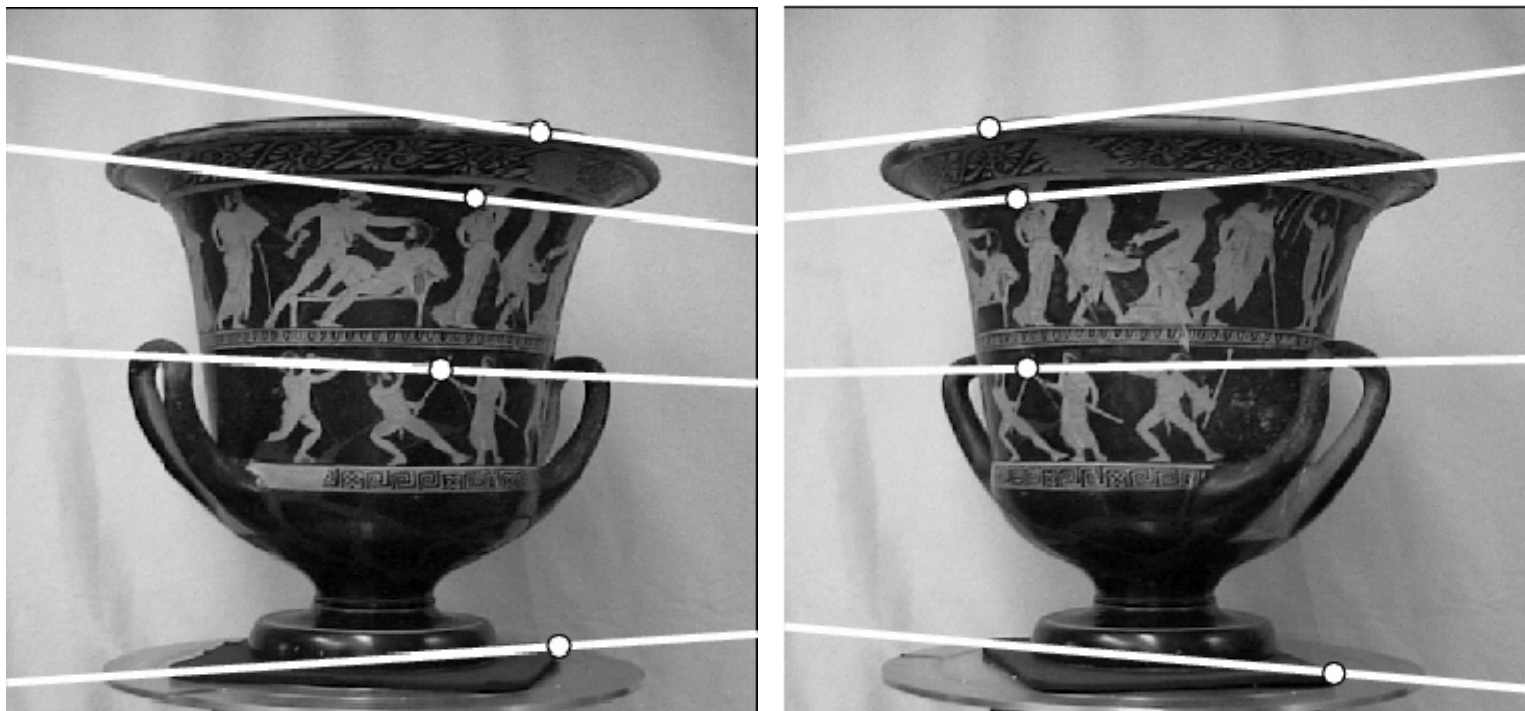
$$\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0 \quad \left(\mathbf{x}'^T \mathbf{1}' = 0 \right)$$

The fundamental matrix F

F is the unique 3×3 rank 2 matrix that satisfies $x'^T F x = 0$
for all $x \leftrightarrow x'$

1. **Transpose:** if F is fundamental matrix for (P, P') , then F^T is fundamental matrix for (P', P)
2. **Epipolar lines:** $l' = Fx$ & $l = F^T x'$
3. **Epipoles:** on all epipolar lines, thus $e'^T F x = 0, \forall x \Rightarrow e'^T F = 0$, similarly $F e = 0$
4. F has 7 d.o.f. , i.e. $3 \times 3 - 1$ (homogeneous) $- 1$ (rank 2)
5. F is a correlation, projective mapping from a point x to a line $l' = Fx$ (not a proper correlation, i.e. not invertible)

The fundamental matrix F



- It can be used for
 - Simplifies matching
 - Allows to detect wrong matches

Estimation of F – 8-point algorithm

- The fundamental matrix F is defined by

$$\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0$$

for any pair of matches \mathbf{x} and \mathbf{x}' in two images.

- Let $\mathbf{x}=(u,v,1)^T$ and $\mathbf{x}'=(u',v',1)^T$, $\mathbf{F} = \begin{bmatrix} f_{11} & f_{12} & f_{13} \\ f_{21} & f_{22} & f_{23} \\ f_{31} & f_{32} & f_{33} \end{bmatrix}$
each match gives a linear equation

$$uu' f_{11} + vu' f_{12} + u' f_{13} + uv' f_{21} + vv' f_{22} + v' f_{23} + uf_{31} + vf_{32} + f_{33} = 0$$

8-point algorithm

$$\begin{bmatrix}
 u_1 u_1' & v_1 u_1' & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 & 1 \\
 u_2 u_2' & v_2 u_2' & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 & 1 \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
 u_n u_n' & v_n u_n' & u_n' & u_n v_n' & v_n v_n' & v_n' & u_n & v_n & 1
 \end{bmatrix}
 \begin{bmatrix}
 f_{11} \\
 f_{12} \\
 f_{13} \\
 f_{21} \\
 f_{22} \\
 f_{23} \\
 f_{31} \\
 f_{32} \\
 f_{33}
 \end{bmatrix}
 = \mathbf{0}$$

- In reality, instead of solving $\mathbf{A}\mathbf{f} = \mathbf{0}$, we seek \mathbf{f} to minimize $\|\mathbf{A}\mathbf{f}\|$, least eigenvector of $\mathbf{A}^T \mathbf{A}$.

8-point algorithm

- To enforce that \mathbf{F} is of rank 2, \mathbf{F} is replaced by \mathbf{F}' that minimizes $\|\mathbf{F} - \mathbf{F}'\|$ subject to $\det \mathbf{F}' = 0$.
- It is achieved by SVD. Let $\mathbf{F} = \mathbf{U}\mathbf{\Sigma}\mathbf{V}^T$, where

$$\mathbf{\Sigma} = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & \sigma_3 \end{bmatrix}, \text{ let } \mathbf{\Sigma}' = \begin{bmatrix} \sigma_1 & 0 & 0 \\ 0 & \sigma_2 & 0 \\ 0 & 0 & 0 \end{bmatrix}$$

then $\mathbf{F}' = \mathbf{U}\mathbf{\Sigma}'\mathbf{V}^T$ is the solution.

8-point algorithm

```
% Build the constraint matrix
A = [x2(1,:)'.*x1(1,:)  x2(1,:)'.*x1(2,:)  x2(1,:)  ...
     x2(2,:)'.*x1(1,:)  x2(2,:)'.*x1(2,:)  x2(2,:)  ...
     x1(1,:)           x1(2,:)           ones(npts,1) ];

[U,D,V] = svd(A);

% Extract fundamental matrix from the column of V
% corresponding to the smallest singular value.
F = reshape(V(:,9),3,3)';

% Enforce rank2 constraint
[U,D,V] = svd(F);
F = U*diag([D(1,1) D(2,2) 0])*V';
```

8-point algorithm

- Pros: it is linear, easy to implement and fast
- Cons: susceptible to noise

Problem with 8-point algorithm

$$\begin{bmatrix}
 u_1 u_1' & v_1 u_1' & u_1' & u_1 v_1' & v_1 v_1' & v_1' & u_1 & v_1 & 1 \\
 u_2 u_2' & v_2 u_2' & u_2' & u_2 v_2' & v_2 v_2' & v_2' & u_2 & v_2 & 1 \\
 \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\
 u_n u_n' & v_n u_n' & u_n' & u_n v_n' & v_n v_n' & v_n' & u_n & v_n & 1
 \end{bmatrix}
 \begin{bmatrix}
 f_{11} \\
 f_{12} \\
 f_{13} \\
 f_{21} \\
 f_{22} \\
 f_{23} \\
 f_{31} \\
 f_{32} \\
 f_{33}
 \end{bmatrix}
 = 0$$

~10000 ~10000 ~100 ~10000 ~10000 ~100 ~100 ~100 1



Orders of magnitude difference
between column of data matrix
→ least-squares yields poor results

Normalized 8-point algorithm

1. Transform input by $\hat{\mathbf{x}}_i = \mathbf{T}\mathbf{x}_i$, $\hat{\mathbf{x}}'_i = \mathbf{T}\mathbf{x}'_i$
2. Call 8-point on $\hat{\mathbf{x}}_i, \hat{\mathbf{x}}'_i$ to obtain $\hat{\mathbf{F}}$
3. $\mathbf{F} = \mathbf{T}'^T \hat{\mathbf{F}} \mathbf{T}$

$$\mathbf{x}'^T \mathbf{F} \mathbf{x} = 0$$

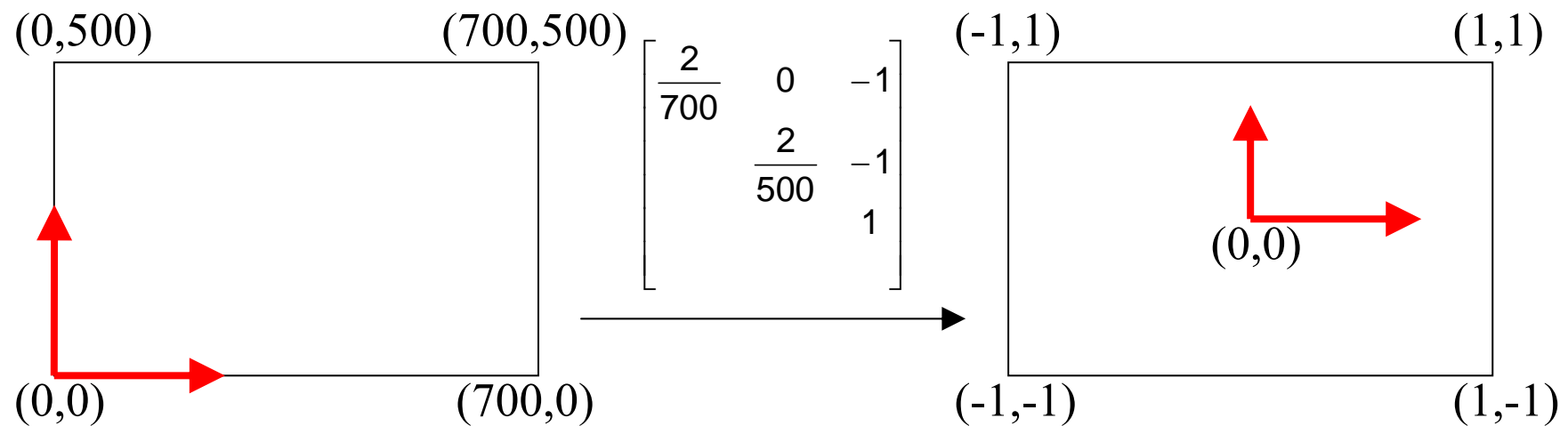
$$\hat{\mathbf{x}}'^T \mathbf{T}'^{-T} \mathbf{F} \mathbf{T}^{-1} \hat{\mathbf{x}} = 0$$

$\underbrace{\hspace{10em}}_{\hat{\mathbf{F}}}$

Normalized 8-point algorithm

normalized least squares yields good results

Transform image to $\sim[-1,1] \times [-1,1]$



Normalized 8-point algorithm

```
[x1, T1] = normalise2dpts(x1);
```

```
[x2, T2] = normalise2dpts(x2);
```

```
A = [x2(1,:)'.*x1(1,:)  x2(1,:)'.*x1(2,:)  x2(1,:)  ...  
     x2(2,:)'.*x1(1,:)  x2(2,:)'.*x1(2,:)  x2(2,:)  ...  
     x1(1,:)           x1(2,:)           ones(npts,1) ];
```

```
[U,D,V] = svd(A);
```

```
F = reshape(V(:,9),3,3)';
```

```
[U,D,V] = svd(F);
```

```
F = U*diag([D(1,1) D(2,2) 0])*V';
```

```
% Denormalise
```

```
F = T2'*F*T1;
```


Normalization

```
function [newpts, T] = normalise2dpts(pts)
```

```
    c = mean(pts(1:2,:))'; % Centroid
```

```
    newp(1,:) = pts(1,:)-c(1); % Shift origin to centroid.
```

```
    newp(2,:) = pts(2,:)-c(2);
```

```
    meandist = mean(sqrt(newp(1,:).^2 + newp(2,:).^2));
```

```
    scale = sqrt(2)/meandist;
```

```
    T = [scale    0  -scale*c(1)
         0    scale -scale*c(2)
         0     0     1      ];
```

```
    newpts = T*pts;
```

RANSAC

repeat

- select minimal sample (8 matches)

- compute solution(s) for F

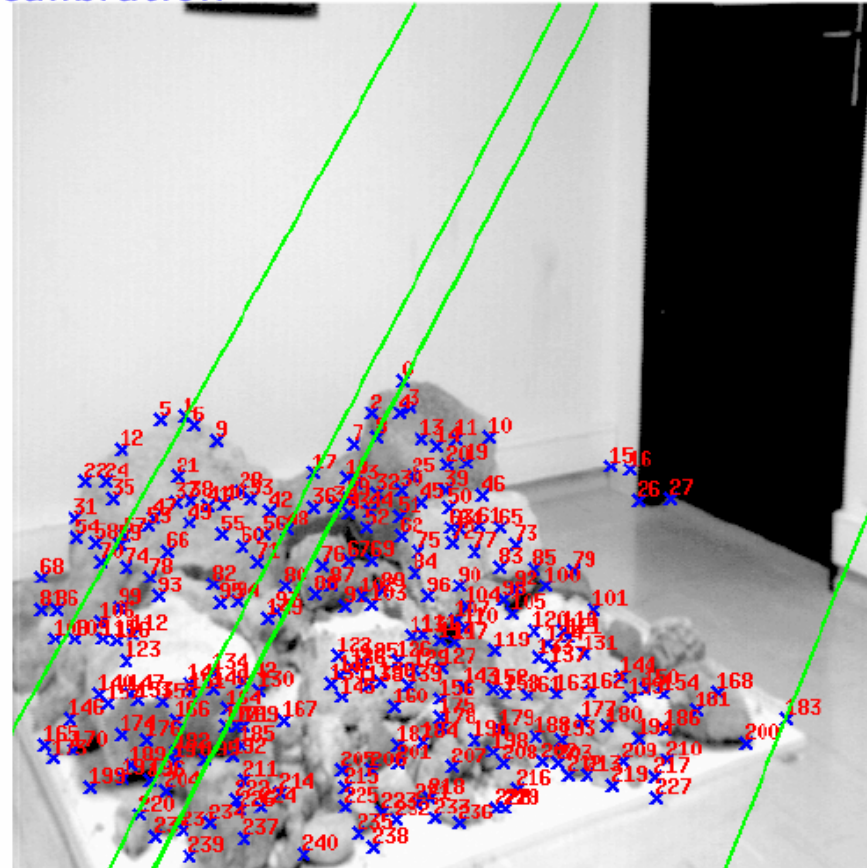
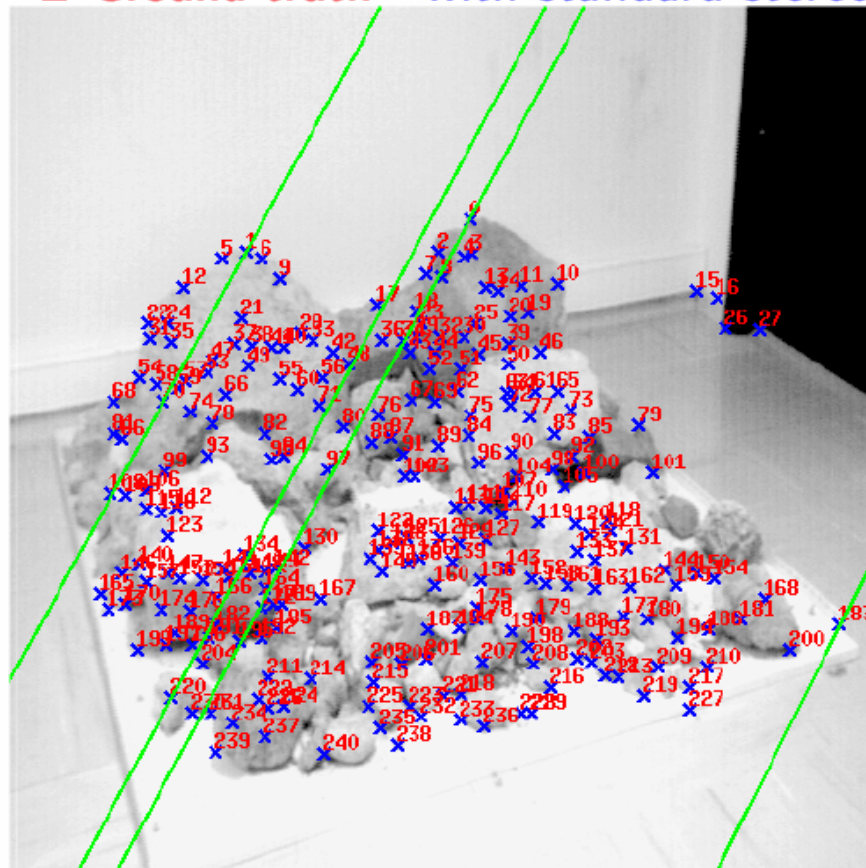
- determine inliers

until $\Gamma(\#inliers, \#samples) > 95\%$ or too many times

compute F based on all inliers

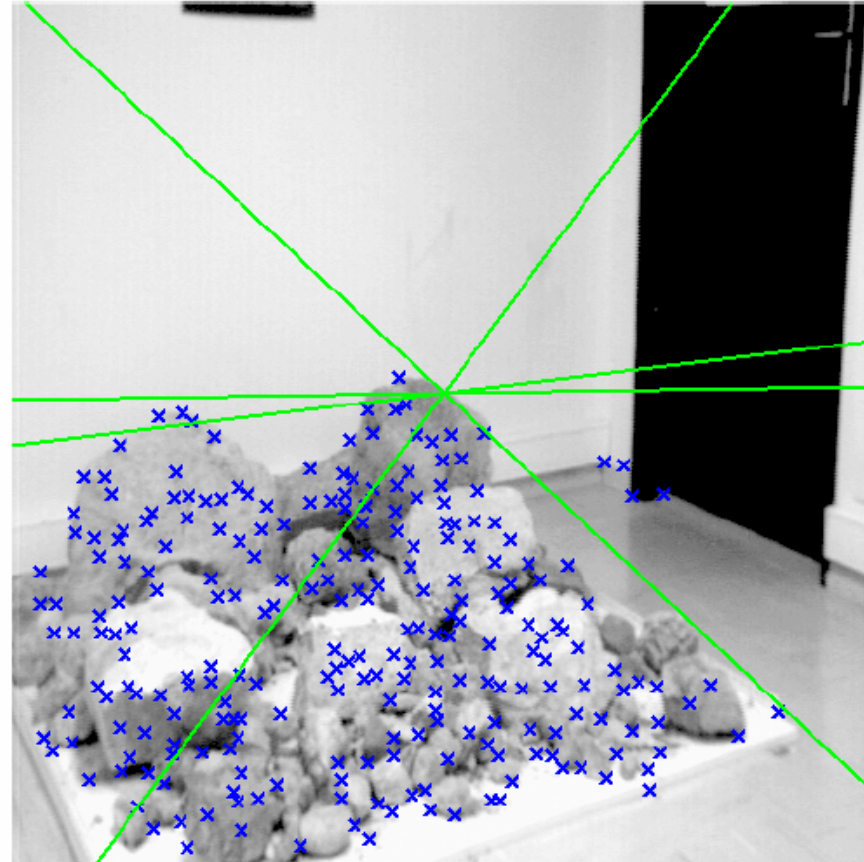
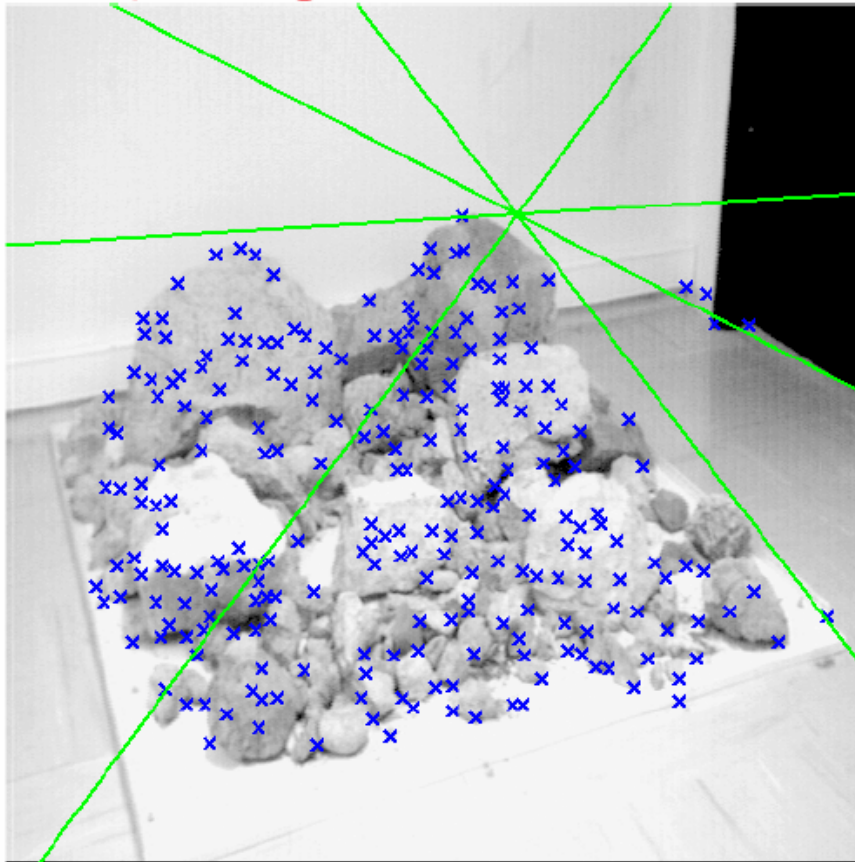
Results (ground truth)

■ Ground truth with standard stereo calibration



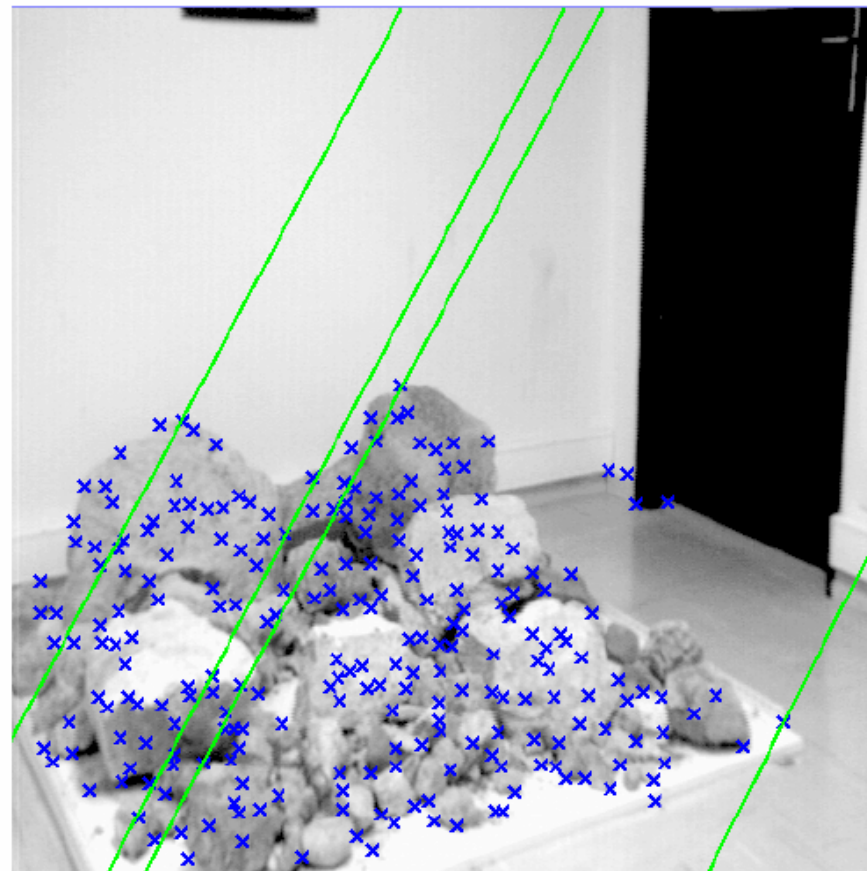
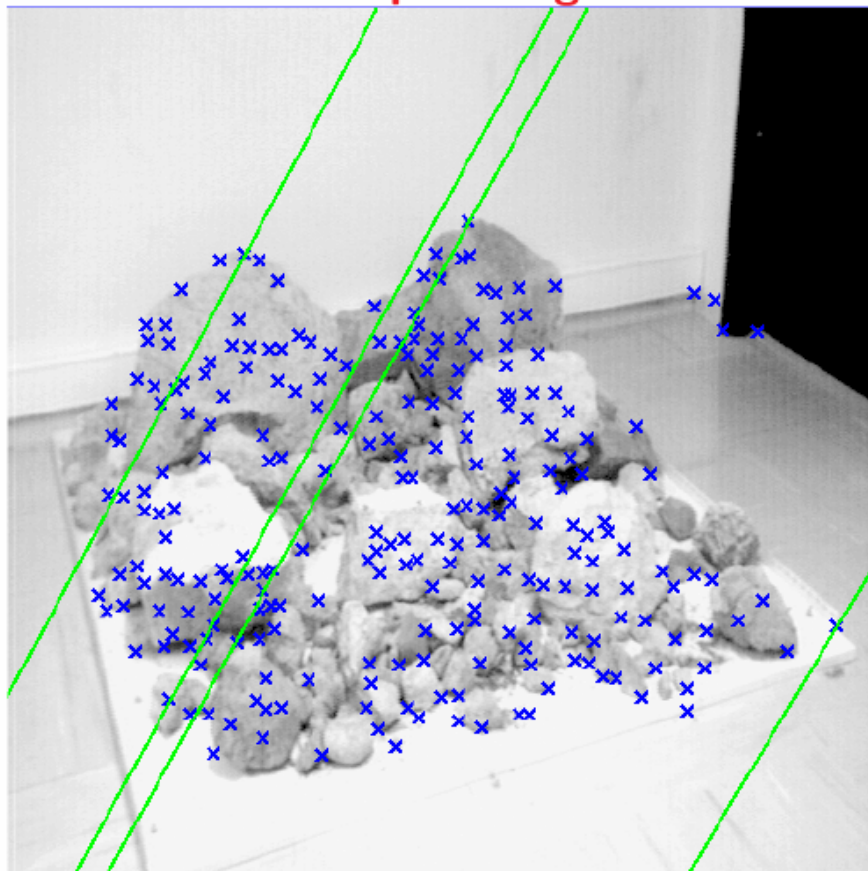
Results (8-point algorithm)

■ 8-point algorithm



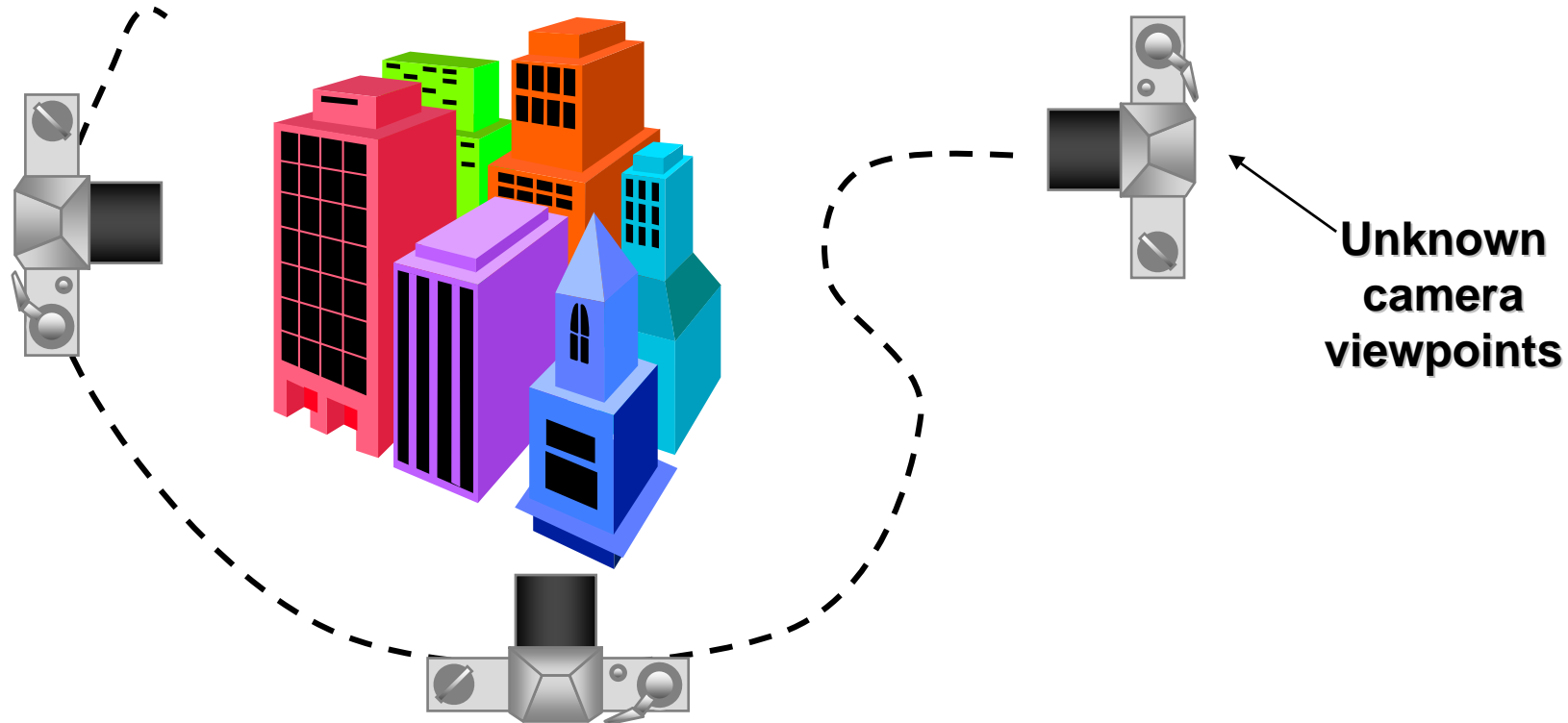
Results (normalized 8-point algorithm)

■ Normalized 8-point algorithm



Structure from motion

Structure from motion

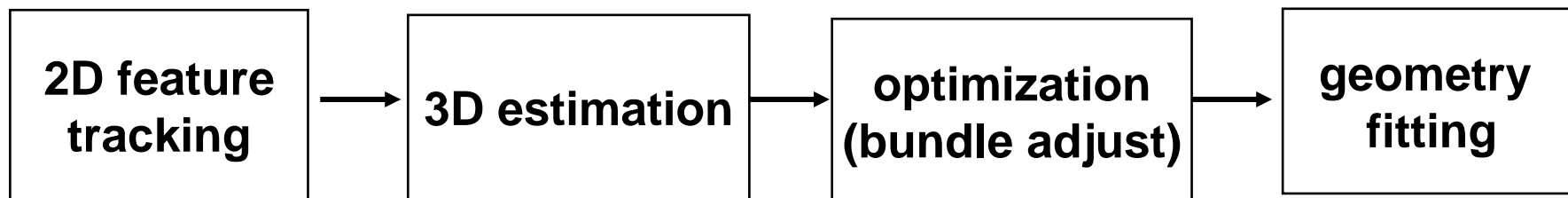


structure from motion: automatic recovery of camera motion and scene structure from two or more images. It is a self calibration technique and called *automatic camera tracking* or *matchmoving*.

Applications

- For computer vision, multiple-view shape reconstruction, novel view synthesis and autonomous vehicle navigation.
- For film production, seamless insertion of CGI into live-action backgrounds

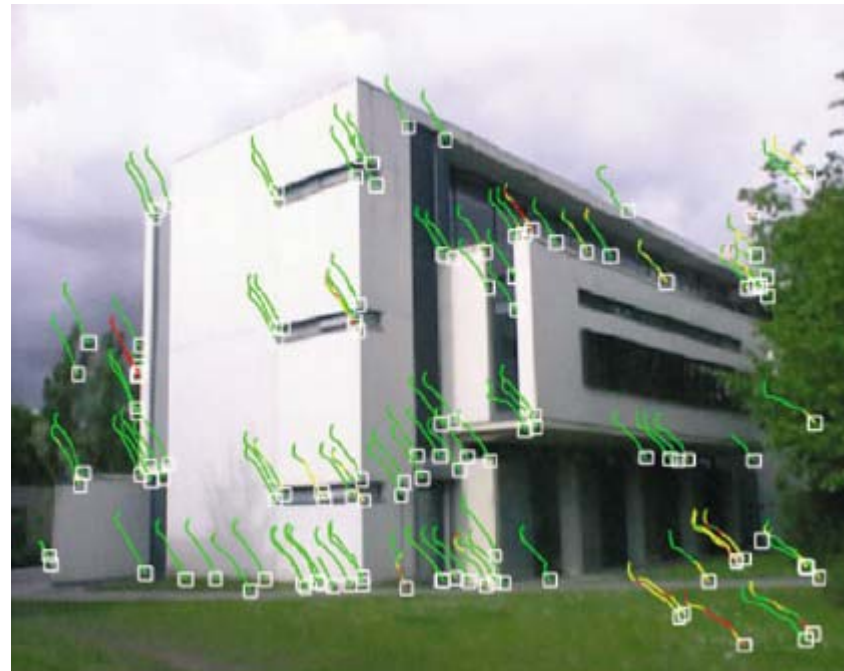
Structure from motion



SFM pipeline

Structure from motion

- Step 1: Track Features
 - Detect good features, Shi & Tomasi, SIFT
 - Find correspondences between frames
 - Lucas & Kanade-style motion estimation
 - window-based correlation
 - SIFT matching



KLT tracking



<http://www.ces.clemson.edu/~stb/klf/>

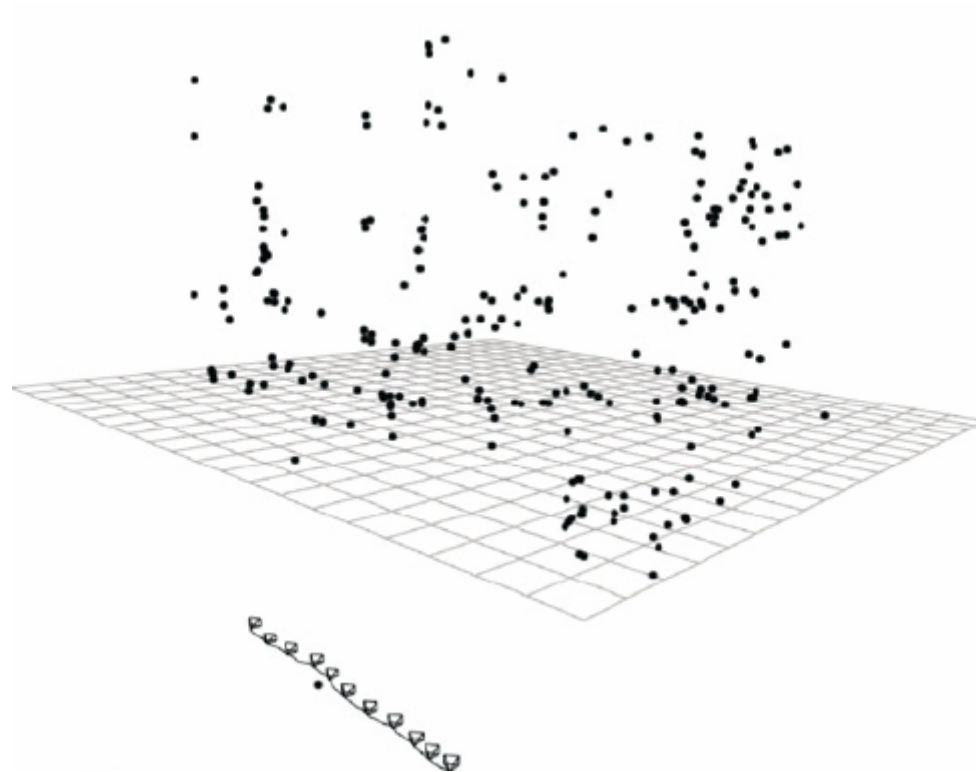
Structure from Motion

- Step 2: Estimate Motion and Structure
 - Simplified projection model, e.g., [Tomasi 92]
 - 2 or 3 views at a time [Hartley 00]



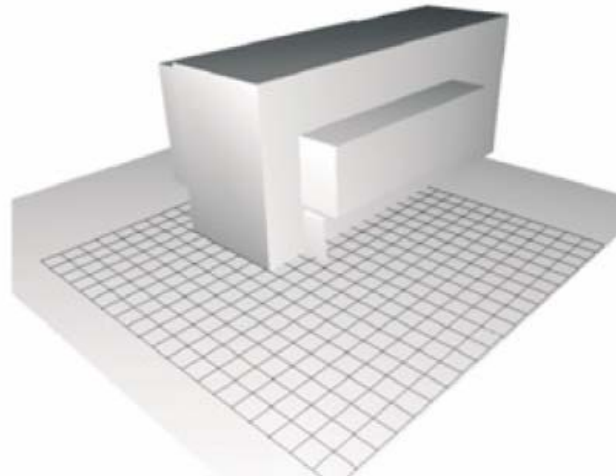
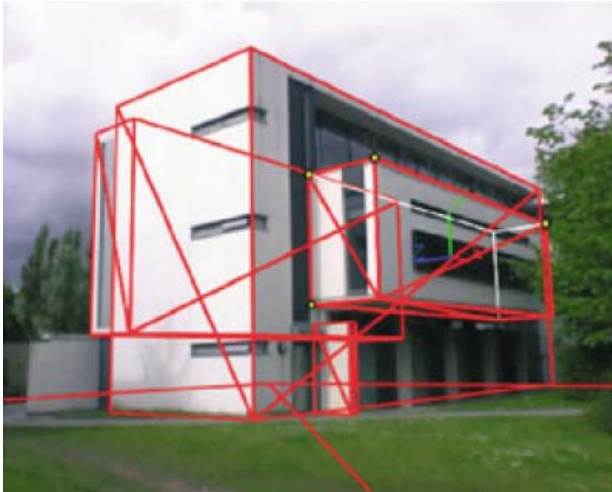
Structure from Motion

- Step 3: Refine estimates
 - “Bundle adjustment” in photogrammetry
 - Other iterative methods



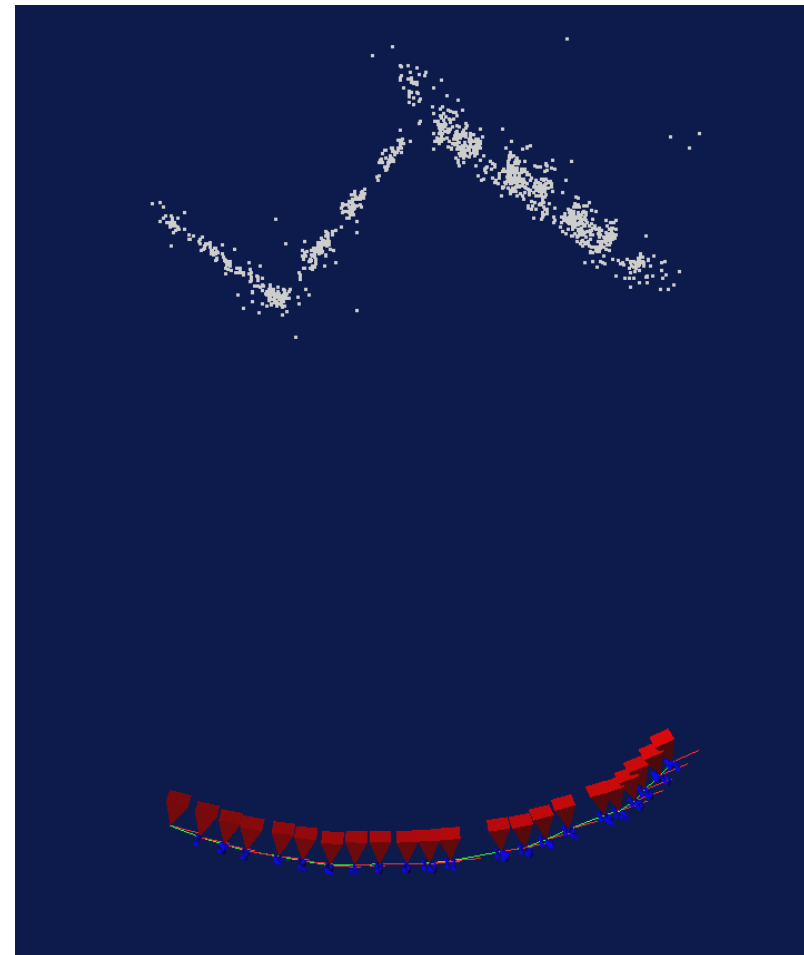
Structure from Motion

- Step 4: Recover surfaces (image-based triangulation, silhouettes, stereo...)



Factorization methods

Problem statement



Notations

- n 3D points are seen in m views
- $\mathbf{q}=(u, v, 1)$: 2D image point
- $\mathbf{p}=(x, y, z, 1)$: 3D scene point
- Π : projection matrix
- π : projection function
- q_{ij} is the projection of the i -th point on image j
- λ_{ij} projective depth of q_{ij}

$$\mathbf{q}_{ij} = \pi(\Pi_j \mathbf{p}_i)$$

$$\pi(x, y, z) = (x / z, y / z)$$

$$\lambda_{ij} = z$$

Structure from motion

- Estimate Π_j and \mathbf{p}_i to minimize

$$\mathcal{E}(\mathbf{\Pi}_1, \dots, \mathbf{\Pi}_m, \mathbf{p}_1, \dots, \mathbf{p}_n) = \sum_{j=1}^m \sum_{i=1}^n w_{ij} \log P(\pi(\mathbf{\Pi}_j \mathbf{p}_i); \mathbf{q}_{ij})$$

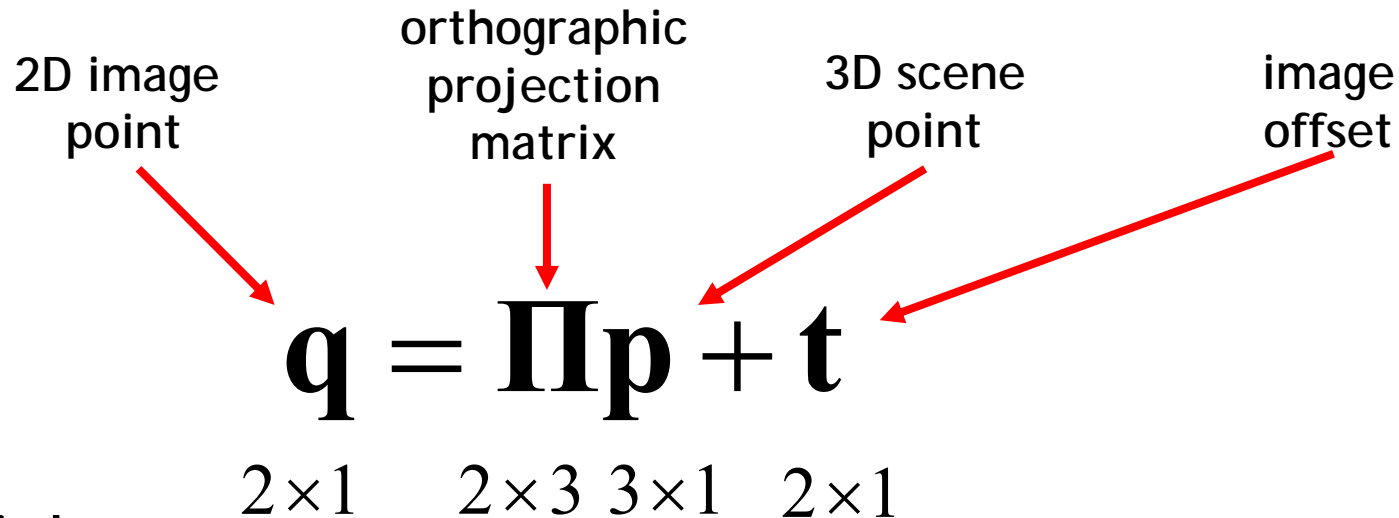
$$w_{ij} = \begin{cases} 1 & \text{if } p_i \text{ is visible in view } j \\ 0 & \text{otherwise} \end{cases}$$

- Assume isotropic Gaussian noise, it is reduced to

$$\mathcal{E}(\mathbf{\Pi}_1, \dots, \mathbf{\Pi}_m, \mathbf{p}_1, \dots, \mathbf{p}_n) = \sum_{j=1}^m \sum_{i=1}^n w_{ij} \left\| \pi(\mathbf{\Pi}_j \mathbf{p}_i) - \mathbf{q}_{ij} \right\|^2$$

SFM under orthographic projection

2D image point orthographic projection matrix 3D scene point image offset


$$\mathbf{q} = \mathbf{\Pi} \mathbf{p} + \mathbf{t}$$

2×1 2×3 3×1 2×1

- Trick
 - Choose scene origin to be centroid of 3D points
 - Choose image origins to be centroid of 2D points
 - Allows us to drop the camera translation:

$$\mathbf{q} = \mathbf{\Pi} \mathbf{p}$$

factorization (Tomasi & Kanade)

projection of n features in one image:

$$\begin{bmatrix} \mathbf{q}_1 & \mathbf{q}_2 & \cdots & \mathbf{q}_n \end{bmatrix} = \prod \begin{bmatrix} \mathbf{p}_1 & \mathbf{p}_2 & \cdots & \mathbf{p}_n \end{bmatrix}$$

$2 \times n$ 2×3 $3 \times n$

projection of n features in m images

$$\begin{bmatrix} \mathbf{q}_{11} & \mathbf{q}_{12} & \cdots & \mathbf{q}_{1n} \\ \mathbf{q}_{21} & \mathbf{q}_{22} & \cdots & \mathbf{q}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{q}_{m1} & \mathbf{q}_{m2} & \cdots & \mathbf{q}_{mn} \end{bmatrix} = \begin{bmatrix} \mathbf{\Pi}_1 \\ \mathbf{\Pi}_2 \\ \vdots \\ \mathbf{\Pi}_m \end{bmatrix} \begin{bmatrix} \mathbf{p}_1 & \mathbf{p}_2 & \cdots & \mathbf{p}_n \end{bmatrix}$$

$2m \times n$ $2m \times 3$ $3 \times n$

W measurement **M** motion **S** shape

Key Observation: $rank(\mathbf{W}) \leq 3$

Factorization

$$\text{known} \rightarrow \underbrace{\mathbf{W}}_{2m \times n} = \underbrace{\mathbf{M} \mathbf{S}}_{\substack{2m \times 3 & 3 \times n}} \rightarrow \text{solve for}$$

- Factorization Technique

- W is at most rank 3 (assuming no noise)
- We can use *singular value decomposition* to factor W :

$$\underbrace{\mathbf{W}}_{2m \times n} = \underbrace{\mathbf{M}' \mathbf{S}'}_{\substack{2m \times 3 & 3 \times n}}$$

- S' differs from S by a linear transformation A :

$$\mathbf{W} = \mathbf{M}' \mathbf{S}' = (\mathbf{M} \mathbf{A}^{-1}) (\mathbf{A} \mathbf{S})$$

- Solve for A by enforcing *metric* constraints on M

Metric constraints

- Orthographic Camera
 - Rows of Π are orthonormal: $\Pi \Pi^T = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}$
- Enforcing “Metric” Constraints
 - Compute \mathbf{A} such that rows of \mathbf{M} have these properties

$$\mathbf{M}' \mathbf{A} = \mathbf{M}$$

Trick (not in original Tomasi/Kanade paper, but in followup work)

- Constraints are linear in $\mathbf{A}\mathbf{A}^T$:

$$\begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} = \Pi \Pi^T = \Pi' \mathbf{A} (\mathbf{A} \Pi')^T = \Pi' \mathbf{G} \Pi'^T \quad \text{where } \mathbf{G} = \mathbf{A}\mathbf{A}^T$$

- Solve for \mathbf{G} first by writing equations for every Π_i in \mathbf{M}
- Then $\mathbf{G} = \mathbf{A}\mathbf{A}^T$ by SVD (since $\mathbf{U} = \mathbf{V}$)

Factorization with noisy data

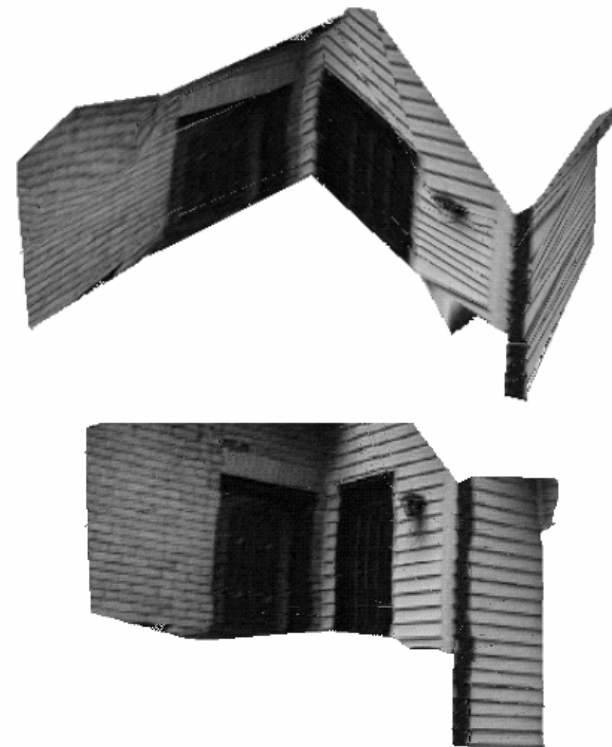
$$\mathbf{W}_{2m \times n} = \mathbf{M}_{2m \times 3} \mathbf{S}_{3 \times n} + \mathbf{E}_{2m \times n}$$

- SVD gives this solution
 - Provides optimal rank 3 approximation W' of W

$$\mathbf{W}_{2m \times n} = \mathbf{W}'_{2m \times n} + \mathbf{E}_{2m \times n}$$

- Approach
 - Estimate W' , then use noise-free factorization of W' as before
 - Result minimizes the SSD between positions of image features and projection of the reconstruction

Results



Extensions to factorization methods



- Projective projection
- With missing data
- Projective projection with missing data

Bundle adjustment

Levenberg-Marquardt method

- LM can be thought of as a combination of steepest descent and the Newton method. When the current solution is far from the correct one, the algorithm behaves like a steepest descent method: slow, but guaranteed to converge. When the current solution is close to the correct solution, it becomes a Newton's method.

Nonlinear least square

Given a set of measurements \mathbf{x} , try to find the best parameter vector \mathbf{p} so that the squared distance $\boldsymbol{\varepsilon}^T \boldsymbol{\varepsilon}$ is minimal. Here, $\boldsymbol{\varepsilon} = \mathbf{x} - \hat{\mathbf{x}}$, with $\hat{\mathbf{x}} = f(\mathbf{p})$.

Levenberg-Marquardt method

For a small $\|\delta_{\mathbf{p}}\|$, $f(\mathbf{p} + \delta_{\mathbf{p}}) \approx f(\mathbf{p}) + \mathbf{J}\delta_{\mathbf{p}}$

\mathbf{J} is the Jacobian matrix $\frac{\partial f(\mathbf{p})}{\partial \mathbf{p}}$

it is required to find the $\delta_{\mathbf{p}}$ that minimizes the quantity

$$\|\mathbf{x} - f(\mathbf{p} + \delta_{\mathbf{p}})\| \approx \|\mathbf{x} - f(\mathbf{p}) - \mathbf{J}\delta_{\mathbf{p}}\| = \|\boldsymbol{\epsilon} - \mathbf{J}\delta_{\mathbf{p}}\|$$

$$\mathbf{J}^T \mathbf{J} \delta_{\mathbf{p}} = \mathbf{J}^T \boldsymbol{\epsilon}$$

$$\mathbf{N} \delta_{\mathbf{p}} = \mathbf{J}^T \boldsymbol{\epsilon}$$

$$\mathbf{N}_{ii} = \mu + \left[\mathbf{J}^T \mathbf{J} \right]_{ii}$$

 *damping term*

Levenberg-Marquardt method


- $\mu = 0 \rightarrow$ Newton's method
- $\mu \rightarrow \infty \rightarrow$ steepest descent method
- Strategy for choosing μ
 - Start with some small μ
 - If error is not reduced, keep trying larger μ until it does
 - If error is reduced, accept it and reduce μ for the next iteration

Bundle adjustment

- Bundle adjustment (BA) is a technique for simultaneously refining the 3D structure and camera parameters
- It is capable of obtaining an optimal reconstruction under certain assumptions on image error models. For zero-mean Gaussian image errors, BA is the maximum likelihood estimator.

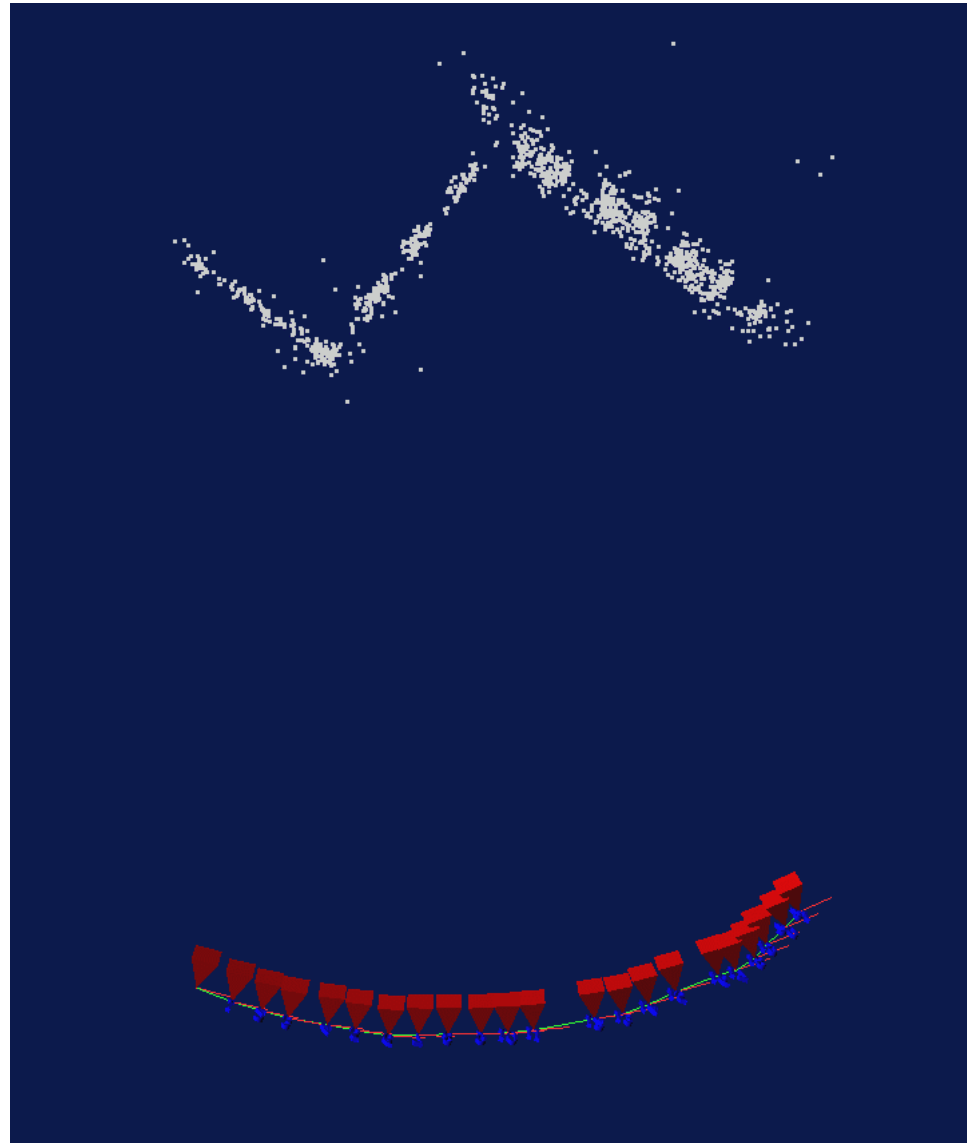
Bundle adjustment

- n 3D points are seen in m views
- x_{ij} is the projection of the i -th point on image j
- a_j is the parameters for the j -th camera
- b_i is the parameters for the i -th point
- BA attempts to minimize the projection error

$$\min_{\mathbf{a}_j, \mathbf{b}_i} \sum_{i=1}^n \sum_{j=1}^m d(\mathbf{Q}(\mathbf{a}_j, \mathbf{b}_i), \mathbf{x}_{ij})^2$$


Euclidean distance

Bundle adjustment



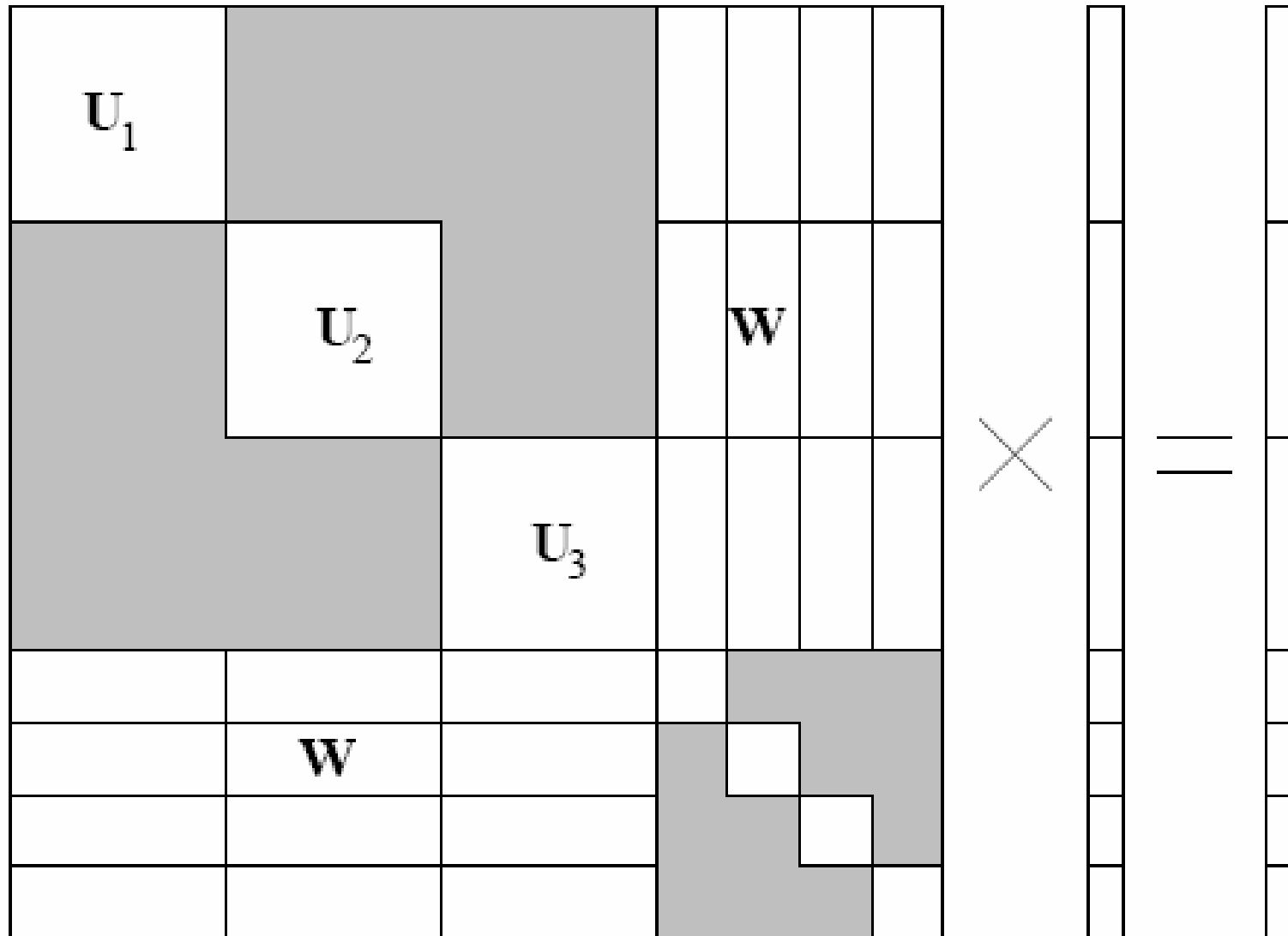
Bundle adjustment

3 views and 4 points $\mathbf{P} = (\mathbf{a}_1^T, \mathbf{a}_2^T, \mathbf{a}_3^T, \mathbf{b}_1^T, \mathbf{b}_2^T, \mathbf{b}_3^T, \mathbf{b}_4^T)^T$

$\mathbf{X} = (\mathbf{x}_{11}^T, \mathbf{x}_{12}^T, \mathbf{x}_{13}^T, \mathbf{x}_{21}^T, \mathbf{x}_{22}^T, \mathbf{x}_{23}^T, \mathbf{x}_{31}^T, \mathbf{x}_{32}^T, \mathbf{x}_{33}^T, \mathbf{x}_{41}^T, \mathbf{x}_{42}^T, \mathbf{x}_{43}^T)^T$

$$\frac{\partial \mathbf{X}}{\partial \mathbf{P}} = \begin{pmatrix} \mathbf{A}_{11} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{11} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{12} & \mathbf{0} & \mathbf{B}_{12} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_{13} & \mathbf{B}_{13} & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{A}_{21} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{21} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{22} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{22} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_{23} & \mathbf{0} & \mathbf{B}_{23} & \mathbf{0} & \mathbf{0} \\ \mathbf{A}_{31} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{31} & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{32} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{32} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_{33} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{33} & \mathbf{0} \\ \mathbf{A}_{41} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{41} \\ \mathbf{0} & \mathbf{A}_{42} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{42} \\ \mathbf{0} & \mathbf{0} & \mathbf{A}_{43} & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{B}_{43} \end{pmatrix}$$

Block structure of normal equation



Issues in SFM

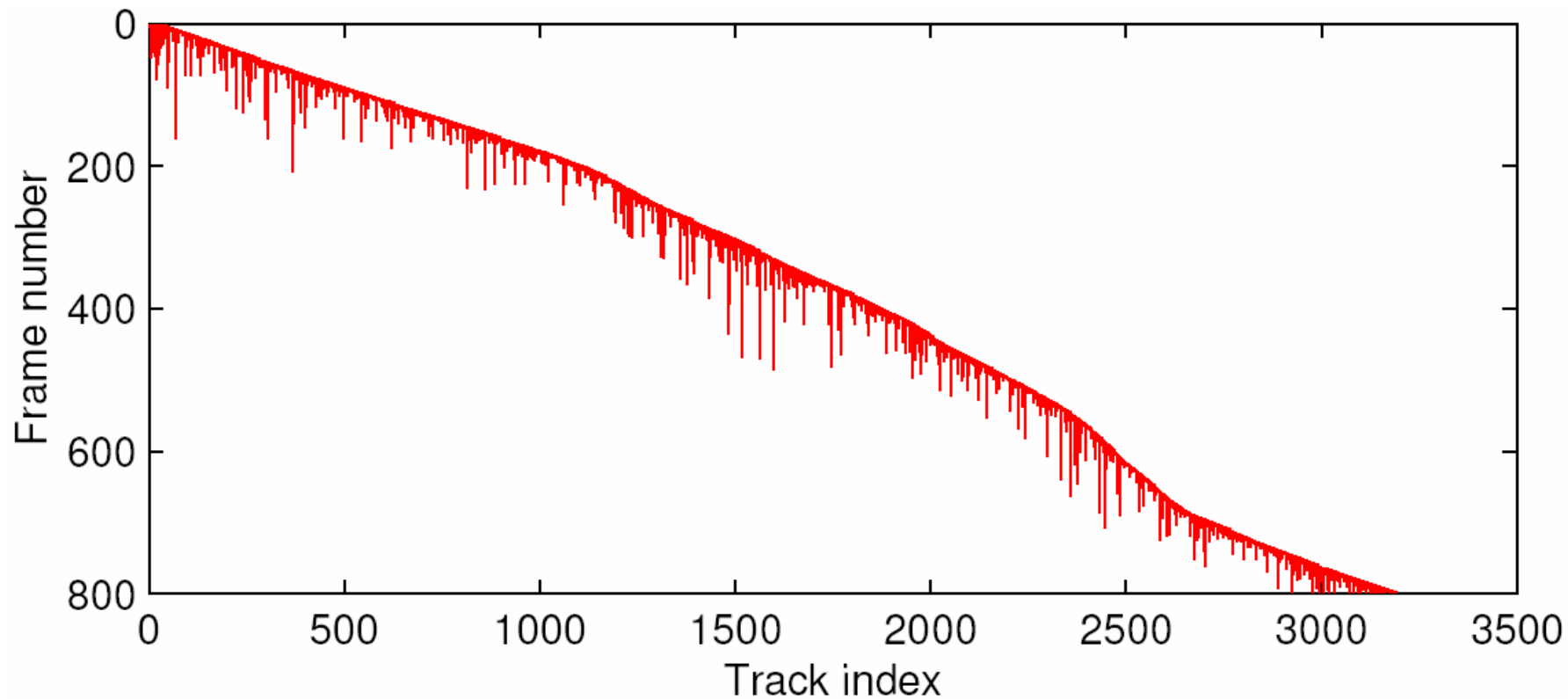
- Track lifetime
- Nonlinear lens distortion
- Degeneracy and critical surfaces
- Prior knowledge and scene constraints
- Multiple motions

Track lifetime



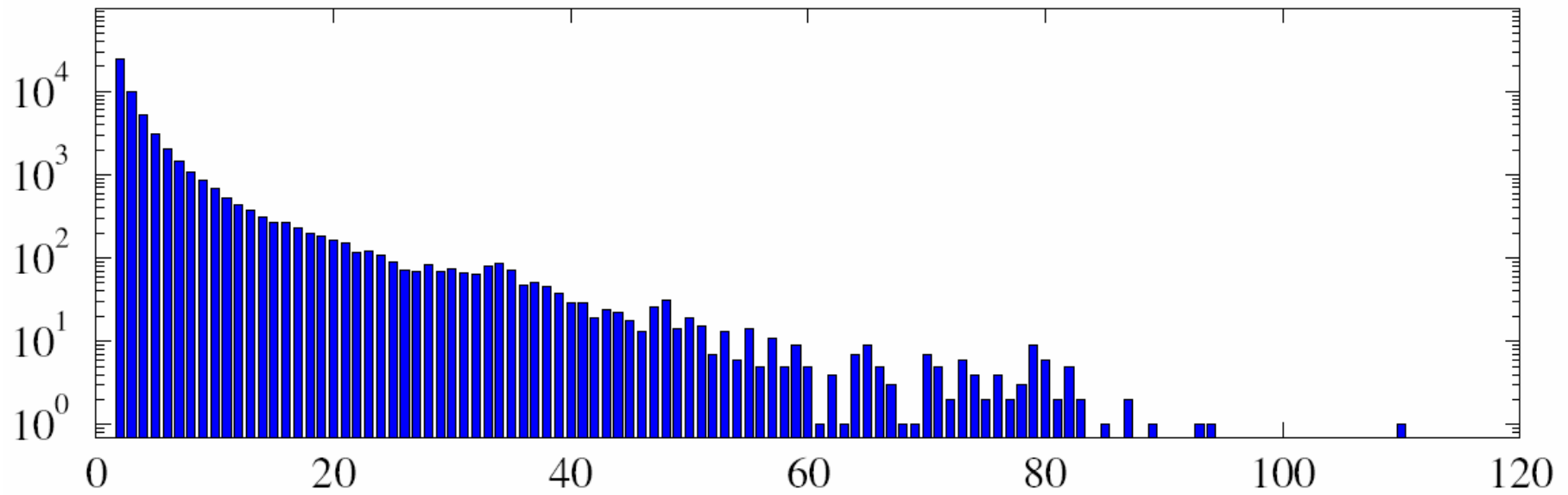
every 50th frame of a 800-frame sequence

Track lifetime



lifetime of 3192 tracks from the previous sequence

Track lifetime

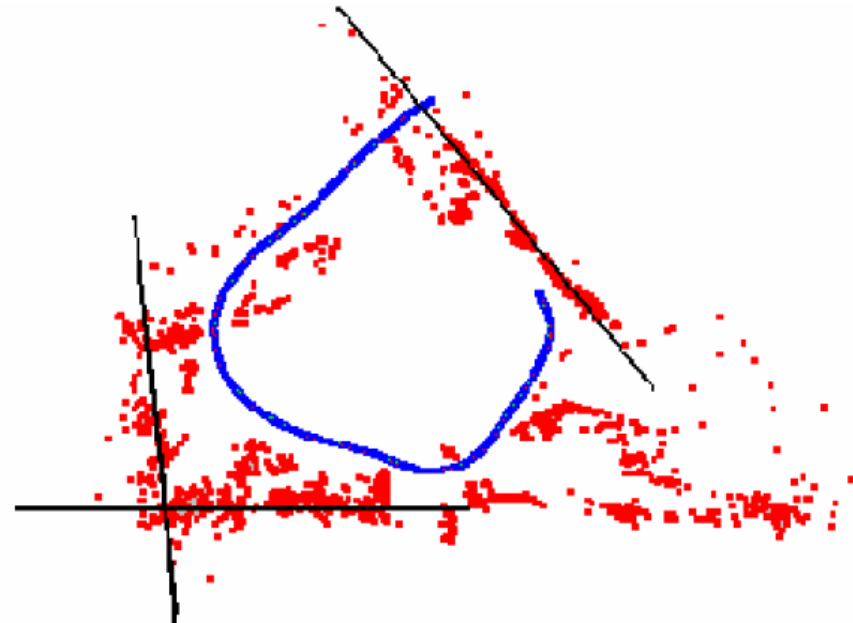
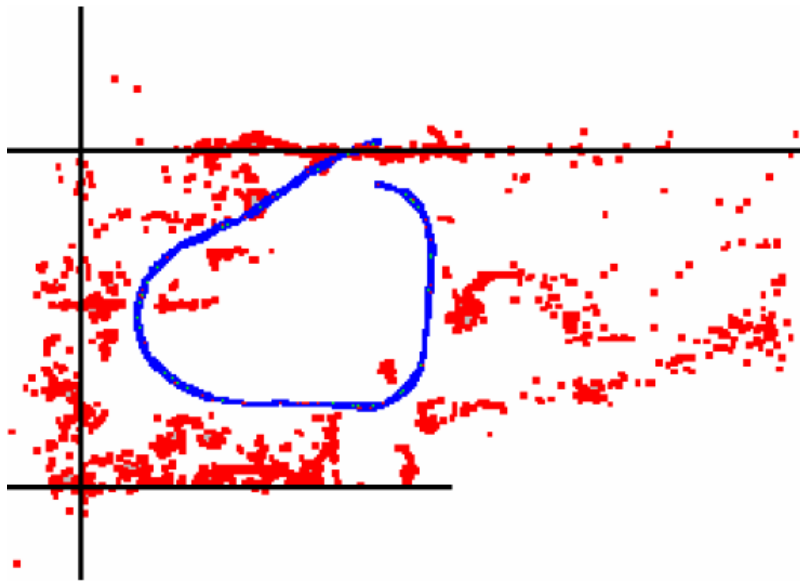


track length histogram

Nonlinear lens distortion



Nonlinear lens distortion



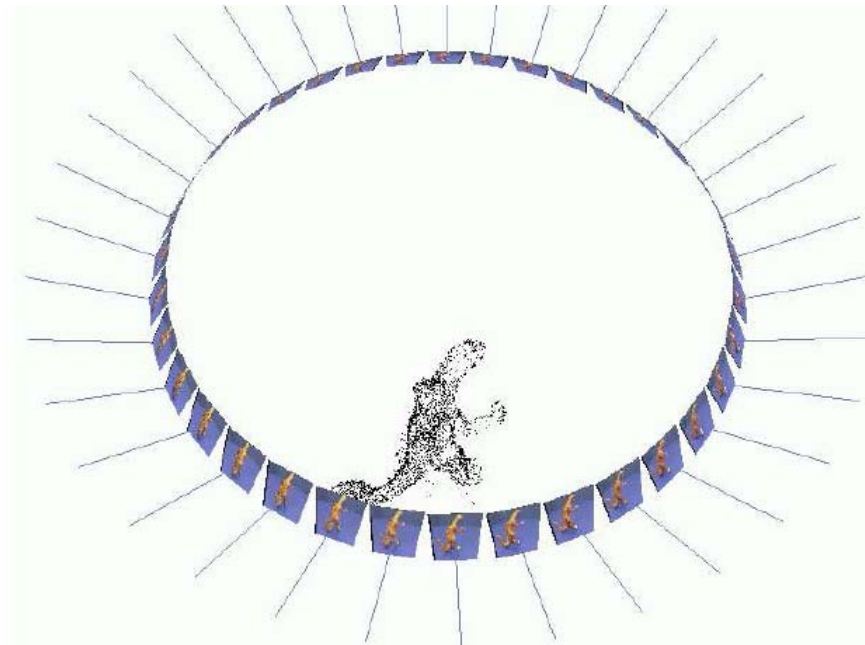
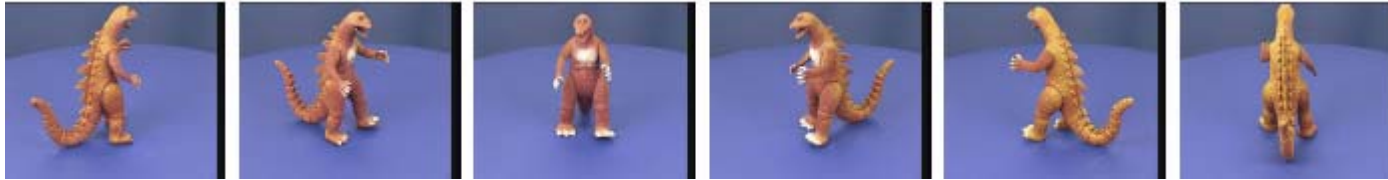
effect of lens distortion

Prior knowledge and scene constraints DigiVFX



add a constraint that several lines are parallel

Prior knowledge and scene constraints



add a constraint that it is a turntable sequence

Applications of matchmove

Applications of matchmove



[More example #1](#)

[More example #2](#)

2d3 boujou



Enemy at the Gate, Double Negative

2d3 boujou



DigiVFX



Enemy at the Gate, Double Negative

Jurassic park

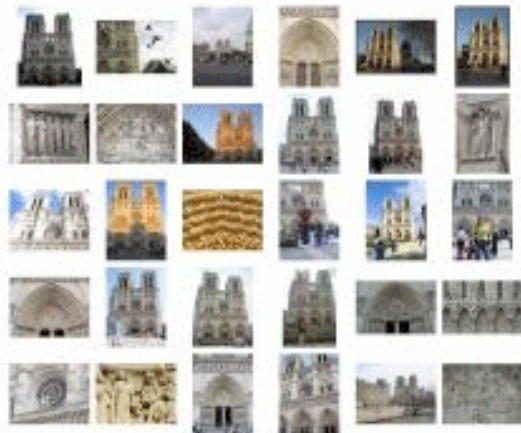


Photo Tourism



Photo Tourism

Exploring photo collections in 3D



(a)



(b)



(c)

Project #3 MatchMove

- It is more about using tools in this project
- You can choose either calibration or structure from motion to achieve the goal
- Calibration [example](#)
- Icarus