

# Matchmoving

Éric Marchand



Vous savez comment on fait ca !





# Stop motion

Jason et les argonautes, 1963

Effets speciaux :

- Ray Harryhausen



LA COLUMBIA PICTURES PRESENTA

UNA PRODUZIONE CHARLES H. SCHNEER



SCENEGGIATURA DI JAN READ e BEVERLEY CROSS  
REGIA DI DON CHAFFEY

PRODUTTORE ASSOCIATO E CREATORE DEGLI EFFETTI VISIVI RAY HARRYHAUSEN  
FILM MORNINGSIDE WORLDWIDE  
EASTMANCOLOR









Et ca ?

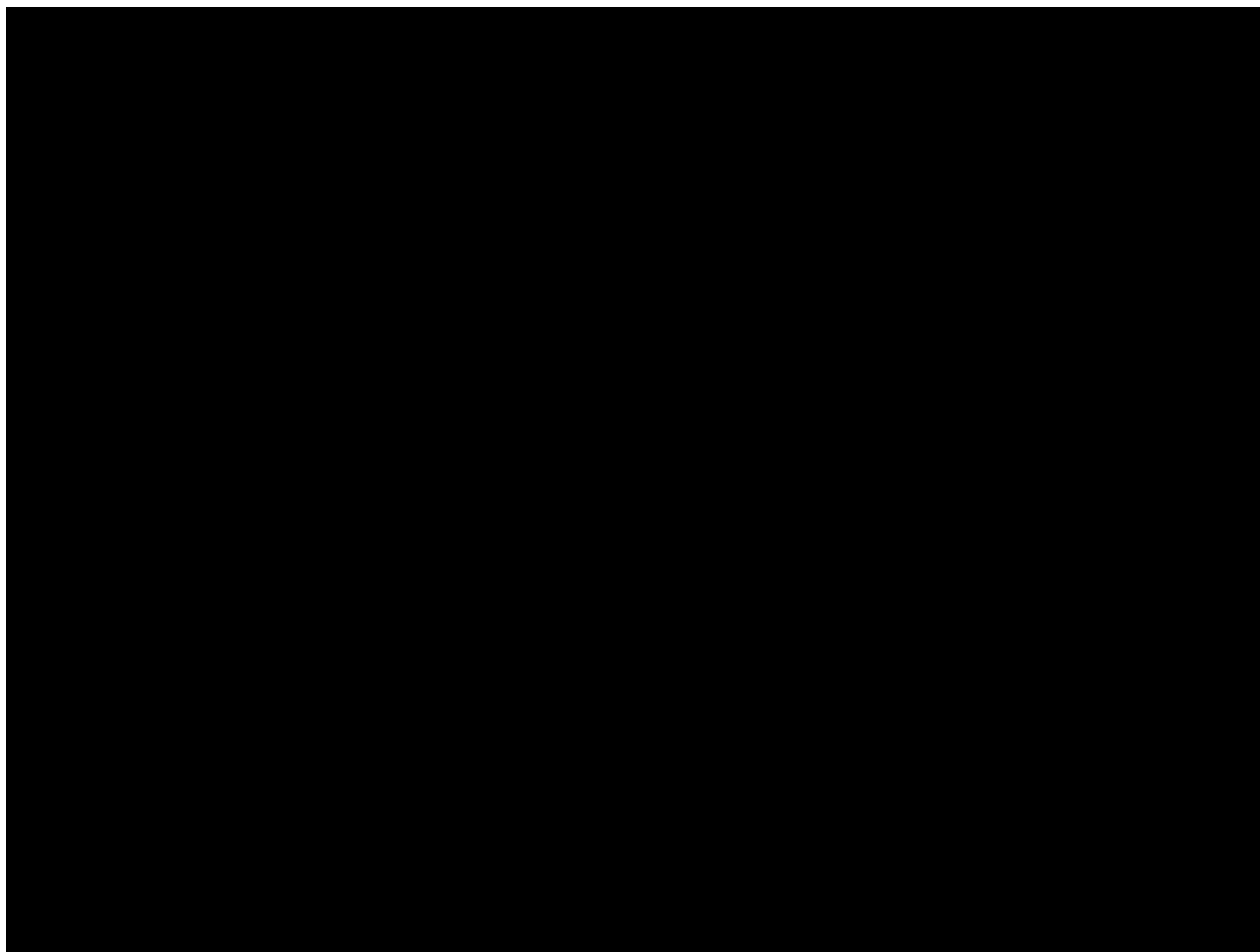


# Matchmoving

Terminator 3: rise of the machines, 2003







# Matchmoving

Match moving is a special effects technology to allow the insertion of virtual objects into real footage with the correct position, scale, orientation and motion in relation to the photographed objects in the scene.

The term is used loosely to refer to several different ways of extracting motion information from a motion picture, particularly camera movement.

Match moving is related to photogrammetry.

It is sometimes referred to as motion tracking or structure from motion or SLAM





# Matchmoving

Computer graphics camera must exactly match the real camera

- Position
- Rotation
- Focal length
- Aperature


Easy when camera is instrumented

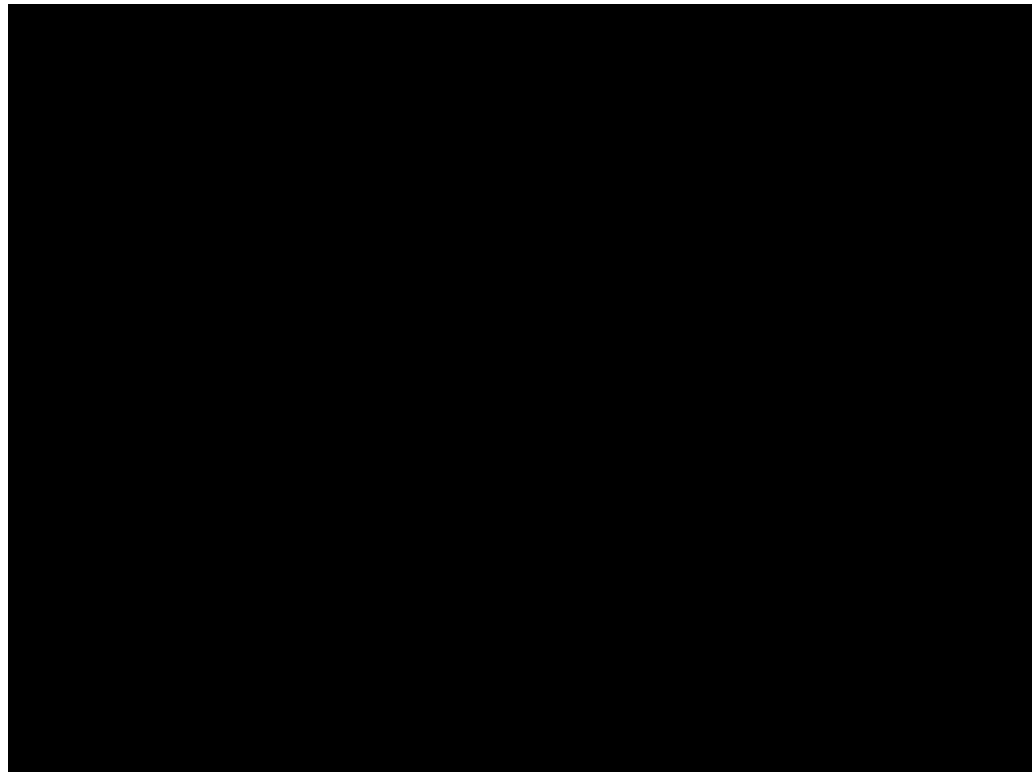
Hard to place CG on moving objects on film



# Motion tracking / match moving

## Motion tracking programs

- Boujou 
- Syntheyes
- Maya Matchmover
- CameraTracker
  - The foundry
  - Plugin After effect
- NukeX
  - The foundry



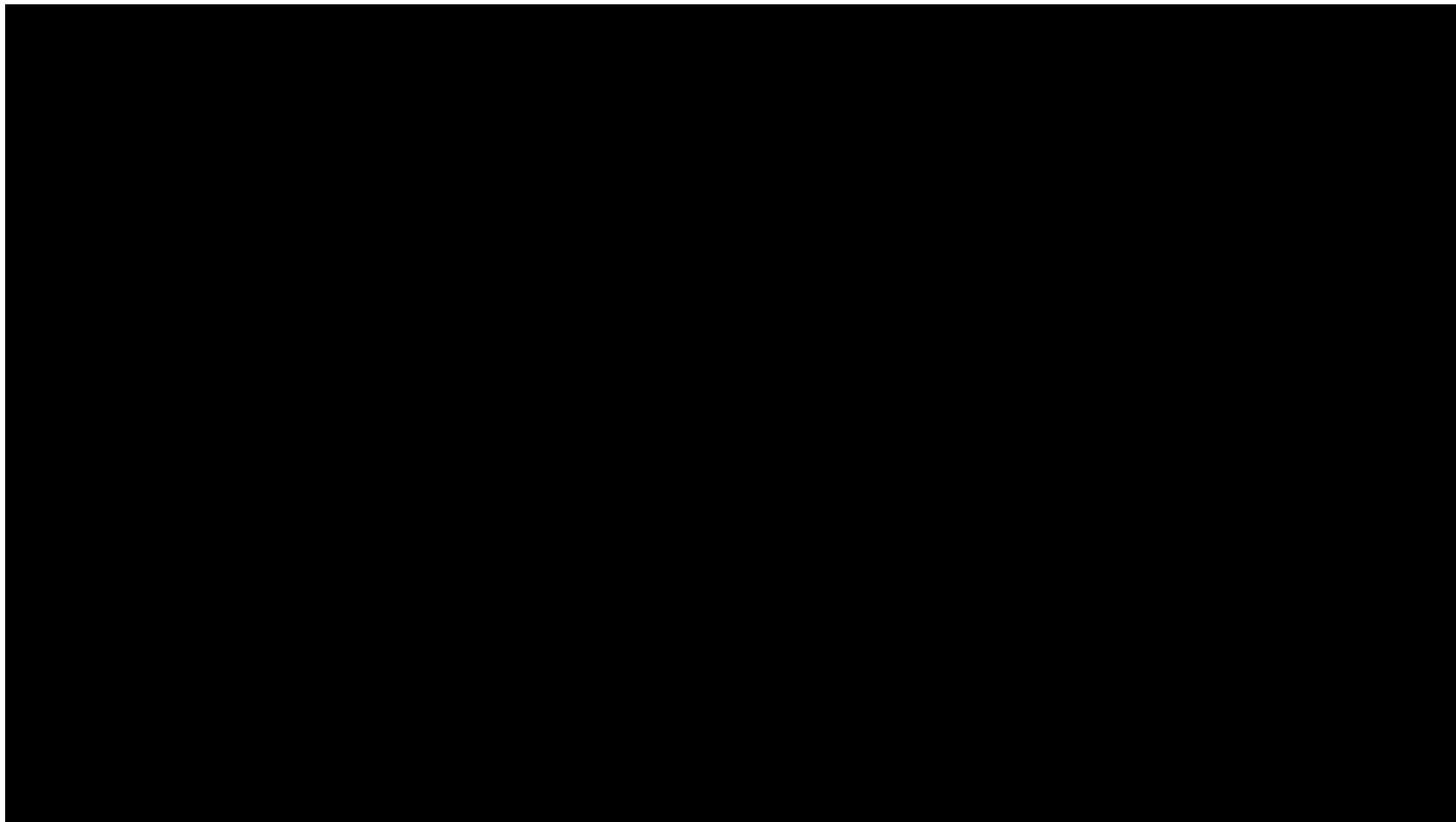


# Final destination (making of)

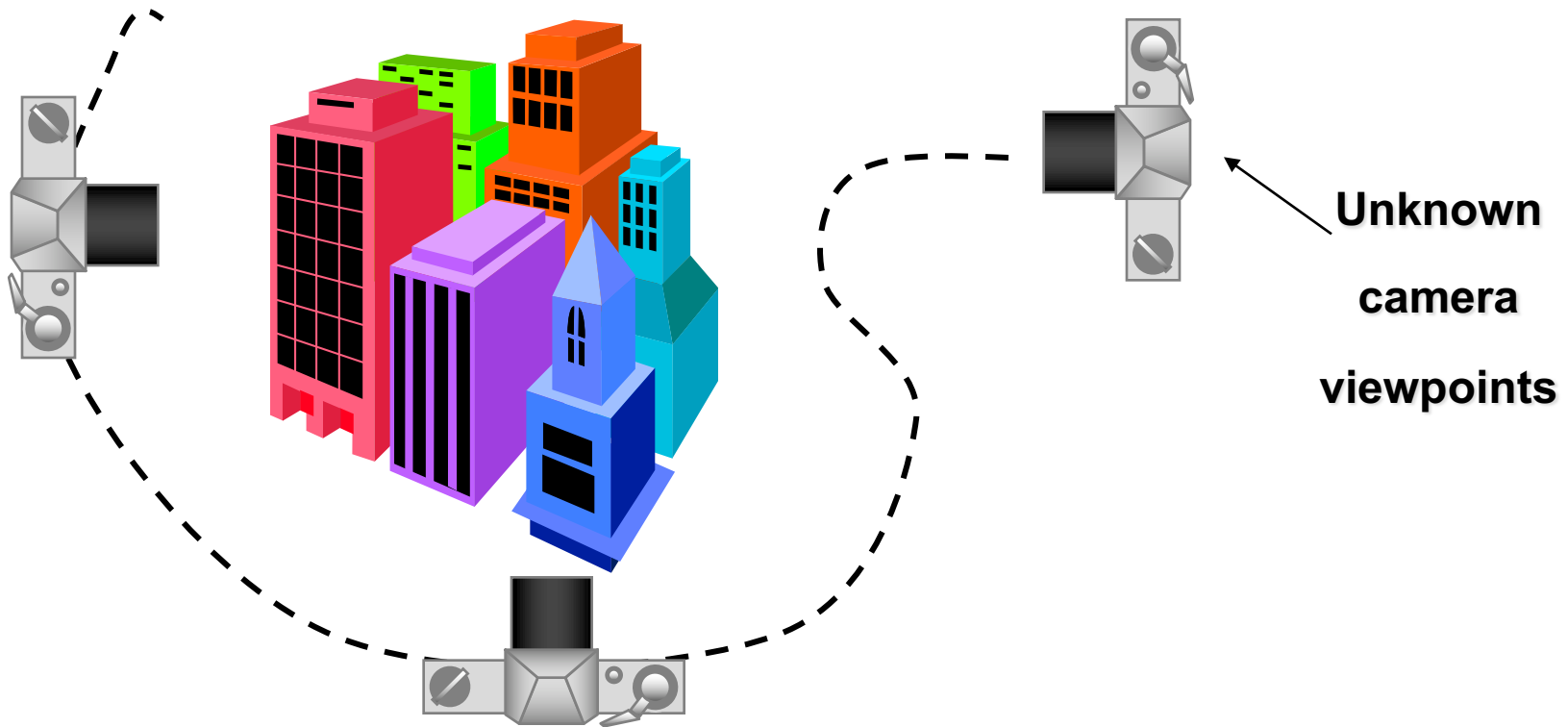




# Game of thrones



# Structure from Motion



## Reconstruct

- Scene geometry
- Camera motion

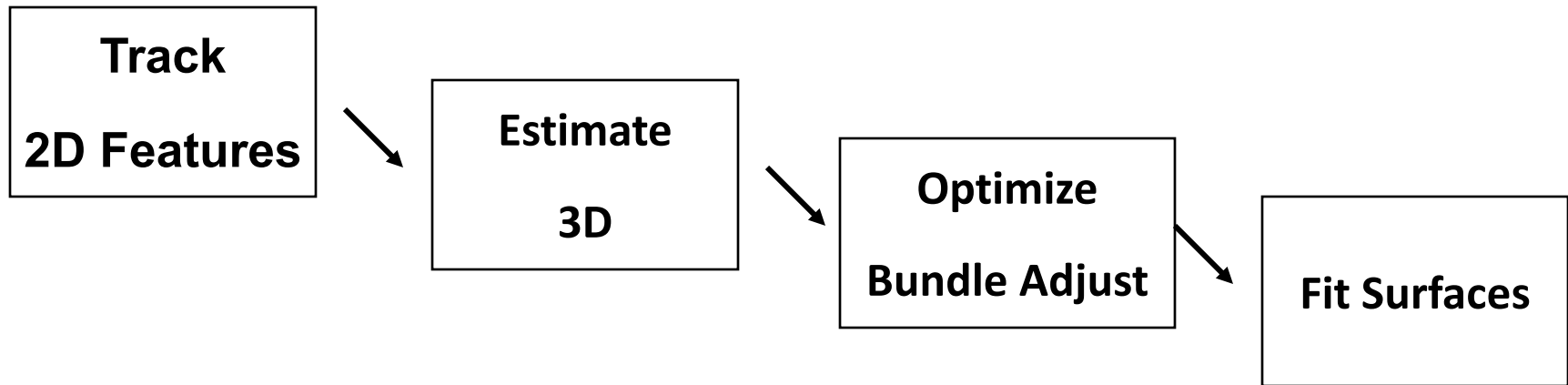




# Structure from Motion

## The SFM Problem

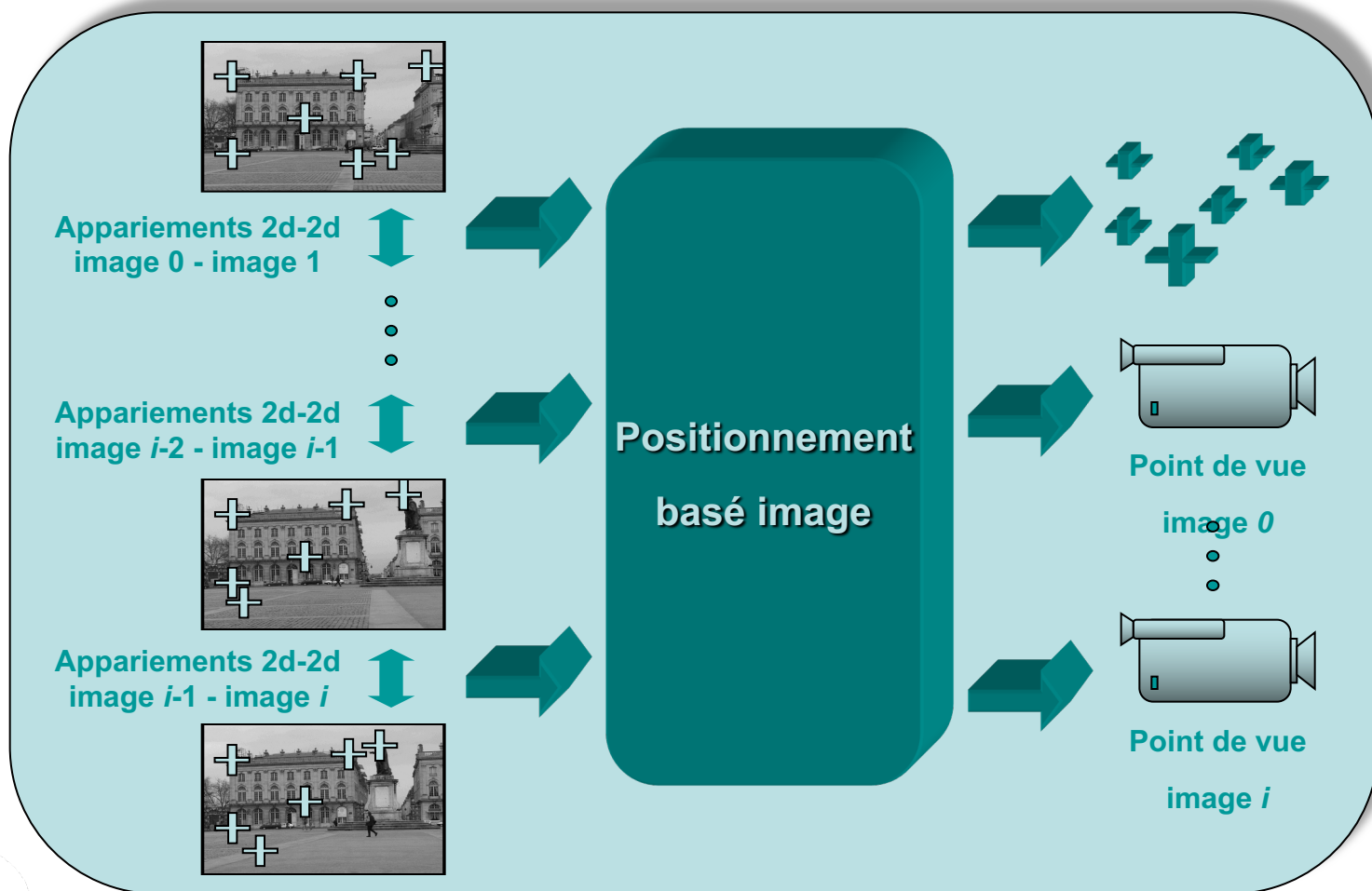
- Reconstruct **scene geometry** and **camera motion** from two or more images



## SFM Pipeline



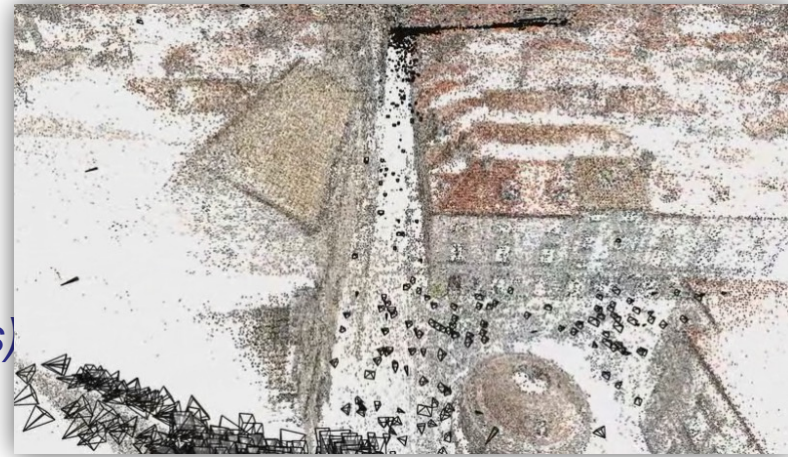
# Principe général



# vSLAM applications

## Contextes applicatifs

- Reconstruction 3D par vision
  - Ensemble d'images (*non ordonnées*)
- Localisation par vision
  - Flux vidéo (*ordonnées*)



Reconstruction de Dubrovnik

## Méthodes de localisation par vision

- Odométrie visuelle
  - Mouvement 2D de zones d'intérêt
- Construction d'une carte de l'environnement
  - Reconstruction à partir du mouvement (*vision*)
    - *Batch Structure-from-Motion*
    - *Structure-from-Motion* incrémental
  - SLAM (*robotique*)



Application de réalité augmentée [Klein'07]



# Structure from motion



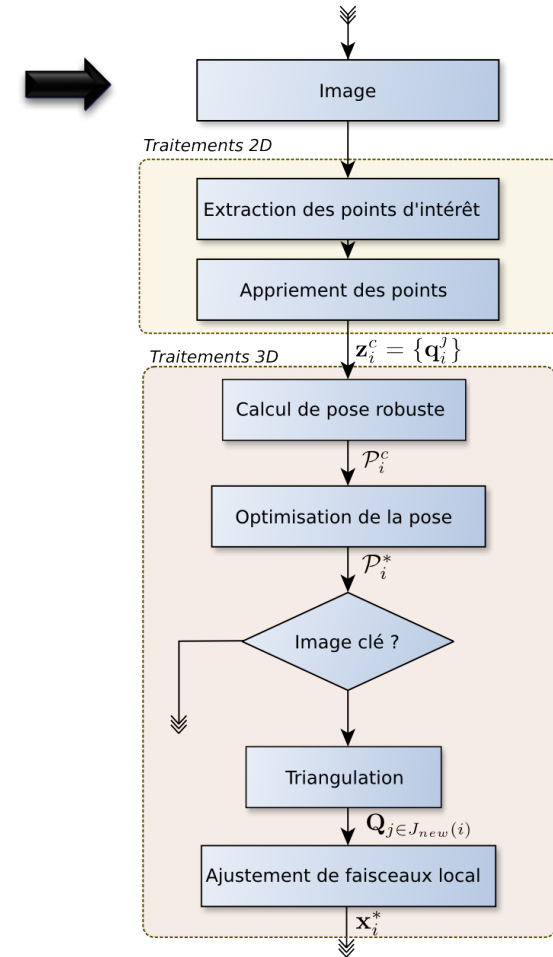
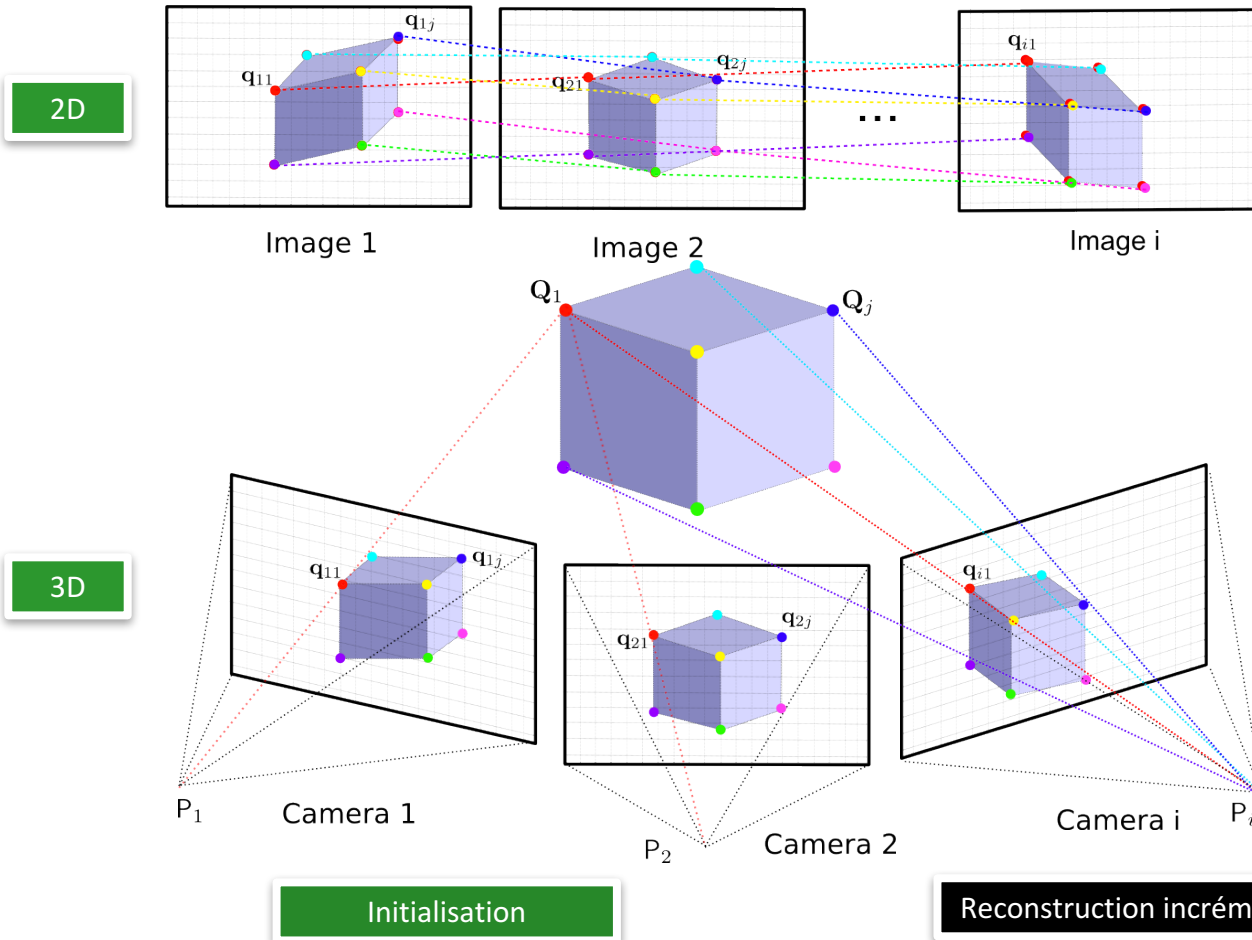
Драконъ, видимый подъ различными углами зрѣнія  
По гравюру на мѣди наз. „Oculus artificialis teledioptricus“ Нант. 1702 года.





# Reconstruction à partir du mouvement

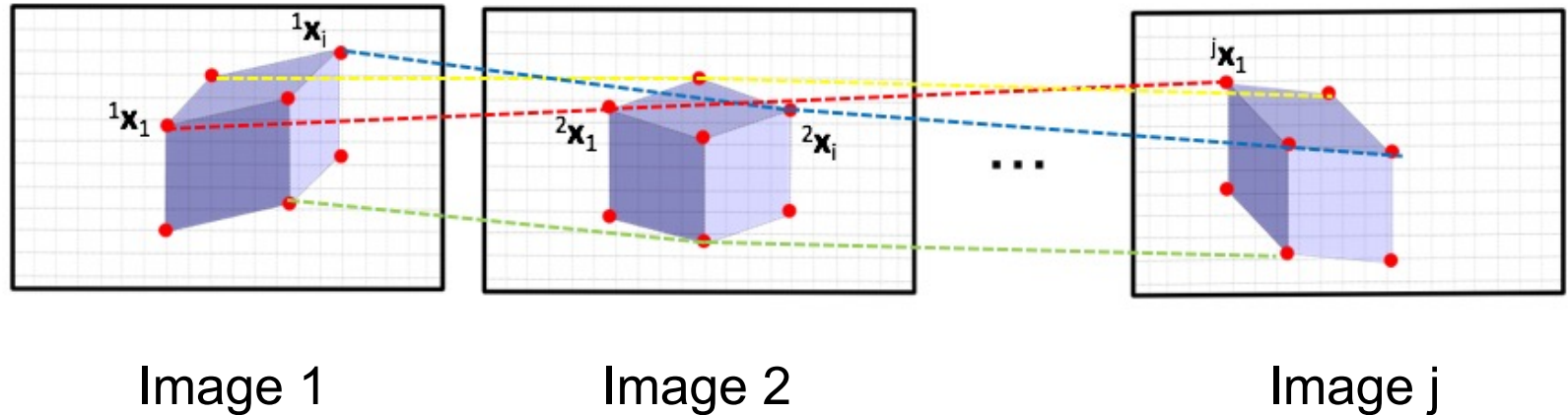
## Méthode incrémentale



Slide: Julien Michot (CEA)

# Structure from motion

First, estimate the camera motion (that is  ${}^1\mathbf{T}_2, \dots, {}^{j-1}\mathbf{T}_j$ )



- Match points (SiFT)
- Estimate the essential matrix
- Extract  $\mathbf{R}, \mathbf{t}$
- Bundle adjustment

# Keypoints Detection



keypoints

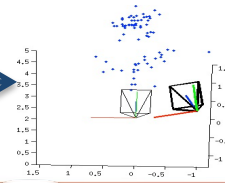
keypoints

match

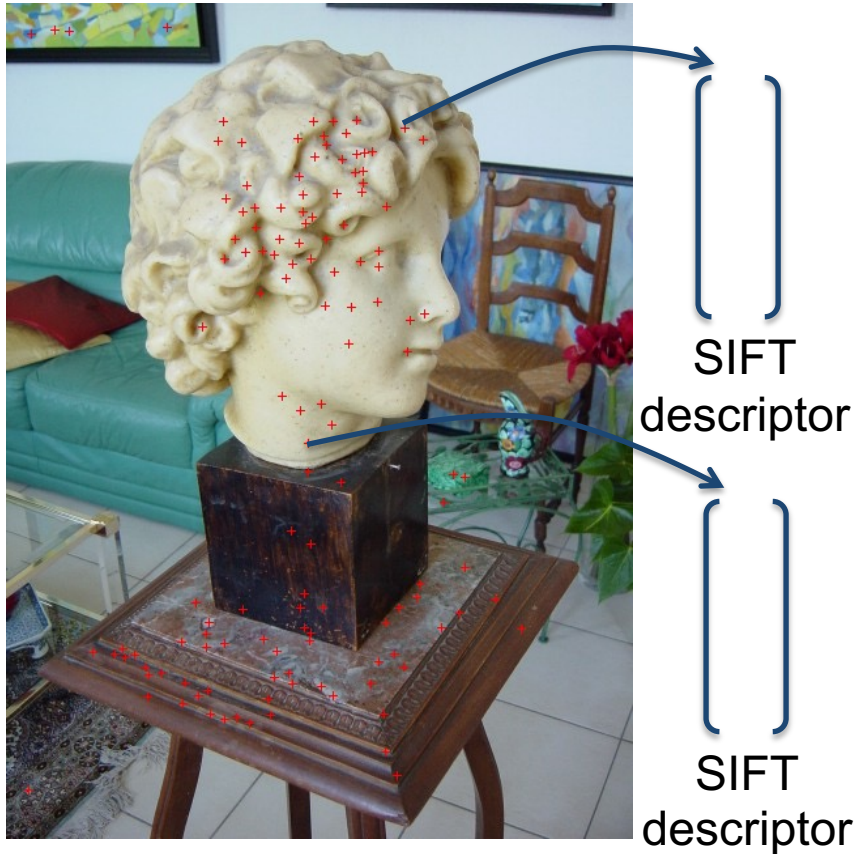
essential  
matrix

$[R|t]$

triangulation



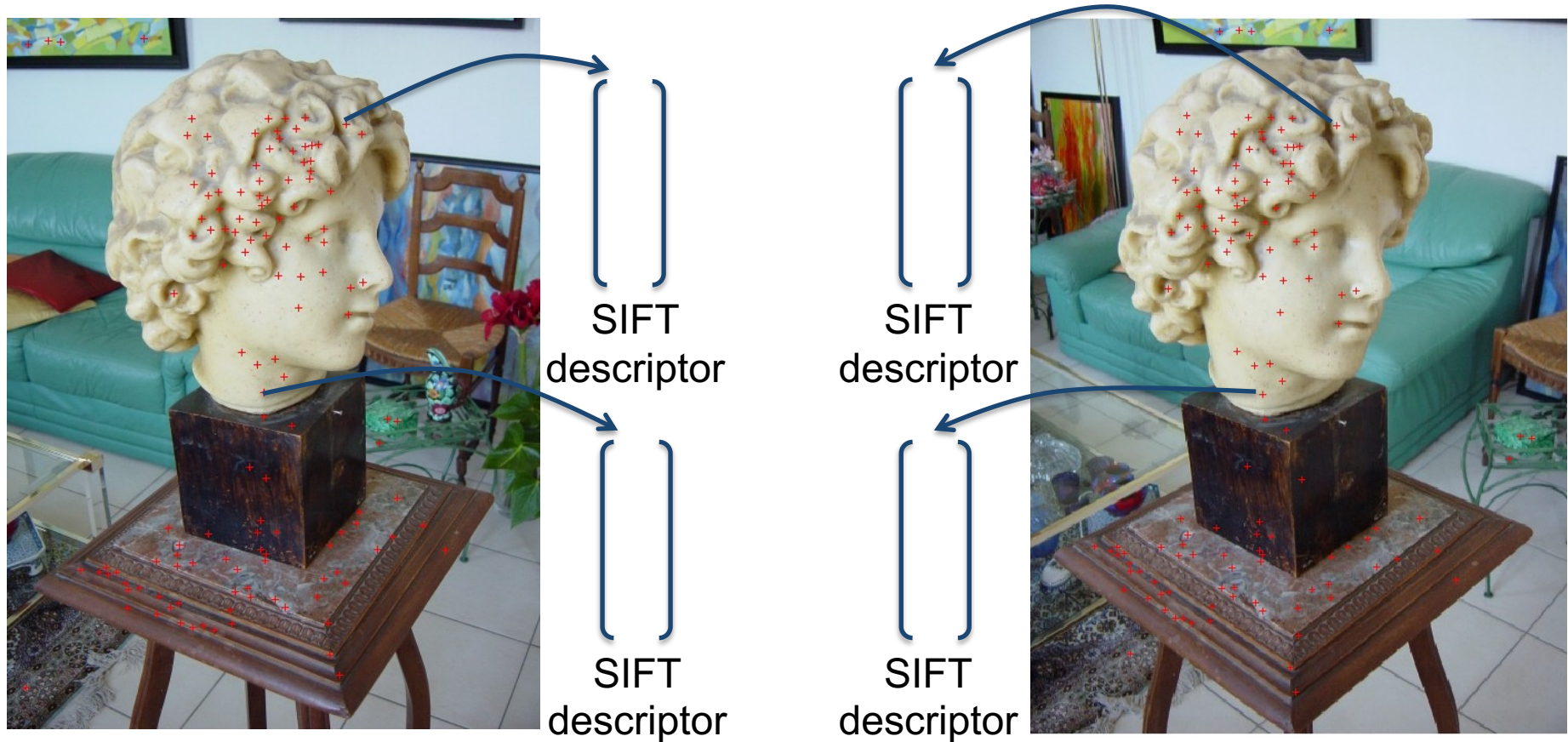
# Descriptor for each point



Slide Jianxiong Xiao

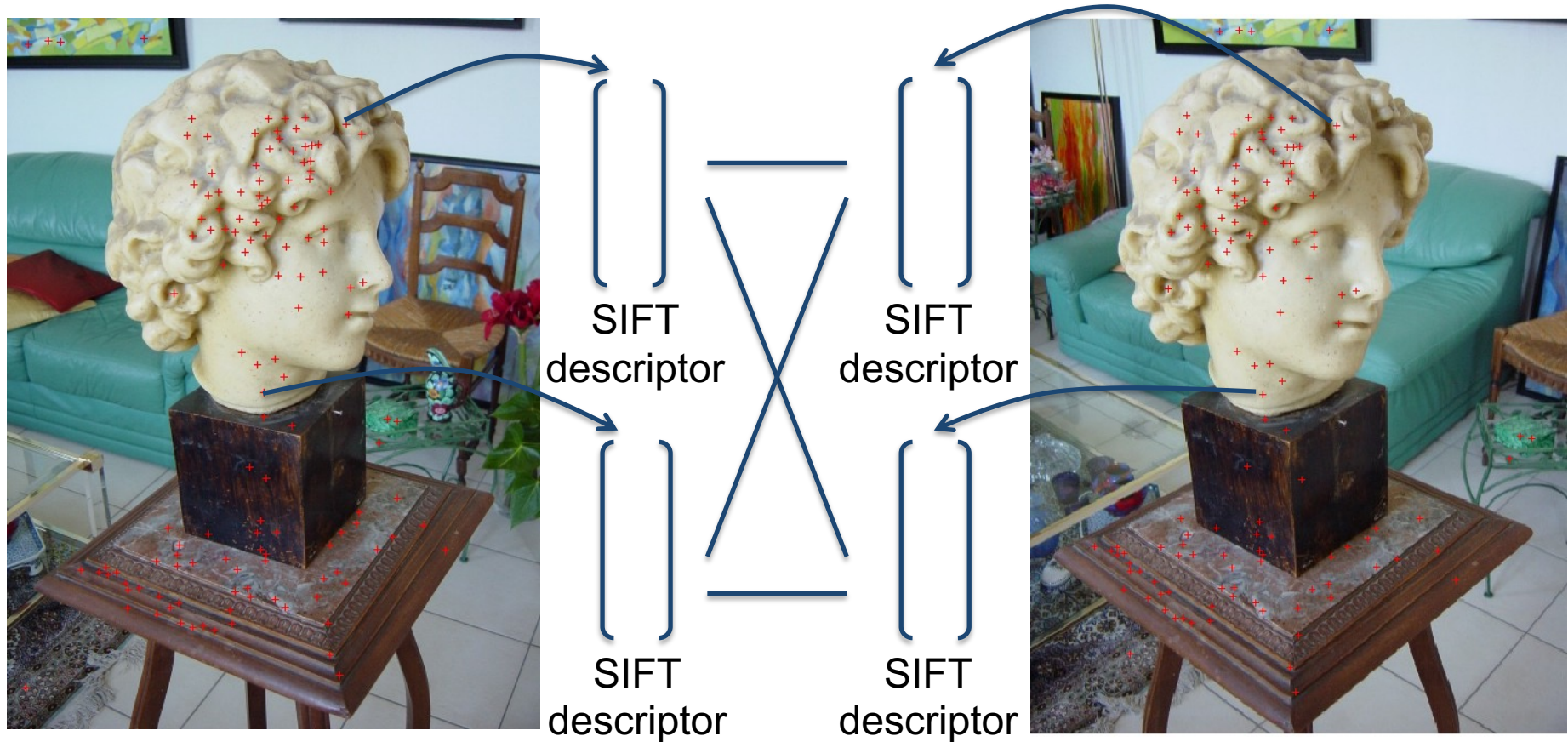


# Same for the other images



Slide Jianxiong Xiao

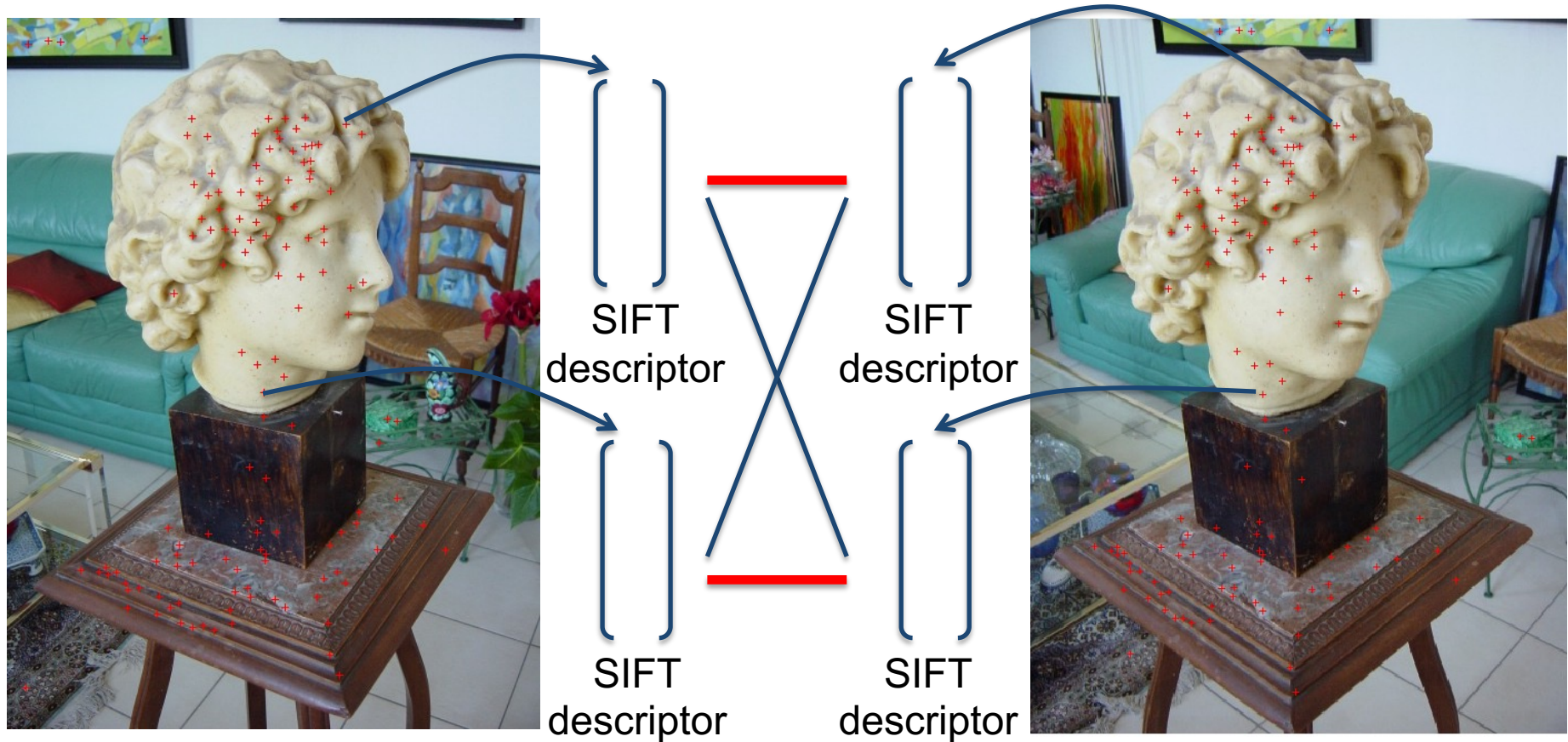
# Point Match for correspondences



Slide Jianxiong Xiao

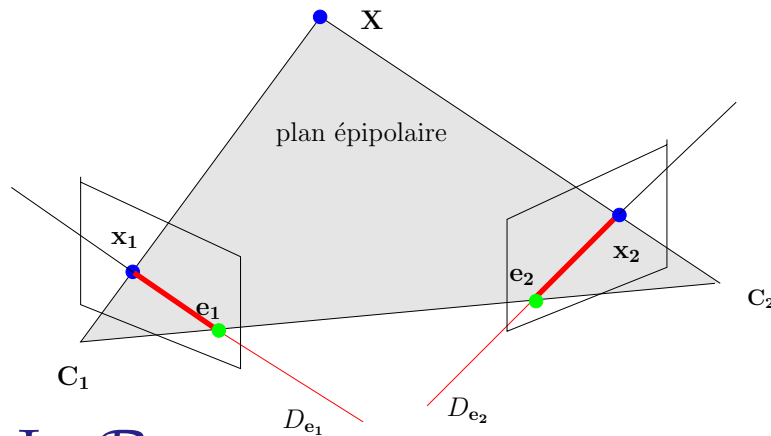


# Point Match for correspondences



Slide Jianxiong Xiao

# Algebraic formulation of the epipolar geometry



## Epipolar constraints

$C_1, C_2, x_1, x_2$  and  $X$  are coplanar

$$C_1 x_1 \cdot (C_1 C_2 \times C_2 x_2) = 0$$

In  $\mathcal{R}_1$

- $C_1 x_1 / \mathcal{R}_1 = x_1^\top = (x_1 \ y_1 \ 1)$
- $C_1 C_2 / \mathcal{R}_1 = {}^1t_2$
- $C_2 x_2 / \mathcal{R}_1 = {}^1R_2 \ C_2 x_2 / \mathcal{R}_{c_2} = {}^{c_1}R_{c_2} x_2 = {}^1R_2 (x_2, y_2, 1)^\top$

$$x_1^\top \cdot ({}^1t_2 \times {}^1R_2 x_2) = 0$$



# Essential matrix

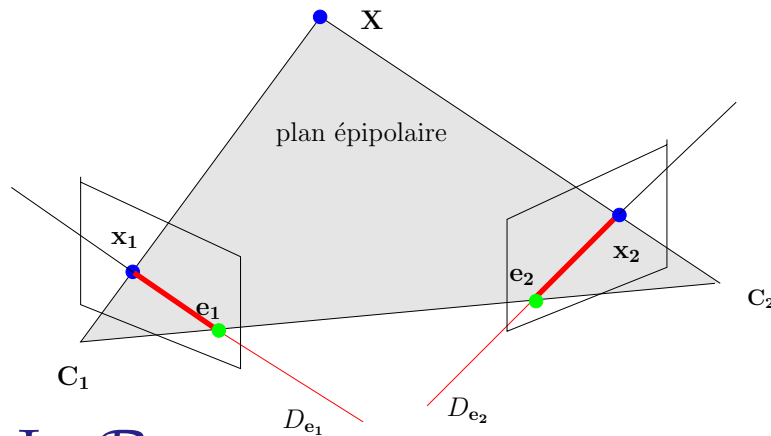
Let  $\mathbf{x}_1^\top \cdot ({}^1\mathbf{t}_2 \times {}^1\mathbf{R}_2\mathbf{x}_2) = 0$

$$[{}^1\mathbf{t}_2]_\times = \begin{pmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{pmatrix} \quad {}^1\mathbf{t}_2 \times {}^1\mathbf{R}_2\mathbf{x}_2 = [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2\mathbf{x}_2$$

Then  $\mathbf{x}_1^\top [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2\mathbf{x}_2 = 0$

${}^1\mathbf{E}_2 = [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2$  is the essential matrix

# Algebraic formulation of the epipolar geometry



## Epipolar constraints

$C_1, C_2, \mathbf{x}_1, \mathbf{x}_2$  and  $\mathbf{X}$  are coplanar

$$C_1 \mathbf{x}_1 \cdot (C_1 C_2 \times C_2 \mathbf{x}_2) = 0$$

In  $\mathcal{R}_1$

- $C_1 \mathbf{x}_1 / \mathcal{R}_1 = \mathbf{x}_1^\top = (x_1 \ y_1 \ 1)$
- $C_1 C_2 / \mathcal{R}_1 = {}^1\mathbf{t}_2$
- $C_2 \mathbf{x}_2 / \mathcal{R}_1 = {}^1\mathbf{R}_2 \ C_2 \mathbf{x}_2 / \mathcal{R}_{c_2} = {}^{c_1}\mathbf{R}_{c_2} \mathbf{x}_2 = {}^1\mathbf{R}_2 (x_2, y_2, 1)^\top$

$$\mathbf{x}_1^\top \cdot ({}^1\mathbf{t}_2 \times {}^1\mathbf{R}_2 \mathbf{x}_2) = 0$$

# Essential matrix

Let  $\mathbf{x}_1^\top \cdot ({}^1\mathbf{t}_2 \times {}^1\mathbf{R}_2\mathbf{x}_2) = 0$

$$[{}^1\mathbf{t}_2]_\times = \begin{pmatrix} 0 & -t_z & t_y \\ t_z & 0 & -t_x \\ -t_y & t_x & 0 \end{pmatrix} \quad {}^1\mathbf{t}_2 \times {}^1\mathbf{R}_2\mathbf{x}_2 = [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2\mathbf{x}_2$$

Then

${}^1\mathbf{E}_2 = [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2$  is the essential matrix

$$\mathbf{x}_1^\top [{}^1\mathbf{t}_2]_\times {}^1\mathbf{R}_2\mathbf{x}_2 = 0$$

# Essential matrix estimation

Considering image 1 and 2

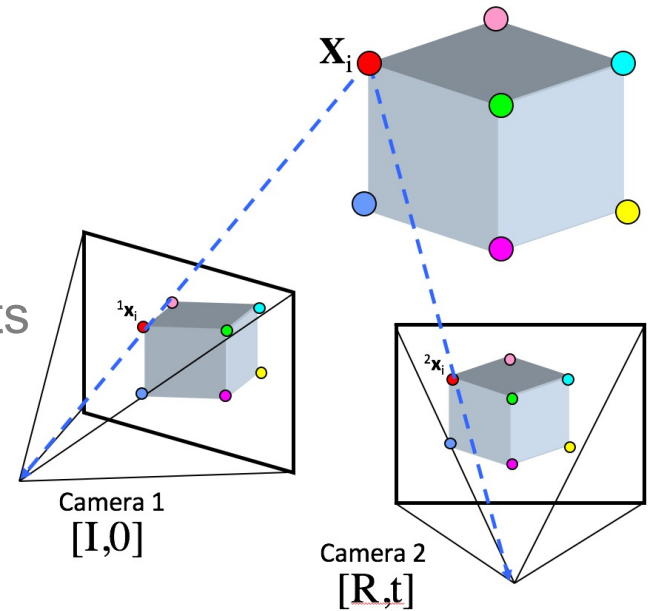
- We have a set  $\{ {}^1\mathbf{x}_i, {}^2\mathbf{x}_i \}_{i=1..N}$  of matched points

- Estimate the essential matrix such that:

$${}^1\mathbf{x}_i^T \mathbf{E} {}^2\mathbf{x}_i = 0$$

- You can use the 8 point algorithm although Niester 5 point algorithm is, nowadays, usually preferred.
- In any case RANSAC is required !
- You then have  $\mathbf{E}$ , a 3x3 rank 2 matrix that encode the camera motion

$$\mathbf{E} = [\mathbf{t}]_{\times} \mathbf{R}$$



## 8 points algorithm [Longuet Higgins 81]

Epipolar constraints  $\mathbf{x}_2^\top \mathbf{E} \mathbf{x}_1 = 0$

The system can be rewritten by:  $\mathbf{A} \mathbf{e} = 0$

Vector  $\mathbf{e}$  contains the elements of the essential matrix  $\mathbf{E}$

$$\mathbf{e} = \begin{pmatrix} E_{11} & E_{12} & \dots & E_{32} & E_{33} \end{pmatrix}^\top$$

$\mathbf{A}$  is a  $n \times 9$  matrix that depends of the observations

$$\mathbf{A} = \begin{pmatrix} \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \\ x_{i_2} x_{i_1} & x_{i_2} y_{i_1} & x_{i_2} & y_{i_2} x_{i_1} & y_{i_2} y_{i_1} & y_{i_2} & x_{i_1} & y_{i_1} & 1 \\ \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots & \dots \end{pmatrix}$$



## 8 points algorithm [Longuet Higgins 81]

There is a least square solution solved assuming that  $\| \mathbf{E} \| = 1$

Let  $\tilde{\mathbf{E}}$  be the obtained essential matrix.

However  $\mathbf{E}$  is a rank 2 matrix, it is necessary to ensure that  $\tilde{\mathbf{E}}$  is actually an essential matrix.

Let us compute the SVD of  $\tilde{\mathbf{E}}$ :  $\tilde{\mathbf{E}} = \mathbf{U}\mathbf{D}\mathbf{V}^T$ .

Let  $\mathbf{D} = \text{diag}(r, s, t)$  with  $r \geq s \geq t$ , then the essential matrix is given by:

$$\mathbf{E} = \mathbf{U}.\text{diag}(r, s, 0).\mathbf{V}^T$$

# Extract [R,t] from E

Assuming  ${}^1T_w = I$  that is the center of the world frame, then there are four position for the second camera position  ${}^1T_2$

Assuming that a SVD decomposition of E is given by

$$E = U \cdot \text{diag}(1, 1, 0) \cdot V^T$$

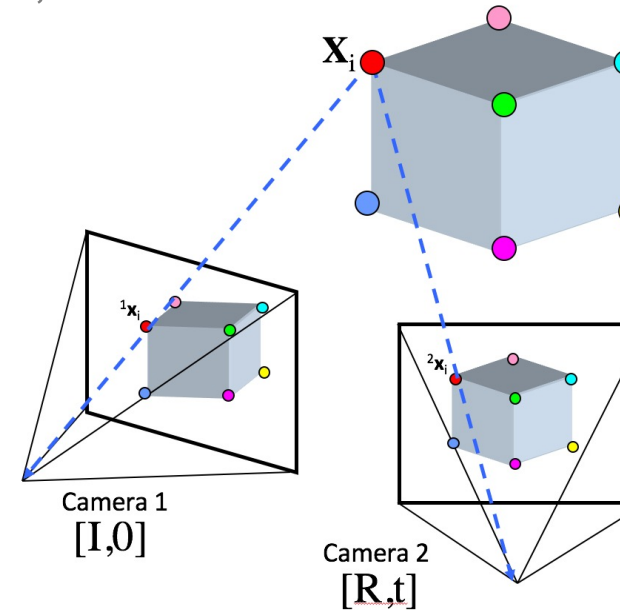
$${}^1T_2 = \begin{pmatrix} UWV^T & +U_{3\bullet} \\ \mathbf{0}_{3 \times 1} & 1 \end{pmatrix}$$

$${}^1T_2 = \begin{pmatrix} UWV^T & -U_{3\bullet} \\ \mathbf{0}_{3 \times 1} & 1 \end{pmatrix}$$

$${}^1T_2 = \begin{pmatrix} UW^T V^T & +U_{3\bullet} \\ \mathbf{0}_{3 \times 1} & 1 \end{pmatrix}$$

$${}^1T_2 = \begin{pmatrix} UW^T V^T & -U_{3\bullet} \\ \mathbf{0}_{3 \times 1} & 1 \end{pmatrix}$$

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



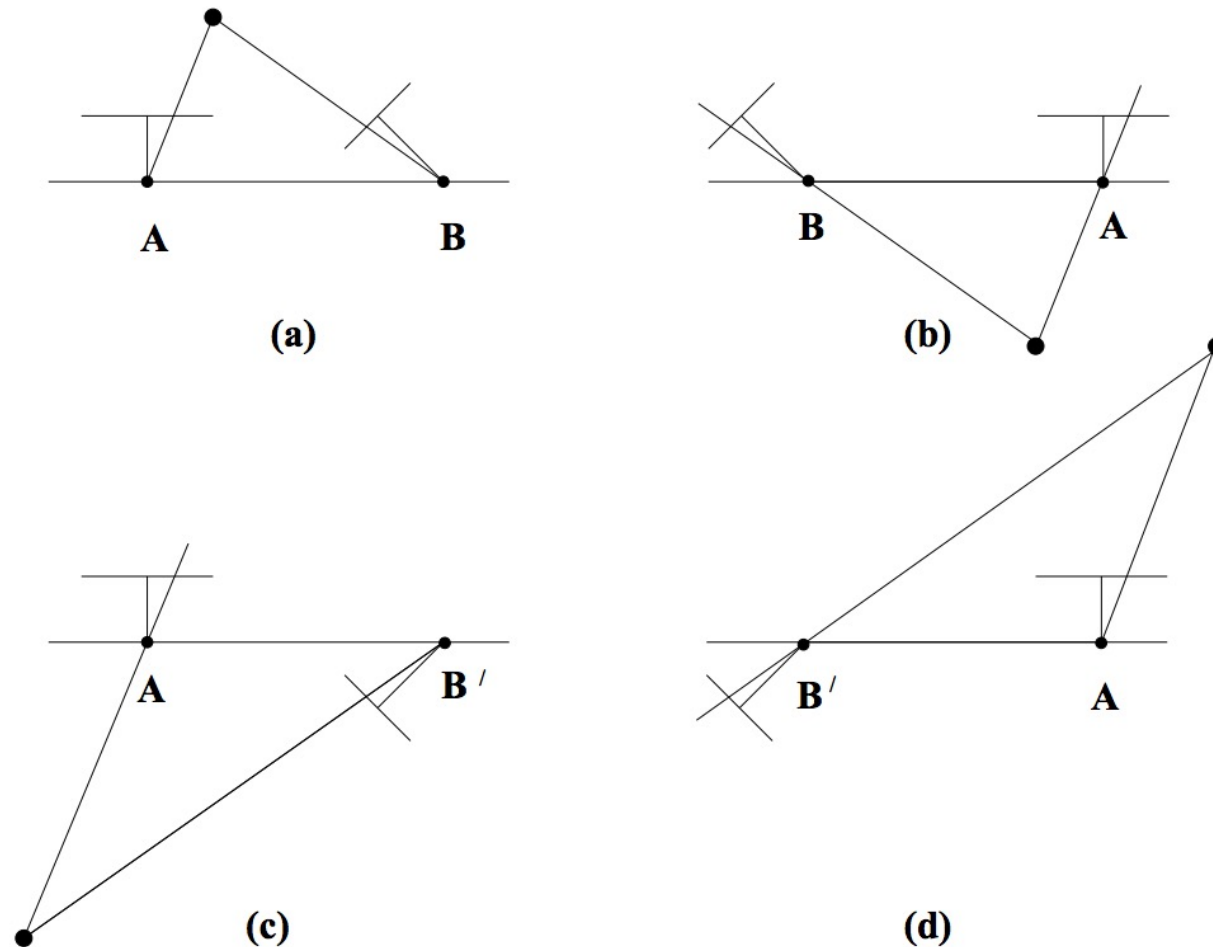
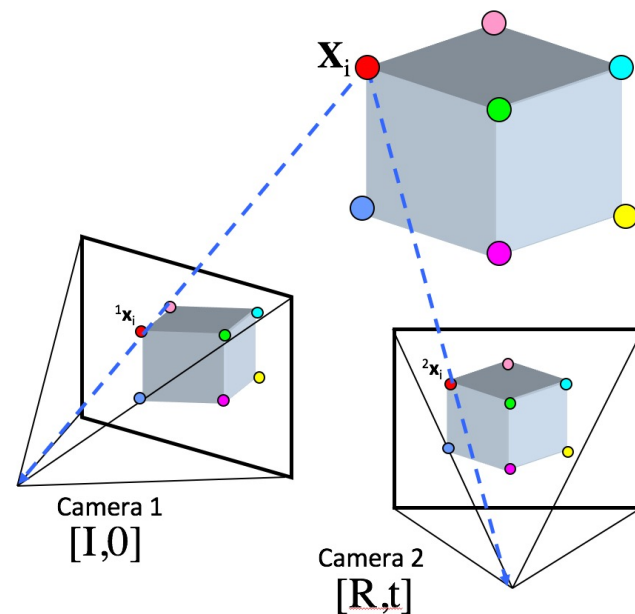
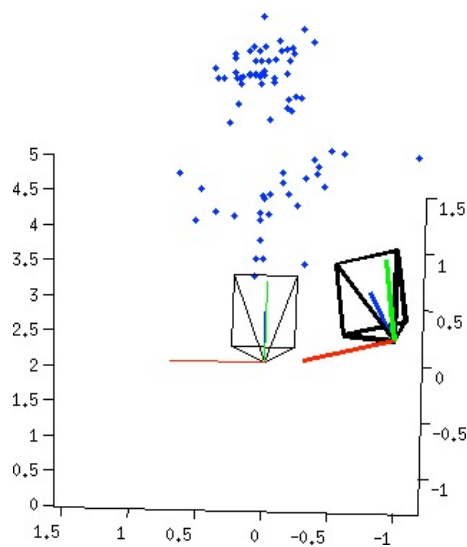


Fig. 9.12. The four possible solutions for calibrated reconstruction from E. Between the left and right sides there is a baseline reversal. Between the top and bottom rows camera B rotates  $180^\circ$  about the baseline. Note, only in (a) is the reconstructed point in front of both cameras.

# Triangulation

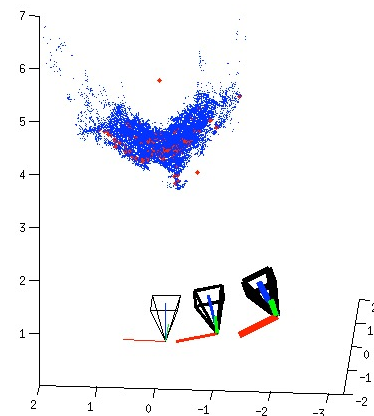
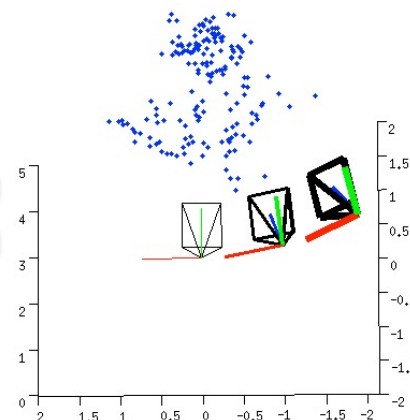
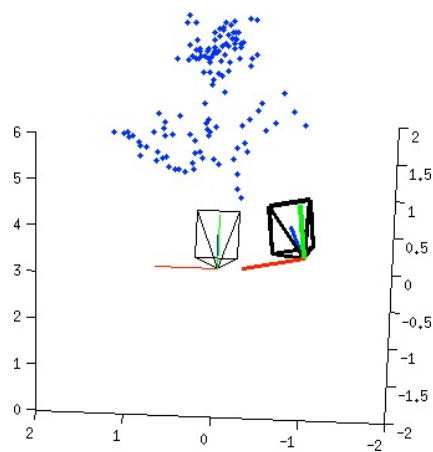
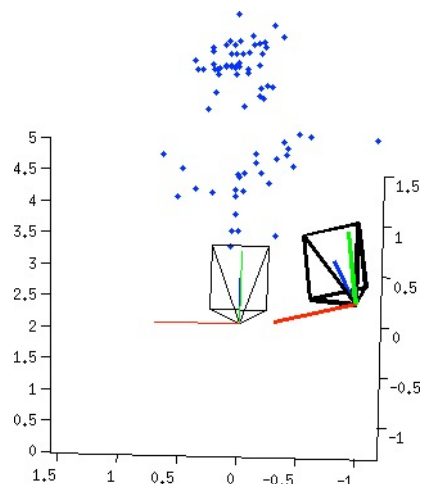
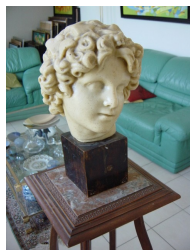
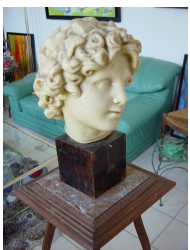
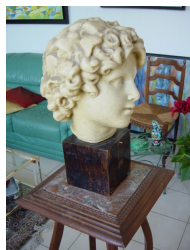
Knowing  $\{ {}^1\mathbf{x}_i, {}^2\mathbf{x}_i \}_{i=1..N}$  and, now, camera motion  $[R, t]$

It is possible to achieve triangulation (see previous lecture)





# For all the image

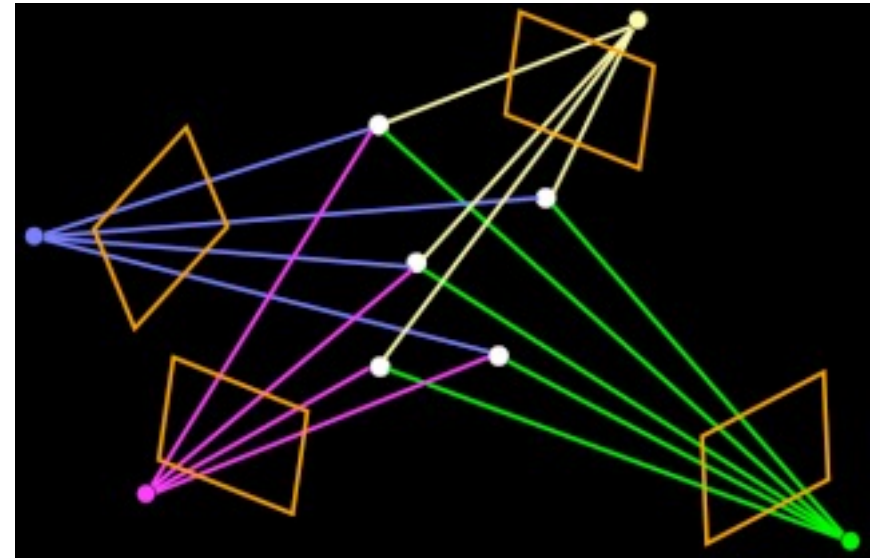


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# Bundle adjustment

One could think that you're set...

- Let  ${}^w\mathbf{X}$  be the 3D points in world frame and  ${}^j\mathbf{x}$  their projection
- Let  ${}^j\mathbf{T}_w$  be the camera location for frame  $j$
- If no noise, you're indeed set...
- But you have noise in  ${}^w\mathbf{X}$  and in  ${}^j\mathbf{T}_w$
- Idea: minimize the reprojection error



# Bundle adjustment

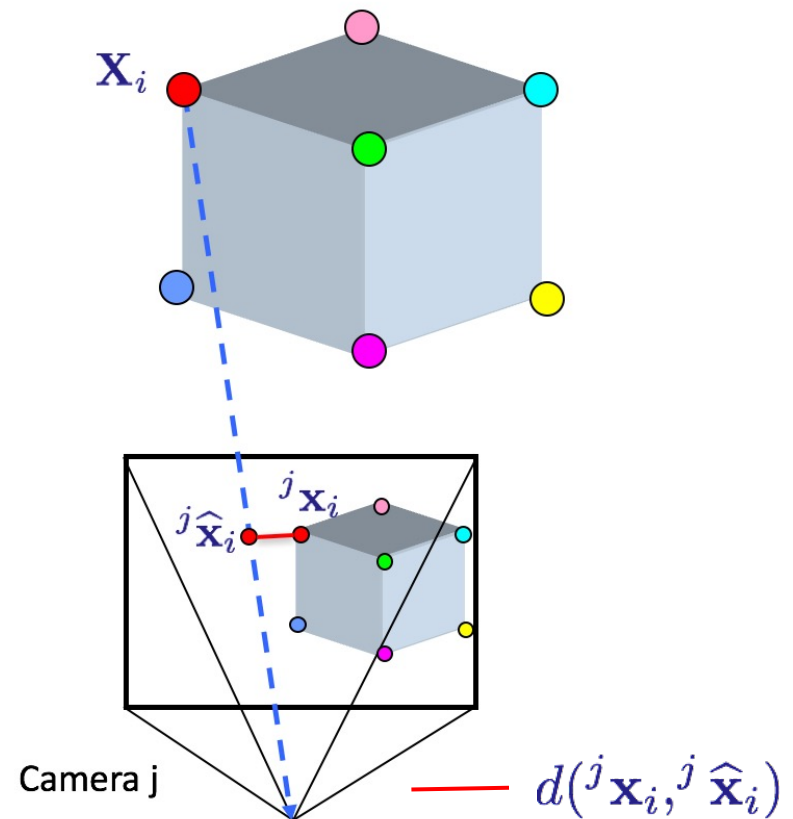
Pour un point de vue et un point 3D arbitraires, la projection du point 3D ne correspond généralement pas au point 2D mesuré dans l'image → distance de reprojection non nulle

This error  $d({}^j\mathbf{x}_i, {}^j\hat{\mathbf{x}}_i)$  is called reprojection error, where

- ${}^j\mathbf{x}_i$  is the observation
- ${}^j\hat{\mathbf{x}}_i$  is the obtain from the model

$$d({}^j\mathbf{x}_i, {}^j\hat{\mathbf{x}}_i) = \|\mathbf{x}_i - \Pi^j \mathbf{T}_w^w \mathbf{X}_i\|$$

That is for one point in one image...



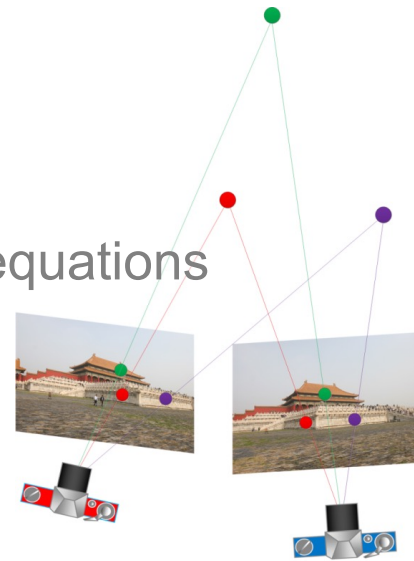
# Bundle adjustment

The reprojection error can be due to error in 3D point position or in camera position

To minimize the reprojection error, with 2 camera, you want to minimize

$$(\widehat{{}^0\mathbf{T}_w}, \widehat{{}^1\mathbf{T}_w}, \widehat{{}^w\mathbf{X}_i}) = \arg \min_{({}^0\mathbf{T}_w, {}^1\mathbf{T}_w, {}^w\mathbf{X}_i)} \left( \sum_{i=1}^N ({}^0\mathbf{x}_i - \mathbf{\Pi}^0 \mathbf{T}_w {}^w\mathbf{X}_i)^2 + \sum_{i=1}^N ({}^1\mathbf{x}_i - \mathbf{\Pi}^1 \mathbf{T}_w {}^w\mathbf{X}_i)^2 \right)$$

- Assuming  ${}^0\mathbf{T}_w = \mathbf{I}$ ,
  - We have  $N+6$  parameters to estimate and we have  $2N$  equations
  - 6 points are at least required.

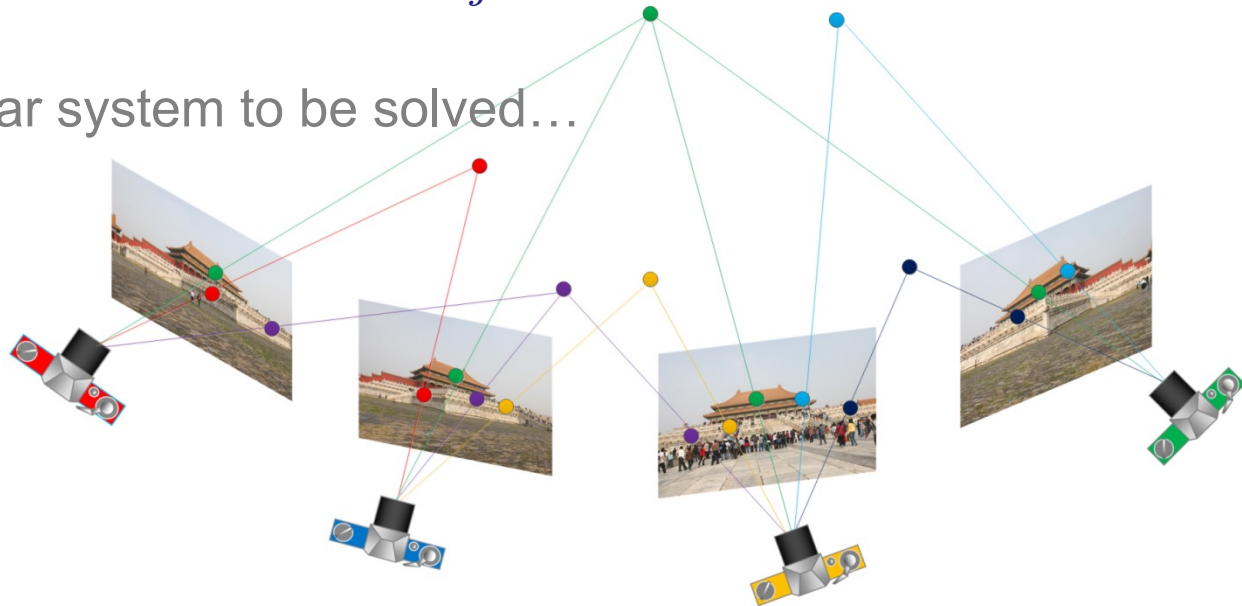


# Bundle adjustment

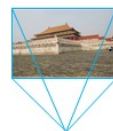
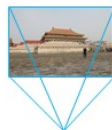
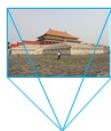
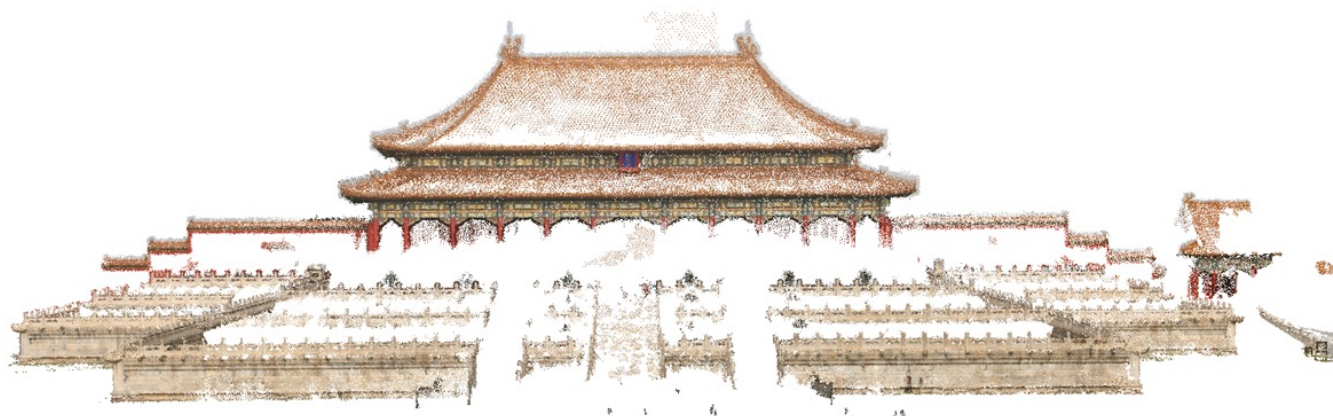
- BA aimed at estimating  ${}^w\mathbf{X}$  and  ${}^j\mathbf{T}_w, j=1..N_c$
- This is done with all the images

$$(\widehat{{}^0\mathbf{T}_w}, \dots, \widehat{{}^{N_c}\mathbf{T}_w}, \widehat{{}^w\mathbf{X}_i}) = \arg \min_{({}^j\mathbf{T}_w, {}^w\mathbf{X}_i)} \sum_{j=0}^{N_c} \sum_{i=1}^N ({}^j\mathbf{x}_i - \Pi^j \mathbf{T}_w {}^w\mathbf{X}_i)^2$$

- This is a huge non linear system to be solved...
- $6N_c + N$  unknown...









# Sparse bundle adjustment

We have to optimize

$$(\hat{\mathbf{q}}_0, \dots, \hat{\mathbf{q}}_{N_c}, \dots, {}^w \hat{\mathbf{X}}_i, \dots) = \underset{\mathbf{q}}{\operatorname{argmin}} \sum_{j=1}^{N_c} \sum_{i=1}^N d({}^j \mathbf{x}_i, \Pi^j \mathbf{T}_w {}^w \mathbf{X}_i)$$

Let us denote

- $\mathbf{q} = (\mathbf{q}_0, \dots, \mathbf{q}_{N_c}, \dots, {}^w \mathbf{X}_i, \dots)^\top$  the vector of unknown and
- $\mathbf{e} = (\dots, d({}^j \mathbf{x}_i, \Pi^j \mathbf{T}_w {}^w \mathbf{X}_i), \dots)^\top$  the error vector
- This is solved by an iterative least square method (GN or LM)  
$$\delta \mathbf{q} = -\mathbf{J}^+ \mathbf{e} \longrightarrow \delta \mathbf{q} = -(\mathbf{J}^\top \mathbf{J})^{-1} \mathbf{J}^\top \mathbf{e}$$
$$\mathbf{q}_{k+1} = \mathbf{q}_k + \delta \mathbf{q}$$
- Huge problem but can be solved efficiently

# Sparse bundle adjustment

We have to optimize

$$(\hat{\mathbf{q}}_0, \dots, \hat{\mathbf{q}}_{N_c}, \dots, {}^w \hat{\mathbf{X}}_i, \dots) = \underset{\mathbf{q}}{\operatorname{argmin}} \sum_{j=1}^{N_c} \sum_{i=1}^N d({}^j \mathbf{x}_i, \Pi^j \mathbf{T}_w {}^w \mathbf{X}_i)$$

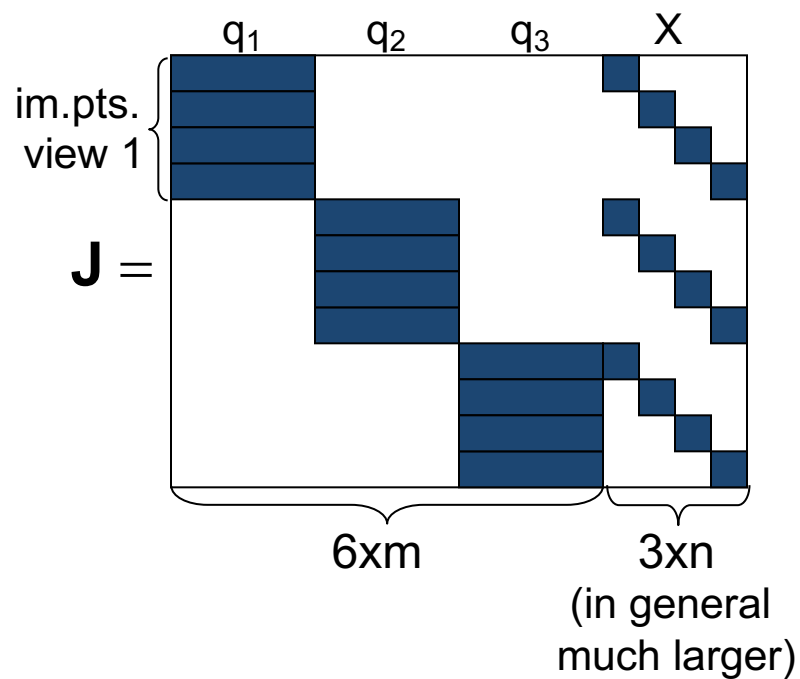
Let use denote

- $\mathbf{q} = (\mathbf{q}_0, \dots, \mathbf{q}_{N_c}, \dots, {}^w \mathbf{X}_i, \dots)^\top$  the vector of unknown and
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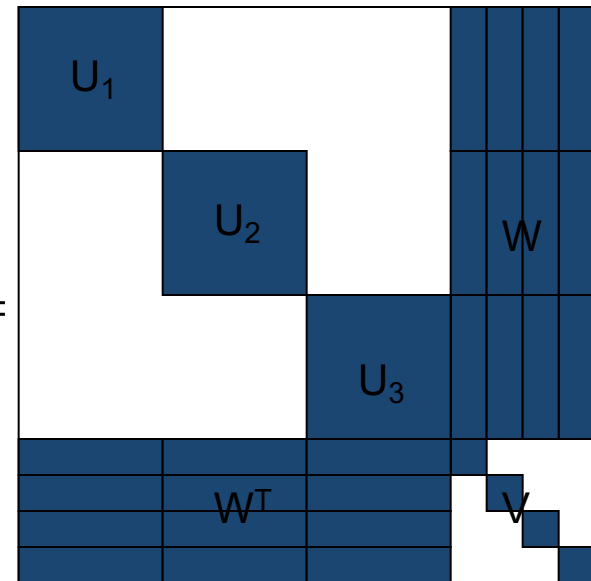
# Jacobian J and Hessian

J and N are needed for non linear optimization

They have a particular and sparse block structure



$$N = J^T J =$$





# Bundle adjustment

$$\begin{pmatrix} \mathbf{U}_1 & \mathbf{0} & \mathbf{0} & \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} \\ \mathbf{0} & \mathbf{U}_2 & \mathbf{0} & \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} \\ \mathbf{0} & \mathbf{0} & \mathbf{U}_3 & \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} \\ \mathbf{W}_{11}^T & \mathbf{W}_{12}^T & \mathbf{W}_{13}^T & \mathbf{V}_1 & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{W}_{21}^T & \mathbf{W}_{22}^T & \mathbf{W}_{23}^T & \mathbf{0} & \mathbf{V}_2 & \mathbf{0} & \mathbf{0} \\ \mathbf{W}_{31}^T & \mathbf{W}_{32}^T & \mathbf{W}_{33}^T & \mathbf{0} & \mathbf{0} & \mathbf{V}_3 & \mathbf{0} \\ \mathbf{W}_{41}^T & \mathbf{W}_{42}^T & \mathbf{W}_{43}^T & \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{V}_4 \end{pmatrix} \begin{pmatrix} \delta_{\mathbf{a}_1} \\ \delta_{\mathbf{a}_2} \\ \delta_{\mathbf{a}_3} \\ \delta_{\mathbf{b}_1} \\ \delta_{\mathbf{b}_2} \\ \delta_{\mathbf{b}_3} \\ \delta_{\mathbf{b}_4} \end{pmatrix} = \begin{pmatrix} \epsilon_{\mathbf{a}_1} \\ \epsilon_{\mathbf{a}_2} \\ \epsilon_{\mathbf{a}_3} \\ \epsilon_{\mathbf{b}_1} \\ \epsilon_{\mathbf{b}_2} \\ \epsilon_{\mathbf{b}_3} \\ \epsilon_{\mathbf{b}_4} \end{pmatrix}$$

$$\mathbf{U}^* = \begin{pmatrix} \mathbf{U}_1^* & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{U}_2^* & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{U}_3^* \end{pmatrix}, \mathbf{V}^* = \begin{pmatrix} \mathbf{V}_1^* & \mathbf{0} & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{V}_2^* & \mathbf{0} & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{V}_3^* & \mathbf{0} \\ \mathbf{0} & \mathbf{0} & \mathbf{0} & \mathbf{V}_4^* \end{pmatrix}, \mathbf{W} = \begin{pmatrix} \mathbf{W}_{11} & \mathbf{W}_{21} & \mathbf{W}_{31} & \mathbf{W}_{41} \\ \mathbf{W}_{12} & \mathbf{W}_{22} & \mathbf{W}_{32} & \mathbf{W}_{42} \\ \mathbf{W}_{13} & \mathbf{W}_{23} & \mathbf{W}_{33} & \mathbf{W}_{43} \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{U}^* & \mathbf{W} \\ \mathbf{W}^T & \mathbf{V}^* \end{pmatrix} \begin{pmatrix} \delta_{\mathbf{a}} \\ \delta_{\mathbf{b}} \end{pmatrix} = \begin{pmatrix} \epsilon_{\mathbf{a}} \\ \epsilon_{\mathbf{b}} \end{pmatrix}$$

# Bundle adjustment

Multiplied by

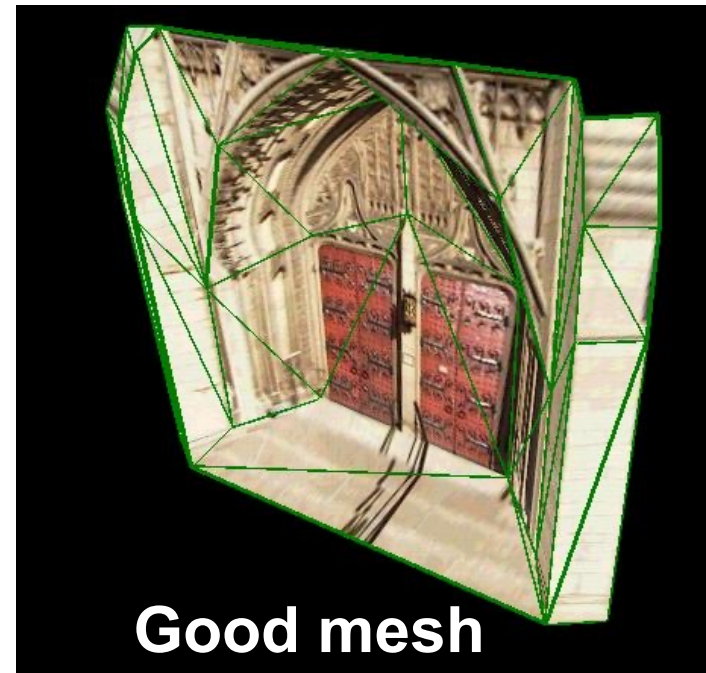
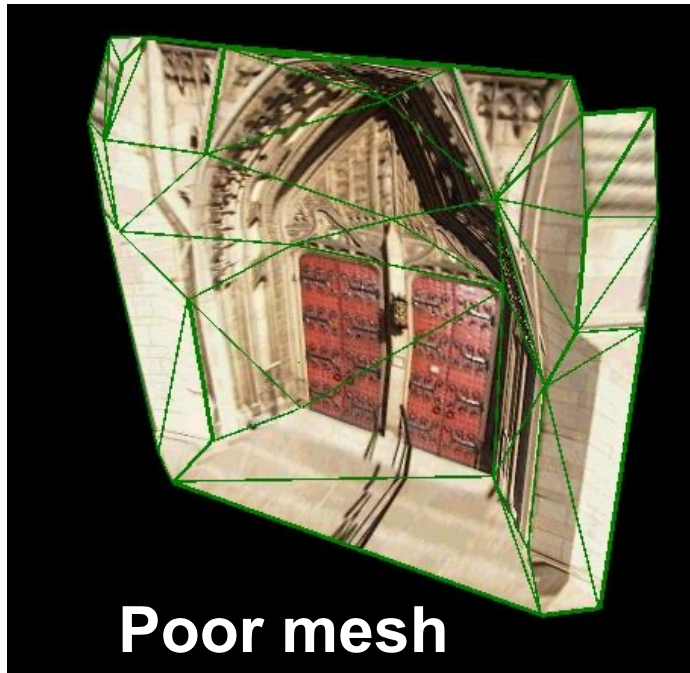
$$\begin{pmatrix} \mathbf{I} & -\mathbf{W} \mathbf{V}^{*-1} \\ \mathbf{0} & \mathbf{I} \end{pmatrix}$$

$$\begin{pmatrix} \mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T & \mathbf{0} \\ \mathbf{W}^T & \mathbf{V}^* \end{pmatrix} \begin{pmatrix} \delta_{\mathbf{a}} \\ \delta_{\mathbf{b}} \end{pmatrix} = \begin{pmatrix} \epsilon_{\mathbf{a}} - \mathbf{W} \mathbf{V}^{*-1} \epsilon_{\mathbf{b}} \\ \epsilon_{\mathbf{b}} \end{pmatrix}$$

$$(\mathbf{U}^* - \mathbf{W} \mathbf{V}^{*-1} \mathbf{W}^T) \delta_{\mathbf{a}} = \epsilon_{\mathbf{a}} - \mathbf{W} \mathbf{V}^{*-1} \epsilon_{\mathbf{b}}$$

$$\mathbf{V}^* \delta_{\mathbf{b}} = \epsilon_{\mathbf{b}} - \mathbf{W}^T \delta_{\mathbf{a}}$$

# Structure from Motion



Morris and Kanade, 2000

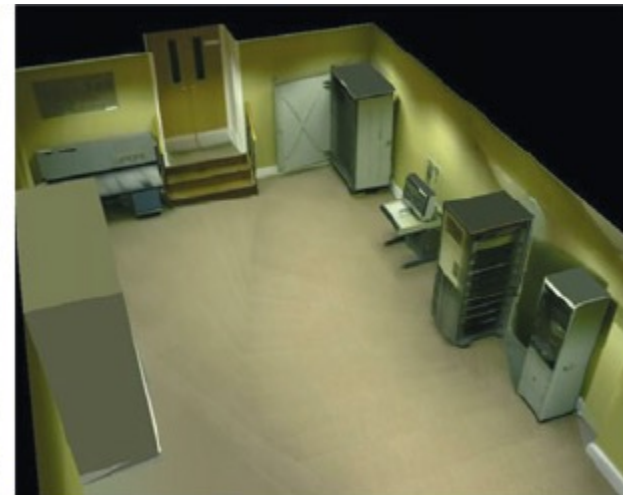
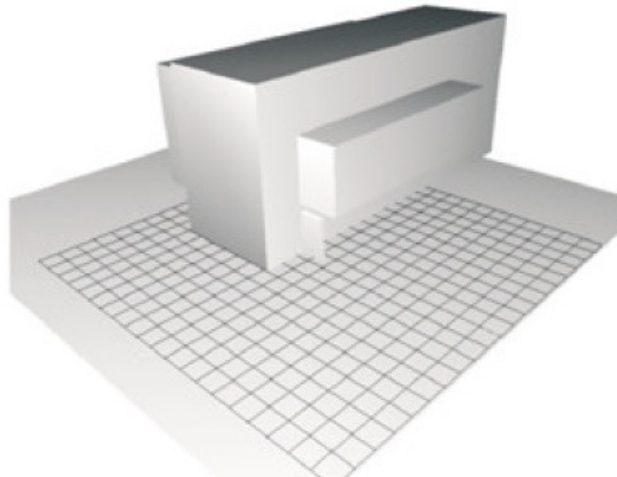
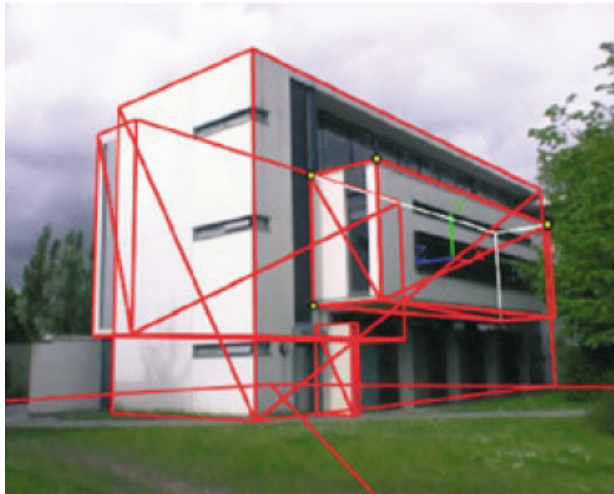
## Step 4: Recover Surfaces

- Image-based triangulation [Morris 00, Baillard 99]
- Silhouettes [Fitzgibbon 98]
- Stereo [Pollefeys 99]



# Structure from Motion

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



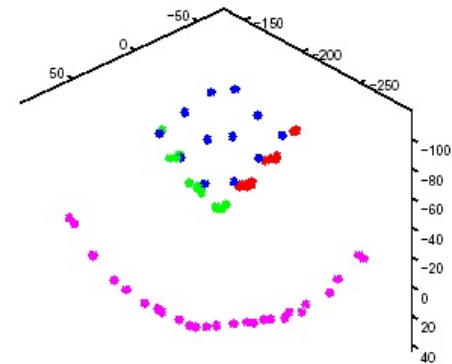
# Structure from motion: limitations

Very difficult to reliably estimate metric structure and motion unless:

- large (x or y) rotation *or*
- large field of view and depth variation

Camera calibration important for Euclidean reconstructions

Need good feature tracker





# Lissage des points de vue

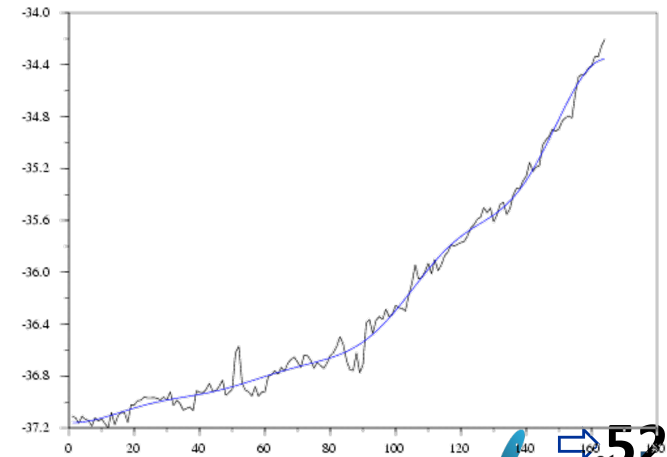
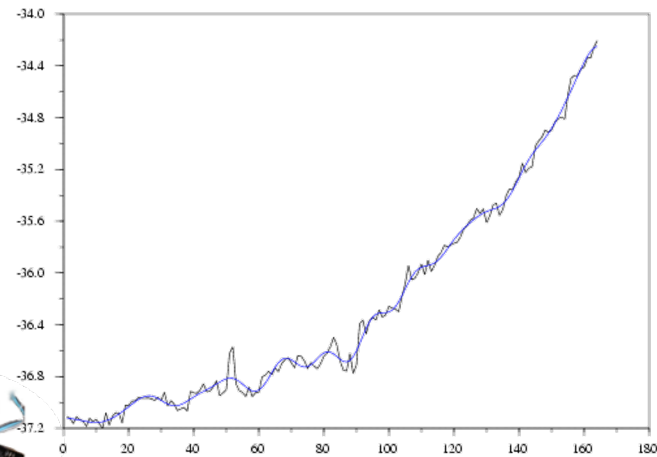
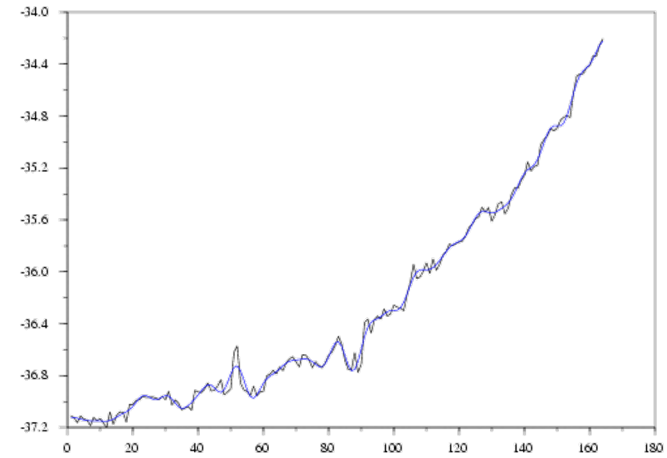
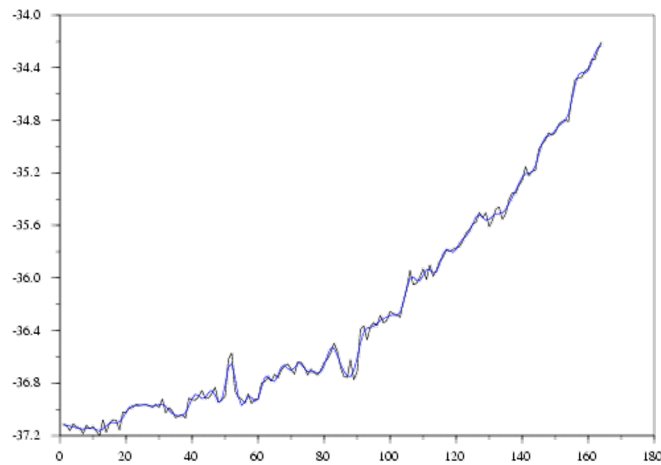
Pour éviter les tremblements (*jittering effect*), il peut être intéressant de lisser les paramètres extrinsèques (spline, transformée de Fourier, ...)

Problème : quel degré de lissage appliquer ?

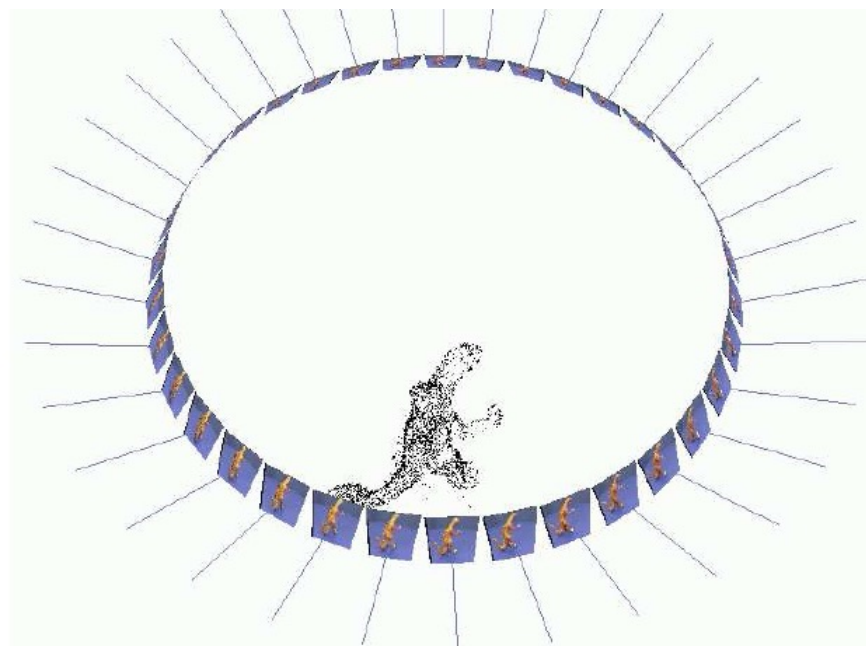
Un lissage trop important remplacerait les tremblements par un effet de glissement (*sliding effect*)



# Lissage des points de vue



# Prior knowledge and scene constraints



add a constraint that it is a turntable sequence













# Photo Tourism



## Photo Tourism

Exploring photo collections in 3D

**Microsoft®**



(a)



(b)



(c)





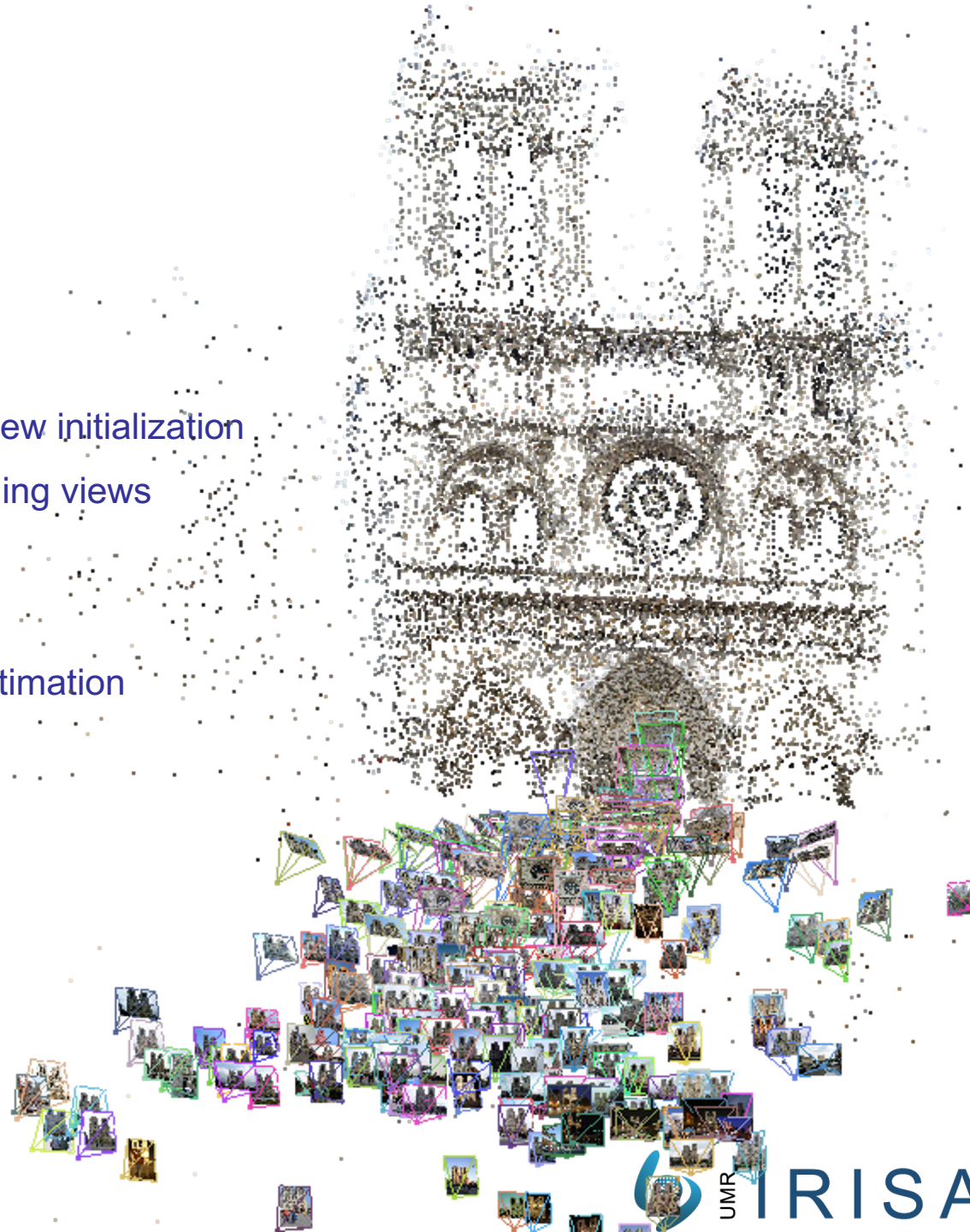
# SfM code

for iconic graph

- uses 5-point+RANSAC for 2-view initialization
- uses 3-point+RANSAC for adding views
- performs bundle adjustment

For additional images

- use 3-point+RANSAC pose estimation





# Parallel Tracking and Mapping for Small AR Workspaces

Extra video results made for  
ISMAR 2007 conference

Georg Klein and David Murray  
Active Vision Laboratory  
University of Oxford



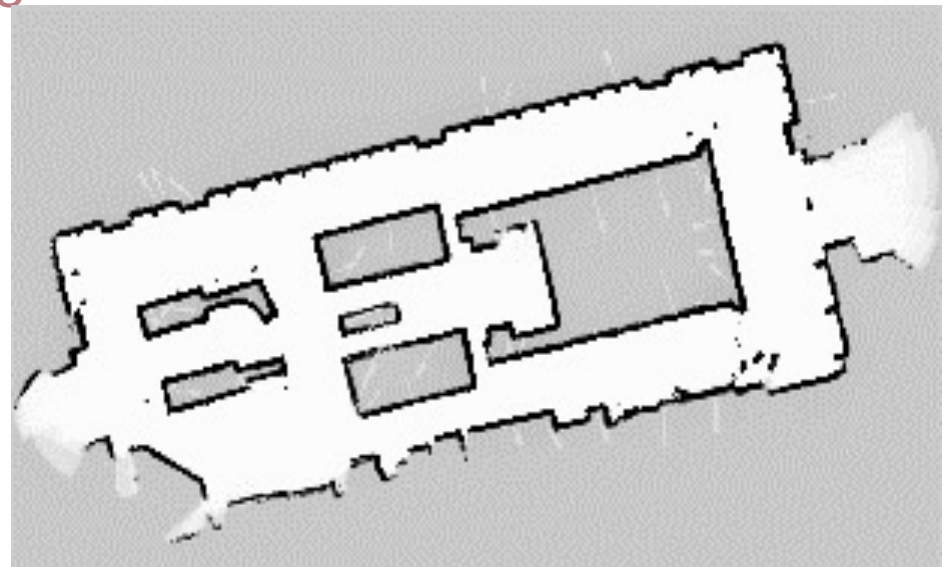
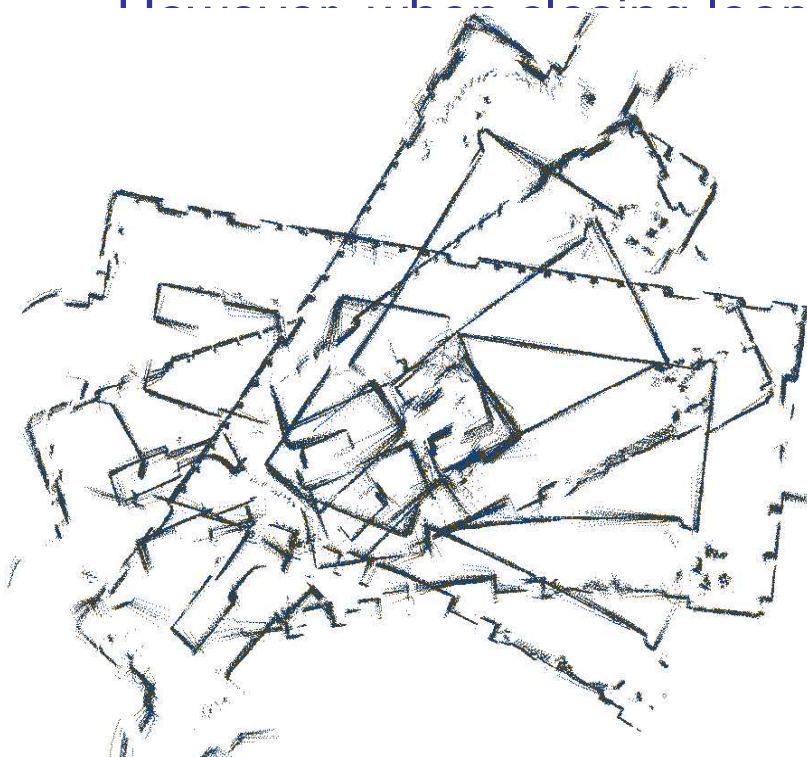


# Cyclic Environments

Small local error accumulate to arbitrary large global errors!

This is usually irrelevant for navigation

However, in cyclic environments, global error does matter



Siegwart and Scaramuzza, ETHZ

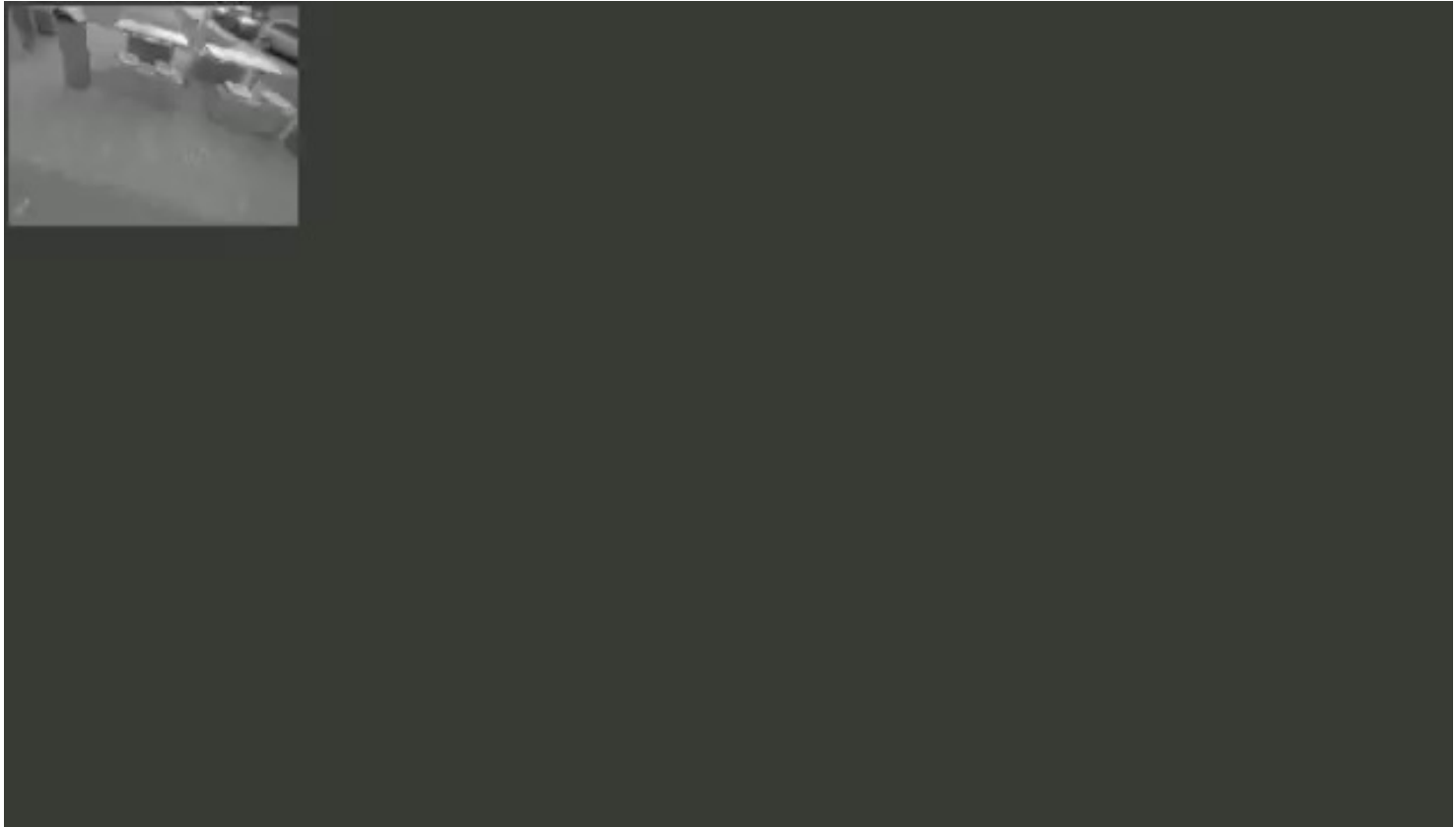
# Large vSLAM

Issue with scale and drift solved thanks to loop closure detection



# An example: LSD-Slam [Engel ECCV 2014]

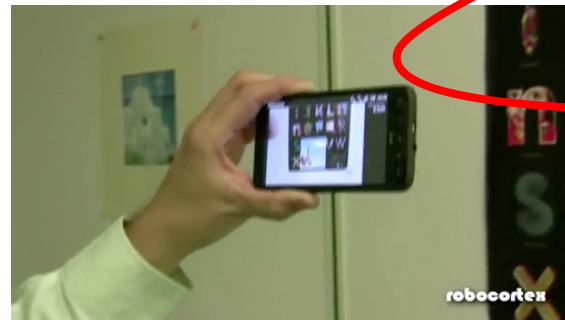
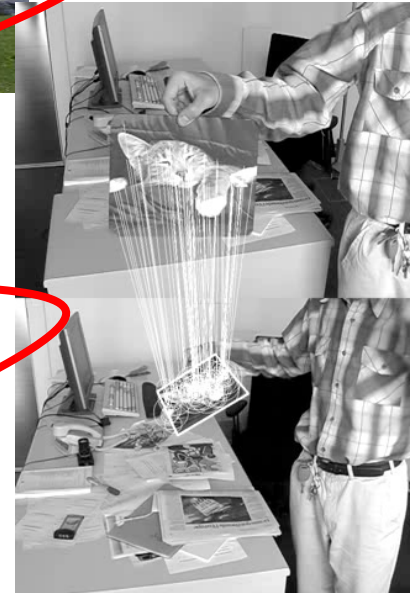
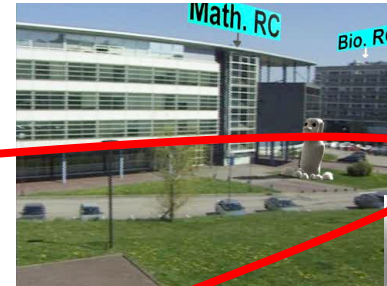
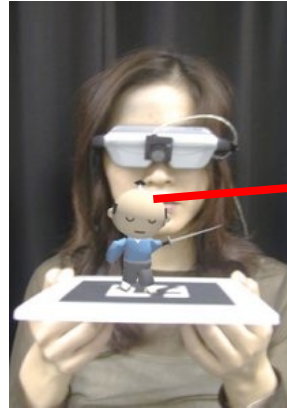
LSD Slam minimize photometric error



# Issue: tracking

- landmark (AR toolkit)
- point tracking
- point matching
- dense tracking
- multimodal tracking

Many progresses, still an open problem



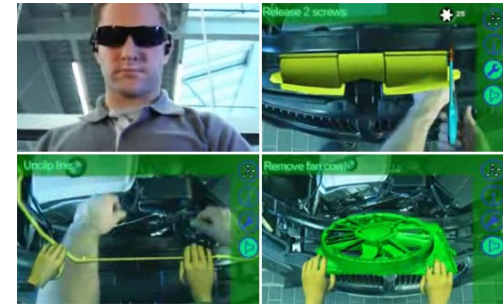


# Why augmented reality

FX: ok

Industry: ok

Game: most certainly



But why RA on your smartphone, glasses ?

Are you ready for that ?

