3D Camera Tracking, Reconstruction and View Synthesis at Interactive Frame Rates

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Introduction

Computer vision enables the computer to visually perceive our world.

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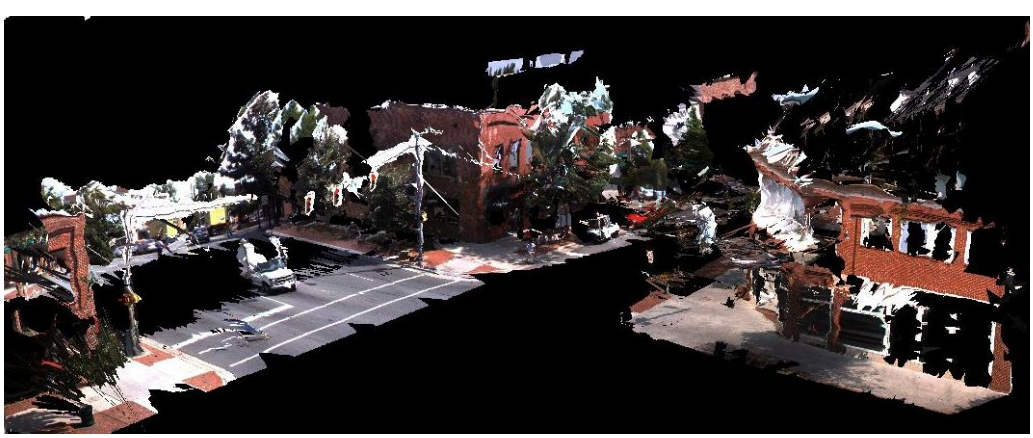

3D model

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Introduction

Imaged based rendering

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Computer Vision

Computer vision enables the computer to visually perceive our world.

To achieve this goal, one needs to extract:

- the camera geometry (calibration)
- scene structure (surface geometry)
- the visual appearance (color and texture) of the scene

This tutorial will introduce:

- the basic mathematical tools (projective geometry)
- models for cameras, image mappings
- robust methods for 2D and 3D tracking
- extraction of 3D structure
- methods to achieve these tasks in real-time

Schedule

- Introduction
- Multi-view Relations
- Feature Tracking
- Coffee Break
- Robust pose estimation
- 3D Modeling and Visualisation
- Applications

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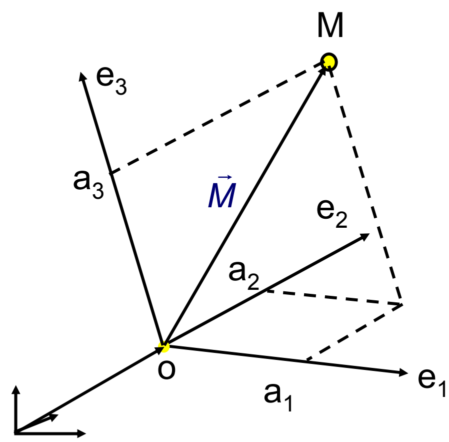
Multiview Relations

- Coordinate systems and Geometric Entities
- Definition and estimation of entities P, H, F, E
- Structure Computation
- Gold Standard Estimation Methods

Basics on affine and projective geometry

- Affine and projective geometry
  - affine points and homogeneous coordinates
  - affine transformations
  - projective points and transformations
- Pinhole camera model
  - Projection and sensor model
  - camera pose and calibration matrix
- Single viewpoint geometry
  - 2D Homography
  - image mapping and mosaicing

Affine coordinates



e_i: affine basis vectors

o: coordinate origin

Vector relative to o:

$$\vec{M} = a_1\vec{e}_1 + a_2\vec{e}_2 + a_3\vec{e}_3$$

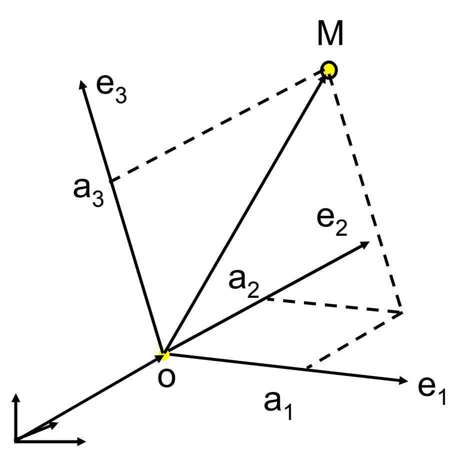
Point in affine coordinates:

$$M = \vec{M} + \vec{o} = a_1\vec{e}_1 + a_2\vec{e}_2 + a_3\vec{e}_3 + \vec{o}$$

Vector: relative to some origin

Point: absolute coordinates

Homogeneous coordinates



Unified notation:

include origin in affine basis

Homogeneous Coordinates of M

$$M = \begin{bmatrix} \vec{e}_1 & \vec{e}_2 & \vec{e}_3 & \vec{o} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} a_1 \\ a_2 \\ a_3 \\ 1 \end{bmatrix}$$

Affine basis matrix

Properties of affine transformation

Transformation T_{affine} combines linear mapping and coordinate shift in homogeneous coordinates

- Linear mapping with A_{3x3} matrix
- coordinate shift with t_3 translation vector

$$M' = T_{affine} M = \begin{bmatrix} \multicolumn{3}{c}{A_{3x3}} & t_3 \\ 0 & 0 & 0 & 1 \end{bmatrix} M \qquad T_{affine} = \begin{bmatrix} a_{11} & a_{12} & a_{13} & t_x \\ a_{21} & a_{22} & a_{23} & t_y \\ a_{31} & a_{32} & a_{33} & t_z \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

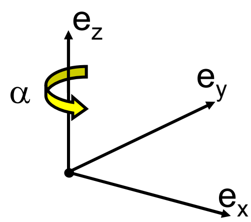
- Parallelism is preserved
- ratios of length, area, and volume are preserved
- Transformations can be concatenated:

  if $M_1 = T_1 M$ and $M_2 = T_2 M_1 \Rightarrow M_2 = T_2 T_1 M = T_{21} M$

Special transformation: Rotation

$$T_{Rotation} = \begin{bmatrix} & & & 0 \\ & R_{3x3} & & 0 \\ & & & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} = \begin{bmatrix} r_{11} & r_{12} & r_{13} & 0 \\ r_{21} & r_{22} & r_{23} & 0 \\ r_{31} & r_{32} & r_{33} & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

- Rigid transformation: Angles and lengths preserved
- R is **orthonormal matrix** defined by three angles around three coordinate axes

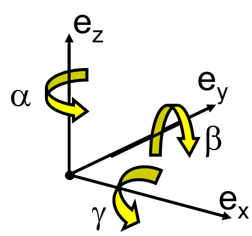


$$R_z = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Rotation with angle α around e_z

Special transformation: Rotation

- Rotation around the coordinate axes can be concatenated:



$$R = R_z R_y R_x$$

$$R_x = \begin{bmatrix} 1 & 0 & 0 \\ 0 & \cos\gamma & -\sin\gamma \\ 0 & \sin\gamma & \cos\gamma \end{bmatrix}$$

$$R_y = \begin{bmatrix} \cos\beta & 0 & \sin\beta \\ 0 & 1 & 0 \\ -\sin\beta & 0 & \cos\beta \end{bmatrix}$$

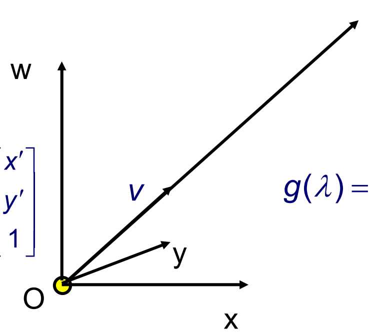
Inverse of rotation matrix is transpose:

$$R^{-1} = R^T$$

$$R_z = \begin{bmatrix} \cos\alpha & -\sin\alpha & 0 \\ \sin\alpha & \cos\alpha & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Projective geometry in 2D

- Projective space is space of rays emerging from *O*
  - view point *O* forms projection center for all rays
  - rays *v* emerge from viewpoint into scene
  - *ray g* is called projective point, defined as scaled *v*: $g=\lambda v$

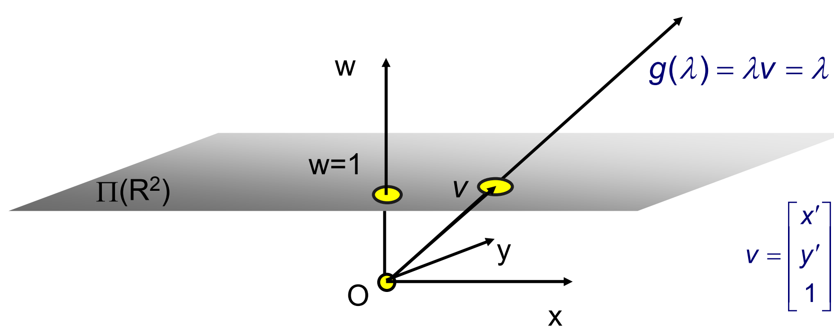


$$v = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix}$$

$$g(\lambda) = \begin{bmatrix} x \\ y \\ w \end{bmatrix} = \lambda v, \lambda \in \Re \neq 0$$

Projective and homogeneous points

- Given: Plane Π in R^2 embedded in R^3 at coordinates w=1
  - viewing ray g intersects plane at v (homogeneous coordinates)
  - all points on ray g project onto the same homogeneous point v
  - projection of g onto Π is defined by scaling $v=g/\lambda = g/w$

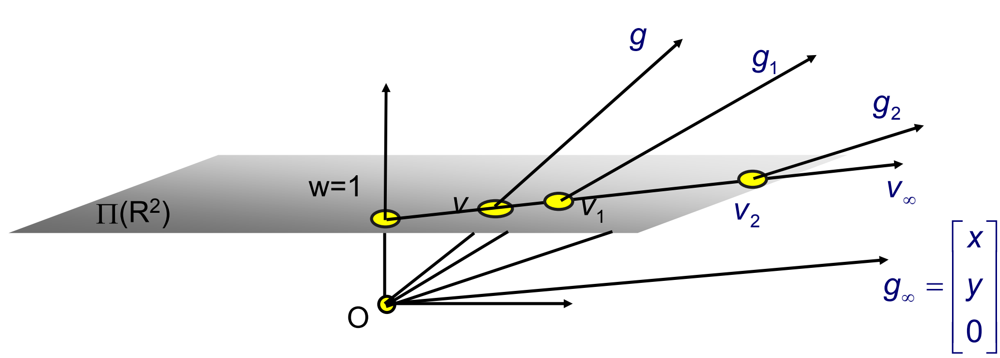


$$g(\lambda) = \lambda v = \lambda \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \begin{bmatrix} x \\ y \\ w \end{bmatrix}$$

$$v = \begin{bmatrix} x' \\ y' \\ 1 \end{bmatrix} = \frac{1}{w} g = \begin{bmatrix} \frac{x}{w} \\ \frac{y}{w} \\ 1 \end{bmatrix}$$

Finite and infinite points

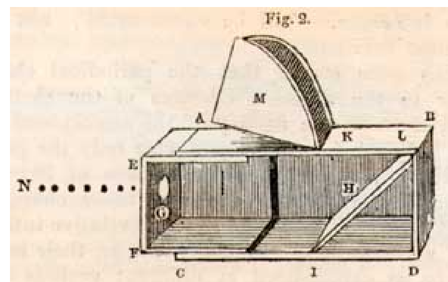
- All rays g that are not parallel to Π intersect at an affine point v on Π.
- The ray g(w=0) does not intersect Π. Hence v_∞ is not an affine point but a direction. Directions have the coordinates $(x,y,0)^T$
- Projective space combines affine space with infinite points (directions).



Pinhole Camera (Camera obscura)

Camera obscura

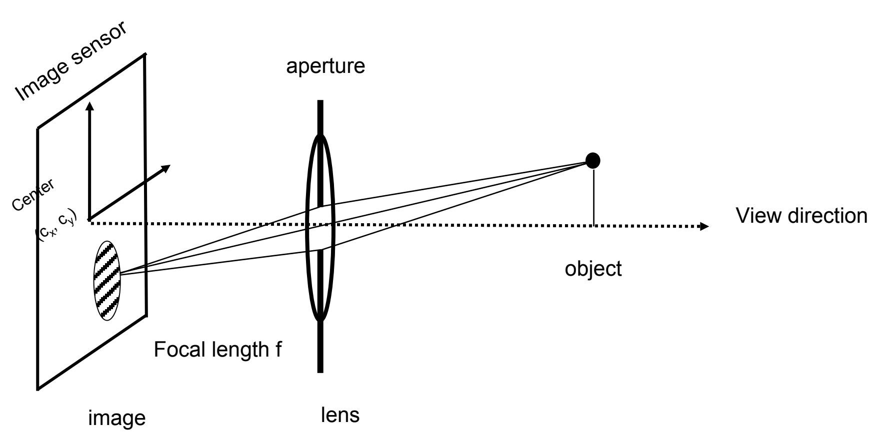
(France, 1830)



Interior of camera obscura

(Sunday Magazine, 1838)

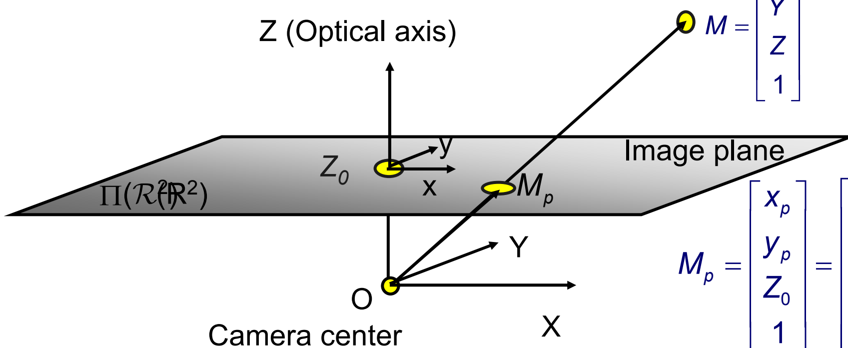
Pinhole camera model



Perspective projection

- Perspective projection models pinhole camera:
  - scene geometry is affine R^3 space with coordinates $M=(X,Y,Z,1)^T$
  - camera focal point in $O=(0,0,0,1)^T$, camera viewing direction along Z
  - image plane (x,y) in $\Pi(R^2)$ aligned with plane (X,Y) at $Z= Z_0$
  - scene point M projects onto point M_p on plane surface

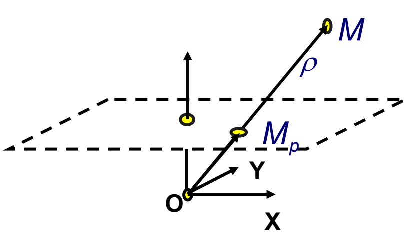
$$M = \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$



$$M_p = \begin{bmatrix} x_p \\ y_p \\ Z_0 \\ 1 \end{bmatrix} = \begin{bmatrix} \frac{Z_0 X}{Z} \\ \frac{Z_0 Y}{Z} \\ \frac{Z_0 Z}{Z} \\ 1 \end{bmatrix} = \frac{Z_0}{Z} \begin{bmatrix} X \\ Y \\ Z \\ \frac{Z}{Z_0} \end{bmatrix}$$

Projective Transformation

- Projective Transformation maps M onto M_p



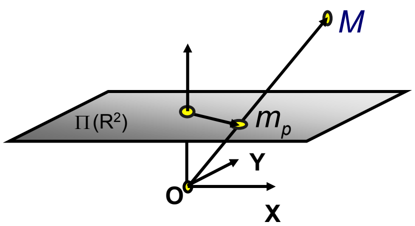
$$\rho M_p = T_p M \Rightarrow \rho \begin{bmatrix} x_p \\ y_p \\ Z_0 \\ 1 \end{bmatrix} = \begin{bmatrix} X \\ Y \\ Z \\ W \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & \frac{1}{Z_0} & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}$$

$$\rho = \frac{Z}{Z_0} = \text{projective scale factor}$$

- Projective Transformation linearizes projection

Perspective Projection

Dimension reduction from R³ into R² by projection onto Π(R²)



$$\begin{bmatrix} x_p \\ y_p \\ Z_0 \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_p \\ y_p \\ Z_0 \\ 1 \end{bmatrix}$$

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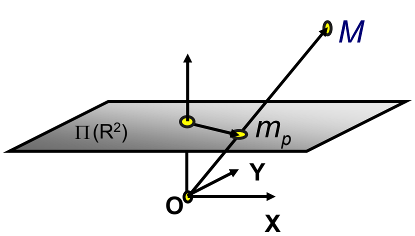
Perspective Projection

Dimension reduction from R³ into R² by projection onto Π(R²)



$$\begin{bmatrix} x_p \\ y_p \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} x_p \\ y_p \\ Z_0 \\ 1 \end{bmatrix}$$

$$\rho m_p = D_p T_p M = P_0 M \Rightarrow \rho \begin{bmatrix} x \\ y \\ 1 \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & \frac{1}{Z_0} & 0 \end{bmatrix} \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix}, \quad \rho = \frac{Z}{Z_0}$$

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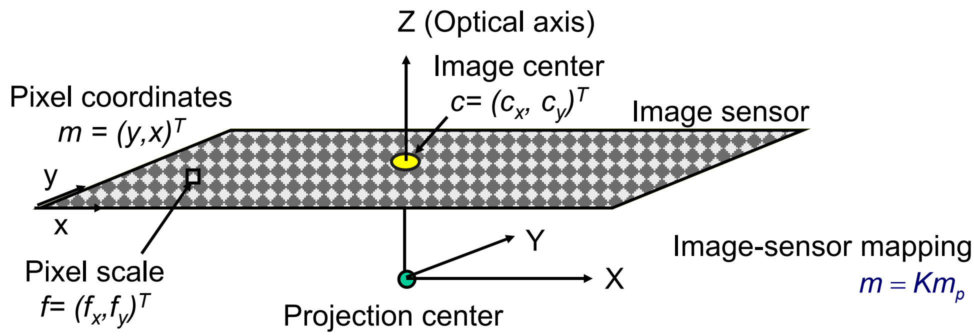
Image plane and image sensor

- A sensor with picture elements (Pixel) is added onto the image plane

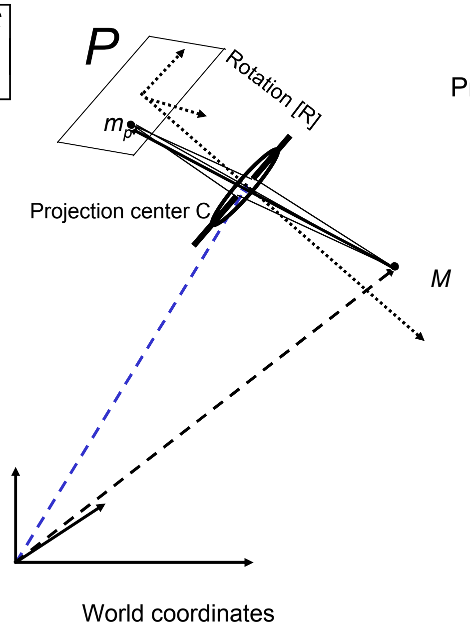


- Pixel coordinates are related to image coordinates by affine transformation *K* with five parameters:
  - Image center $c=(c_x,c_y)^T$ defines optical axis
  - Pixel size and pixel aspect ratio defines scale $f=(f_x,f_y)^T$
  - image skew s to model angle between pixel rows and columns

$$K = \begin{bmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$$

Projection in general pose

$$T_{cam} = \begin{bmatrix} R & C \\ 0^T & 1 \end{bmatrix}$$



Projection: $\rho m_p = PM$

$$T_{scene} = T_{cam}^{-1} = \begin{bmatrix} R^T & -R^T C \\ 0^T & 1 \end{bmatrix}$$

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Projection matrix P

- Camera projection matrix P combines:
  - inverse affine transformation T_{cam}^{-1} from general pose to origin
  - Perspective projection P_0 to image plane at $Z_0 = 1$
  - affine mapping K from image to sensor coordinates

scene pose transformation: $T_{scene} = \begin{bmatrix} R^T & -R^T C \\ 0^T & 1 \end{bmatrix}$

projection: $P_0 = \begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \end{bmatrix} = \begin{bmatrix} I & 0 \end{bmatrix}$ sensor calibration: $K = \begin{bmatrix} f_x & s & c_x \\ 0 & f_y & c_y \\ 0 & 0 & 1 \end{bmatrix}$

$$\Rightarrow \rho m = PM, \quad P = K P_0 T_{scene} = K\begin{bmatrix} R^T & -R^T C \end{bmatrix}$$

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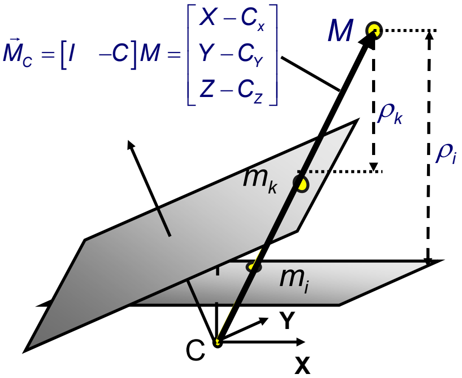
Single Viewpoint relations: rotating Camera

- Camera with fixed projection center: $C_i = C$
- Camera rotates freely with R_i and changing calibration K_i

$$\vec{M}_C = \begin{bmatrix} I & -C \end{bmatrix} M = \begin{bmatrix} X - C_x \\ Y - C_Y \\ Z - C_Z \end{bmatrix}$$



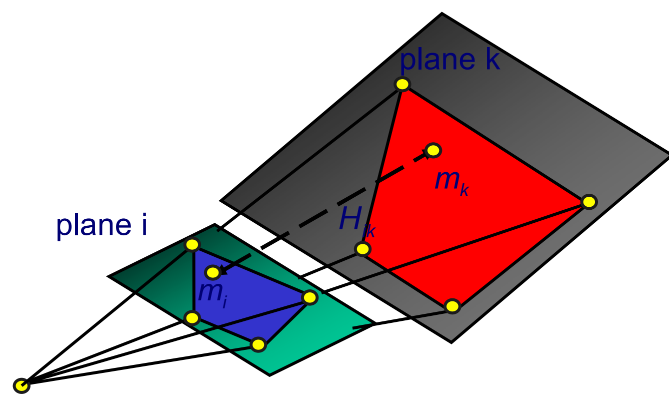
$$\rho_i m_i = P_i M = K_i \begin{bmatrix} R_i^T & -R_i^T C_i \end{bmatrix} M$$
$$= K_i R_i^T \begin{bmatrix} I & -C \end{bmatrix} M = K_i R_i^T \vec{M}_C$$
$$\rho_k m_k = K_k R_k^T \begin{bmatrix} I & -C \end{bmatrix} M = K_k R_k^T \vec{M}_C$$
$$\Rightarrow \vec{M}_C = R_i K_i^{-1} \rho_i m_i = R_k K_k^{-1} \rho_k m_k$$

$$\rho_k m_k = K_k R_k^{-1} R_i K_i^{-1} \rho_i m_i = \rho_i H_{ik} m_i$$

- H_{ik} is a planar projective 2D-transformation (3x3) that maps points m_i on plane i to points m_k on plane k

The planar homography H

- The 2D projective transformation H_{ik} is a planar homography
  - maps any point on plane i to corresponding point on plane k
  - defined up to scale (8 independent parameters)
  - defined by 4 corresponding points on the planes with not more than any 2 points collinear



$$m_k \cong H_{ik} m_i$$

$$H_{ik} \cong \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$$

Estimation of H from image correspondences

- H_{ik} can be estimated linearily from corresponding point pairs:
  - select 4 corresponding point pairs, if known noise-free
  - select N>4 corresponding point pairs, if correspondences are noisy
  - compute H such that correspondence error d is minimized

Projective mapping (linear):

$$m_k = \rho_k \begin{bmatrix} x_k \\ y_k \\ 1 \end{bmatrix} = Hm_i = \begin{bmatrix} h_1 x_i + h_2 y_i + h_3 \\ h_4 x_i + h_5 y_i + h_6 \\ h_7 x_i + h_8 y_i + h_9 \end{bmatrix}$$

Image coordinate mapping (nonlinear):

$$\rho x_k = \frac{h_1 x_i + h_2 y_i + h_3}{h_7 x_i + h_8 y_i + h_9}$$

$$\rho y_k = \frac{h_4 x_i + h_5 y_i + h_6}{h_7 x_i + h_8 y_i + h_9}$$

Error functional d:

$$d = \sum_{n=0}^{N} (m_{k,n} - H_{ik} m_{i,n})^2 \Rightarrow \min!$$

$$H_{ik} = \begin{bmatrix} h_1 & h_2 & h_3 \\ h_4 & h_5 & h_6 \\ h_7 & h_8 & h_9 \end{bmatrix}$$

Estimation of H with Direct Linear Transform (DLT)

$$m_k = \mathbf{H}\cdot m_i \Rightarrow \begin{bmatrix} x_k \\ y_k \\ w_k \end{bmatrix} = \begin{bmatrix} \mathbf{h}_1^T \cdot m_i \\ \mathbf{h}_2^T \cdot m_i \\ \mathbf{h}_3^T \cdot m_i \end{bmatrix}, \text{ with } \mathbf{H} = \begin{bmatrix} \mathbf{h}_1^T \\ \mathbf{h}_2^T \\ \mathbf{h}_3^T \end{bmatrix}$$

exploit collinearity: $m_{k,n} \times m_{k,n} = m_{k,n} \times (\mathrm{H} m_{i,n}) = \vec{0}$

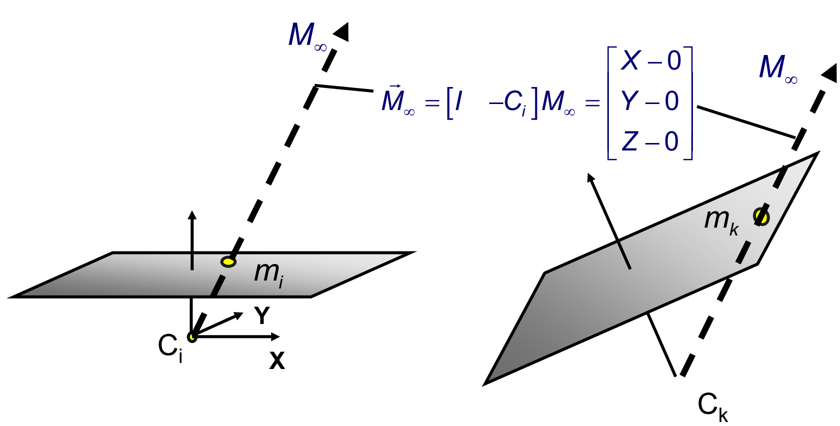
$$m_{k,n} \times \mathbf{H}\cdot m_{i,n} = \begin{pmatrix} y_{k,n}\mathbf{h}_3^T \cdot m_{i,n} - w_{k,n}\mathbf{h}_2^T \cdot m_{i,n} \\ w_{k,n}\mathbf{h}_1^T \cdot m_{i,n} - x_{k,n}\mathbf{h}_3^T \cdot m_{i,n} \\ x_{k,n}\mathbf{h}_2^T \cdot m_{i,n} - y_{k,n}\mathbf{h}_1^T \cdot m_{i,n} \end{pmatrix} = \vec{0}$$

2 linear independent Equations per correspondence pair ($m_{i,n}$, $m_{k,n}$) gives a matrix **A** with (2n x 9) entries and solution vector **h** with 9 elements of Homography H. Solution **h** is the right Nullspace of **A**.

$$\mathbf{A}\cdot\mathbf{h} = \vec{0} \quad \Rightarrow \quad \begin{bmatrix} \mathbf{0}^T & -w_{k,n}\cdot m_{i,n}^T & y_{k,n}\cdot m_{i,n}^T \\ w_{k,n}\cdot m_{i,n}^T & \mathbf{0}^T & -x_{k,n}\cdot m_{i,n}^T \\ \vdots & \ddots & \vdots \end{bmatrix}_{(2nx9)} \bullet \begin{pmatrix} \mathbf{h}_1 \\ \mathbf{h}_2 \\ \mathbf{h}_3 \end{pmatrix}_{(9)} = \vec{0}_{(2n)}$$

Homography with plane at infinity Π_∞

- All scene points are at infinity: M_∞ are points on Π_∞
- Camera rotates freely with R_i and changing calibration K_i



$$\vec{M}_\infty = R_i K_i^{-1} \rho_i m_i = R_k K_k^{-1} \rho_k m_k \qquad \Rightarrow \rho_k m_k = K_k R_k^{-1} R_i K_i^{-1} \rho_i m_i = \rho_i H_{ik} m_i$$

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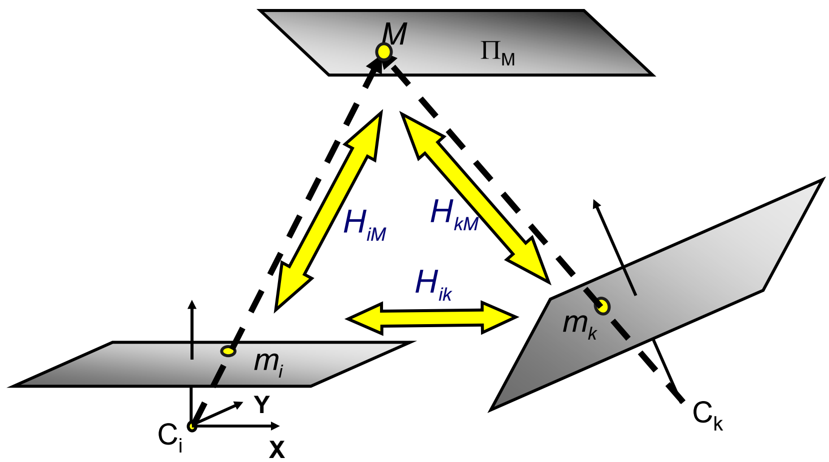
Image mapping of planar scene Π_M

- All scene points are on plane Π_M
- Camera is completely free in *K,R,C*



Transfer between images i,k over Π_M: $H_{ik} = H_{iM} H_{kM}^{-1}$

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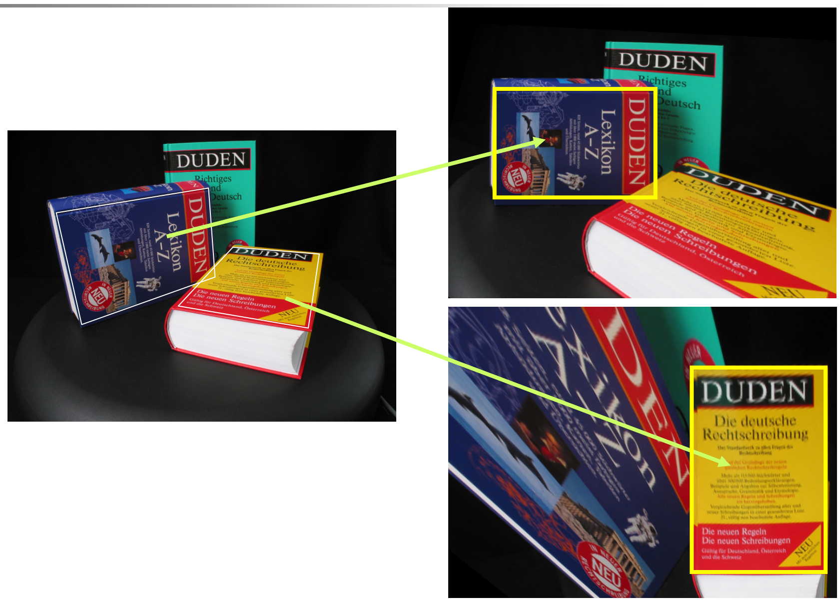
Image mapping with homographies

- Homographies are 2D projective transformations H_{3x3}
- Homographies map points between planes
- 2D homographies can be used to map images between different camera views for three equivalent cases:
  - (a) all cameras share the same view point C_i = C, or
  - (b) all scene points are at (or near to) infinity, or
  - (c) the observed scene is planar.
- Homographies are used for projective texture mapping!

Homography mapping example



From: O.Schreer: Stereoanalyse und Bildsynthese. Springer 2005.

Application: Image mosaicing

- Original images are mapped onto virtual mosaic plane
- Interpolation and blending of color values

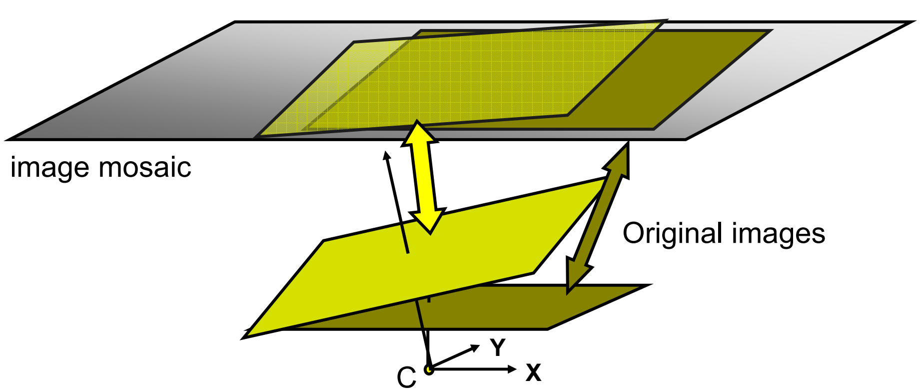
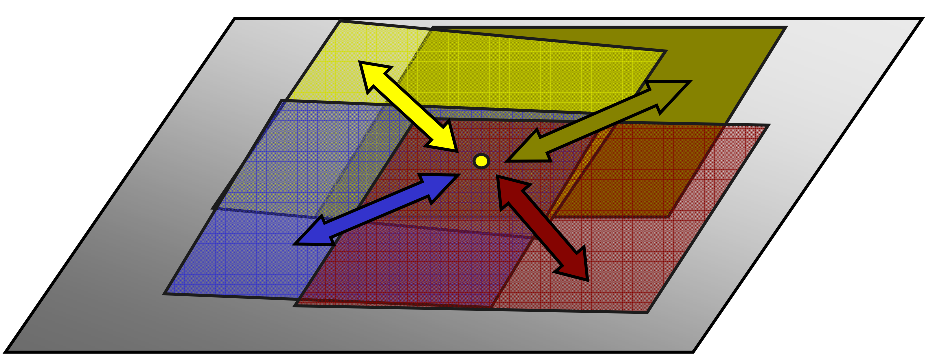


Image pair registration with homography

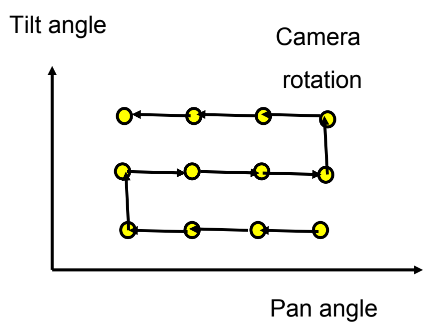
Global registration of mosaic sequence



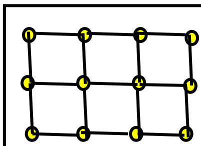
Global registration of mosaic sequence

Pan-tilt camera move

12 images



Global Registration and mapping



Full 2D-Topology

Multiview relations

- 2-view epipolar constraint
  - Uncalibrated cameras: Fundamental Matrix F
  - Calibrated cameras: Essential Matrix E
- Relative pose and structure
  - Relative pose estimation from E
  - 3D Structure triangulation
  - Pose estimation

2-view geometry: The uncalibrated F-Matrix

Projection onto two views:

$$\boxed{P_0 = K_0 R_0^T [I \quad 0]}$$

$$\rho_0 m_0 = P_0 M = K_0 R_0^T [I \quad 0] M$$

$$\Rightarrow \rho_0 m_0 = K_0 R_0^T [I \quad 0] M_\infty$$

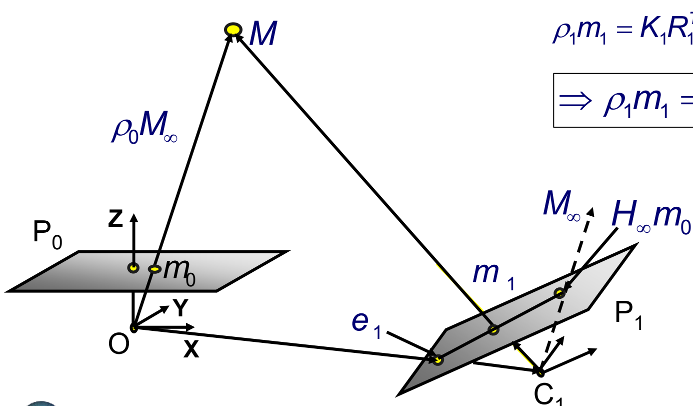
$$\boxed{P_1 = K_1 R_1^T [I \quad -C_1]}$$

$$\rho_1 m_1 = P_1 M = K_1 R_1^T [I \quad -C_1] M$$

$$= K_1 R_1^T [I \quad 0] M_\infty + K_1 R_1^T [I \quad -C_1] O$$

$$\rho_1 m_1 = K_1 R_1^T R_0 K_0^{-1} \rho_0 m_0 - K_1 R_1^T C_1$$

$$\boxed{\Rightarrow \rho_1 m_1 = \underbrace{\rho_0 H_\infty m_0 + e_1}_{\text{Epipolar line}}}$$



$$M = \begin{bmatrix} X \\ Y \\ Z \\ 1 \end{bmatrix} = \begin{bmatrix} X \\ Y \\ Z \\ 0 \end{bmatrix} + \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix} = M_\infty + O$$

The Fundamental Matrix *F*

- The projective points e_1 and $(H_\infty m_0)$ define a plane in camera 1 (epipolar plane Π_e)
- the epipolar plane intersects the image plane 1 in a line (epipolar line u_e)
- the corresponding point m_1 lies on line u_e: $m_1^T u_e = 0$
- If the points (e_1),(m_1),$(H_\infty m_0)$ are all collinear, then the colinearity theorem applies: $m_1^T (e_1 \times H_\infty m_0) = 0$.

$$\text{collinearity of } m_1, e_1, H_\infty m_0 \Rightarrow m_1^T (\underbrace{[e_1]_x H_\infty}_{F_{3x3}} m_0) = 0$$

$$[e]_x = \begin{bmatrix} 0 & -e_z & e_y \\ e_z & 0 & -e_x \\ -e_y & e_x & 0 \end{bmatrix}$$

Fundamental Matrix F

$$F = [e_1]_x H_\infty$$

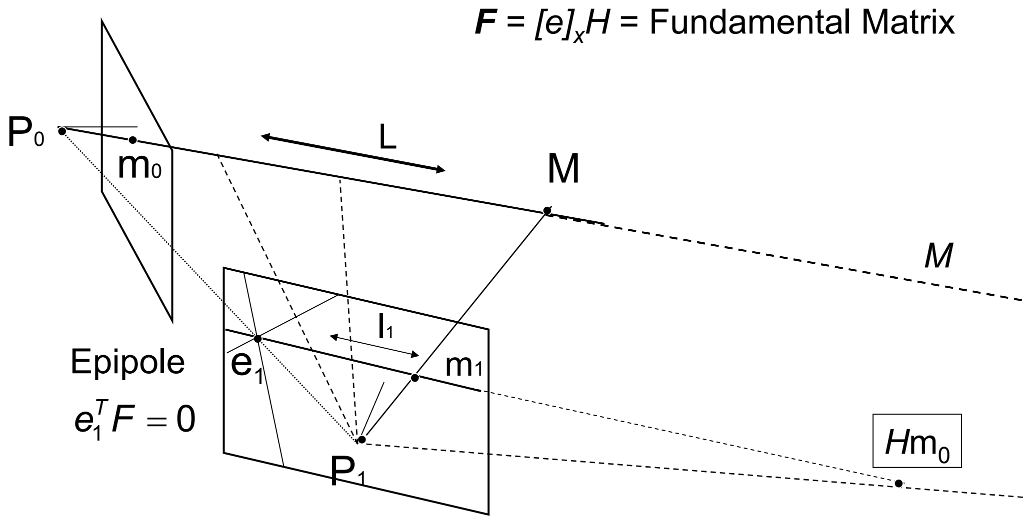
Epipolar constraint

$$m_1^T F m_0 = 0$$

The Fundamental Matrix F

$$m_1^T l_1 = 0 \qquad l_1 = F m_0 \qquad m_1^T F m_0 = 0$$

F = $[e]_x H$ = Fundamental Matrix



Estimation of *F* from image correspondences

- Given a set of corresponding points, solve linearly for the 9 elements of *F* in projective coordinates
- since the epipolar constraint is homogeneous up to scale, only eight elements are independent
- since the operator $[e]_x$ and hence *F* have rank 2, *F* has only 7 independent parameters (all epipolar lines intersect at e)
- each correspondence gives 1 collinearity constraint

=> solve F with minimum of 7 correspondences

for N>7 correspondences minimize distance point-line:

$$\sum_{n=0}^{N}(m_{1,n}^T F m_{0,n})^2 \Rightarrow \min!$$

$$m_{1i}^T F m_{0i} = 0 \qquad \det(F) = 0 \quad \text{(rank 2 constraint)}$$

Linear Estimation of F with 8-Point-Algorithm

solve F linearly with 8 correspondences using the normalized 8-point algorithm (Hartley 1995):

- normalize image coordinates of 8 correspondences for numerical conditioning
- solve the rank 8 equation **Af = 0** for the elements f_k of matrix **F**.
- apply the rank-2 constraint det(**F**)=0 as additional condition to fix epipole
- denormalize **F**.

$$\text{Foreach i = 1 to 8: } m_{1i}^T F m_{0i} = 0 \Rightarrow a_i^T \cdot f = 0$$

with $a_i = (x_{0i}x_{1i}, y_{0i}x_{1i}, w_{0i}x_{1i}, x_{0i}y_{1i}, y_{0i}y_{1i}, w_{0i}y_{1i}, x_{0i}w_{1i}, y_{0i}w_{1i}, w_{0i}w_{1i})$

and $f = (F_{11}, F_{12}, F_{13}, F_{21}, F_{22}, F_{23}, F_{31}, F_{32}, F_{33})$

$$\text{Foreach i = 1 to 8: } a_i^T \cdot f = 0 \Rightarrow A_{(8x9)} f_{(9)} = \vec{0}_{(8)}$$

The Essential Matrix *E*

- F is the most general constraint on an image pair. If the camera calibration matrix K is known, then a calibrated matrix E can be computed using normalised coordinates $Km_p = m$:

$$m_1^T F m_0 = 0 \Rightarrow (Km_{p1})^T F (Km_{p0}) = 0$$

$$\Rightarrow m_{p1}^T (K^T F K) m_{p0} = m_{p1}^T (E) m_{p0} = 0$$

$$\Rightarrow E = K^T F K$$

$$F = [e]_x H_{ik} = [e]_x (K_k R_{ik} K_i^{-1})$$

$$E = [e]_x R_{ik} \qquad \det(E) = 0, \;\; EE^T E - \frac{1}{2} trace(EE^T) E = 0$$

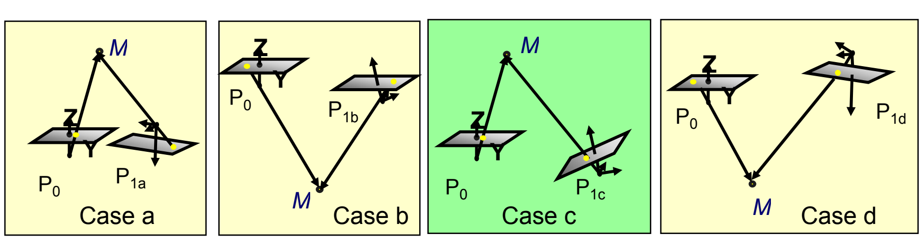
- E holds the relative orientation of a calibrated camera pair. It has 5 degrees of freedom: 3 from rotation matrix R_{ik}, 2 from direction of translation e, the epipole.
- E has a cubic constraint that restricts E to 5 dof (Nister 2004)

Relative Pose P from E

E holds the relative orientation between 2 calibrated cameras P_0 and P_1:

$$E = [e]_x R \Leftrightarrow P_0 = [I_{3x3} \quad 0_3], \;\; P_1 = [R \quad e]$$

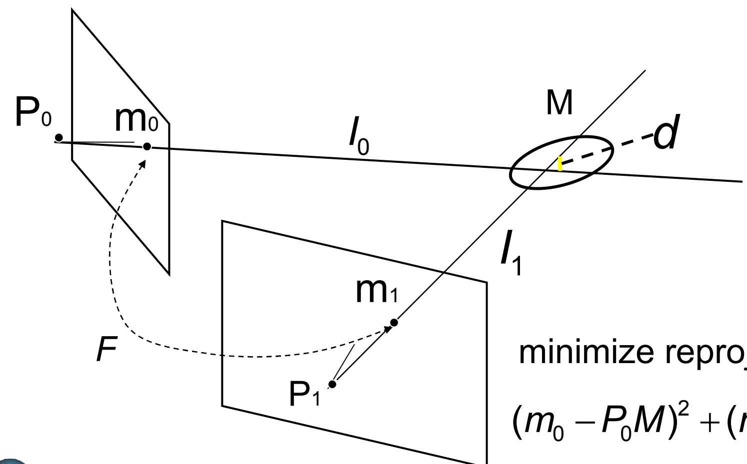
Given $\mathbf{P_0}$ as coordinate frame, the relative orientation of $\mathbf{P_1}$ is determined directly from **E** up to a 4-fold rotation ambiguity ($\mathbf{P_{1a}}$ - $\mathbf{P_{1d}}$). The ambiguity is resolved by correspondence triangulation: The 3D point **M** of a corresponding 2D image point pair must be in front of both cameras. The epipolar vector **e** has norm 1.



Relative Pose from E and correspondence: Case c is correct relative pose in this case

3D Structure Triangulation

- 3D Structure triangulation by intersection of rays from (m_0, m_1)
- M is reconstructed from rays (l_0, l_1)
- M has minimum distance of intersection between rays



$\|d\|^2 \Rightarrow \text{min!}$

constraints:

$l_0^T d = 0$

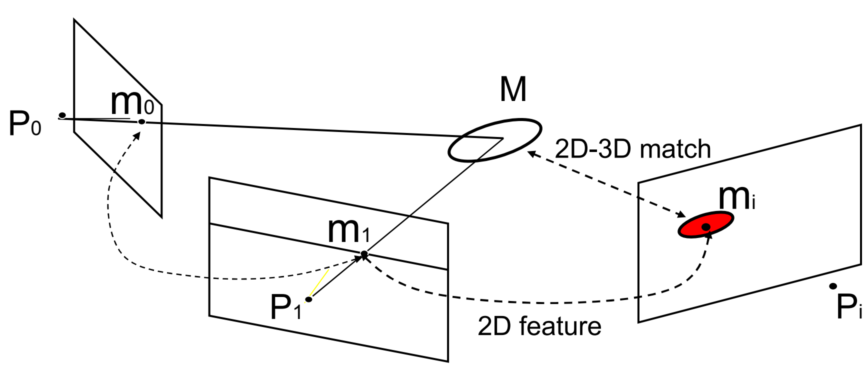
$l_1^T d = 0$

minimize reprojection error:

$(m_0 - P_0 M)^2 + (m_1 - P_1 M)^2 \Rightarrow \text{min.}$

Camera Pose from 2D-3D correspondences

- 3D point M from triangulation of 2D correspondences
- 2D feature tracking from image 1 to image i
- 3D Pose estimation of P_i with m_i - P_i M => min. with DLT



Minimize global reprojection error: $\sum_{i=0}^{N}\sum_{k=0}^{K}\|m_{k,i} - P_i M_k\|^2 \Rightarrow \text{min!}$

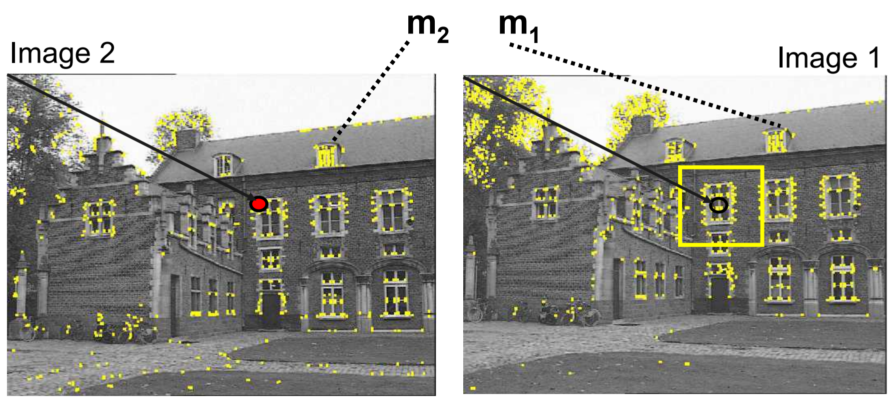
Gold Standard Methods for F,E,H,P,M

- Gold standard methods are the best method, given a specific noise model (e.g. Gaussian noise on correspondences yields a Maximum Likelhood estimate)
- Gold standard methods are in general nonlinear optimizations that yield the unbiased minimum reprojection error
- The Gold standard methods are initialized with the linear projective estimates (DLT) of the entity (F,E,H,P,M) as described before
- The Gold standard is in general slow, but fast approximations exist. All (nonlinear) constraints are directly exploited.

Structure from motion: an example

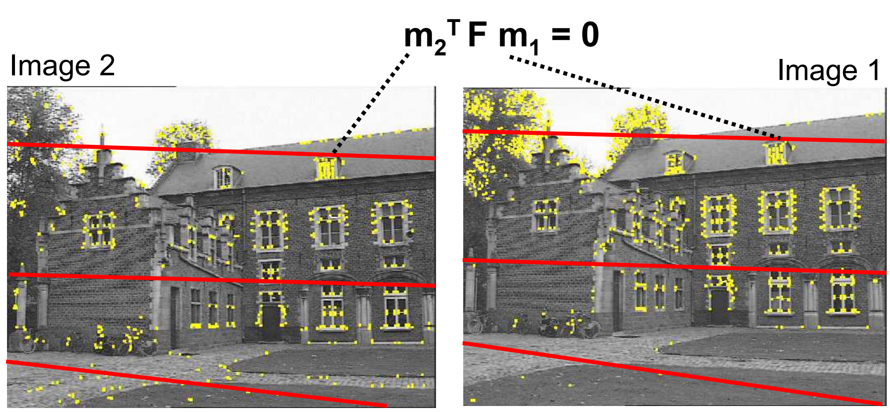
Image Sequence

Extraction of image features



- features $\mathbf{m}_{1,2}$ (Harris Cornerdetector)
- Select candidates (based on similarity)
- Test candidates

Estimation of Fundamental Matrix



Robust correspondence selection $\mathbf{m}_1$ **<->** $\mathbf{m}_2$
Estimation of F (or E) from correspondences

Camera Pose and 3D structure estimation

Reconstruction of 3D features and cameras

Multiview relations: Summary

- Projective formulation linearizes multiview relations
- linear estimators yield good starting values
- Gold standard (nonlinear optimization) for optimum estimates
- Camera pose tracking and structure computation

- Practical implementation issues:
  - robust estimators
  - outlier handling
  - realtime implementations

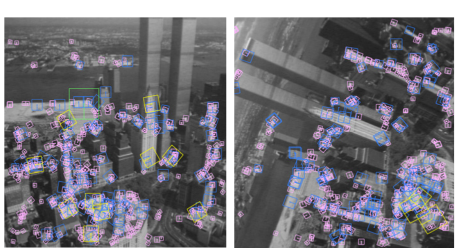
Schedule

- Introduction
- Multi-view Relations
- Feature Tracking
- Coffee Break
- Robust pose estimation
- 3D Modeling and Visualisation
- Applications

Correspondences matching vs. tracking

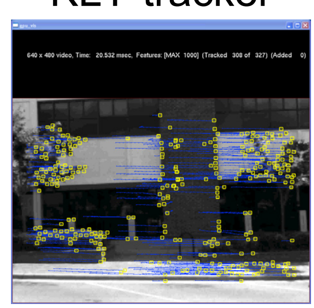
- Image-to-image correspondences are essential to 3D reconstruction

SIFT-matcher



Extract features independently and then match by comparing descriptors [Lowe 2004]

KLT-tracker



Extract features in first images and find same feature back in next view [Lucas & Kanade 1981] , [Shi & Tomasi 1994]

- Small difference between frames
- potential large difference overall

Optical flow

- Brightness constancy assumption

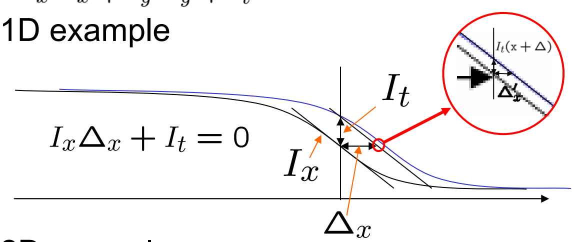
$$I(x+\Delta_x, y+\Delta_y, t+1) = I(x,y,t)$$

$$I(x+u, y+v, t+1) = I(x,y,t) + I_x\Delta_x + I_y\Delta_y + I_t \quad \text{(small motion)}$$

$$I_x\Delta_x + I_y\Delta_y + I_t = 0$$

- 1D example

$$I_x\Delta_x + I_t = 0$$



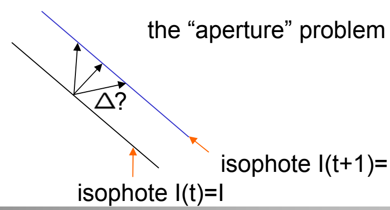
futher iterative refinement possible

- 2D example

$$I_x\Delta_x + I_y\Delta_y + I_t = 0$$

(1 constraint)

Δ_x, Δ_y (2 unknowns)



Optical flow

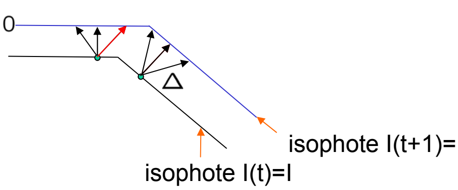
- How to deal with aperture problem?
  - 3 constraints if color gradients are different

$$R_x\Delta_x + R_y\Delta_y + R_t = 0$$
$$G_x\Delta_x + G_y\Delta_y + G_t = 0$$
$$B_x\Delta_x + B_y\Delta_y + B_t = 0$$

- Assume neighbors have same displacement

$$I_x(\mathrm{x})\Delta_x + I_y(\mathrm{x})\Delta_y + I_t(\mathrm{x}) = 0$$
$$I_x(\mathrm{x}')\Delta_x + I_y(\mathrm{x}')\Delta_y + I_t(\mathrm{x}') = 0$$

$$I_x\Delta_x + I_y\Delta_y + I_t = 0$$



Lucas-Kanade

- Assume neighbors have same displacement

$$I_x(\mathrm{x})\Delta_x + I_y(\mathrm{x})\Delta_y + I_t(\mathrm{x}) = 0$$
$$I_x(\mathrm{x}')\Delta_x + I_y(\mathrm{x}')\Delta_y + I_t(\mathrm{x}') = 0$$

least-squares:

$$\begin{bmatrix} I_x(\mathrm{x}) & I_y(\mathrm{x}) \\ I_x(\mathrm{x}) & I_y(\mathrm{x}) \\ I_x(\mathrm{x}) & I_y(\mathrm{x}) \end{bmatrix} \Delta = \begin{bmatrix} -I_t(\mathrm{x}) \\ -I_t(\mathrm{x}') \\ -I_t(\mathrm{x}'') \end{bmatrix} \qquad \mathbf{A}\Delta = \mathbf{b}$$

$$\left(\sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} \begin{bmatrix} I_x & I_y \end{bmatrix}\right) \Delta = -\sum \begin{bmatrix} I_x \\ I_y \end{bmatrix} I_t \qquad \mathbf{A}^\top \mathbf{A} \Delta = \mathbf{A}^\top \mathbf{b}$$

$$\Delta = (\mathbf{A}^\top \mathbf{A})^{-1} \mathbf{A}^\top \mathbf{b}$$

Revisiting the small motion assumption

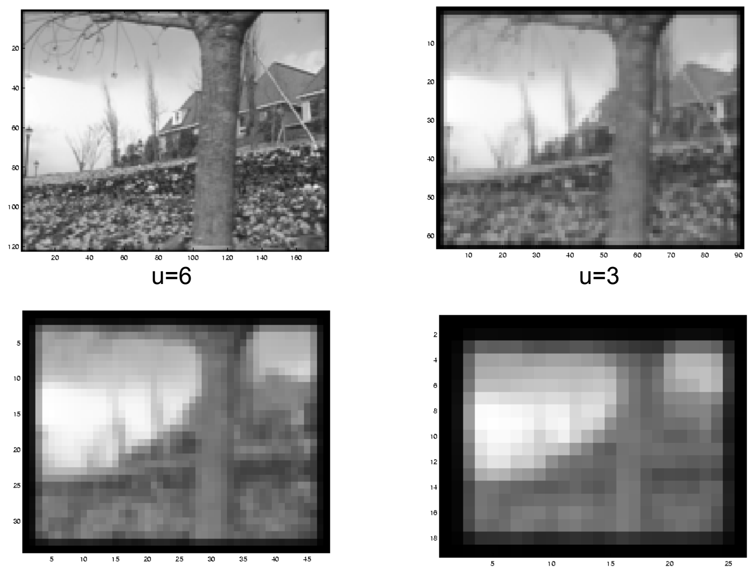
Is this motion small enough?

Most likely not—it's much larger than one pixel (not linear)

Solution?

* From Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Reduce the resolution with Gaussian Pyramid!



u=6 u=3

u=1.5 u=0.75

*images from Khurram Hassan-Shafique CAP5415 Computer Vision 2003

Good feature to track

- Tracking

$$\left(\iint_W \begin{bmatrix}\frac{\partial I}{\partial x}\\ \frac{\partial I}{\partial y}\end{bmatrix}\begin{bmatrix}\frac{\partial I}{\partial x} & \frac{\partial I}{\partial y}\end{bmatrix} w(x,y)\mathrm{d}x\mathrm{d}y\right)\Delta = \iint_W \begin{bmatrix}\frac{\partial I}{\partial x}\\ \frac{\partial I}{\partial y}\end{bmatrix}(J-I)w(x,y)\mathrm{d}x\mathrm{d}y$$

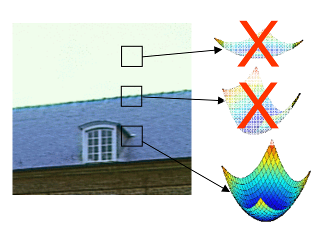
- Use same window in feature selection as for tracking itself

$$\mathrm{M} = \iint_W \begin{bmatrix}\frac{\partial I}{\partial x}\\ \frac{\partial I}{\partial y}\end{bmatrix}\begin{bmatrix}\frac{\partial I}{\partial x} & \frac{\partial I}{\partial y}\end{bmatrix} w(x,y)\mathrm{d}x\mathrm{d}y$$

maximize minimal eigenvalue of M

Strategy:

- Look for strong well distributed features, typically few hundreds
- initialize and then track, renew feature when too many are lost



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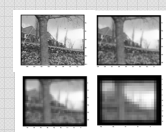
KLT-Tracking Flow



Build-Pyramids

- build intensity pyramids from images ***I* , *J***
- build and gradient

Track

For all pyramid levels from coarse to fine
 For each feature ***f***
  For multiple iterations
  solve tracking equation **A d = b**
   evaluate **d** and update track of feature

If (replace needed)

Re-select-Features

mask = mask_out_region (***ft_list***)
c_map = evaluate cornerness measure ***c*** over whole image
// Perform non-maximal suppression
pts = find_features (***#max_feats***, ***mask***, sort (***c_map***))
add_new_features (***ft_list***, ***pts***)

3D Camera Tracking, Reconstruction and View Synthesis at interactive frame rates

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Results

3D Camera Tracking, Reconstruction and View Synthesis at interactive frame rates

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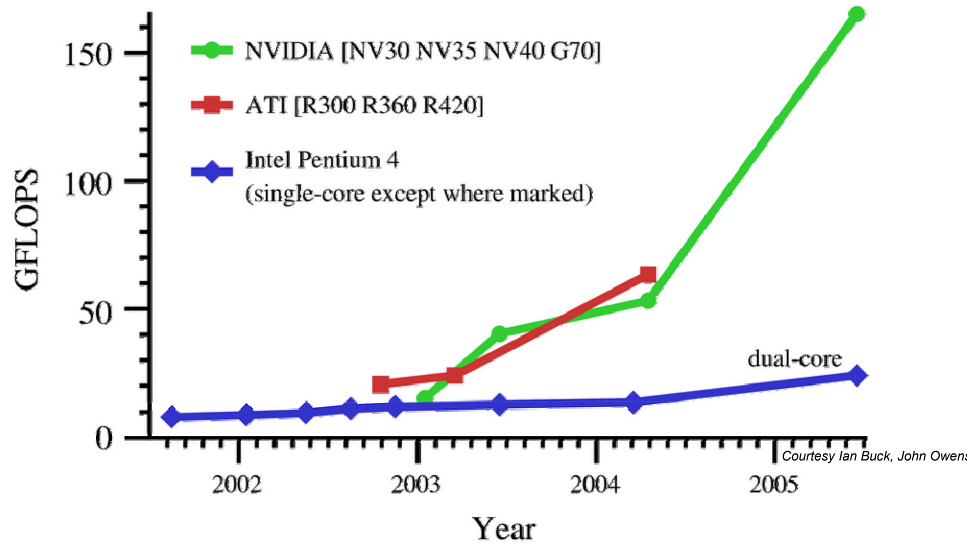
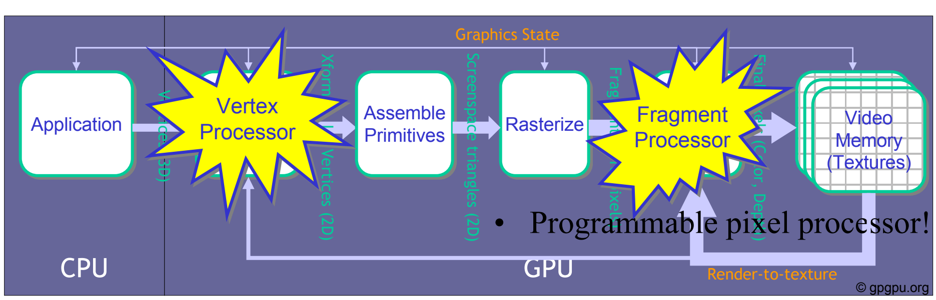
GP-GPU



GPU

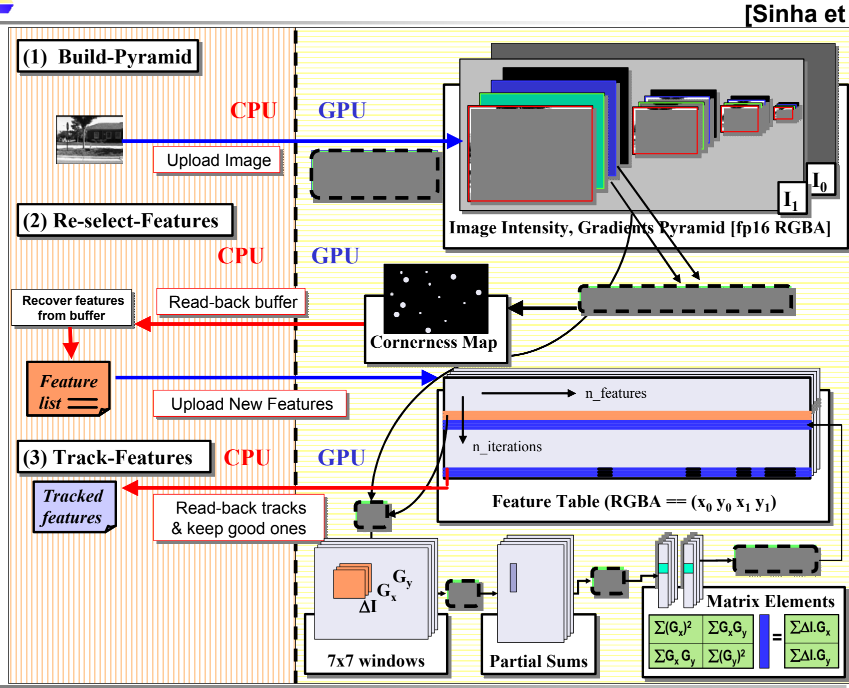


- Programmable pixel processor!

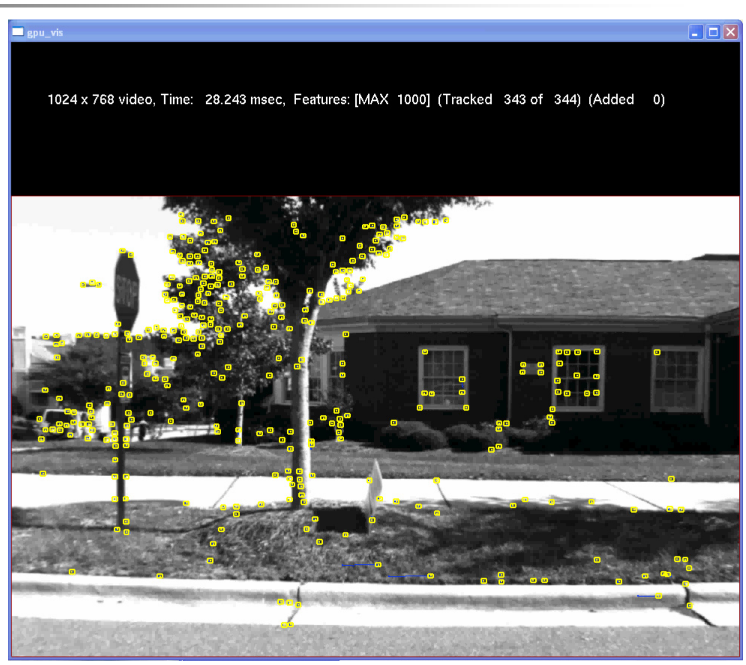
- Programmable vertex processor!

GPU-KLT

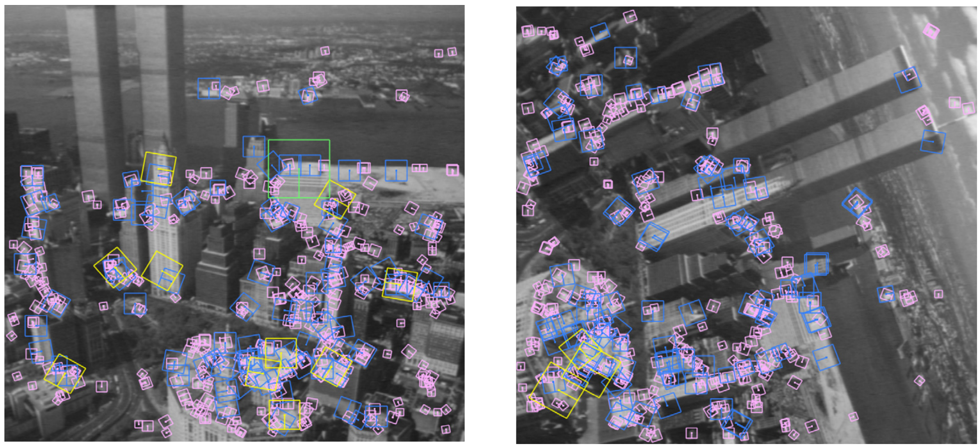
[Sinha et al. 2006]



Results KLT-tracking

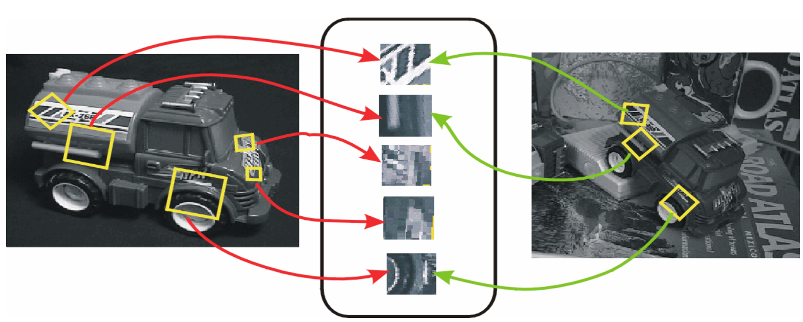


SIFT-detector



SIFT-detector

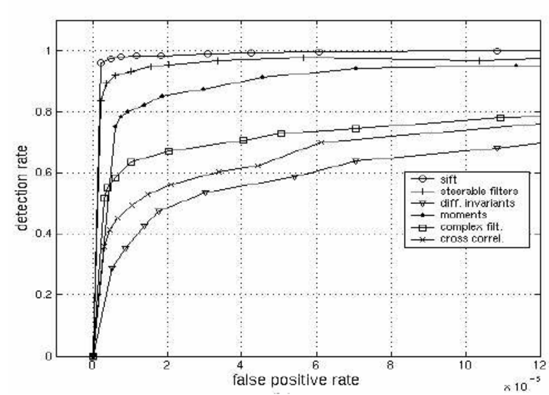
- Scale and image-plane-rotation invariant feature descriptor [Lowe 2004]
  - Image content is transformed into local feature coordinates that are invariant to translation, rotation, scale, and other imaging parameters



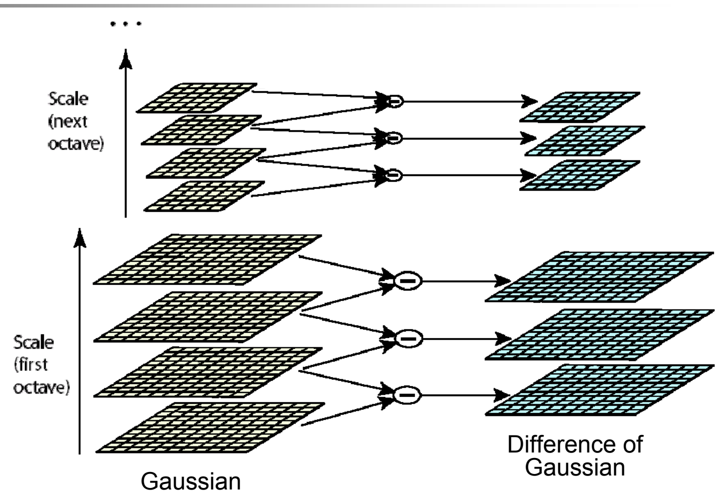
SIFT-detector

- Empirically found to perform very good **[Mikolajczyk 2003]**

Scale = 2.5
Rotation = 45^0

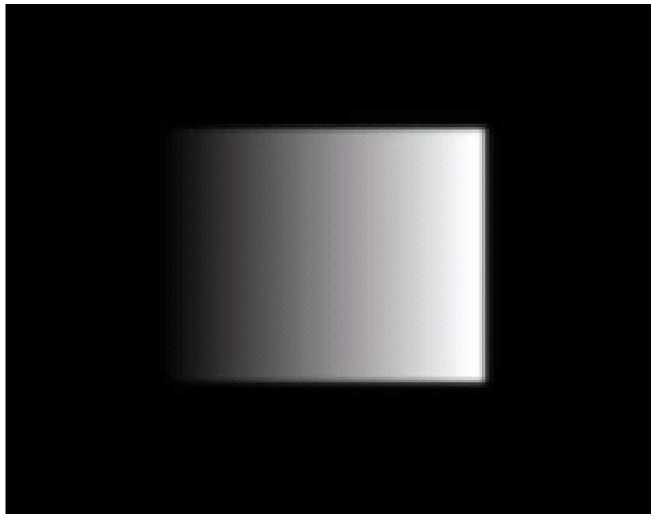


Difference of Gaussian for Scale invariance



- Difference-of-Gaussian with constant ratio of scales is a close approximation to Lindeberg's scale-normalized Laplacian [Lindeberg 1998]

Difference of Gaussian for Scale invariance



- Difference-of-Gaussian with constant ratio of scales is a close approximation to Lindeberg's scale-normalized Laplacian [Lindeberg 1998]

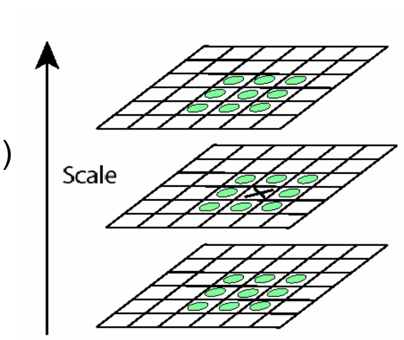
Key point localization

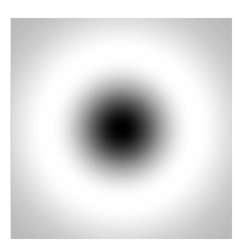
- Detect maxima and minima of difference-of-Gaussian in scale space
- Fit a quadratic to surrounding values for sub-pixel and sub-scale interpolation (Brown & Lowe, 2002)
- Taylor expansion around point:

$$D(\mathbf{x}) = D + \frac{\partial D^T}{\partial \mathbf{x}} \mathbf{x} + \frac{1}{2} \mathbf{x}^T \frac{\partial^2 D}{\partial \mathbf{x}^2} \mathbf{x}$$

- Offset of extremum (use finite differences for derivatives):

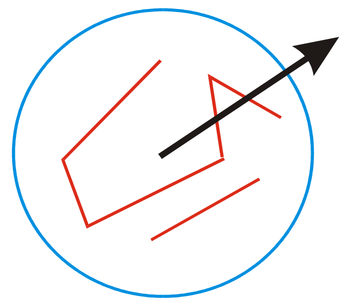
$$\hat{\mathbf{x}} = -\frac{\partial^2 D}{\partial \mathbf{x}^2}^{-1} \frac{\partial D}{\partial \mathbf{x}}$$

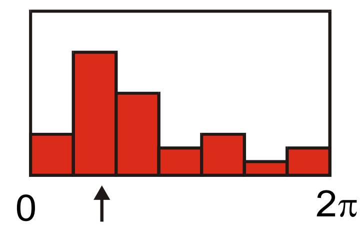




Orientation normalization

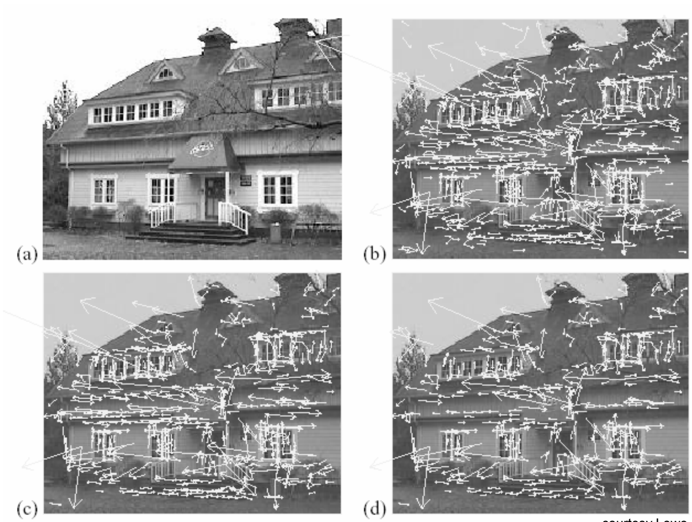
- Histogram of local gradient directions computed at selected scale
- Assign principal orientation at peak of smoothed histogram
- Each key specifies stable 2D coordinates (x, y, scale, orientation)





Example of keypoint detection

Threshold on value at DOG peak and on ratio of principle curvatures (Harris approach)

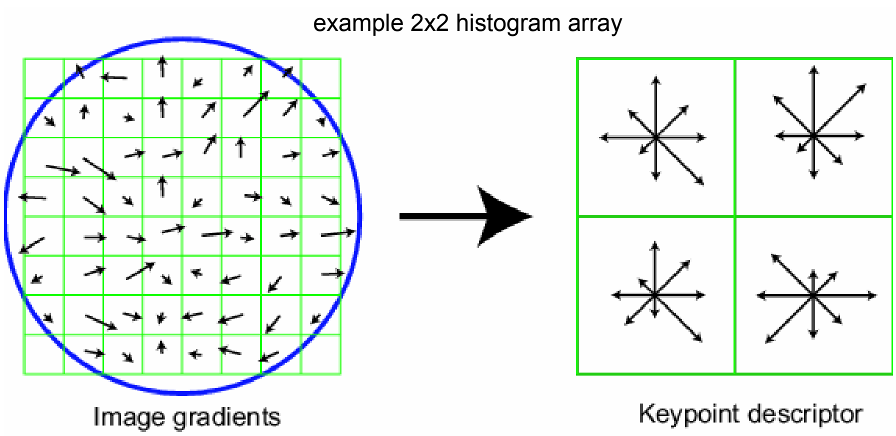


(a) 233x189 image
(b) 832 DOG extrema
(c) 729 left after peak value threshold
(d) 536 left after testing ratio of principle curvatures

3D Camera Tracking, Reconstruction and View Synthesis at interactive frame rates
C A U

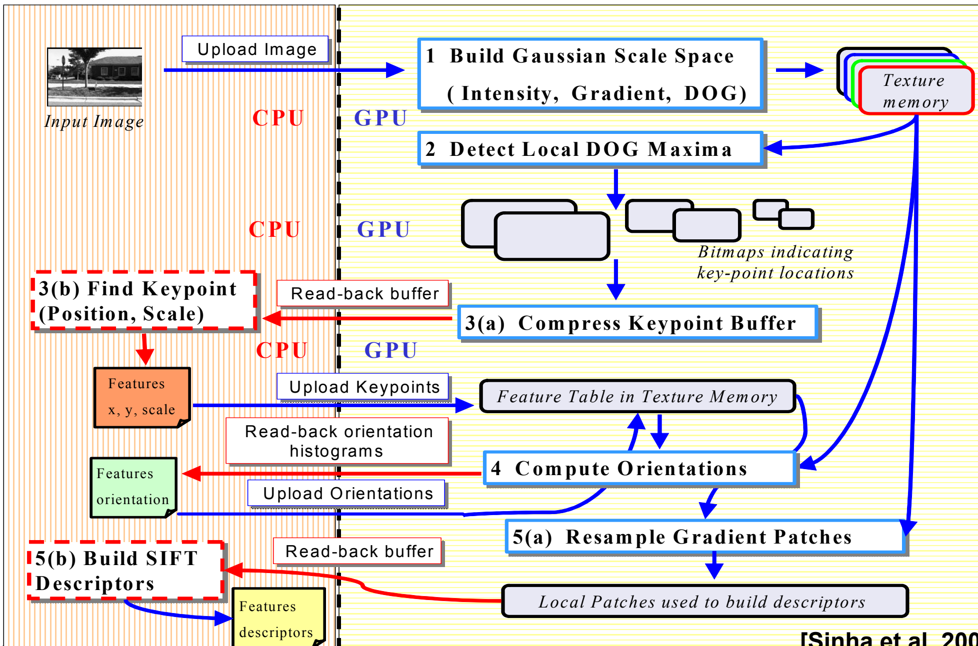
SIFT vector formation

- Thresholded image gradients are sampled over 16x16 array of locations in scale space
- Create array of orientation histograms
- 8 orientations x 4x4 histogram array = 128 dimensions



Sift feature detector

GPU-SIFT-detector



[Sinha et al. 2006]

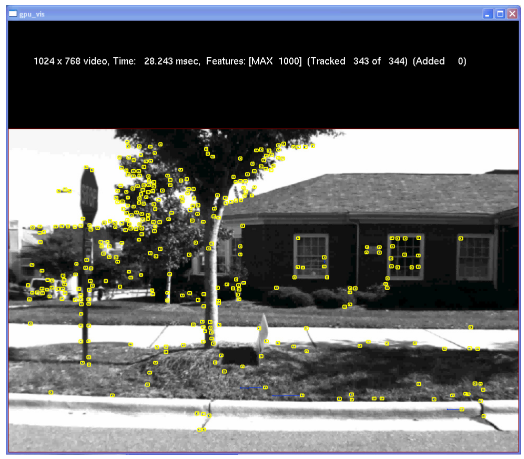
Coffee Break

Please be back at 15:40.

Robust pose estimation

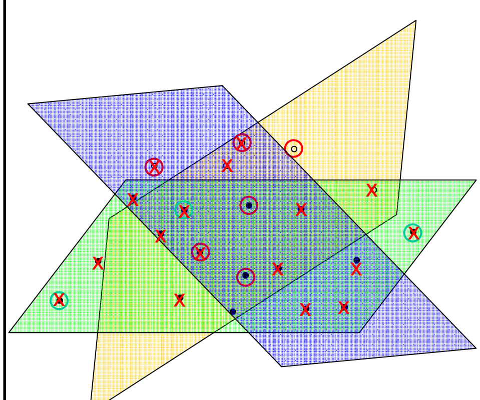
- Problem: 2D Feature tracking is not perfect!

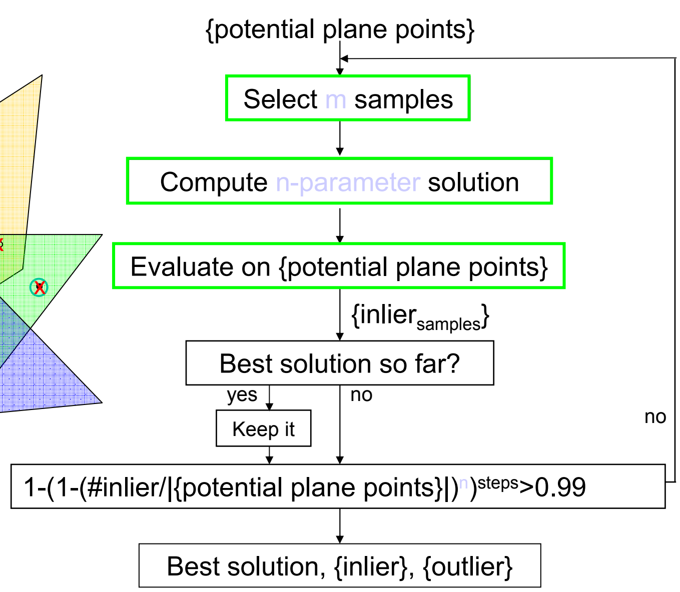
❾ data selection needed



Robust data selection: RANSAC

- Estimation of plane from point data

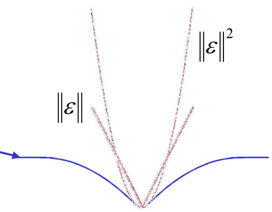


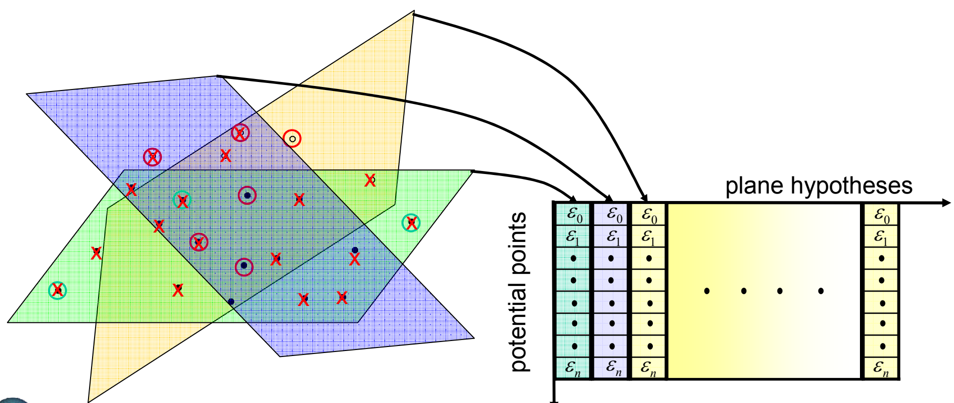


RANSAC: Evaluate Hypotheses

- Evaluate cost function

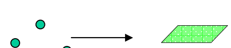
$$\rho = \begin{cases} \lambda^2\varepsilon^2 & 0 \le \lambda^2\varepsilon^2 \le \frac{c}{1+c} \\ 2\lambda\|\varepsilon\|\sqrt{c+c^2} - c\left(1+\lambda^2\varepsilon^2\right) & \text{if } \frac{c}{1+c} \le \lambda^2\varepsilon^2 < \frac{1+c}{c} \\ 1 & \text{else} \end{cases}$$



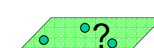


RANSAC Adaptive Stopping

Hypothesis Generator

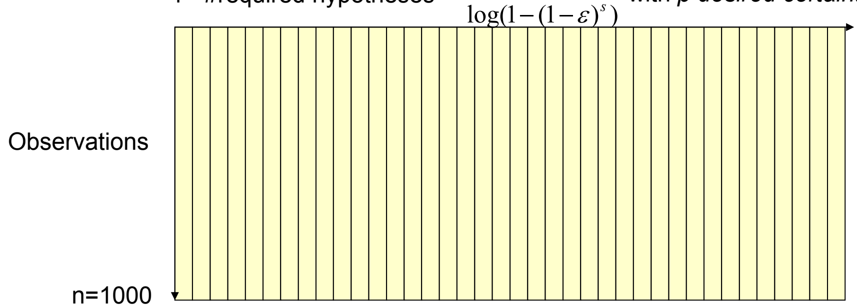


Observation Likelihood correct sample



$P_s = 1-\left(1-\varepsilon_d^s\right)^S$ with ε_d inlier fraction

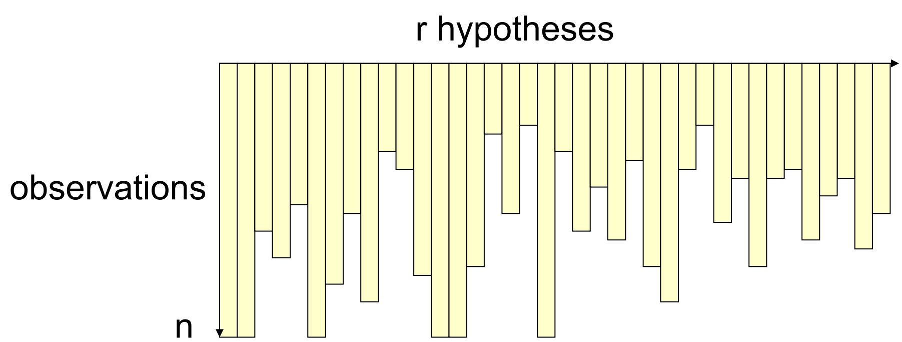
r= #required hypotheses $= \dfrac{\log(1-p)}{\log(1-(1-\varepsilon)^s)}$ with *p desired certainty*



r x n cost function evaluations for example r =500: 500 x 1000 = 500K

Preemptive RANSAC

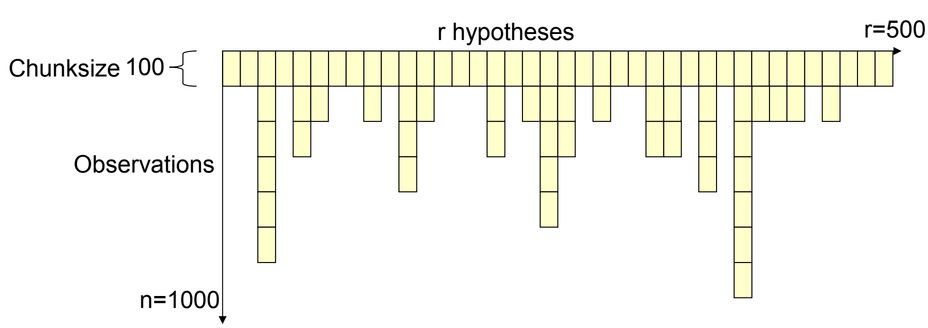
Depth-first Preemption



r x ???? = ???????

Preemptive RANSAC

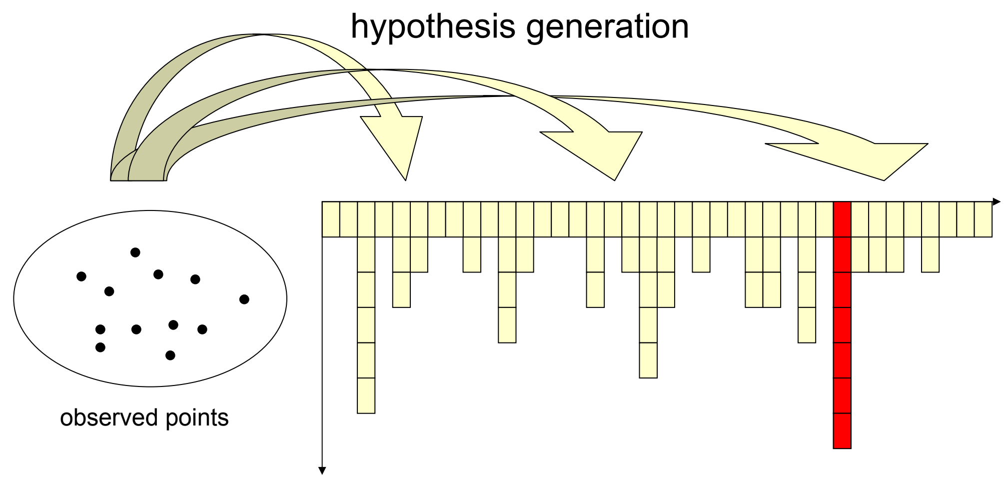
Breadth-first Preemption [Nister 2003]



500 x 200 = 100.000

Overhead ~100 microseconds

Preemptive RANSAC



Total Time for Preemptive RANSAC:

r * hypothesis generator+ 2*r*chunk size * observation likelihood

(+Iterative Refinement)

Robust Pose Estimation Calibrated Camera

Bootstrap

{2D-2D correspondences}
↓
E-RANSAC(5-point algorithm)
↓ E
Estimate P_0,P_1
↓ P_0,P_1
nonlinear refinement with all inliers
↓ P_0,P_1
triangulate points

known 3D points

{2D-3D correspondences}
↓
RANSAC(3-point algorithm)
↓ P_3
nonlinear refinement with all inliers
↓ P_3

RANSACs

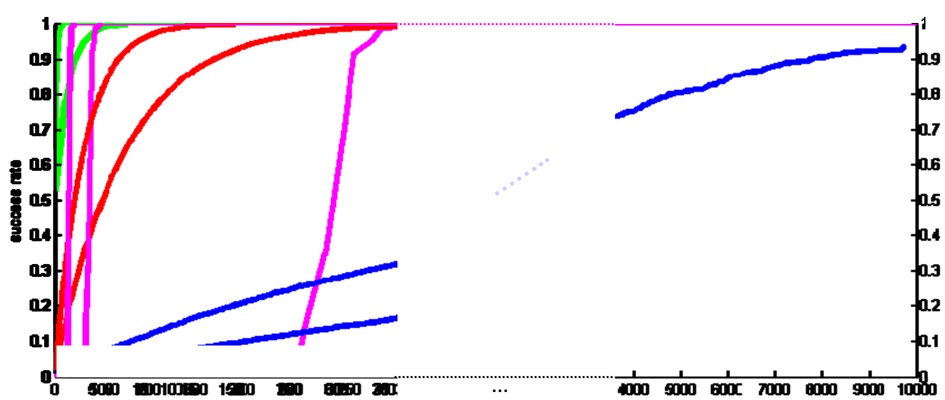
- Fast RANSACs
  - WaldSAC – Optimal Randomised RANSAC **[WaldSAC 2005]**
  - PROSAC - Progressive Sampling and Consensus **[Prosac 2005]**
  - LO-RANSAC – Locally optimized RANSAC **[LO-RANSAC 2003]**

- RANSACs for (Quasi-)degenerate data
  - DEGENSAC –Epipolar geometry for quasi-degenerate data **[DEGENSAC 2005]**
  - QDEGSAC – RANSAC for (quasi-)degenerate data **[QDEGSAC 2006]**

Problem

$P_s = 1-\left(1-\varepsilon_d^8\right)^S$ with $\varepsilon_d = 0.9$

$P_s = 1-\left(1-\sum_{j=0}^{6}\binom{m}{j}\varepsilon_d^j\left(\varepsilon-\varepsilon_d\right)^{m-j}\right)^S = 1-\left(1-0.02\right)^S$



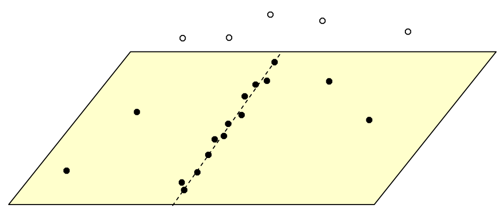
- Theoretical success rate RANSAC
- Real success rate RANSAC
- Theoretical success rate RANSAC with true probability
- Success rate QDEGSAC

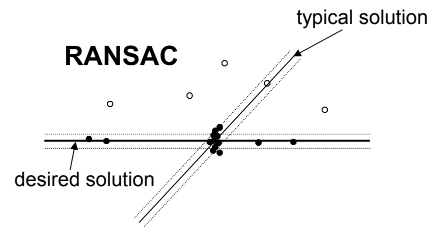
RANSAC for quasi-degenerate data

[Frahm and Pollefeys 2006]

- Robust estimation for (quasi-)degenerate data configurations

  Example: points on plane, but mostly on line

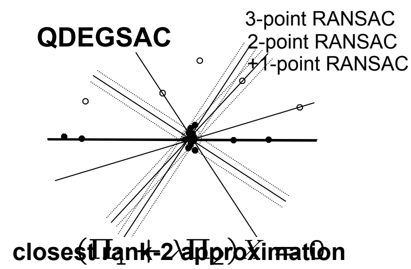




Robust rank estimation of data-matrix

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

(i.e. large % of rows approx. fit in a lower dim. subspace)
(works for any linear estimation problem)



Schedule

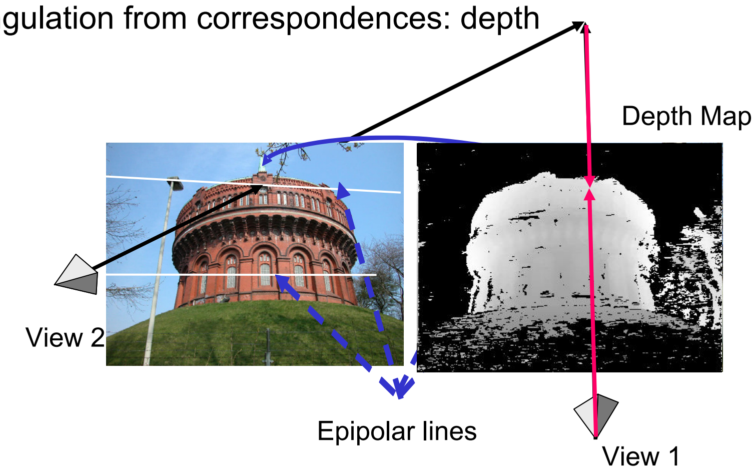
- Introduction
- Multi-view Relations
- Feature Tracking
- Coffee Break
- Robust pose estimation
- 3D Modeling and Visualisation
- Applications

3D Modelling & Visualisation

- Dense Surface Reconstruction
  - Plane Sweep multiview stereo
  - Mesh creation
- Visualisation
  - Single Model
  - Multiple local model
  - Plane Sweep view interpolation

Dense Depth Estimation

- Required: Calibration for all views
- pairwise: correspondence search along epipolar lines
- triangulation from correspondences: depth



Known Stereo Algorithms

- Multiview Stereo results [http://vision.middlebury.edu/mview]
  - Dino, Sparse Ring, 16 images, comparable quality, normalized @3GHz
    - Furukawa UIUC 2006: 360 min
    - Hernandez CVIU 2004: 106 min
    - Pons CVPR 2005: 3 min
    - Vogiatzis CVPR 2005: 40 min
- (Near-) Interactive
  - [Woetzel, Koch 04] 4 images 1280x960: 760 ms
  - UNC Plane Sweep
- Here only: Plane Sweep Multiview Stereo

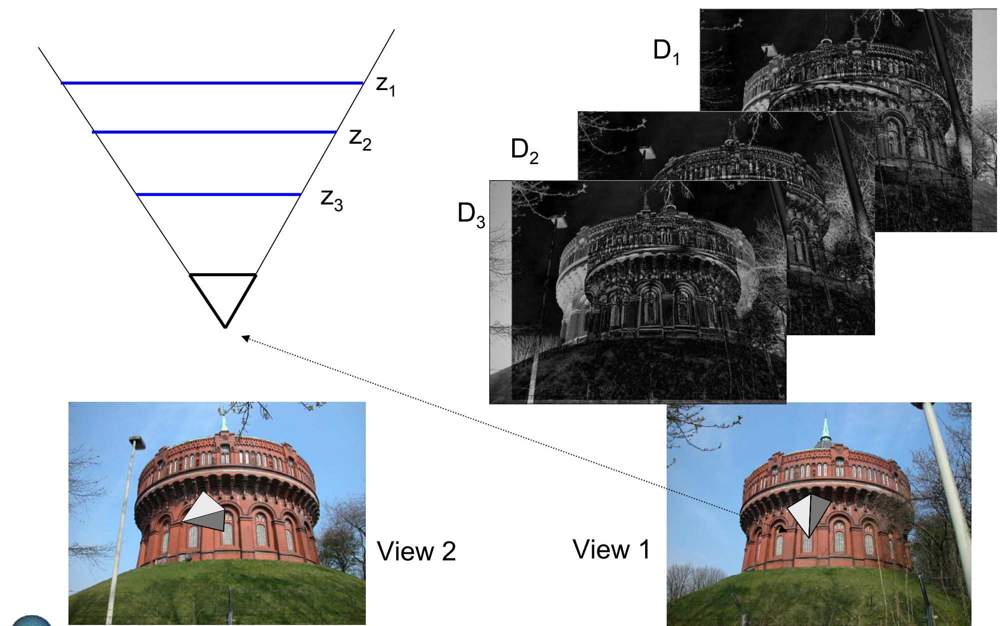
Correspondence Search

- Classic stereo
  - for each pixel x in I_1
    - for each pixel y on epipolar line in I_2
      - compute similarity of regions around x and y
      - similarity function: SAD, SSD, NCC, ...
    - chose correspondence with maximum similarity
    - add some constraints

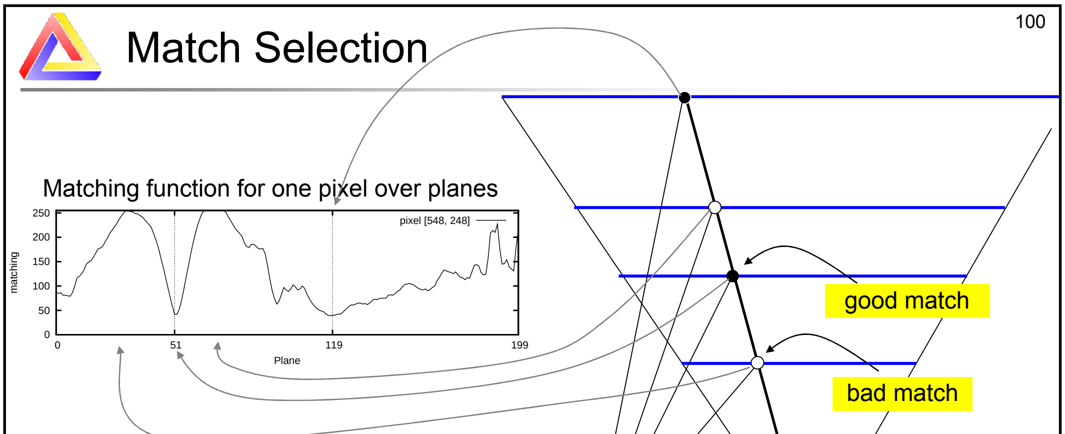
SAD: Sum of Absolute Differenes
SSD: Sum of Squared Differences
NCC: Normalized Cross Correlation

- Plane Sweep Stereo [Collins 96]
  - for planes with distance z_i coplanar to I_1
    - project I_1 and I_2 onto plane
    - compute similarity image D_i from projected I_1 and I_2 ($D_i = || I_1 - I_2 ||$)
  - per pixel: chose maximum over all similarity images
- Plane Sweep: Perfectly suited for GPU usage [Yang, Welch, Bishop, 02]

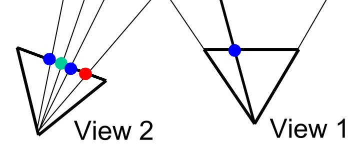
Plane Sweep Stereo



Match Selection



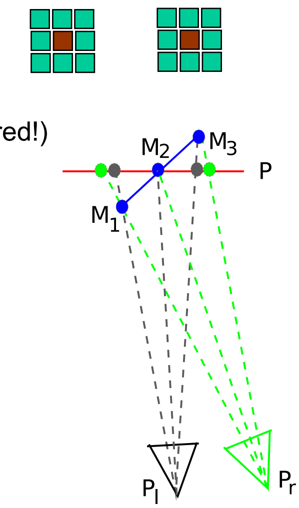
- for each plane
  - Compute matching SSD = $(I_1-I_2)^2$



- Chose minimum dissimilarity as best match
- Avoid multiple minima

Region Matching

- Block Matching (SSD, SAD)
  - possible but expensive on GPU
  - 3x3: 18 texture look-ups instead of 2 (bilinear filtered!)
  - problems with perspective distortion

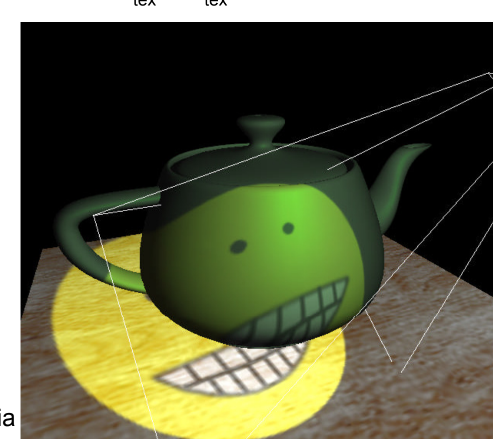


- Pyramid matching
  - create resolution pyramid image
  - match on every level $(I_1-I_2)^2$
  - sum-up all levels i $SSD = \Sigma_i(I_1-I_2)^2$
  - implicit correlation window
  - Supported by MIPMAP-textures

[Yang, Pollefeys 03]

Projective Texture Mapping

- Project texture onto geometry
  - use projection matrix $P = K [R^T|-R^TC]$ from calibration
  - adapt K to K_{Tex} to map to [0,1]x[0,1]: $P_{tex} = K_{tex} [R^T|-R^TC]$
  - compute texture coordinates from vertices: $m_{tex} = P_{tex} M$
  - Result: Homography
    - polygon <=> image plane
- Can be automated on GPU
  - texture coordinate generation facility



Courtesy: NVidia

Plane Sweep on the GPU

For all planes i
at depth z_i do {

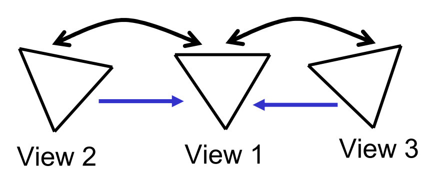
- First Pass:
  - set virtual camera according to view 1
  - setup projective texture mapping for two texture units
  - setup similarity-shader
  - render quad as plane at distance z_i
  - store result as difference image D_i
- Second Pass:
  - Set virtual camera to ortho
  - load difference image (1.pass) as texture (D_i)
  - load accumulation image as texture (A)
  - render quad with shader for each pixel x:
    - if $D_i(x) < A(x)$ then (accept fragment)
      - $A(x)= D_i(x)$;
      - $Z(x) = z_i$ (Update z-buffer)

}

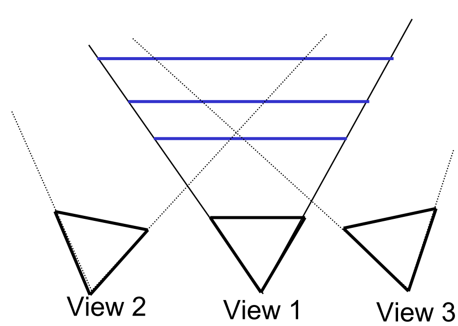
Read depth map from z-buffer

Fusion vs. Multiview P-S

- Classic Multiview Fusion
  - compute disparity maps pairwise
  - fuse disparities into single depth map



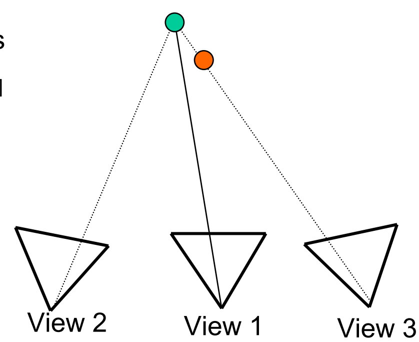
- Multiview Plane Sweep
  - use multiple support views at once
  - Similarity metric has to be adapted (Shader)



[Woetzel, Koch 04],[Nozick, Michelin, Arques 06]

Multiview Plane Sweep

- For each plane
  - compute pairwise matching for I1,I2,I3
  - I1-I2, I1-I3
  - select best combined matching as score for this plane
- Problem: Occlusions (outlier)
  - combine matches with small differences
    - discard up to two outlier [Woetzel, Koch 04]
    - statistical approach using average and variance [Nozick, Michelin, Arques 06]



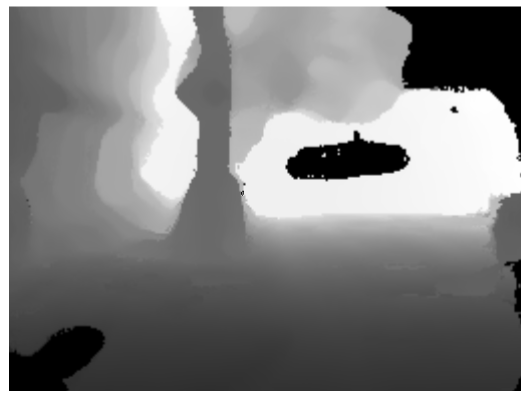
Plane Sweep Results

- Performance:
  - 11 Images @ 512 x 384 RGB
  - Out: 512 x 384, 48 planes
  - 7Hz (140ms)

NVidia GeForce FX 7900

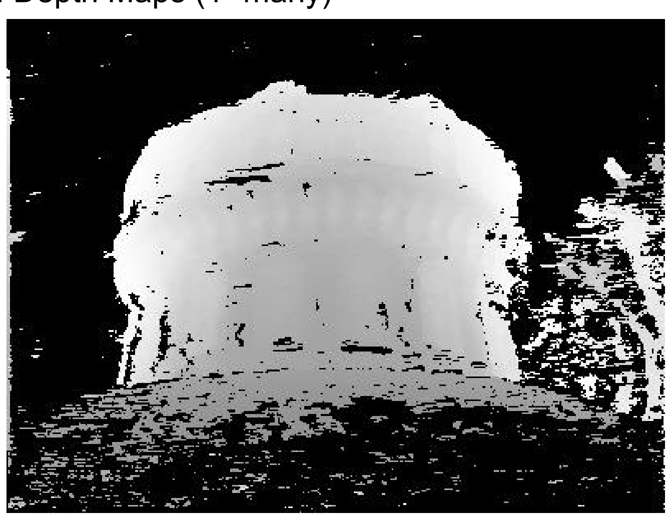
Additional Fusion

- Each depth map from 11 views
- fuse 7 depth maps (more details in section Applications)



Result: Depth Maps

- Results: Depth Maps (1- many)



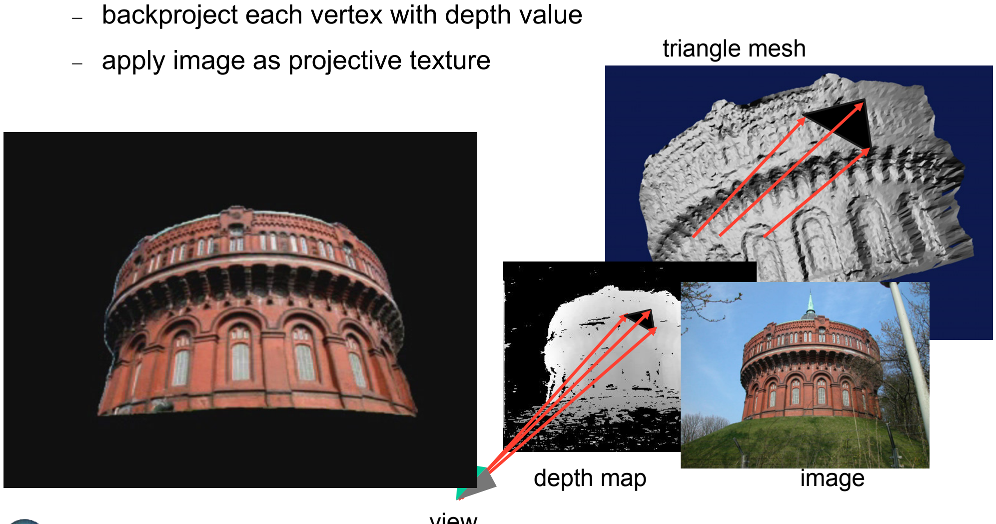
What now?

Reconstruct to ...

- Measure distances, sizes, areas, ...
  - Model required
- Interactive inspection (visualisation)
  - generate standard model for standard viewer (VRML !)
    - globally consistent model: not always possible
  - more sophisticated approaches: Image Based Rendering
    - needs special viewer

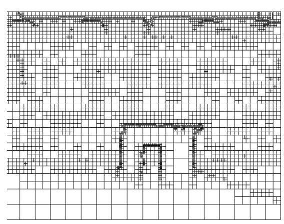
Surface Modelling

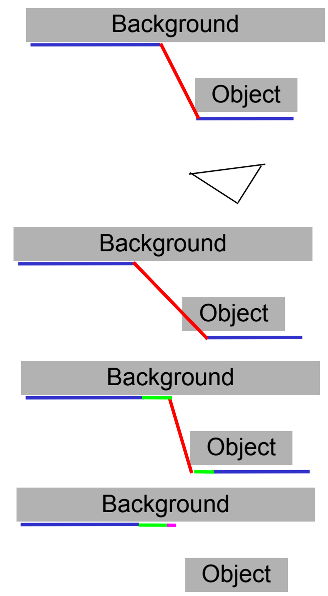
- Generate 3D mesh from depth map
  - triangles based on 2D neighbourhood
  - backproject each vertex with depth value
  - apply image as projective texture



Adaptive Surface Modelling

- Problem: Triangles connect layers
- Adaptive modelling:
  - Divide depth map into tiles (32×32)
  - backproject corners + center: Quad
  - verify quality of quad
  - refine by subdivison if necessary

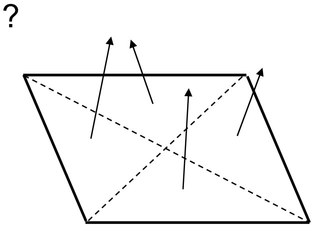


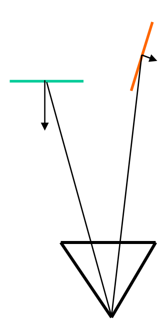


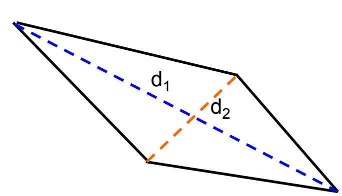
[Evers, Koch VMV03]

Quad Evaluation

- Does a quad approximate the surface well?
  1. Test Planarity: compare normals
  2. Test Deformation: ratio of diagonals
  3. Test Orientation: mean normal to line-of-sight

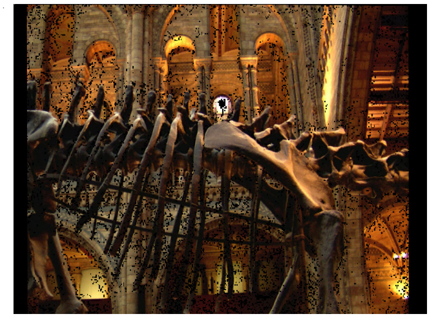






$q = d_1 / d_2$

Example: Adaptive Modelling



Visualisation

One single model using adaptive quads

Multiple Local Model

- Generate local models for all views
- switch between best suited view
- blend several views to fill holes
  - blending according to PJ Naya
- Pros: Use all views, fill holes, visualise non-lambertian surfaces, GPU-supported
- Cons: need special viewer (no standards like VRML), rendering more expensive, Amount of data

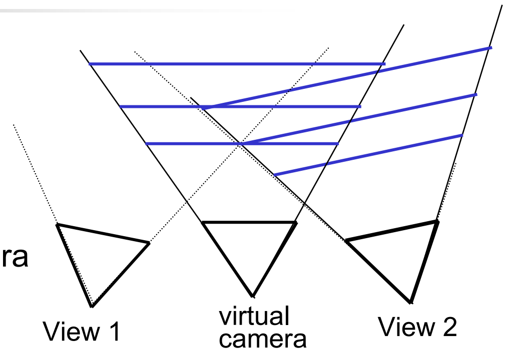
[Evers, Koch VMV03], [Verlani, Goswami, Narayanan 06]

Multiple Local Models

Plane Sweep Rendering

- Relaxed problem:
  - precise Depth: not of interest
  - Image interpolation: find color
- Sweep coplanar to virtual camera
- Per pixel:
  - find plane with best photo consistency
  - define color as weighted average of all views
- Problem:
  - HQ-matching non-interactive

[Yang, Welch, Bishop, 02]

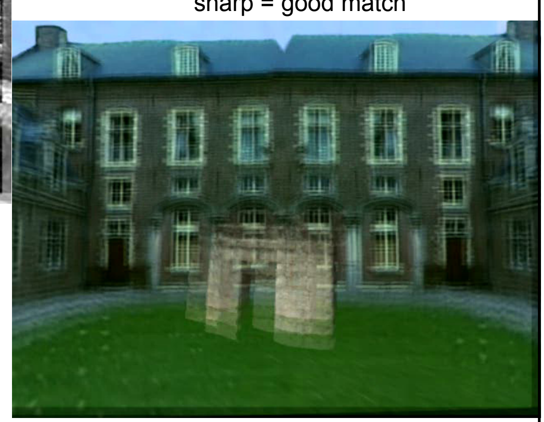


Sweep over 50 planes

Matching Function (SSD)
black = good match
white = bad match

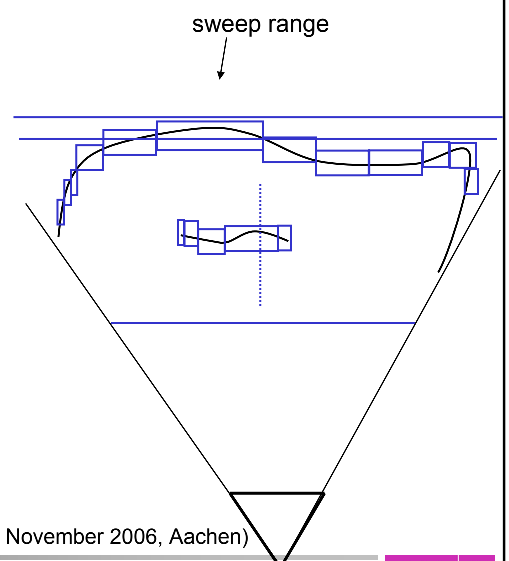
4 real views

Output Color
blurred = bad match
sharp = good match



Depth Guided PS-Rendering

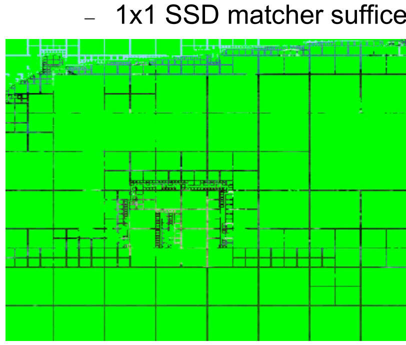
- Idea:
  - use rough depth estimation
  - reduces number of planes
  - partial sweep only in small depth intervalls
  - Use non-hierarchical simple SSD matching
- Pros:
  - can compensate errors in depth
  - highly efficient, fewer mismatches
- Cons:
  - needs some depth information

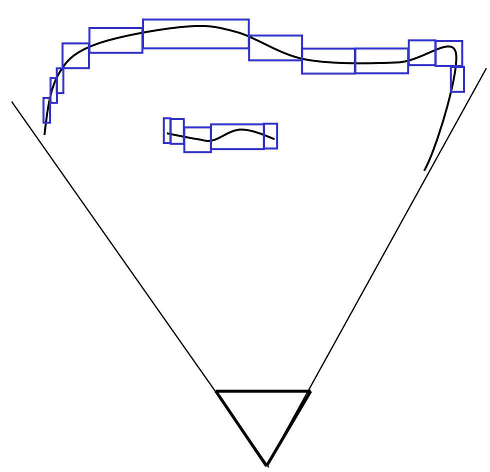


[Evers, Niemann, Koch 06] (to be presented on VMV, November 2006, Aachen)

Partial Sweep

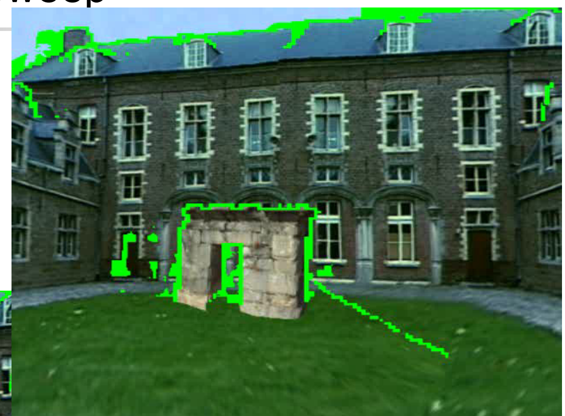
- Offline:
  - create adaptive quad tree from depth map
  - per quad: determin sweep space
- Online:
  - sweep tiles in predefined ranges
  - 1x1 SSD matcher suffices





Example Partitial Sweep

Depth only



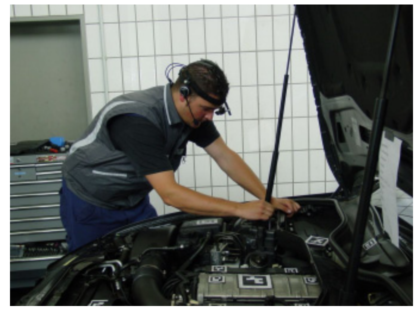
Partial Sweep

Schedule

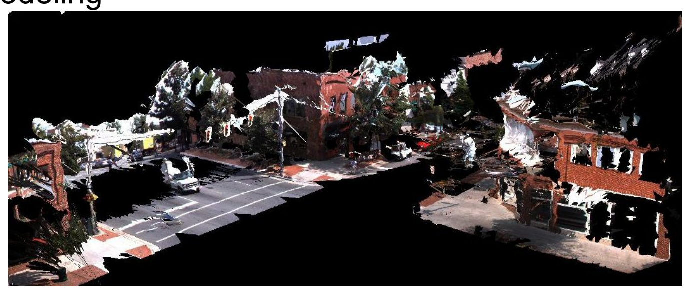
- Introduction
- Multi-view Relations
- Feature Tracking
- Coffee Break
- Robust pose estimation
- 3D Modeling and Visualisation
- Applications

Applications

- ARTESAS Augmented Reality
  - small and leightweight system
  - initial registration
  - model based tracking

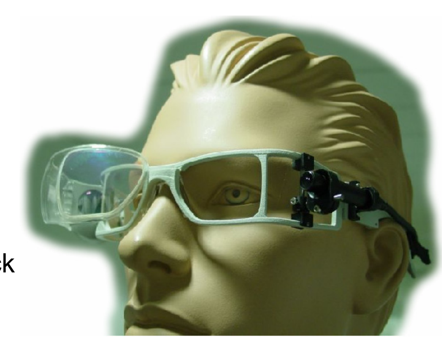


- Urbanscape city modeling
  - S-f-M Tracking
  - global registration
  - depth estimation
  - mesh creation



Artesas

- Augmented Reality for Industrial Service App.
- User:
  - BMW Car Maintenance
  - EADS Military Aircraft
  - Siemens Automation & Drives
- Developement:
  - Frauenhofer IGD, Siemens, CAU Kiel, Metaio, RWTH Aachen, ZGDV Rostock
  - Carl Zeiss



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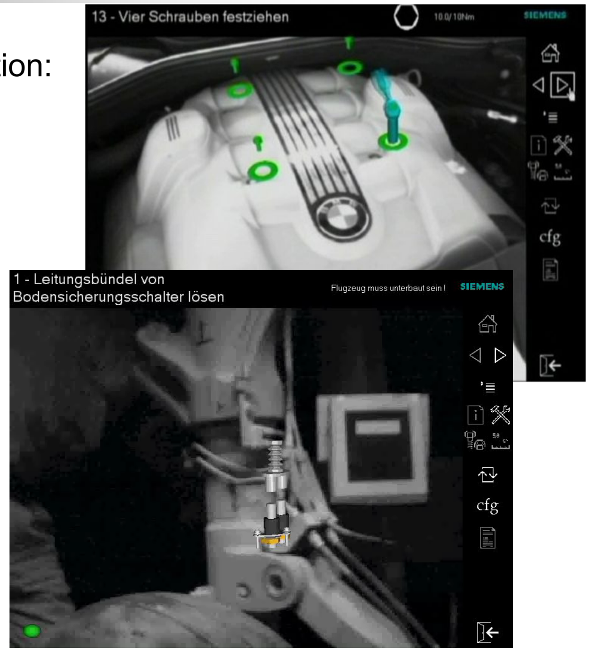
AR for Industrial Service

- Display detailed Information:
  - Parts, Tools, Movements
  - (Dis-)assembly instruction
- Head-Mounted Display
- Voice-control
- Tracking:
  - No markers !
  - 20-30 fps
  - Robust non-interactive reinitialisation



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Markerless Tracking

- 3 Phases: Init, Track, Re-Init
- Initialisation from CAD-Model
  - no reference views, keyframes
  - small user interaction
  - 2D-3D Line Matching algorithm
- Frame-to-Frame Tracking
  - Based on point features (KLT)
  - Establish 2D-3D correspondences (CAD-Model +Init)
  - Track 2D-2D (KLT), compute pose + S-f-M
- Re-Init
  - SIFT-Matching against key frames
  - automatic key frame generation

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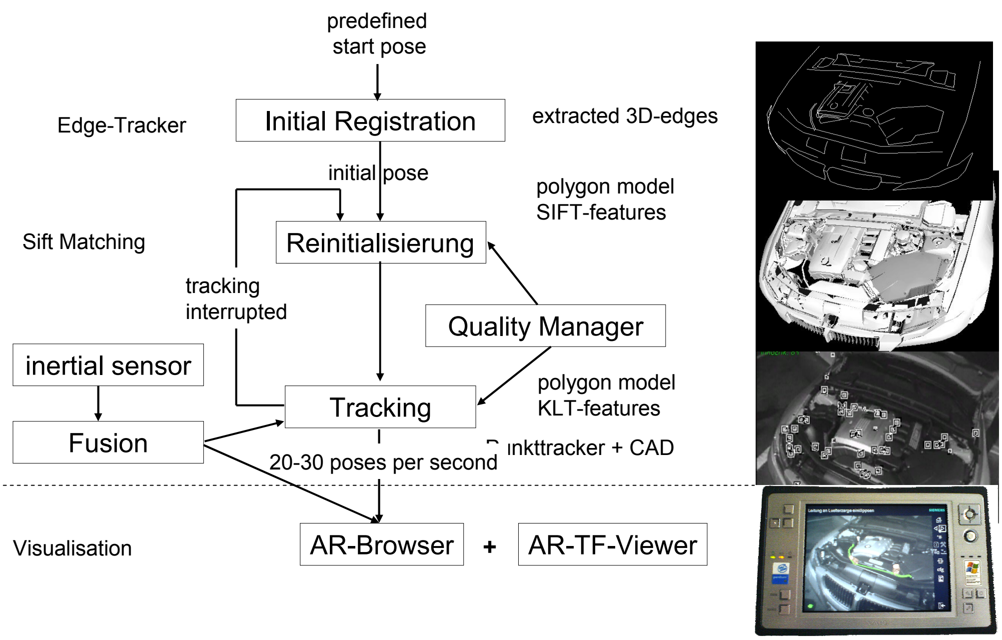
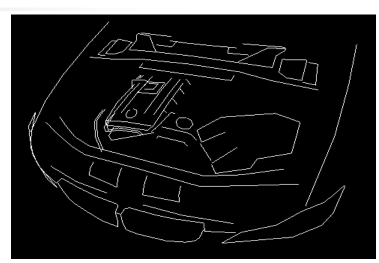
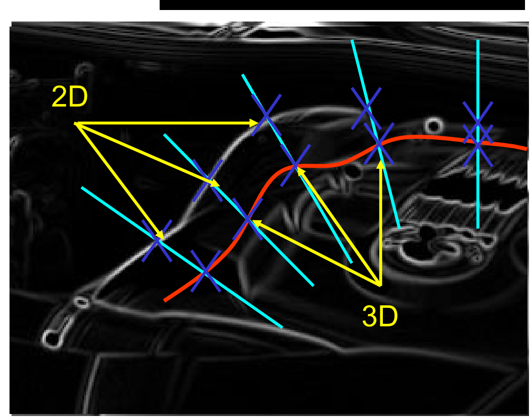
Modules & Phases



Init: Edge Tracking

- Required: Line-Model, rough pose
  - projection of line-model
  - search lines perpendicular to projected lines
  - search gradients
  - build 2D-3D correspondences
  - estimate pose from 2D

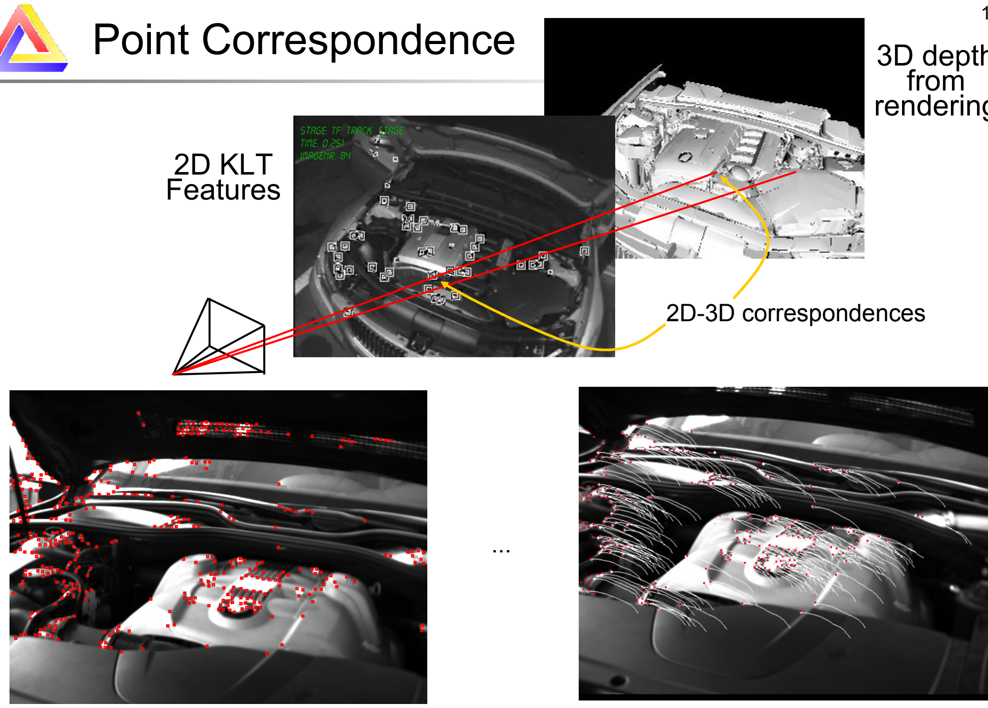




Frame-to-Frame: Hybrid Point Tracking

- Combine Model-based and Structure-from-Motion
  - First frame (requires precise pose):
    - extract KLT features in camera image
    - render model for given pose (depth buffer!)
    - back-project features "onto" the model: 2D-3D correspondences
  - All other frames:
    - track known features, update 2D of correspondences
    - compute pose
    - triangulate features not on model (S-f-M)
    - eventually extract new features (2D-3D)

Point Correspondence

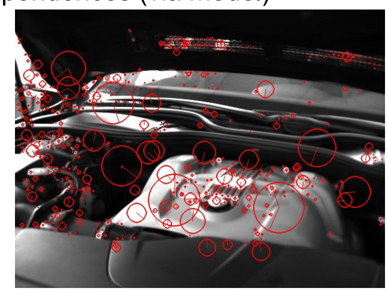


First image (Features)

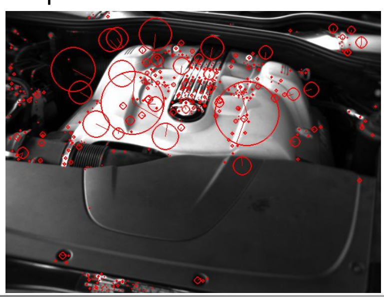
Tracked Features 35th image

Re-Init: SIFT Matching

- Learn-Mode
  - take every Nth image & pose as reference
  - extract SIFT-keys and create 2D-3D correspondences (via model)
- Re-Init Mode
  - extract SIFT-keys on current image
  - match against reference keys
  - compute pose



Reference Image



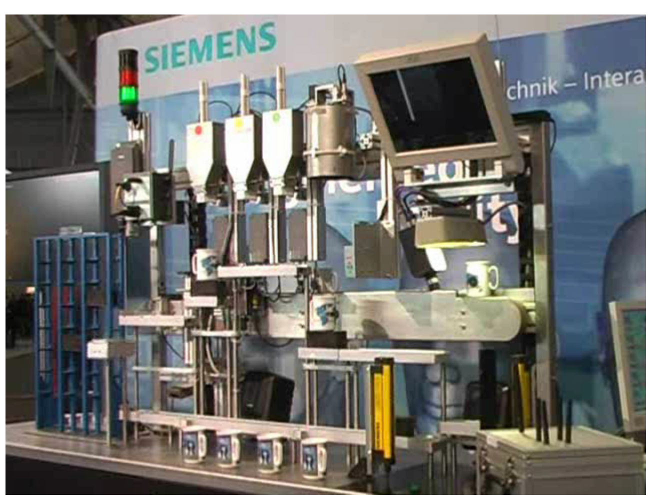
Current Image

Artesas Example

Mobile AR

- Problem: "wearable" computation device
  - PDA: not enough power
  - Laptop: to heavy, display + keyboard not necessary
  - Xybernaut MA-X(1.6GHz Pentium-M): To hot !
- Solution: Transmit video streams wireless
  - Camera image from user to workstation
  - VGA-image from workstation to user
  - Standard off-the-shelf *analog* video transmitter & receiver
  - Noise, frame- (line-) drops
- Integrated into waistcoat
  - transmitter, receiver, batteries, power-regulator
  - signal-converter for HMD

Artesas on CeBit 2006



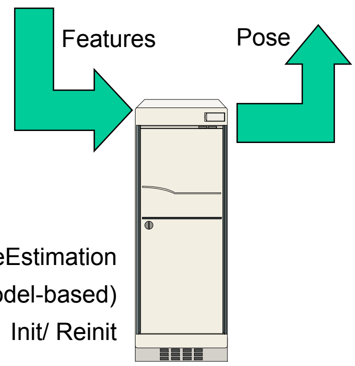
Smart-AR

[Evers, Petersen, Koch 06]

- Analog video
  - massive waste of bandwidth, not reliable
- "Smart"-wireless AR solution
  - Digital (WLAN), compression to save bandwidth
  - avoid sending image: Distributed Tracking
    - extract & send features (mobile to backend)
    - send pose (backend to mobile)
    - render on mobile
  - Plug-In architecture for existing frame work
  - Re-use existing implementation (Init, Reinit)
  - Init & Reinit: send JPEG-compressed images

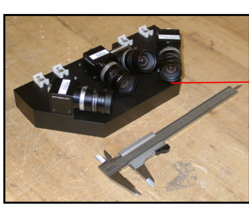
Feature Tracking

Rendering



Live Demo

Urban modeling



2x4 cameras, 1024x768@30Hz

[Akbarzadeh, Frahm, …, Nister, Pollefeys 06]

Process flow

Capture → images → 2D-Tracking

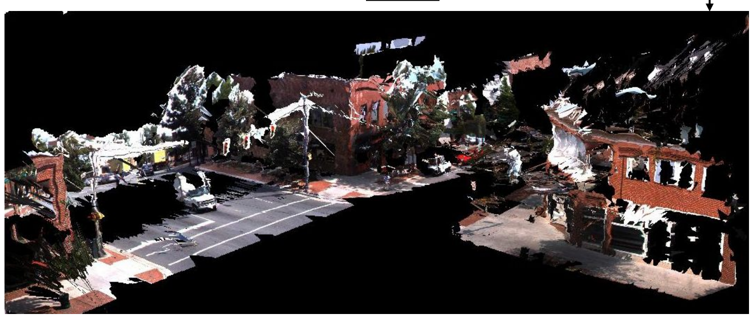
2D-Tracking → 2D tracks → 3D-Tracking/Geo-registration

3D-Tracking/Geo-registration → $P_0, \ldots$ → Stereo

Stereo → depth maps → Stereofusion

Stereofusion → fused depth maps → Model creation

Model creation → 3D model



Process flow

Capture → images → **2D-Tracking**

2D-Tracking → 2D tracks → 3D-Tracking/Geo-registration

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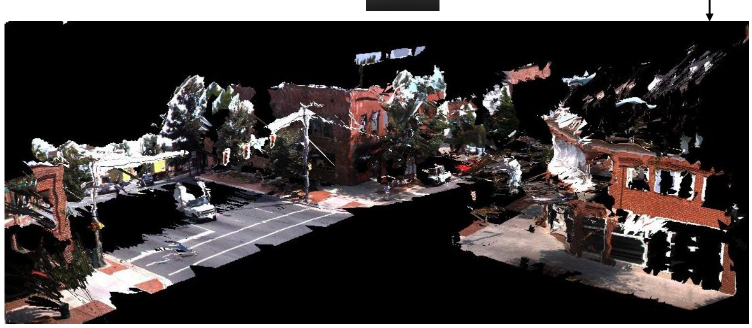
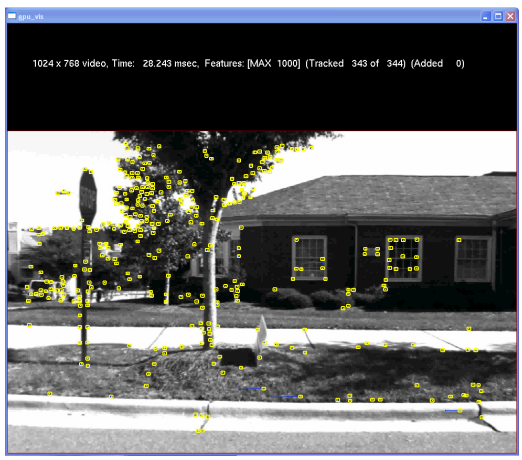
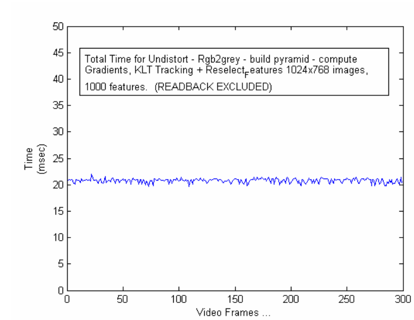


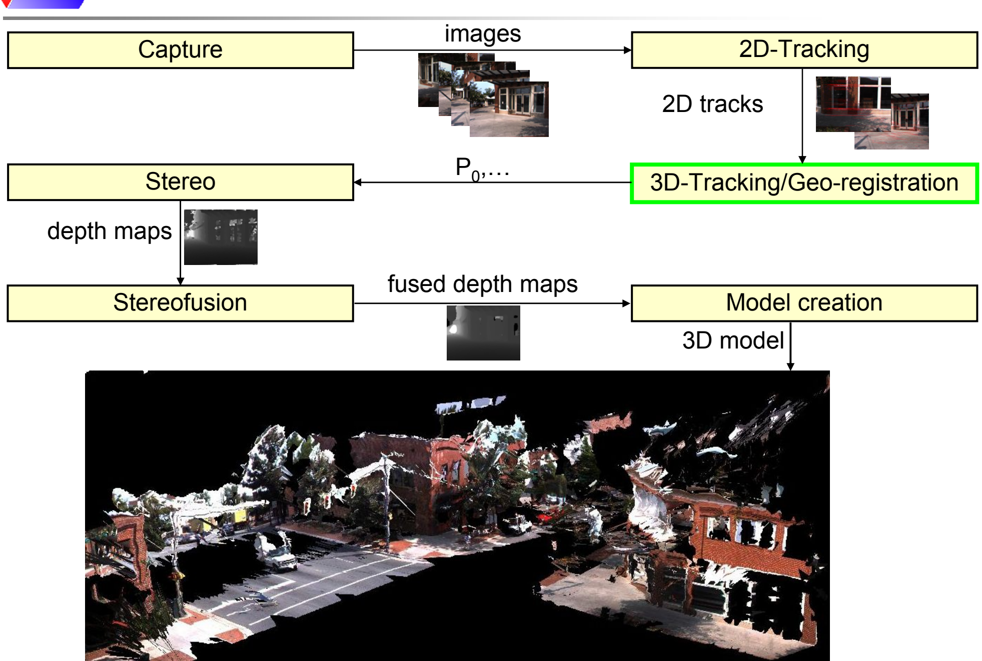
GPU-based KLT Tracker

- Combined with removal of radial distortion and construction of Gaussian pyramid
- Tracks 1000 features with 34Hz on 1024x768 image





Process flow



Video based 3D tracking

- Pure video tracking shows drift!

Geo-spatial data

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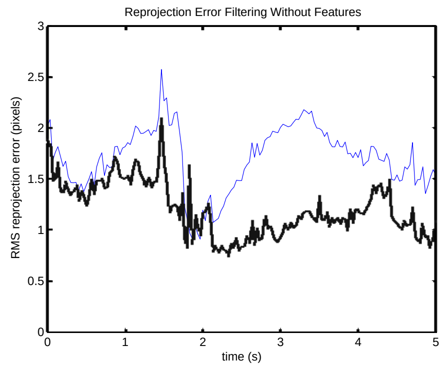
Kalman Filter Based Sensor Fusion

6 DOF (pose, orientation on earth) | image based 2D tracks

→ Extended Kalman filter



3D Camera Tracking, Reconstruction and View Synthesis at interactive frame rates

CAU

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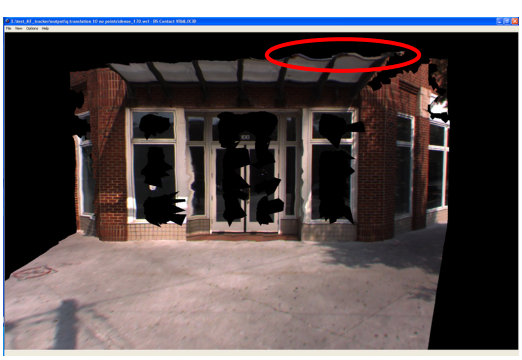
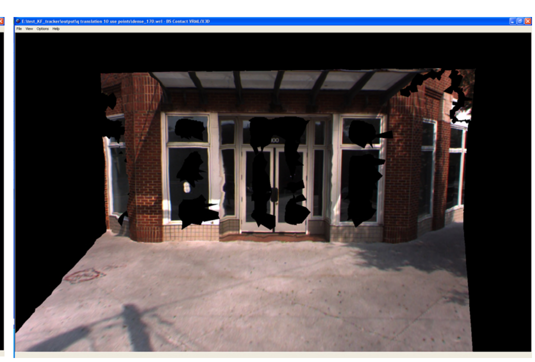
EKF Multi-Camera Geo-Registration

6DOF measurements Only



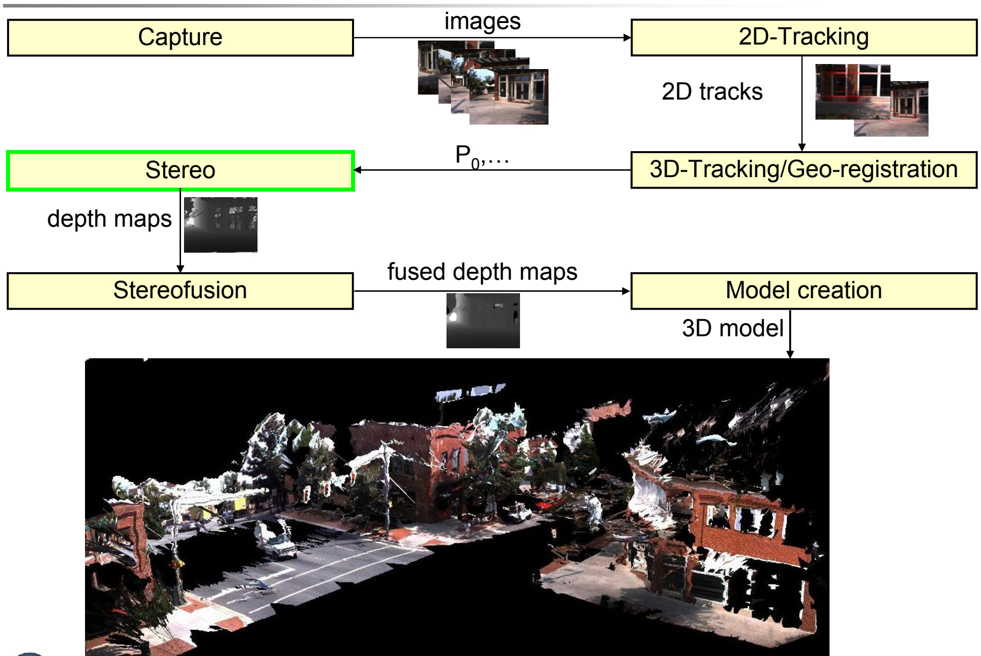
EKF filtered measurement



3D Camera Tracking, Reconstruction and View Synthesis at interactive frame rates

CAU

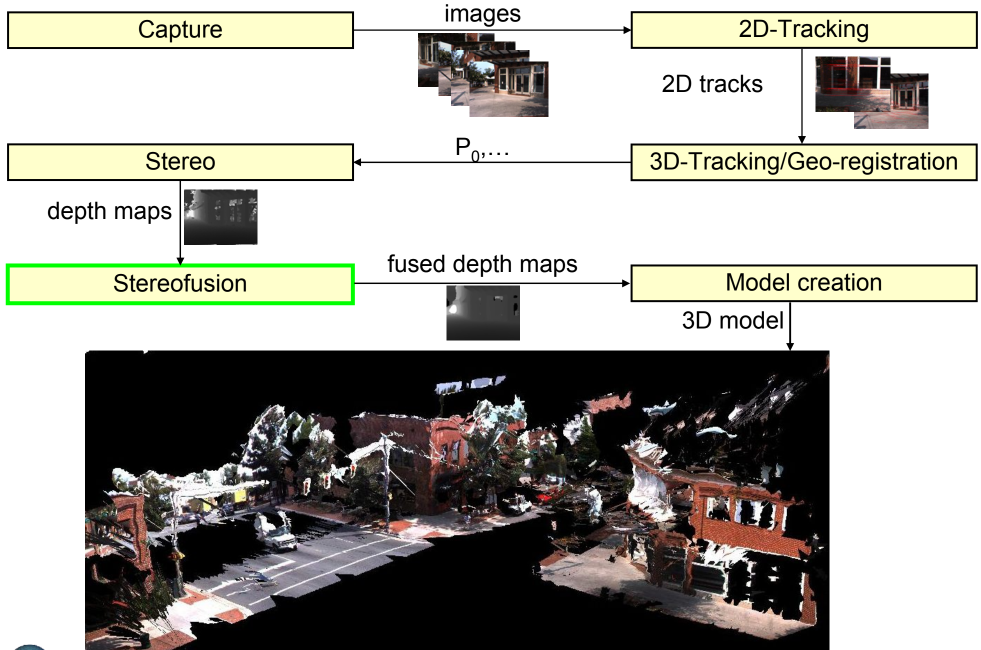
Process flow



Stereo

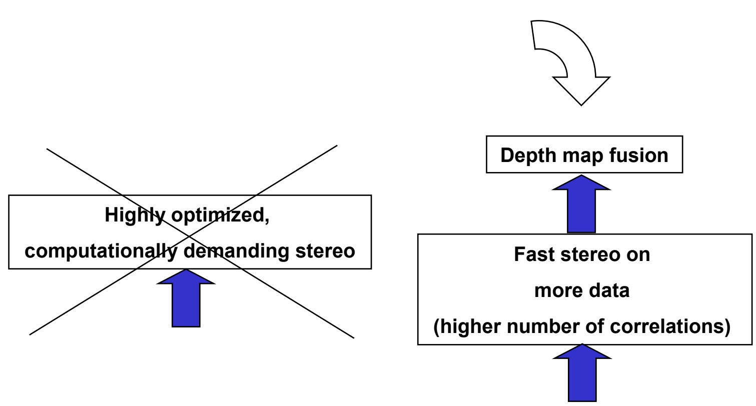
- Multi-view plane sweep stereo on GPU with gain correction

Process flow

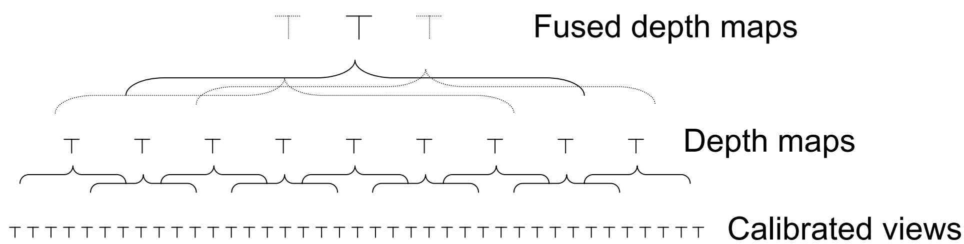


Depth Map Fusion

- Main lesson: Fast stereo with many correlations on many images + fusion is the winning recipe

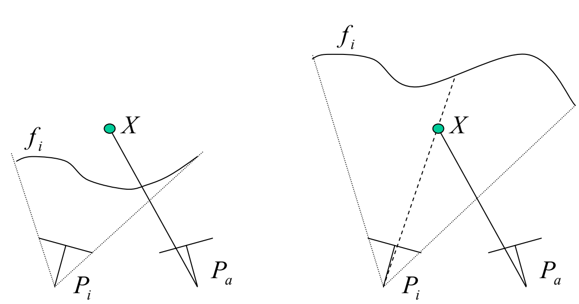


Depth Map Fusion



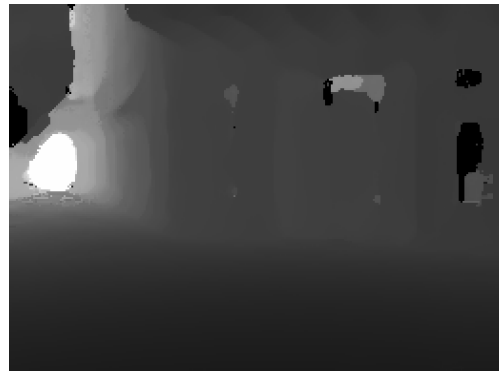
Depth Map Fusion

- Resolves inconsistencies. Cleans up results very efficiently
- Possibility to include confidence measure, smoothness prior
- Suited for GPU implementation (essentially consists of rendering back and forth many times), possible simplifications

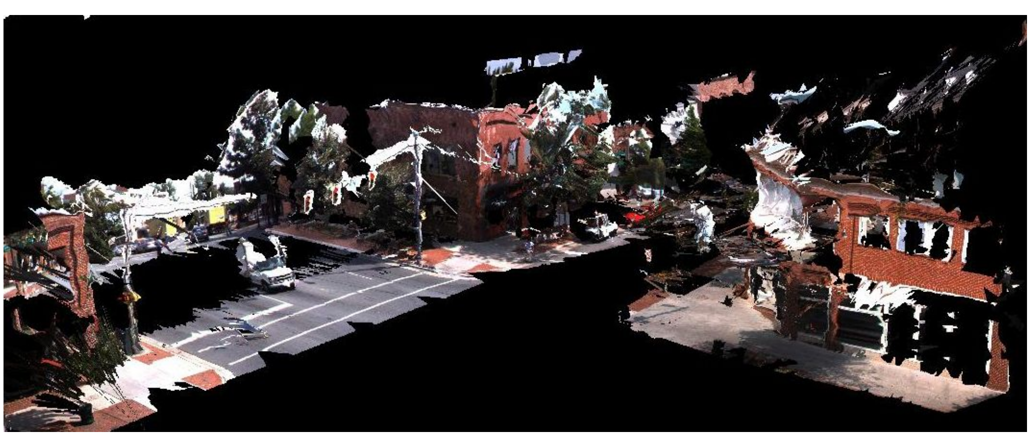


Depth map fusion


single depth map


fused depth map

Model



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