

Inverse Depth Monocular SLAM

J. Civera, A.J. Davison and J.M.Montiel



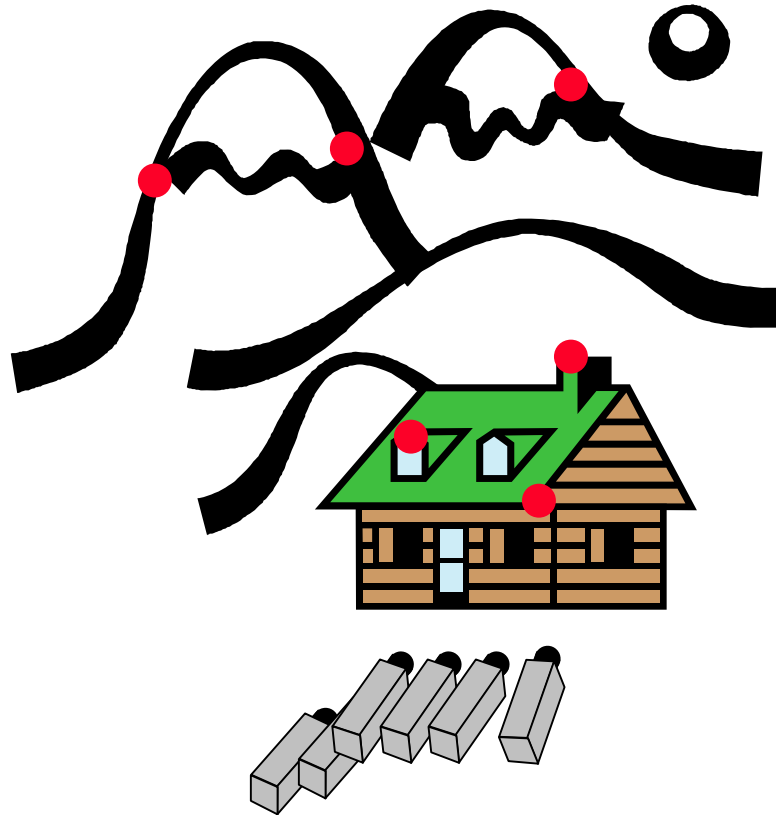
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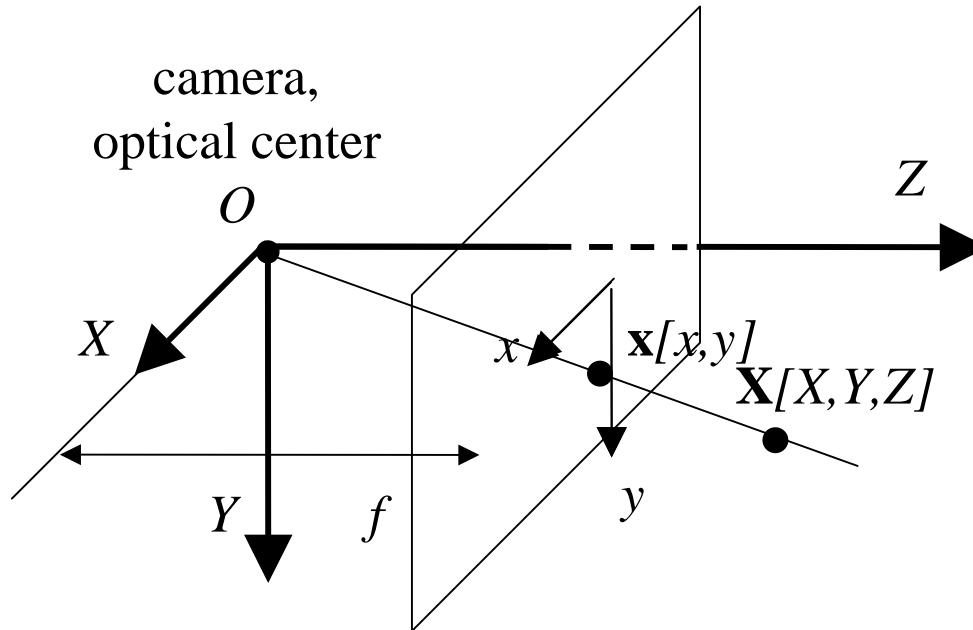
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Problem Statement



- **Sequential simultaneous sensor location and map building at frame rate, 30Hz.**
- **Camera moves freely in 3D, 6dof camera motion**
- **Outdoors real scenes contains close and distant, even at infinity, features**
- **Main contribution codifying scene points with its inverse depth:**
 1. **Deals with low parallax cases**
 2. **Deals with both distant and close points**
 3. **Map features are initialised just from one image**

Camera Geometry: Pure Bearing-only Sensor



- Camera detects rays
- A ray is defined by the optical center O and the observed point
- The image is used as the method to determine the detected ray
- Depth is not detected

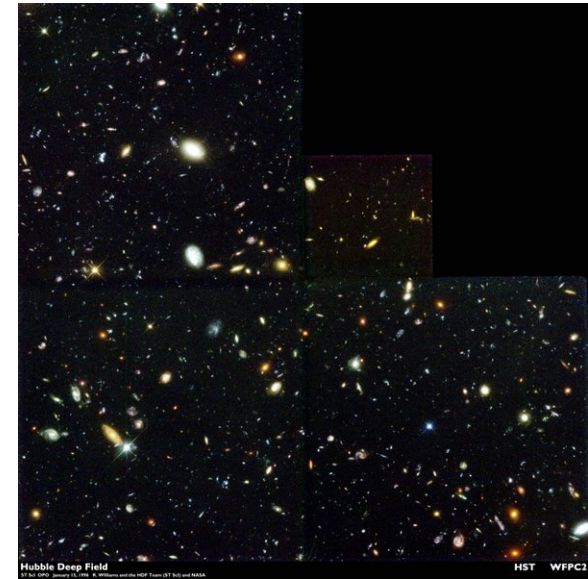


image of galaxies
at 10^9 years light far from
the Earth

Points at Infinity

- projective cameras *do* observe points at infinity
- parallel lines meet at infinity, a projective camera does observe this intersection point as vanishing point
- we intend to code and exploit this points at infinity in the monocular SLAM problem



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Parallax



- **No parallax geometries**
 - Camera rotation
 - Camera observing a scene plane
- **Low parallax cases**
 - Distant features compared with camera translation
 - Initial feature observation



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State of the Art

- **SLAM, initially proposed by Smith and Cheesman, 1986, widespread usage in robotics for multisensor fusion [Casetellanos 1999], [Ferder 1999] [Thrun 2004]**
 - Sequential approach
 - Ability to close loops, identifying features previously observed as reobserved. Complexity is linked to the scene not to the number of observations processed.
- **SLAM used for computer vision, [Castellanos 2000], [Davison 1998] combined with odometry**
- **Monocular SLAM vision [Davison 2003]**
 - Camera "following the laws of mechanics" motion model
 - Vision as the only sensor, no odometry.
 - Synergic usage of vision geometry and vision photometric map
 - Low parallax points avoided:
 - » Points represented as XYZ, only works with points close to the camera
 - » Delayed initialization
- **Monocular SLAM Fast SLAM, inverse depth delayed initialization [Eade 2006]**

SFM, computer vision methods



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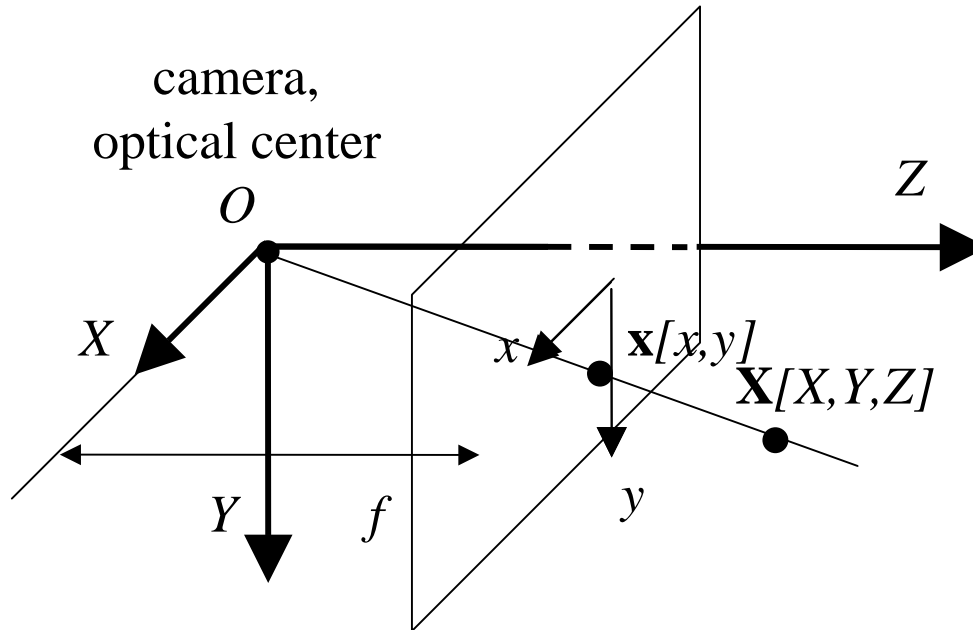
State of the Art

SLAM methods

- **Photogrammetric bundle adjustment, 60's**
 - Normally only close points
- **Computer vision geometry Hartley & Zisserman [Hartley 2003]**
 - Robust statistics
 - Matching between several shots enforcing a coherence with a projective camera model
 - Applied to individual shots, to sequences with varying camera parameters
 - Applied for robot navigation [Nister 2003, Mouragnon 2006]
 - Not sequential
 - Wide-baseline performance
 - Routine usage of points at infinity
- **Model selection problem [Torr ICCV98]**
 - No parallax, homography model
 - Parallax epipolar geometry model
 - Increasing the frame rate, the interframe motion closes to a homography



Camera Geometry: Pure Bearing-only Sensor



- Camera detects rays
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- The image is used as the method to determine the detected ray
- Depth is not detected

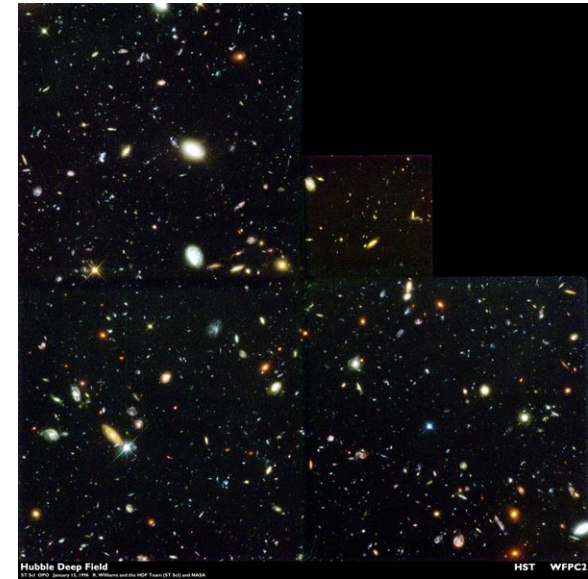
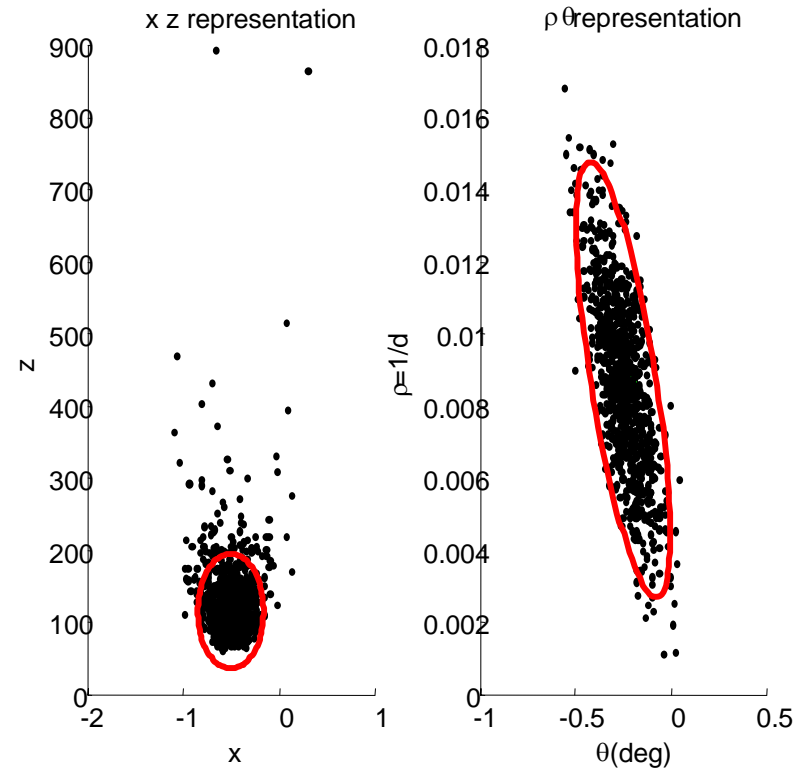
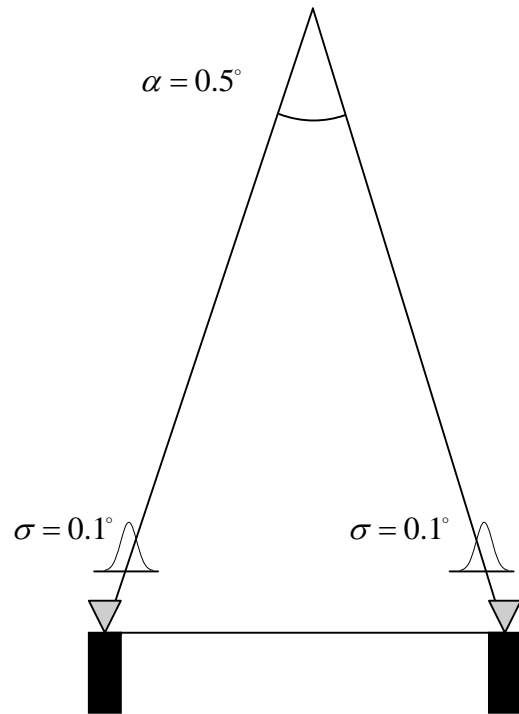


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Gaussianity of the Inverse Depth Coding



Simulation: computing depth of a point from 2 views at known camera locations

- Non Gaussian in XZ
- Gaussian in 1/d, theta

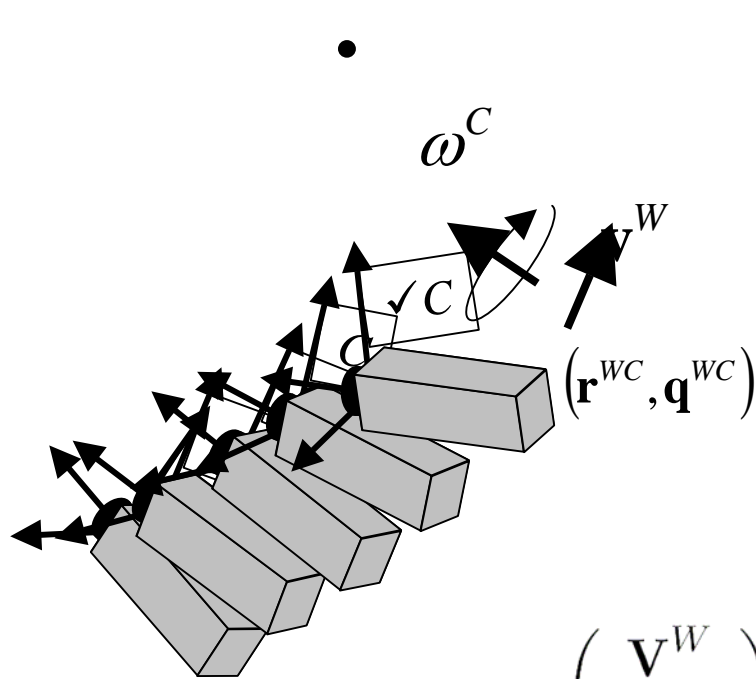


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Camera Motion Priors



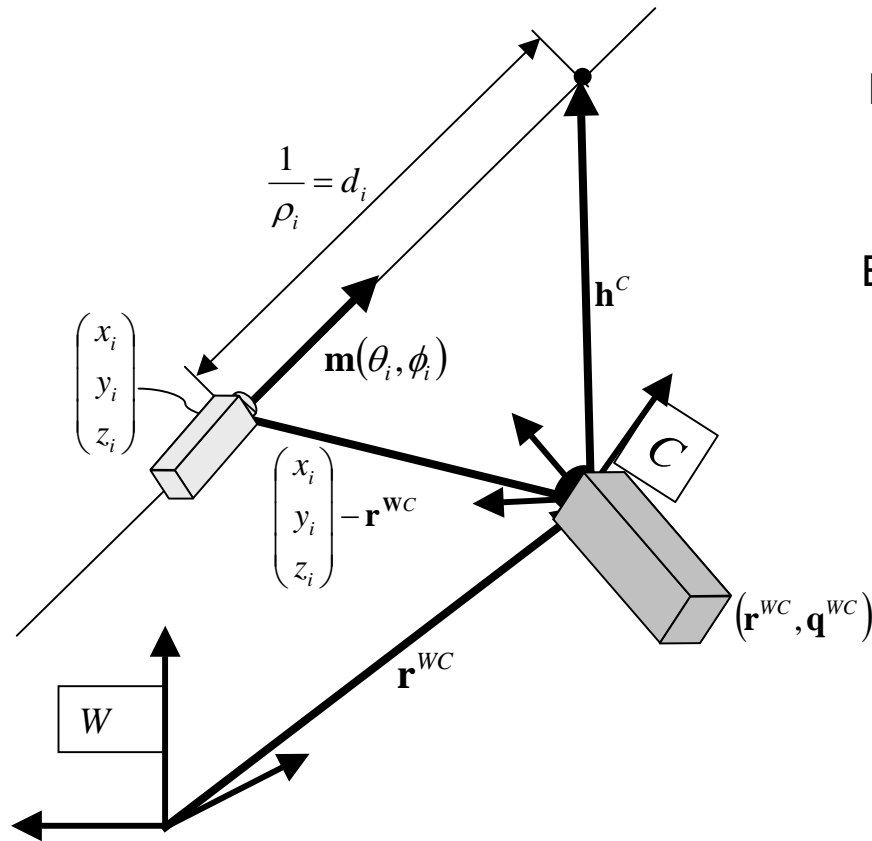
$$\mathbf{x}_v = \begin{pmatrix} \mathbf{r}^{WC} \\ \mathbf{q}^{WC} \\ \mathbf{V}^W \\ \omega^C \end{pmatrix}$$

Constant Velocity Motion Model
smooth camera motion
impulse acceleration noise

$$\mathbf{n} = \begin{pmatrix} \mathbf{V}^W \\ \Omega^W \end{pmatrix} = \begin{pmatrix} \mathbf{a}^W \Delta t \\ \alpha^W \Delta t \end{pmatrix}$$

$$\mathbf{f}_v = \begin{pmatrix} \mathbf{r}_{k+1}^{WC} \\ \mathbf{q}_{k+1}^{WC} \\ \mathbf{v}_{k+1}^W \\ \omega_{k+1}^C \end{pmatrix} = \begin{pmatrix} \mathbf{r}_k^{WC} + v_k^W \Delta t + a_k^W \Delta t^2 \\ \mathbf{q}_k^{WC} \times \mathbf{q}(\omega_k^C \Delta t + \alpha_k^C \Delta t^2) \\ \mathbf{v}_k^W + a_k^W \Delta t \\ \omega_k^C + \alpha_k^C \Delta t \end{pmatrix}$$

Scene Point Coding in Inverse Depth. Measurement Equation



Inverse depth point coding

$$\mathbf{y}_i = \left(x_i \quad y_i \quad z_i \quad \theta_i \quad \phi_i \quad \rho_i \right)^\top$$

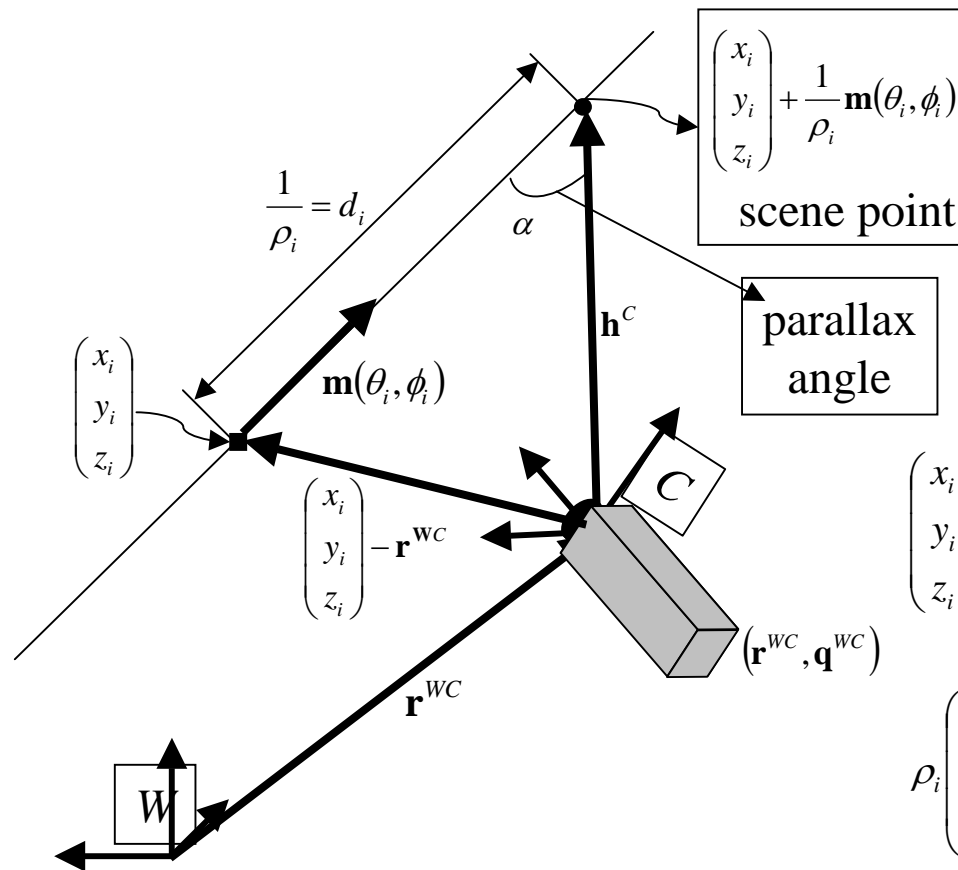
Bearing only camera measurement

$$u = u_0 - \frac{f}{d_x} \frac{h_x}{h_z} \quad v = v_0 - \frac{f}{d_y} \frac{h_y}{h_z}$$

Measurement equation

$$\mathbf{h}^c = \begin{pmatrix} h_x \\ h_y \\ h_z \end{pmatrix} = \mathbf{R}^{CW} \left(\rho_i \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} - \mathbf{r}^{WC} \right) + \mathbf{m}(\theta_i, \phi_i)$$

Scene Point Coding in Inverse Depth. Measurement Equation



$$u = u_0 - \frac{f}{d_x} \frac{h_x}{h_z} \quad v = v_0 - \frac{f}{d_y} \frac{h_y}{h_z}$$

$$\mathbf{h}^C = \begin{pmatrix} h_x \\ h_y \\ h_z \end{pmatrix} = \mathbf{R}^{CW} \left(\begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} + \frac{1}{\rho_i} \mathbf{m}(\theta_i, \phi_i) - \mathbf{r}^{WC} \right) =$$

$$\mathbf{R}^{CW} \left(\rho_i \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} - \mathbf{r}^{WC} + \mathbf{m}(\theta_i, \phi_i) \right)$$

$\begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix}, \mathbf{m}(\theta_i, \phi_i)$, those of the first time the feature

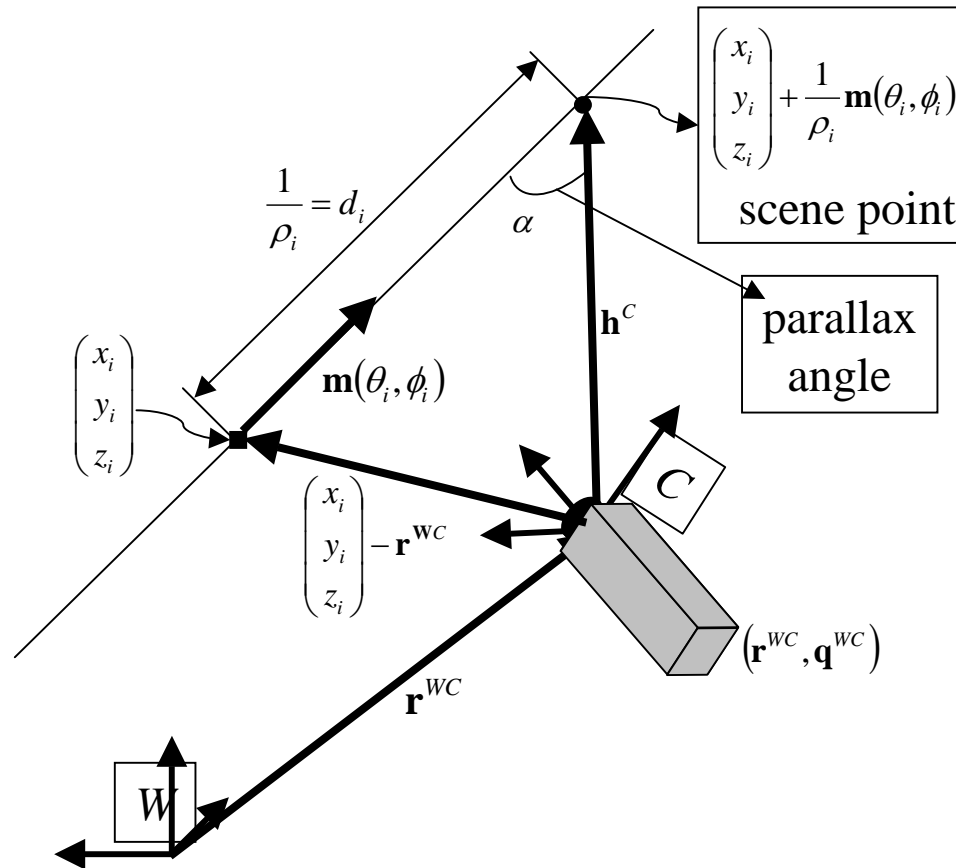
is observed

$\rho_i \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} - \mathbf{r}^{WC}$, parallax

distant point, $\rho_i \rightarrow 0, \Rightarrow$ parallax goes to zero

close camera locations, low baseline, $\begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} - \mathbf{r}^{WC}$, goes to zero

Scene Point Coding in Inverse Depth. Measurement Equation



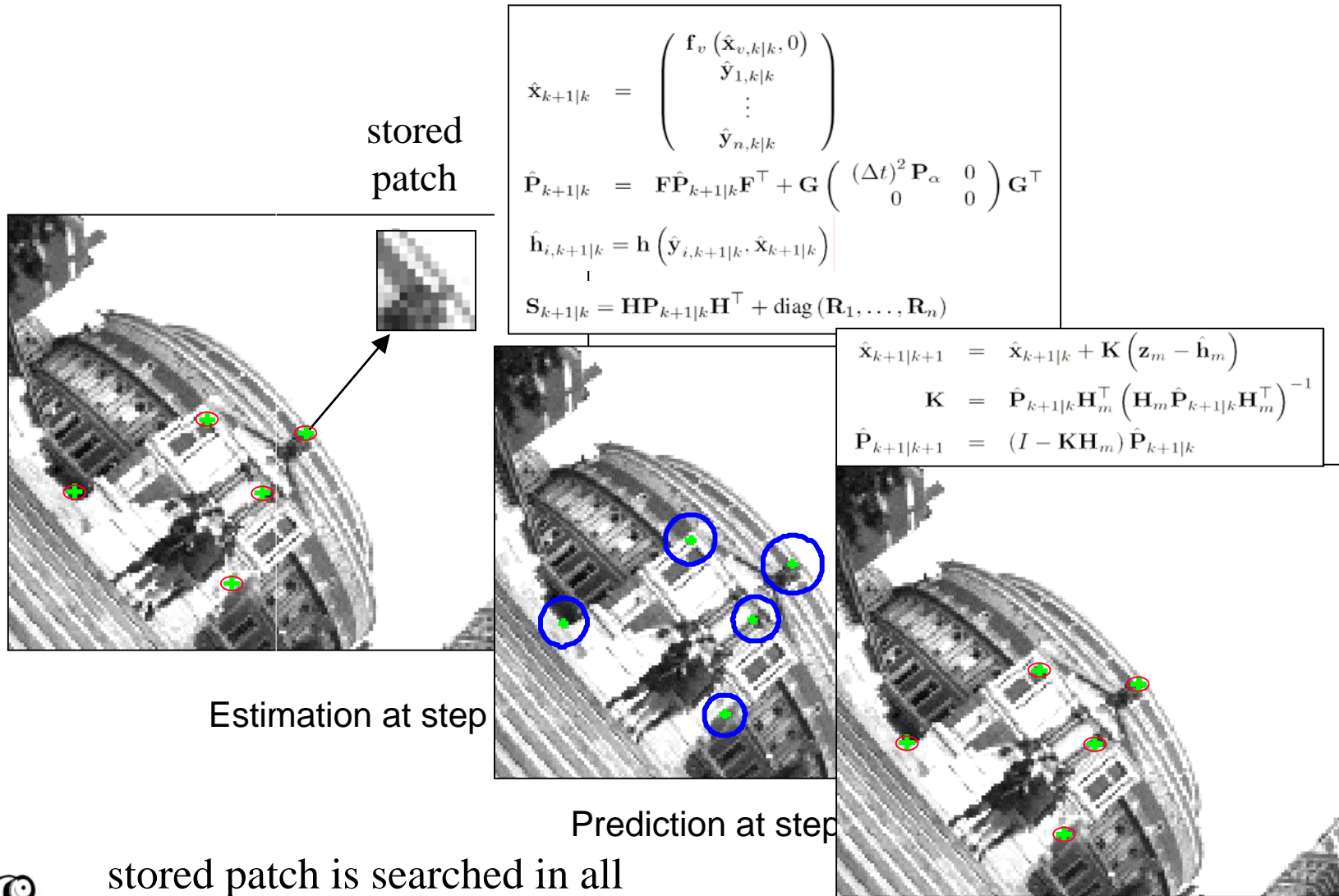
$$u = u_0 - \frac{f}{d_x} \frac{h_x}{h_z} \quad v = v_0 - \frac{f}{d_y} \frac{h_y}{h_z}$$

$$\mathbf{h}^C = \mathbf{R}^{CW} \left(\rho_i \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} - \mathbf{r}^{WC} \right) + \mathbf{m}(\theta_i, \phi_i)$$

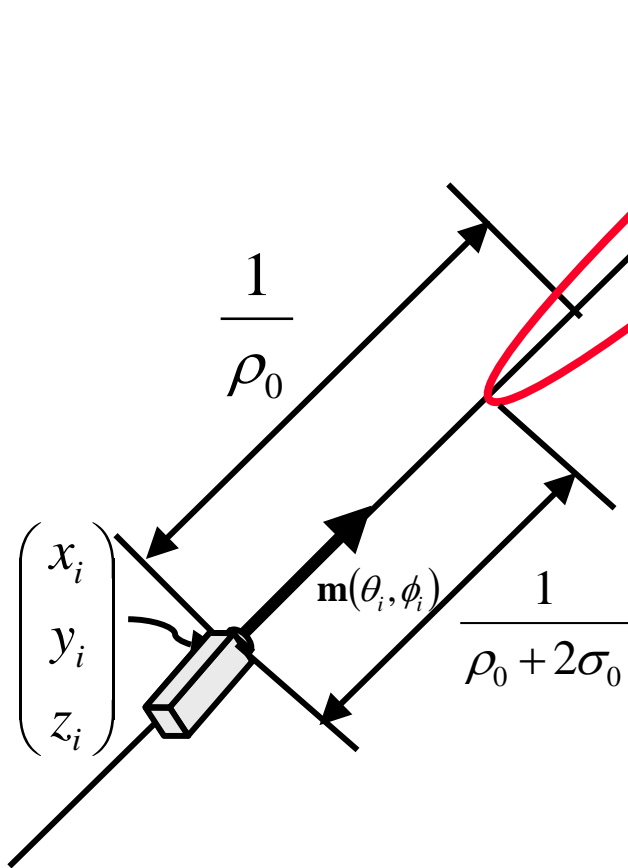
low parallax, only point at infinity is observed :

$$\mathbf{h}^C \approx \mathbf{R}^{CW} (\mathbf{m}(\theta_i, \phi_i))$$

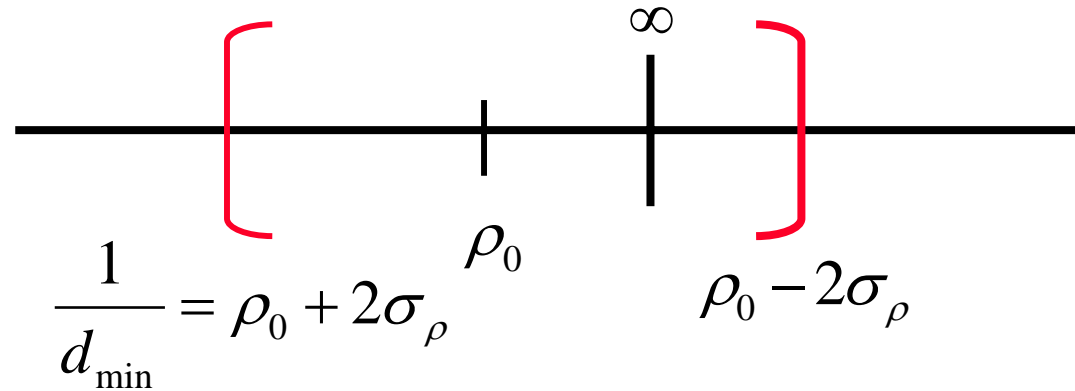
EKF sequential processing



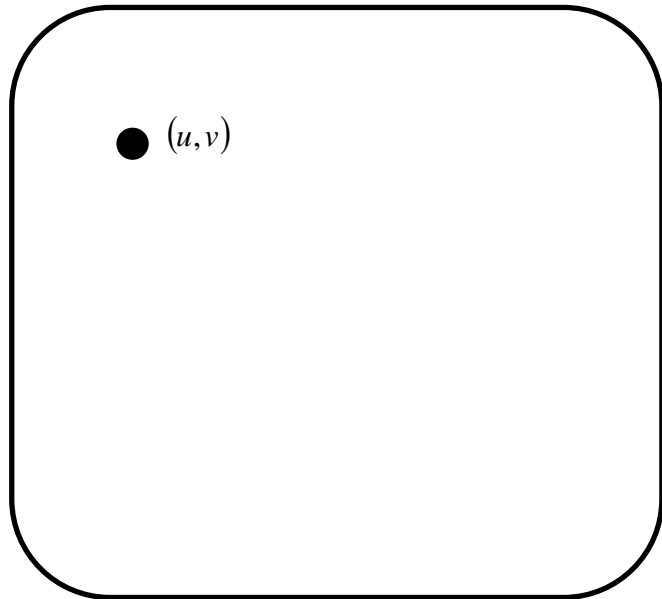
Inverse Depth Feature Initialization Priors



New points are observed from just an observation x, y, z, θ, ϕ and the corresponding covariance are initialized from the first feature observation ρ at ρ_0 and its covariance σ_ρ is initialized so that the interval $[\rho - 2\sigma_\rho, \rho + 2\sigma_\rho]$ covers a region from d_{\min} and including infinite



Inverse Depth Feature Initialization



$$\hat{\mathbf{x}}_v = \begin{pmatrix} \hat{\mathbf{r}}_{k|k}^{WC} \\ \hat{\mathbf{q}}_{k|k}^{WC} \\ \hat{\mathbf{V}}_{k|k}^W \\ \hat{\omega}_{k|k}^C \end{pmatrix} \begin{bmatrix} \mathbf{y}_1 \\ \vdots \\ \mathbf{y}_n \end{bmatrix} \hat{\mathbf{P}}_{k|k}$$

Current camera and map
 location estimate

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$$\left(\hat{x}_i \quad \hat{y}_i \quad \hat{z}_i \quad \hat{\theta}_i \quad \hat{\phi}_i \quad \hat{\rho}_i \right)^\top,$$

$$\begin{pmatrix} \hat{x}_i \\ \hat{y}_i \\ \hat{z}_i \end{pmatrix} = \hat{\mathbf{r}}^{WC} \quad \left| \quad \rho_i = \rho_0 \right.$$

$$\begin{pmatrix} \theta_i \\ \phi_i \end{pmatrix} = \begin{pmatrix} \arctan \left(-\mathbf{h}_y^W, \sqrt{\mathbf{h}_x^{W^2} + \mathbf{h}_z^{W^2}} \right) \\ \arctan \left(\mathbf{h}_x^W, \mathbf{h}_z^W \right) \end{pmatrix} \left| \right.$$

$$\mathbf{h}^W = \mathbf{R}_{WC} \left(\mathbf{q}_{k|k}^{WC} \right) \begin{pmatrix} v \\ \nu \\ 1 \end{pmatrix} \left| \right.$$

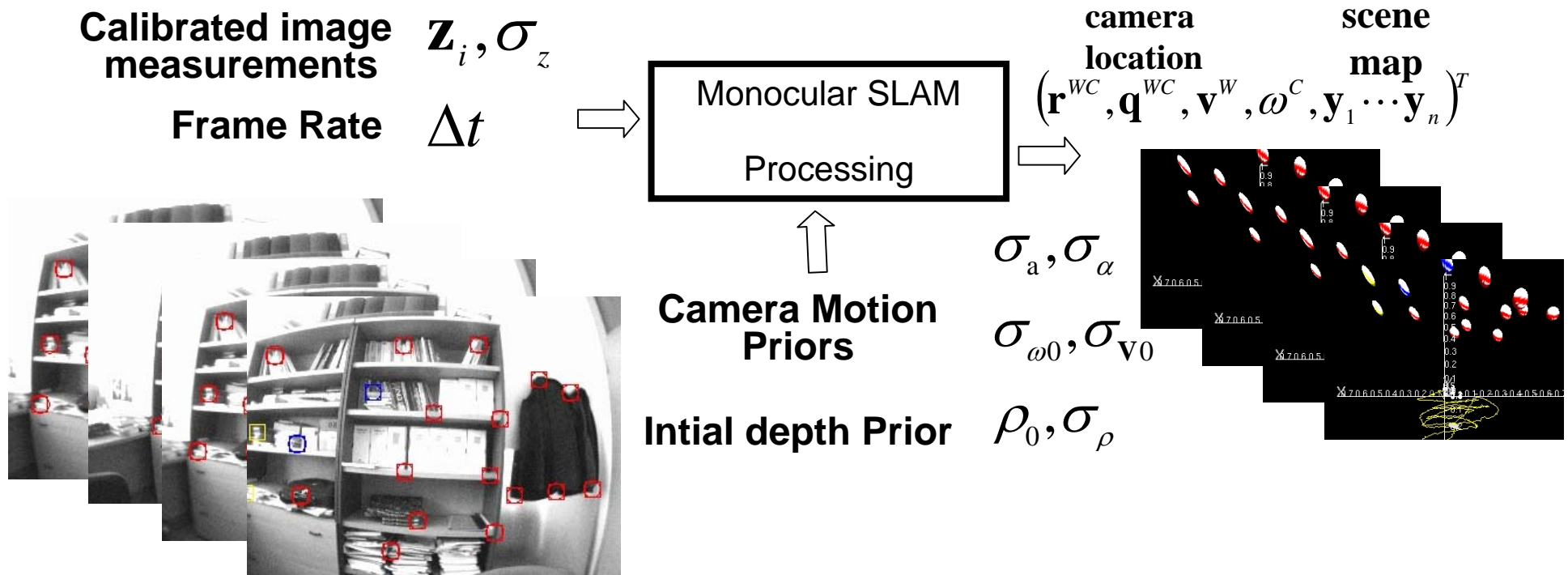
$$\hat{\mathbf{P}}_{k|k}^{\text{new}} = \mathbf{J} \begin{pmatrix} \hat{\mathbf{P}}_{k|k} & 0 & 0 \\ 0 & \mathbf{R}_j & 0 \\ 0 & 0 & \sigma_\rho^2 \end{pmatrix} \mathbf{J}^\top \left| \right.$$

$$\mathbf{J} = \left(\begin{array}{c|cc} I & & 0 \\ \hline \frac{\partial \mathbf{y}}{\partial \mathbf{r}^{WC}}, \frac{\partial \mathbf{y}}{\partial \mathbf{q}^{WC}}, 0, \dots, 0 & \frac{\partial \mathbf{y}}{\partial \mathbf{h}}, \frac{\partial \mathbf{y}}{\partial \rho} \end{array} \right)$$

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Dimensional Monocular SLAM



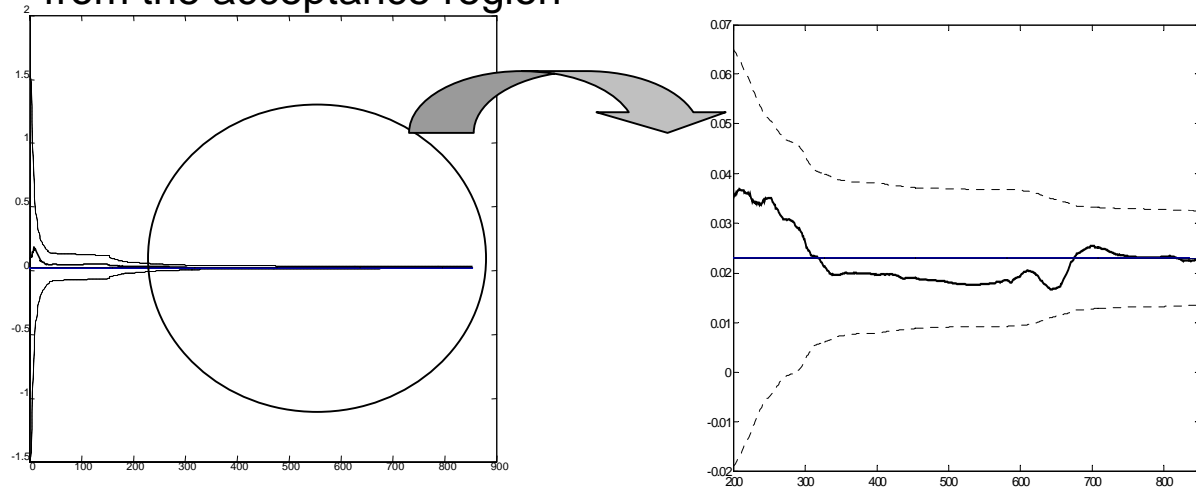
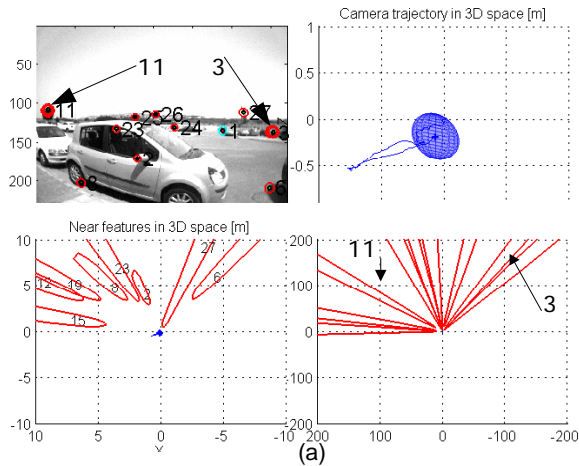
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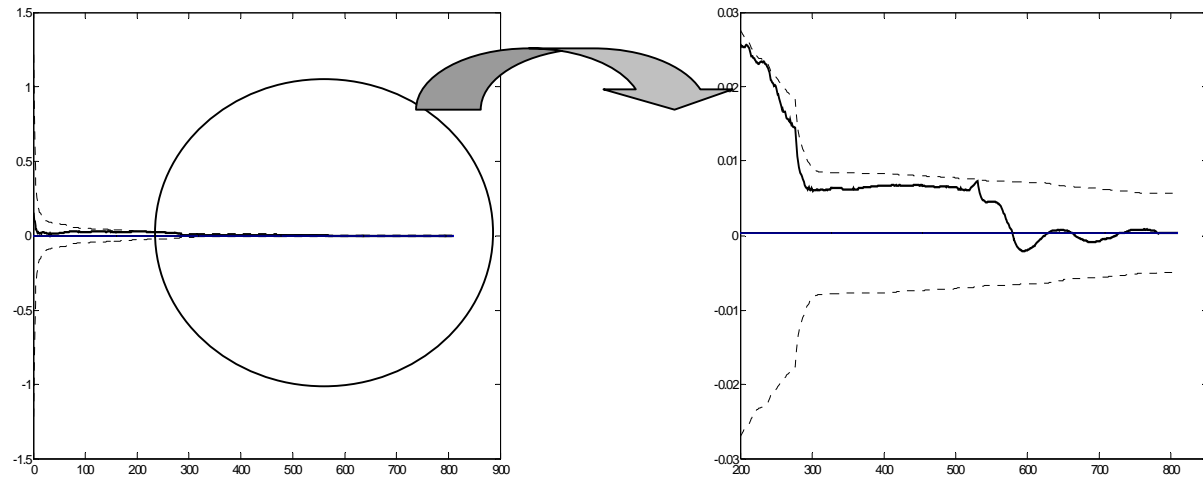
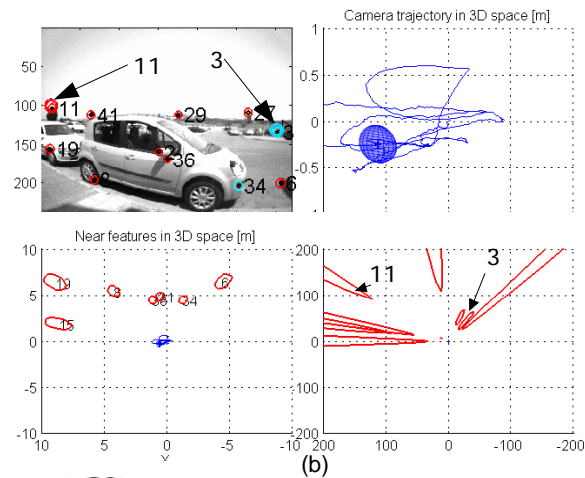
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Inverse Depth Estimation History

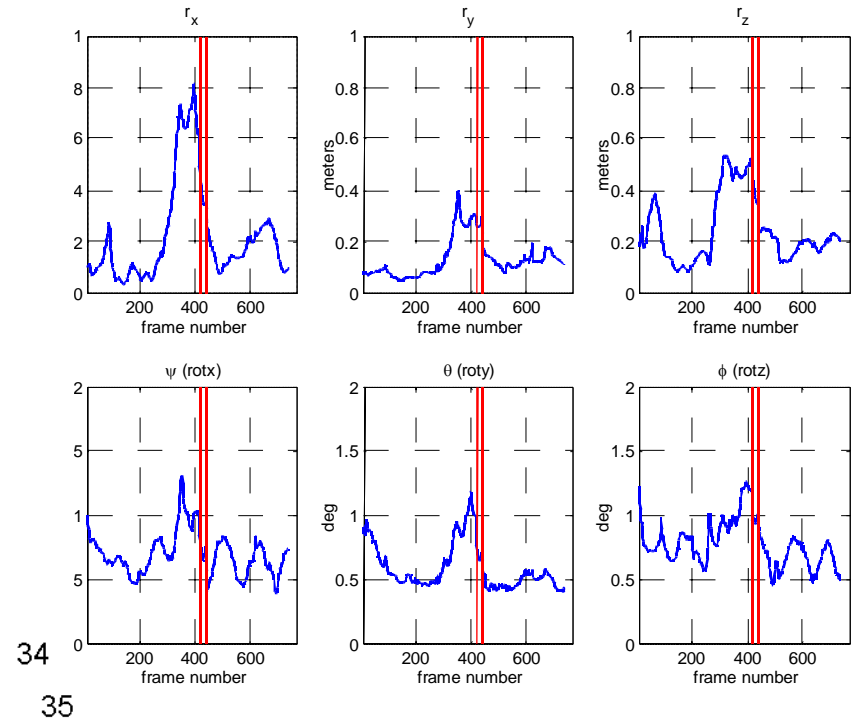
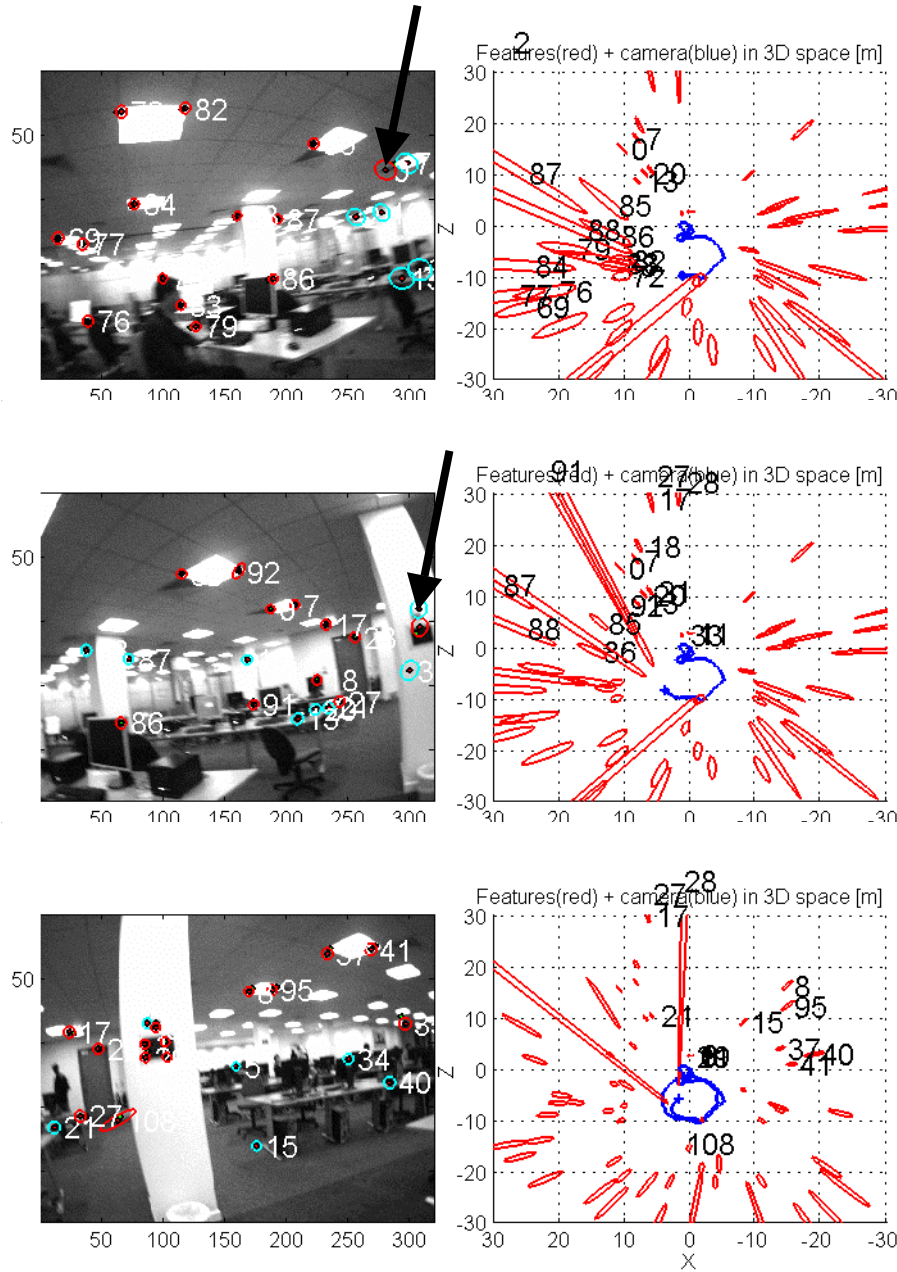
near feature (3), eventually excludes infinite from the acceptance region



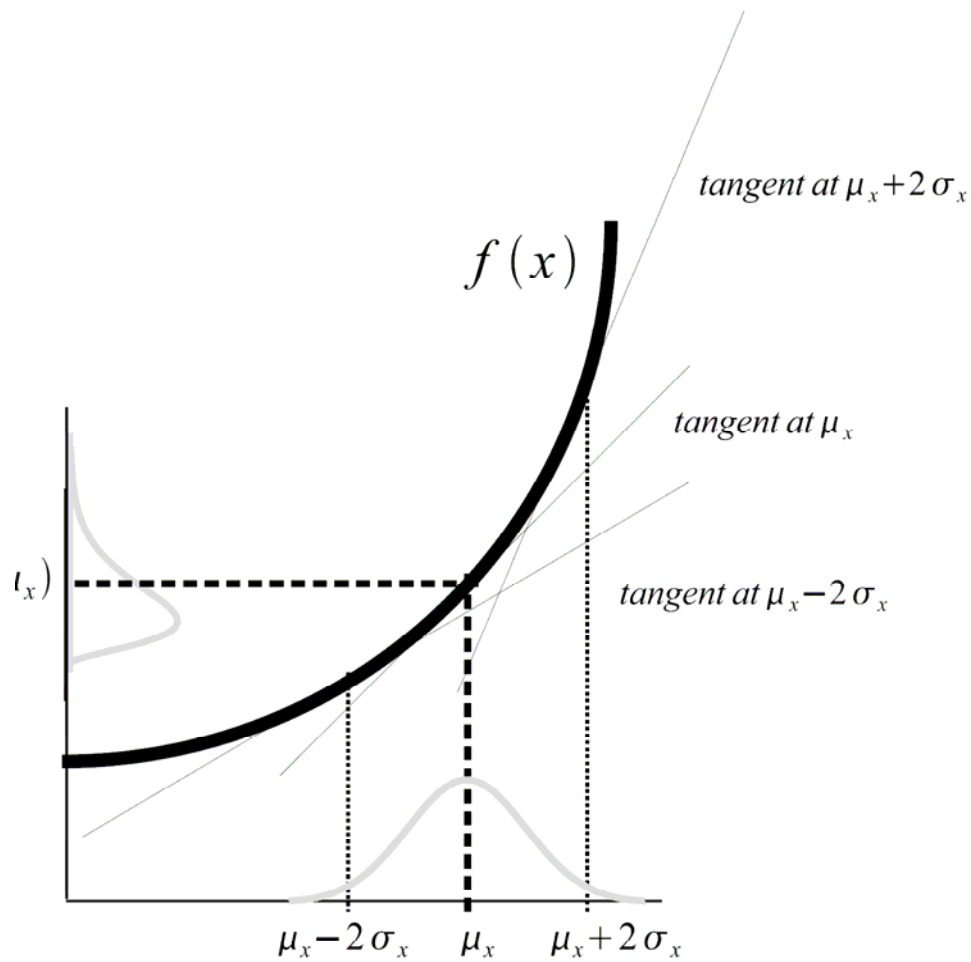
distant feature (11), infinite always included in the acceptance region



Loop Closing

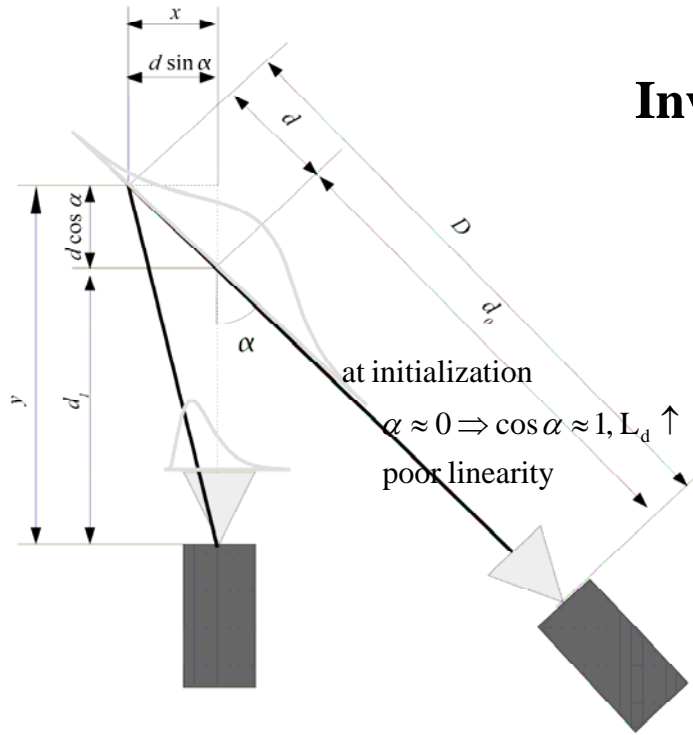


Linearity Index



$$L = \left| \frac{\frac{\partial^2 f}{\partial x^2} \Big|_{\mu_x} 2\sigma_x}{\frac{\partial f}{\partial x} \Big|_{\mu_x}} \right|$$

Inverse depth linearity analysis

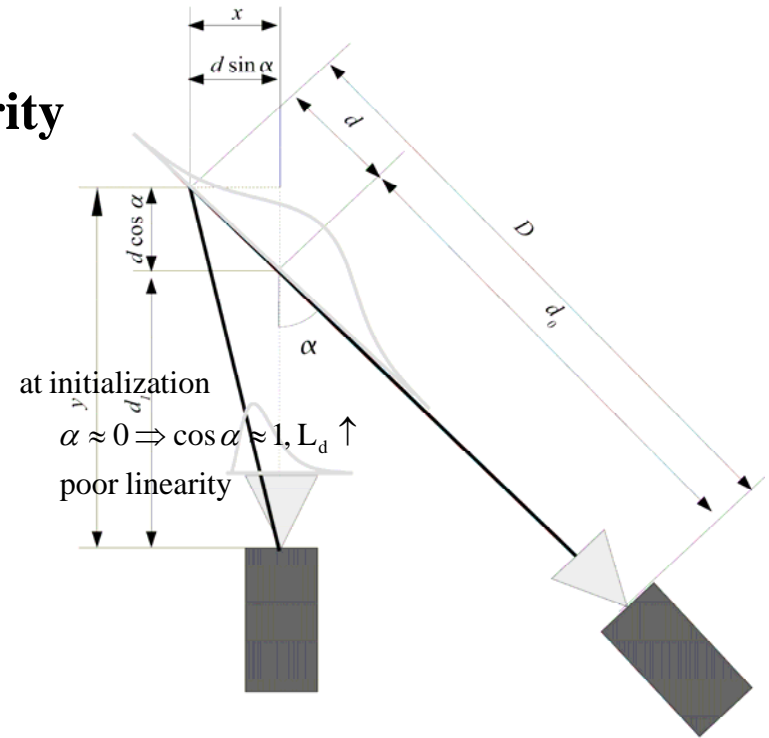


$$L_d = \frac{4\sigma_d}{d_1} |\cos\alpha|$$

at initialization

$$\alpha \approx 0 \Rightarrow \cos\alpha \approx 1, L_d \uparrow$$

poor linearity



$$L_\rho = \frac{4\sigma_\rho}{\rho_0} \left| 1 - \frac{d_0}{d_1} \cos\alpha \right|$$

at initialization

$$\alpha \approx 0 \Rightarrow 1 - \cos\alpha \approx 0, L_\rho \downarrow$$

linearity

after parallax gathering,

$$1 - \cos\alpha, \text{ but } \sigma_\rho$$

linearity

good performance along the whole estimation



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Inverse depth to XYZ conversion

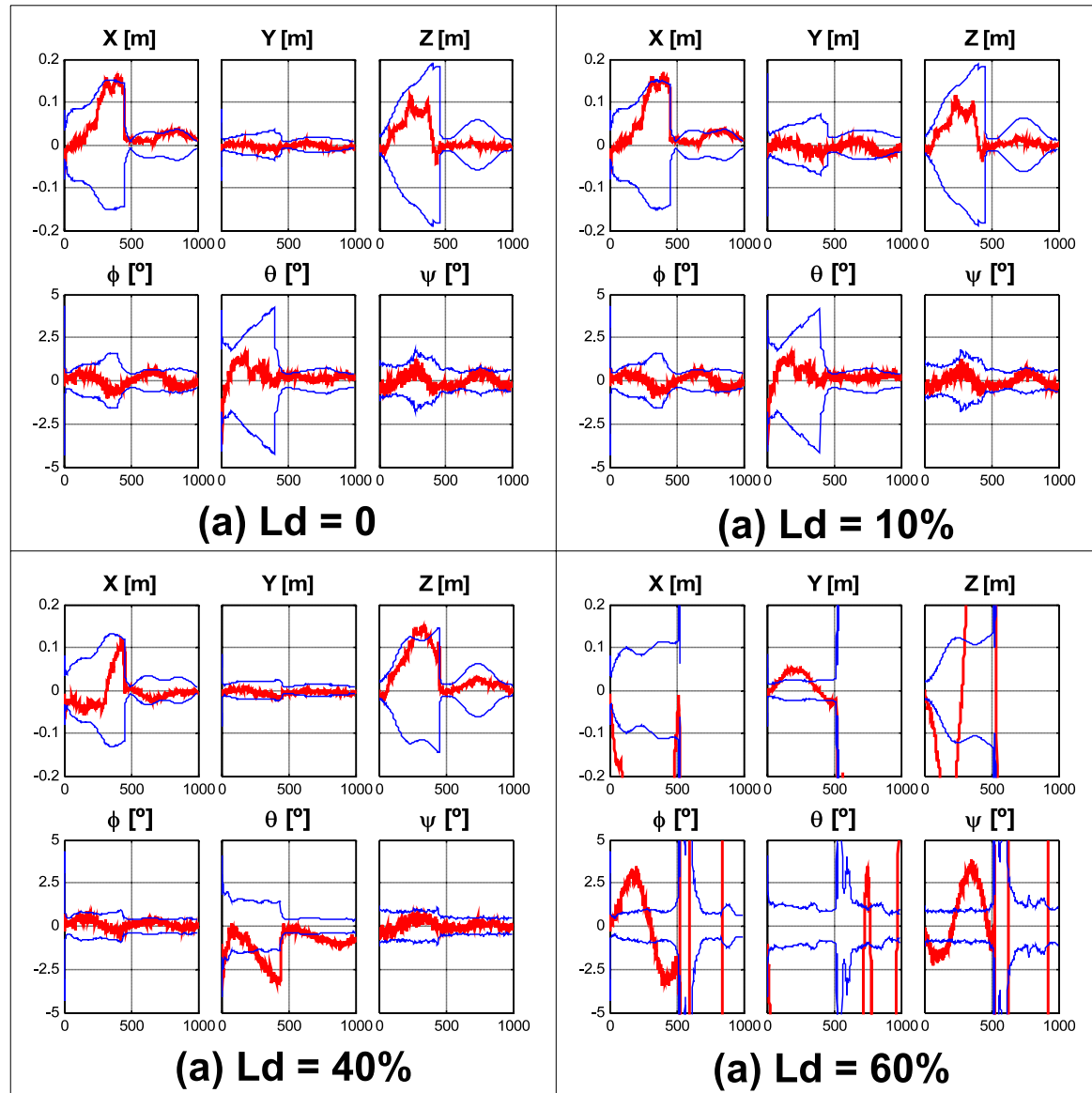
- Inverse depth good performance along the whole estimation process
- Inverse depth coding needs 6 parameters
- XYZ coding good performance for reduced depth uncertainty
- So, it is not mandatory to switch from inverse depth to XYZ, but computing overhead can be reduce
- Switching criteria based on the linearity index

$$L_d = \frac{4\sigma_d}{d_1} |\cos \alpha| < 10\% \quad \left| \begin{array}{l} d_i = \|\mathbf{h}^C\|, \quad \mathbf{h}^C = \mathbf{x}_i - \mathbf{r}^{WC} \\ \sigma_d = \frac{\sigma_\rho}{\rho_i^2}, \quad \sigma_\rho = \sqrt{\mathbf{P}_{\mathbf{y}_i \mathbf{y}_i}(6,6)} \\ \cos \alpha = \mathbf{m}^\top \mathbf{h}^C \|\mathbf{h}^C\|^{-1} \end{array} \right.$$

$$\mathbf{x}_i = \begin{pmatrix} X_i \\ Y_i \\ Z_i \end{pmatrix} = \begin{pmatrix} x_i \\ y_i \\ z_i \end{pmatrix} + \frac{1}{\rho_i} \mathbf{m}(\theta_i, \phi_i) \quad \left| \begin{array}{l} \mathbf{P}_{\text{new}} = \mathbf{J} \mathbf{P} \mathbf{J}^\top, \quad \mathbf{J} = \text{diag} \left(\mathbf{I}, \frac{\partial \mathbf{x}_i}{\partial \mathbf{y}_i}, \mathbf{I} \right) \end{array} \right.$$



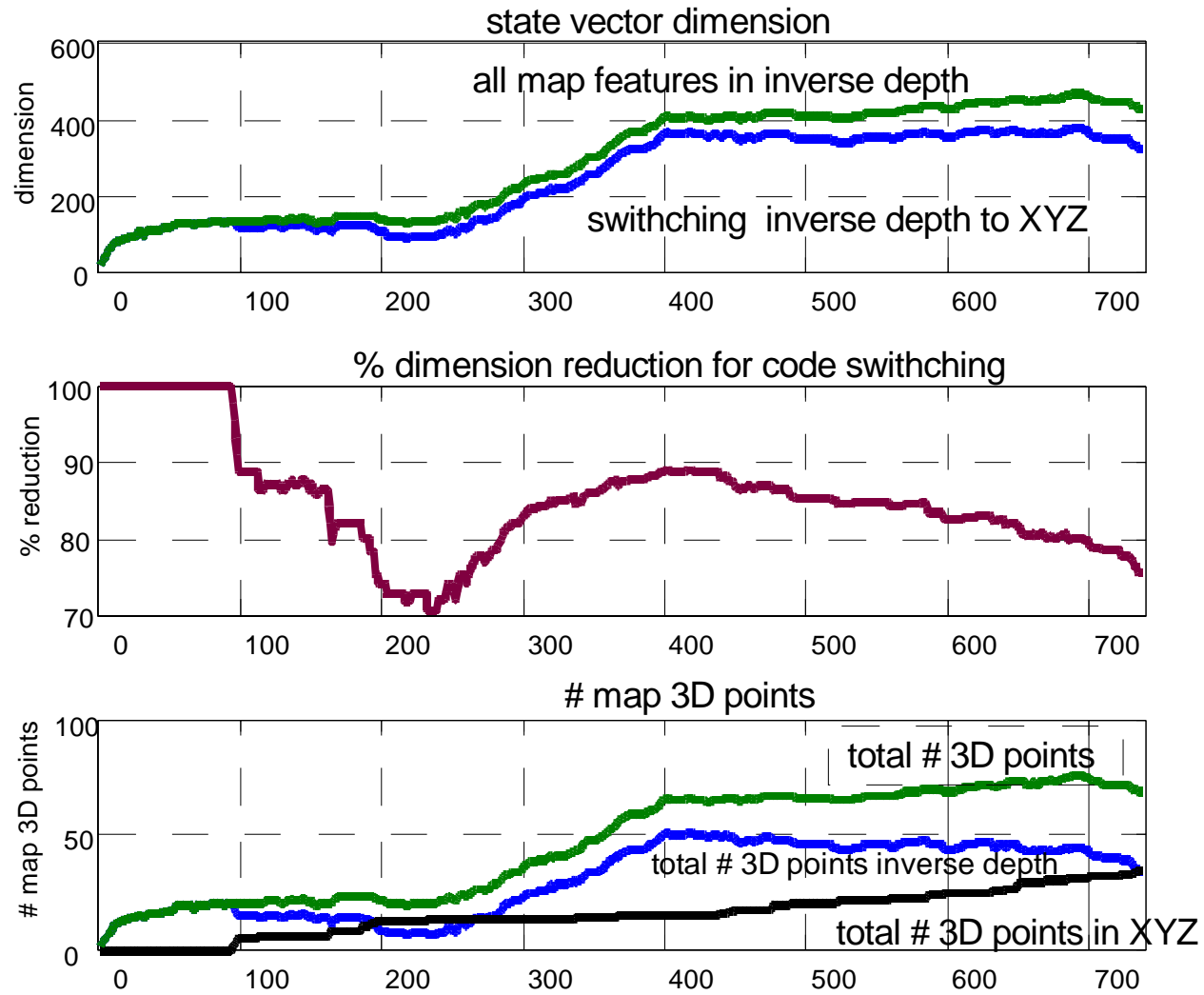
Inverse depth to XYZ conversion threshold



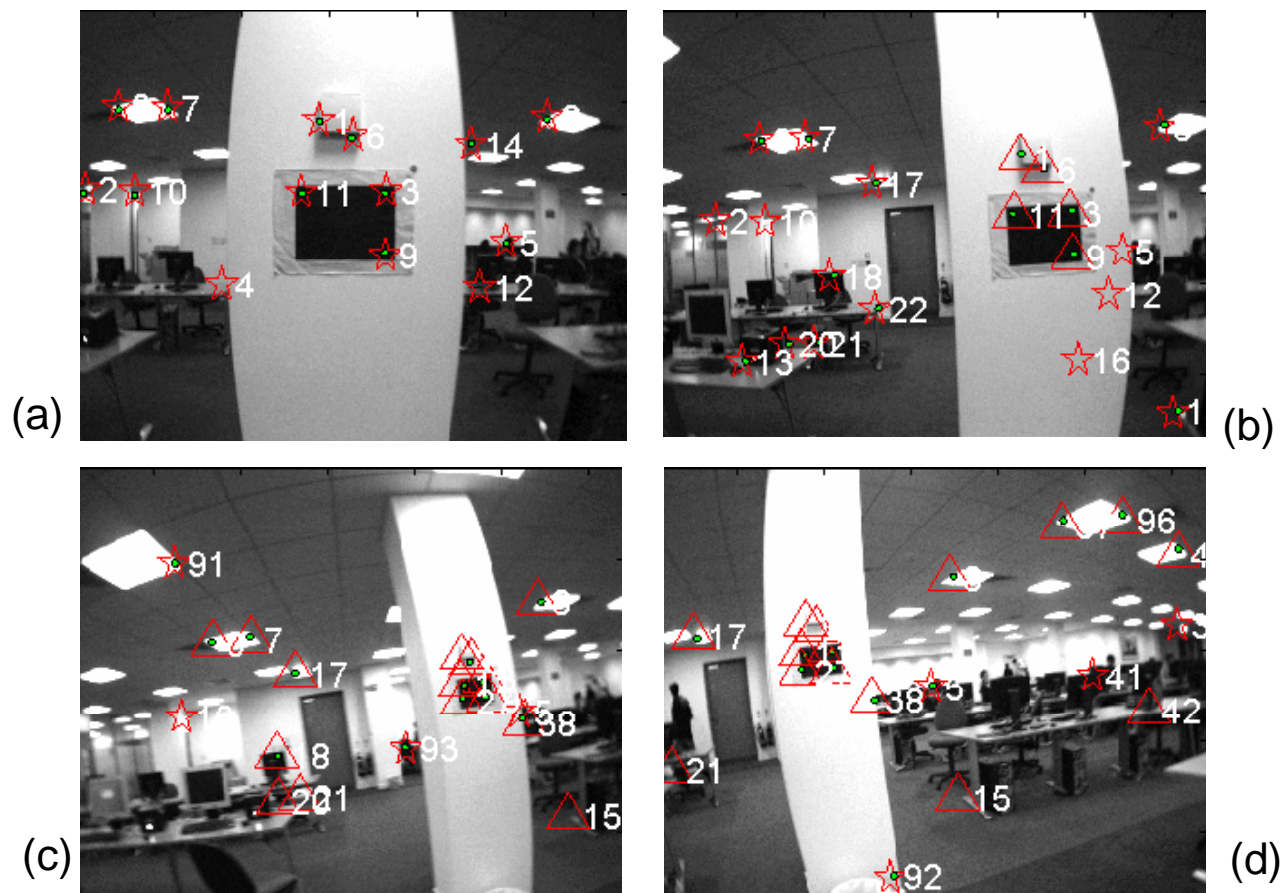
█ Camera location error
 █ 95% acceptance error



Switching evolution



Switching evolution



★ *Inverse depth coding*

△ *Depth coding*



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