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Navigation in GPS Denied Environments: Feature-Aided Inertial Systems

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Outline

- Motivation—why alternative navigation techniques?
- Image-aided INS
  - Single aperture vision aiding
  - Multi-aperture vision aiding
- Ladar-aided INS
- Multi-Sensor Fusion Techniques

Navigation Trends That Push Us Towards Alternative (non-GPS) Navigation

Then		*Now/Future*
Single, stand-alone systems	→	Multiple interdependent vehicles work together to achieve goal (requires navigation)
Precise navigation as a "nice-to-have"	→	Complete dependence on reliable navigation (PNT as an assumed infrastructure)
Navigation accuracy: 5-10 m is just fine	→	Sub-meter to cm-level accuracy *required* ("Accuracy is Addictive")
We want to know where the "big things" are	→	We want to know where everything is

Where Do These Trends Lead?

- **Position, Nav, & Time (PNT) is increasingly important**
  - We want to be sure we have it, anywhere, at any time
- **GPS by itself cannot guarantee anywhere, any time availability**
  - We must therefore turn to alternative approaches
  - Alternative approaches may be (and usually are) inferior to GPS, at least in some measure
- **On principle, it's not a good idea to set up a single point of failure**
  - Reliance on GPS alone means that anything that disrupts GPS (intentionally or unintentionally) will have significant impact
  - If backup systems are in place, then GPS disruptions are not nearly as significant

Or This??

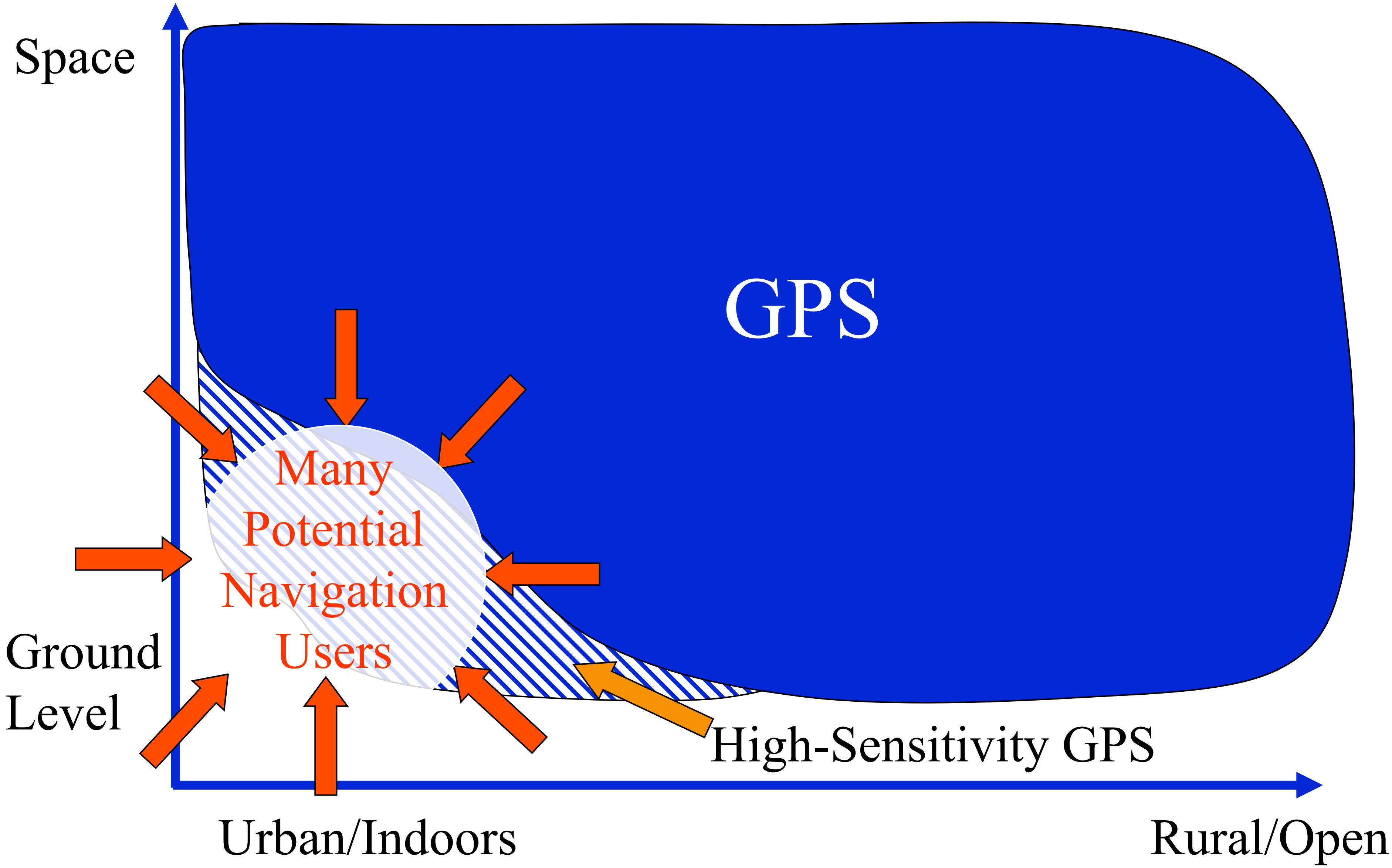
- GPS leads driver into tight spot, stays wedged for three days

- Driver turns right and drives onto train tracks

- Driver follows GPS onto pedestrian walkway, into cherry tree

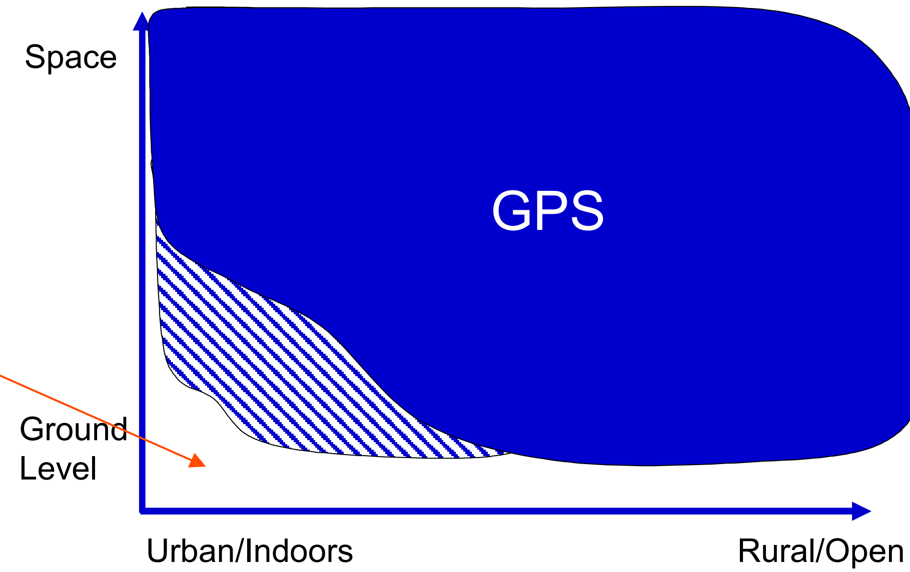
5

The Navigation Gap



How Can We Fill

How can we fill the gap?

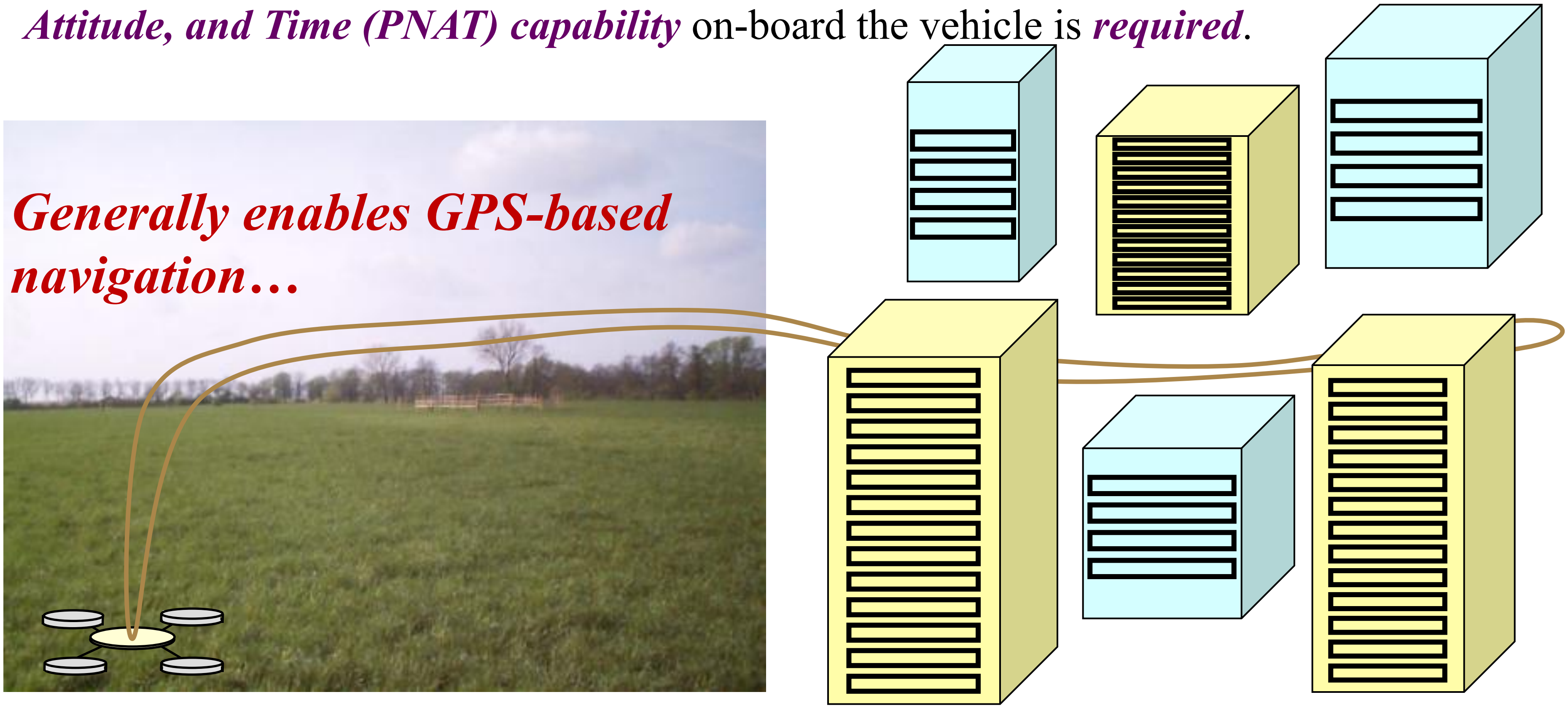


- **Inertial?…Not by itself**
- **High-sensitivity GPS?…Helps, but doesn't fill the gap**
- **Alternative Navigation Approaches**
  - Image/lidar/doppler/DR aiding of inertial
  - Beacon-based navigation (includes pseudolites)
  - Navigation using signals of opportunity (SoOP)
    - RF signals that are not intended for navigation
    - Bio-Inspired Navigation

Motivation: Example

Example: UAV mission

To enable operation of UAVs at ***any time*** in ***any environment***, a ***Precision Navigation, Attitude, and Time (PNAT) capability*** on-board the vehicle is ***required***.



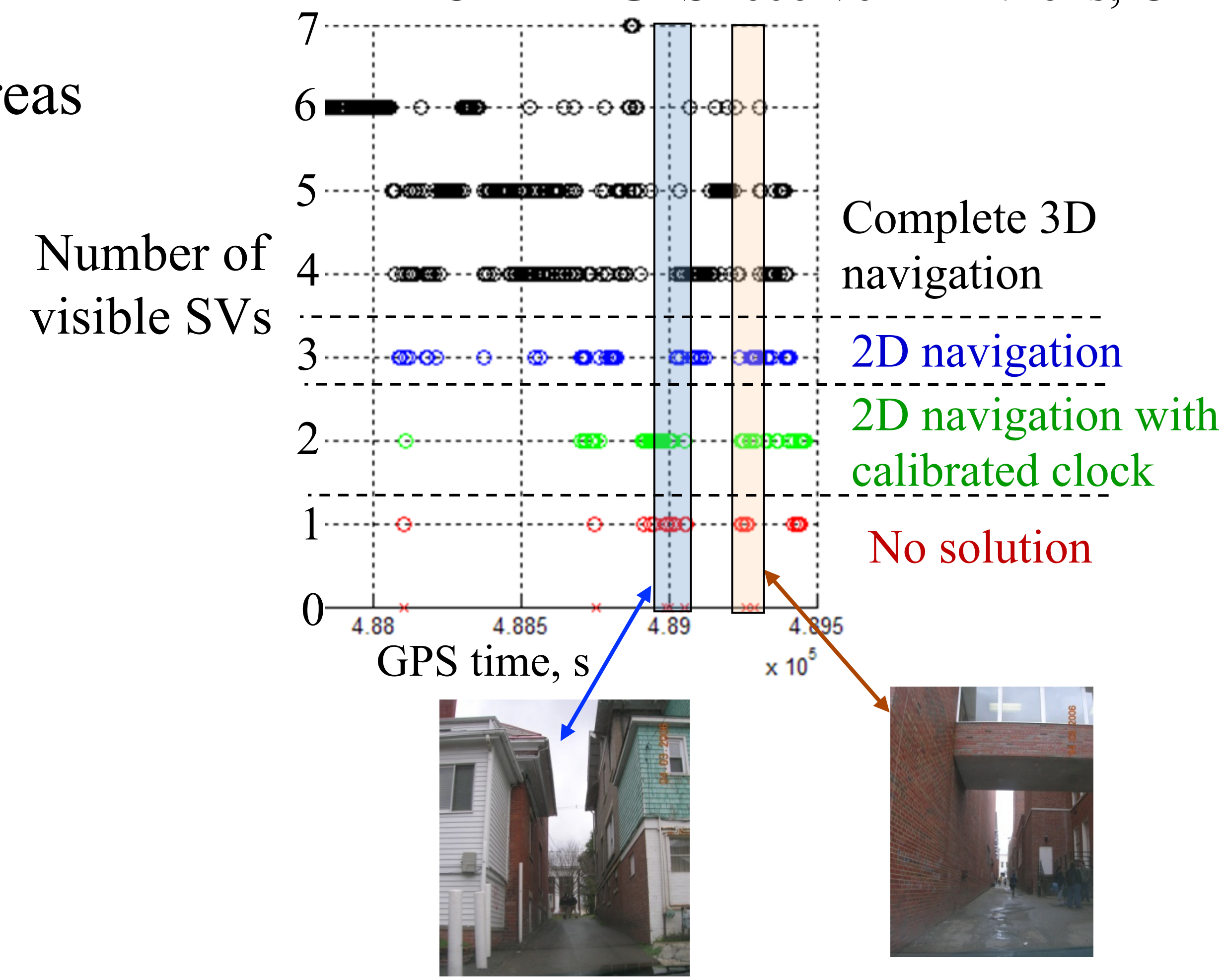
UAV

Fragmented GPS Performance

GPS Limitations

Most GPS receivers report ***fragmented satellite availability*** in urban areas

Satellite availability with NovAtel OEM-4 GPS receiver in Athens, OH



Outline

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  - Multi-aperture vision aiding
- **Ladar-aided INS**
- **Multi-Sensor Fusion Techniques**

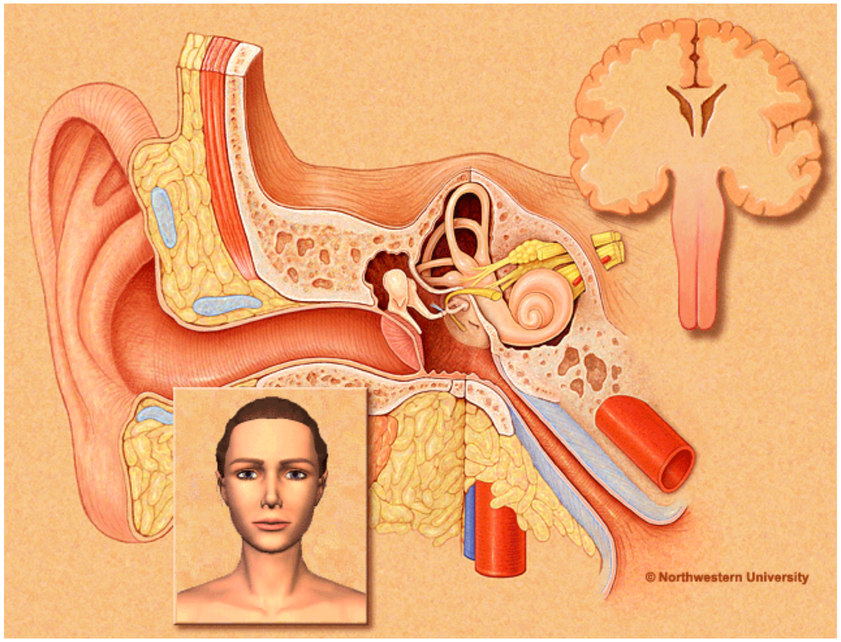
System Examples





How do they do it?

- **Physical sensors:**
  – Mammals: Vestibular (Inertial) and Optical
  – Insects: Horizon, Sun Sensors, Optical, Olfactory (Smell), Magnetic
- **Processing:**
  – Neural processors
  – Tightly coupled sensors
  – Exploits the relative nature of navigation at a different level

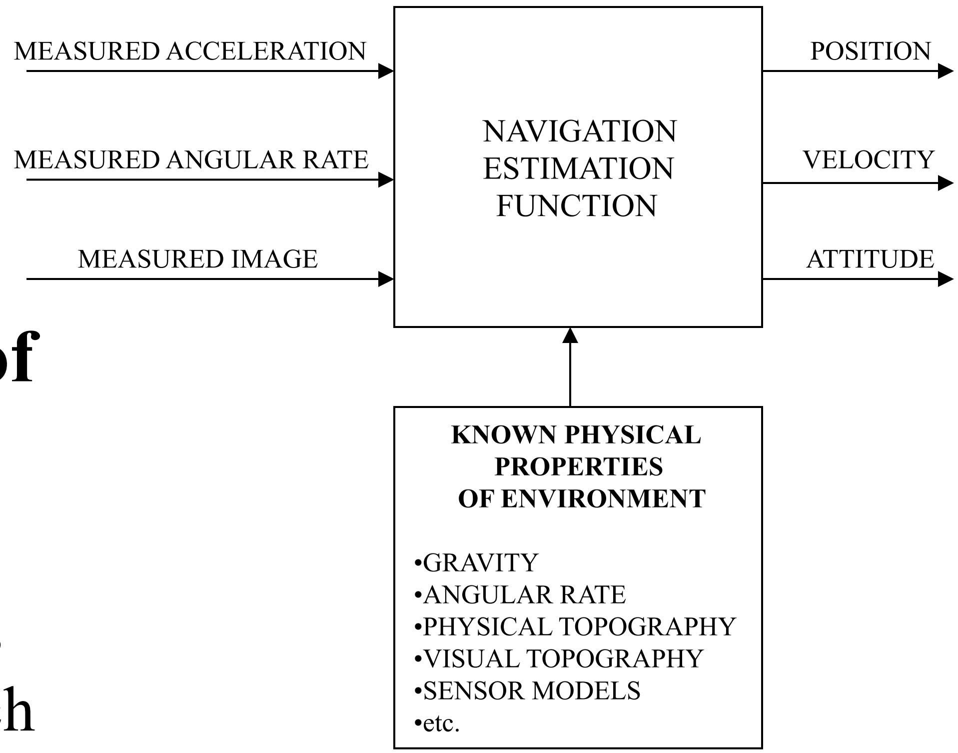


Approach

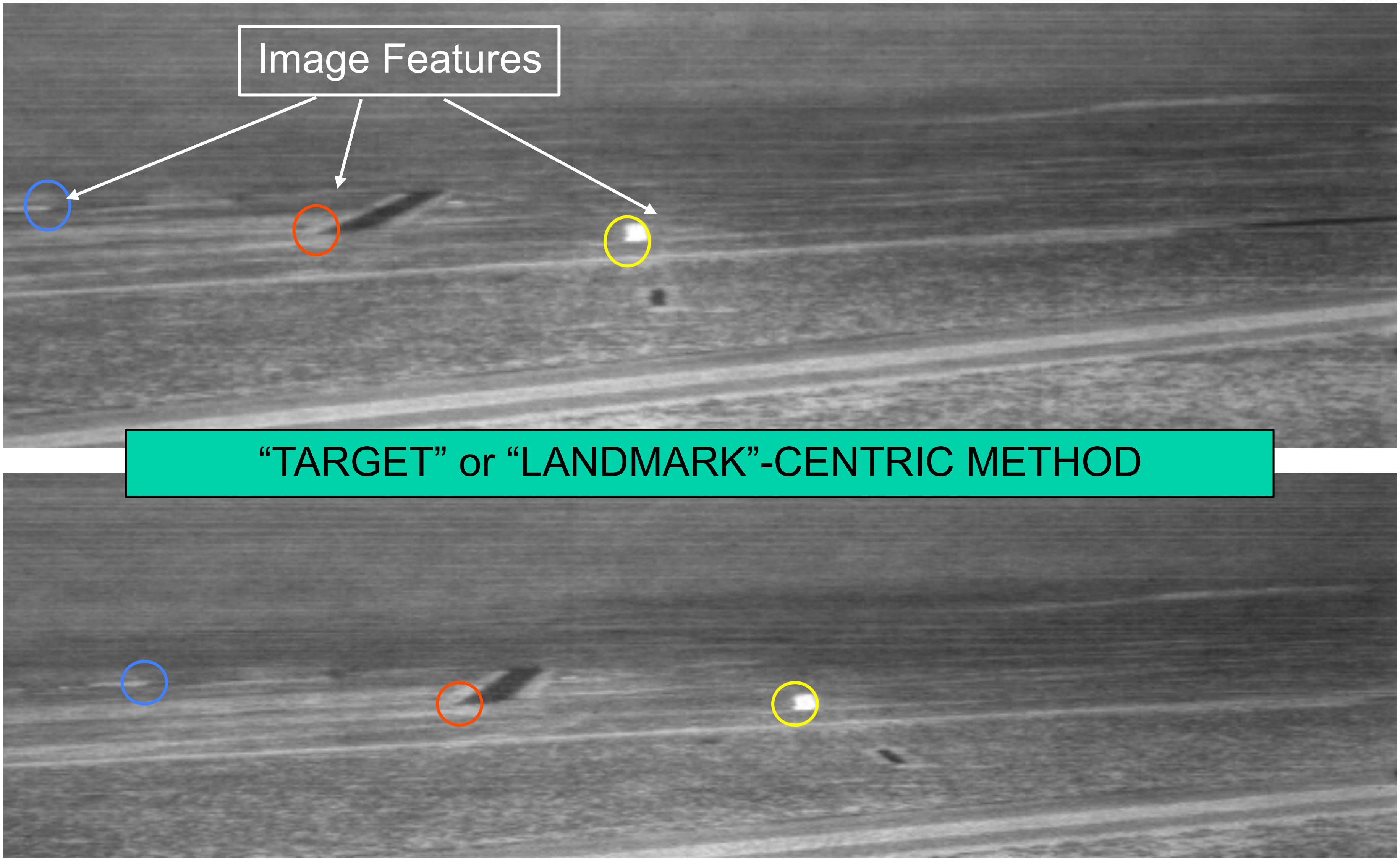
- **Precision navigation through fusion of imaging and inertial systems**
  - Exploits natural synergy between two measurement types
    - Inspired by nature
  - Recent technology improvements makes this physically and computationally realizable
  - Greatly expands the operational reach of precision combat to areas not serviced by GPS

General Problem Statement

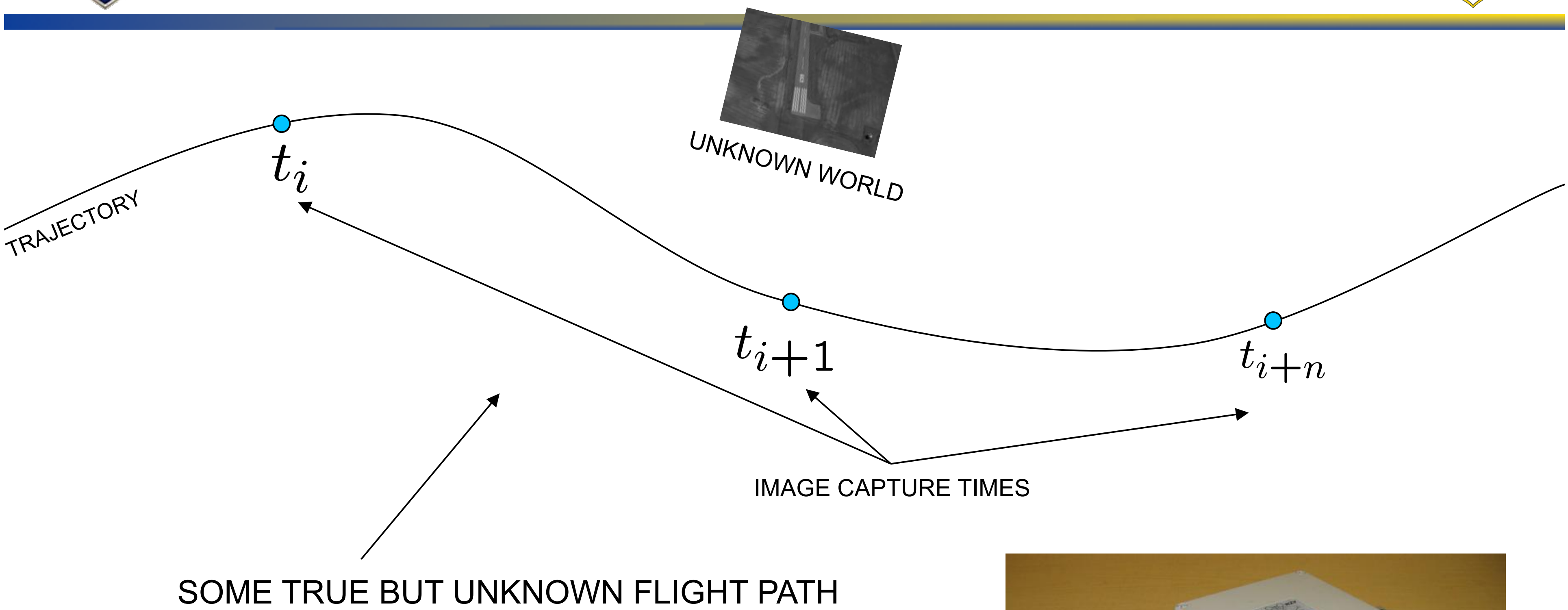
- **Develop a statistically rigorous, online method to estimate a vehicle’s trajectory through deep integration (fusion) of optical and inertial sensors.**
  - Requires contributions and integration research in multiple areas.



Feature Tracking Example



Theory Walkthrough



AVAILABLE SENSORS:
IMAGER (CAMERA)
INERTIAL MEASUREMENT UNIT

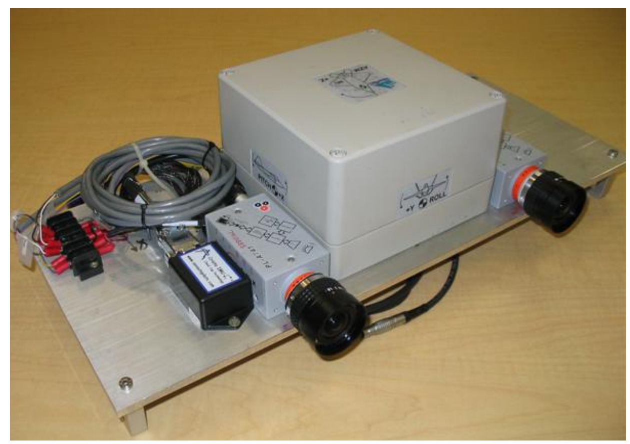


Image Capture

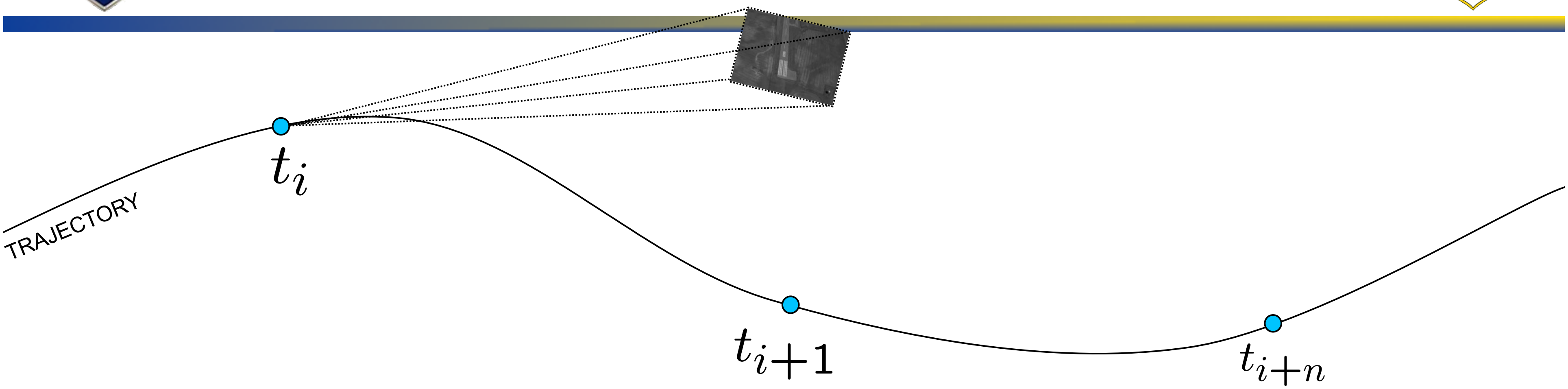
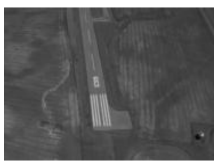


IMAGE i



$$\mathbb{R}^3_{image} = \Pi(\mathbb{R}^m_{world})$$

Projection of world onto image plane.

Transform to Feature Space

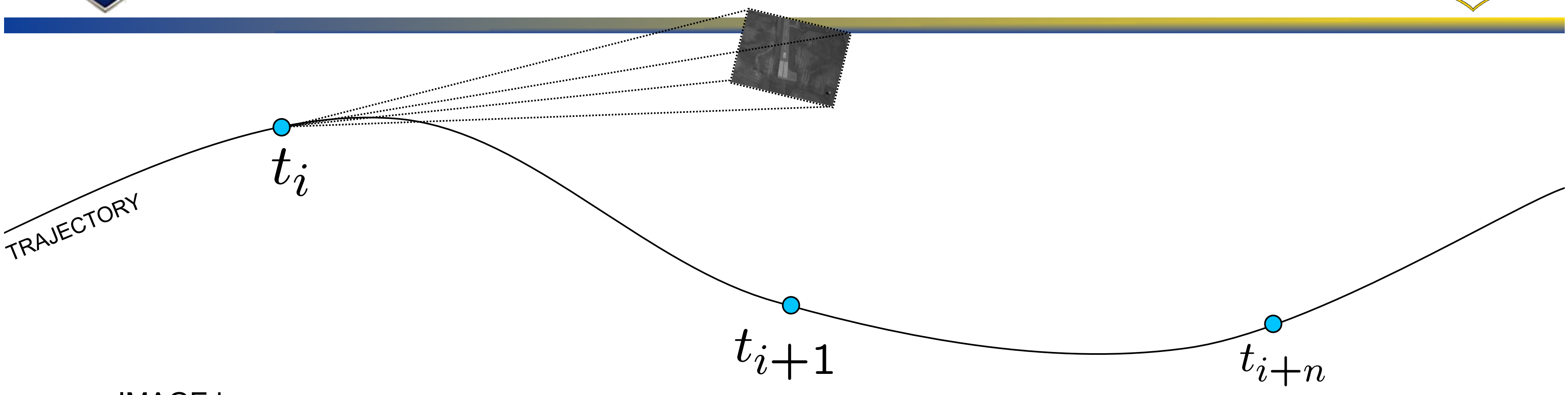
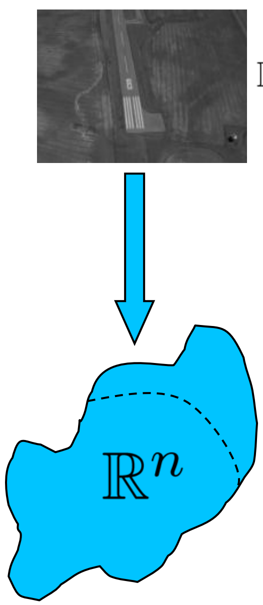


IMAGE i



$\mathbb{R}^3_{image} = \Pi(\mathbb{R}^m_{world})$

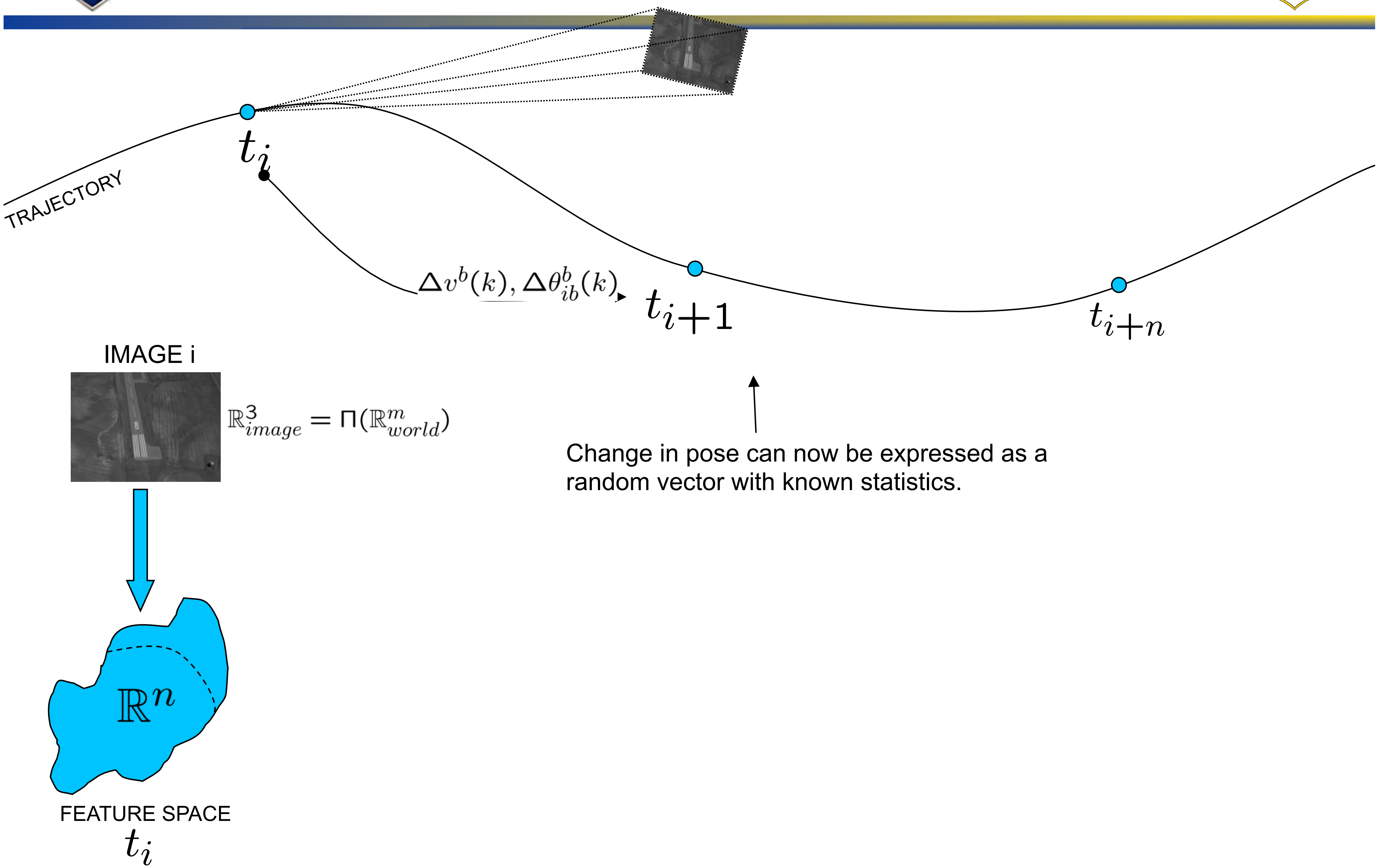
FEATURE SPACE

t_i

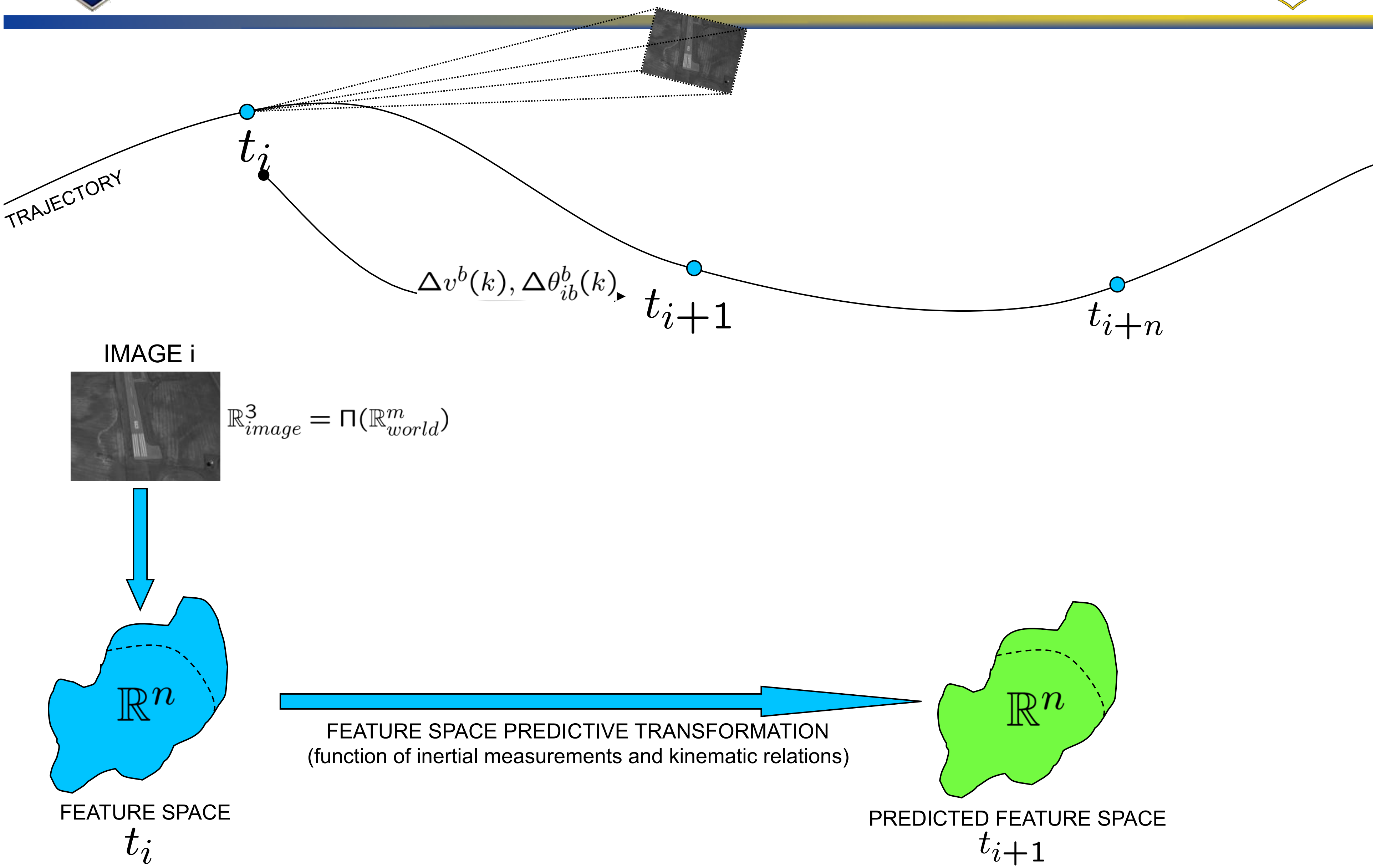
DIMENSIONS:
LOCATOR – Strongly dependent on pose
DESCRIPTOR – Invariant to pose and illumination

NOTE:
- No current algorithm can achieve true independence between the pose and object bases – like humans can.
- Feature transformation algorithms have been proposed which display scale and rotation independence.
  Ex: The scale-invariant feature-tracking (SIFT) algorithm developed by Lowe [19][4].

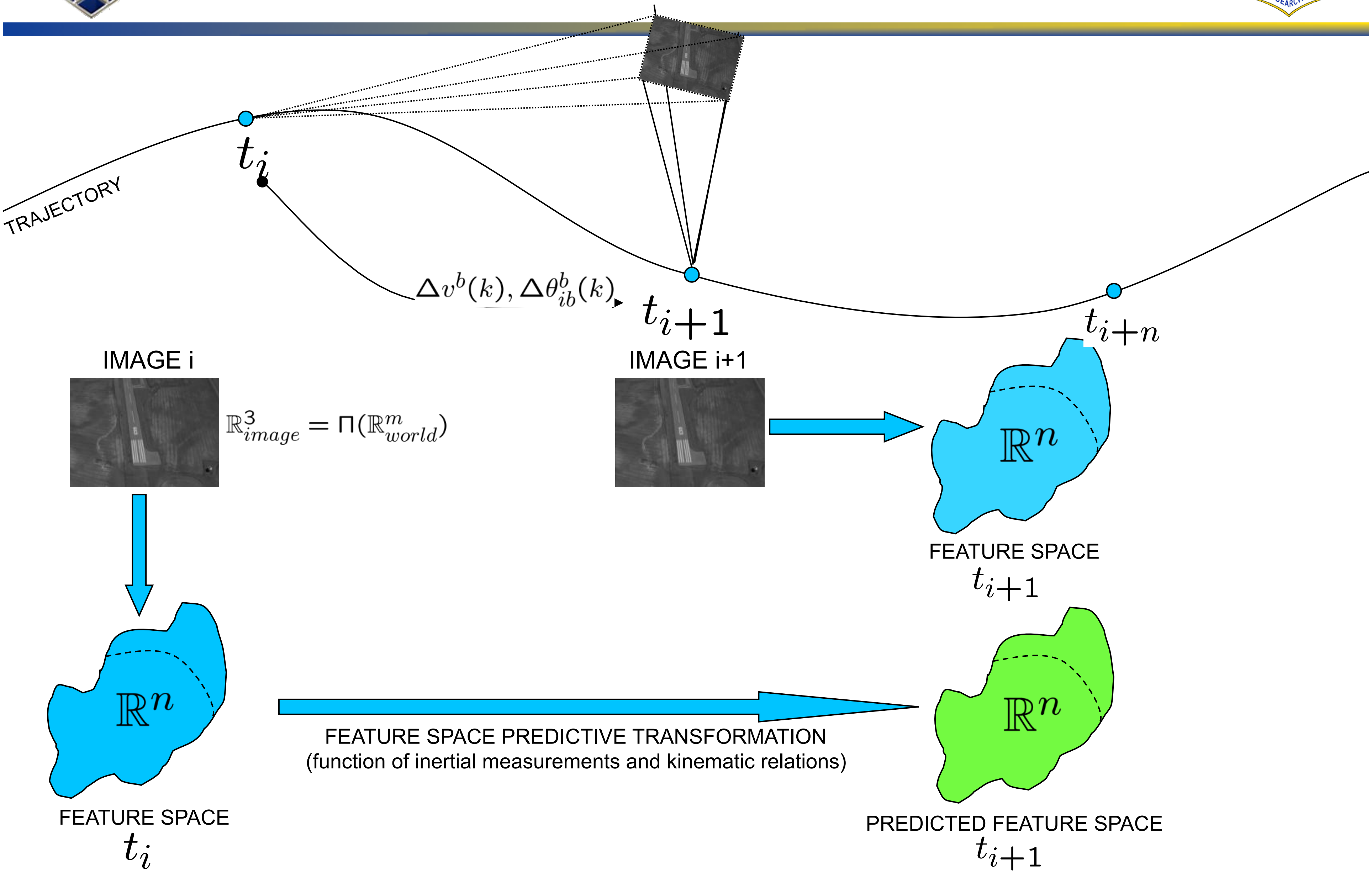
Integrate Inertial Measurements



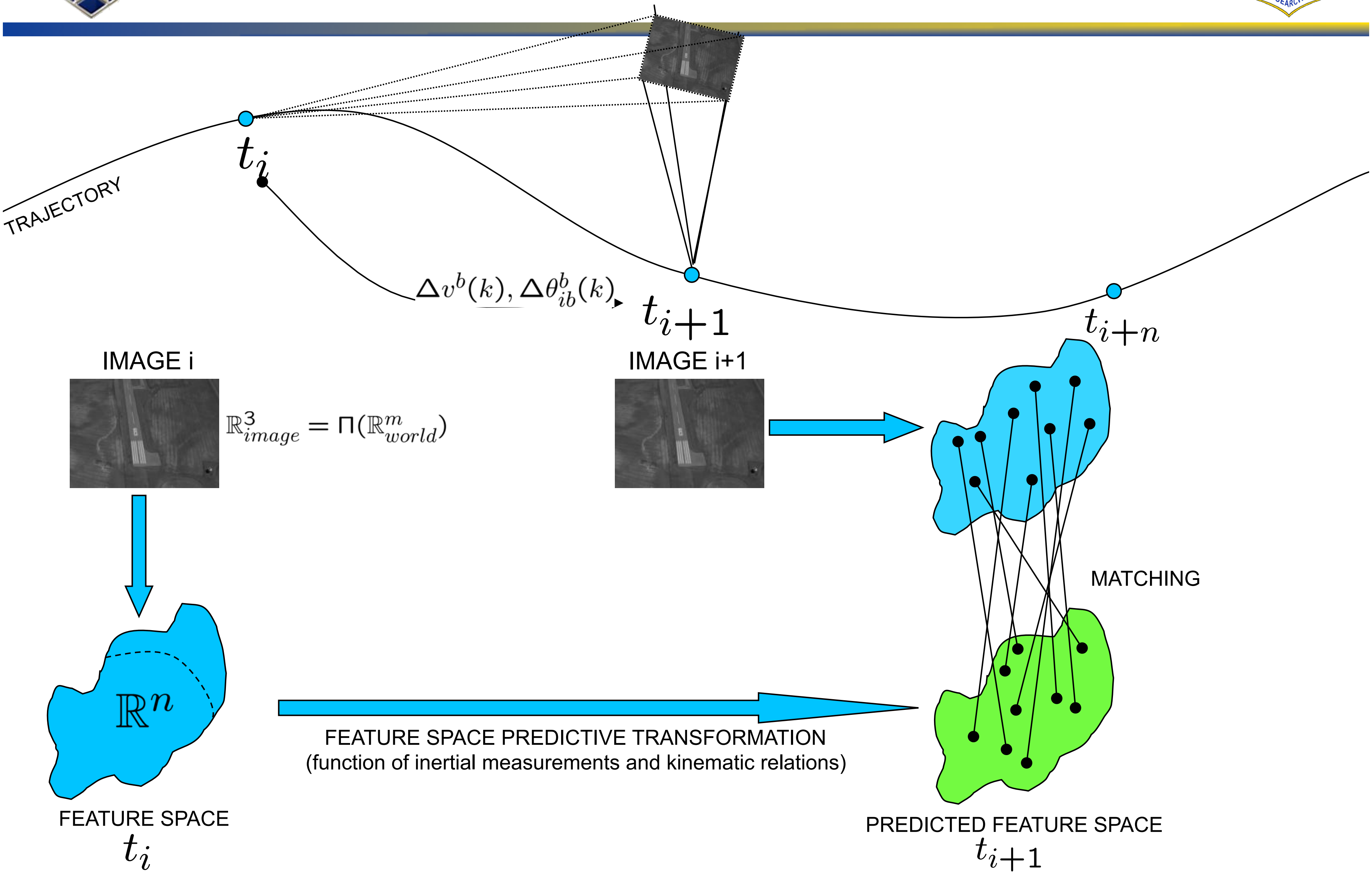
Transform Feature Space



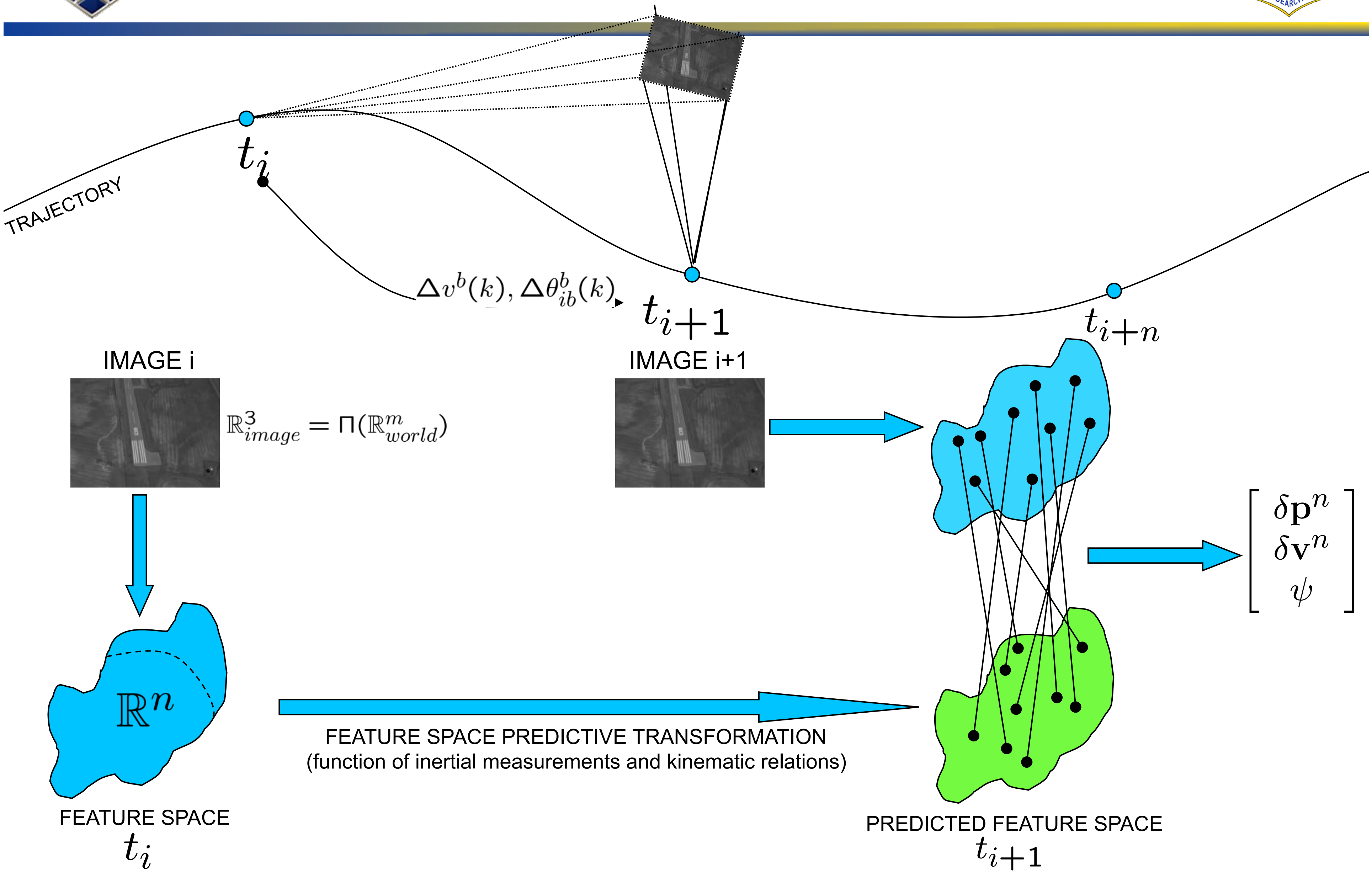
Capture Image and Transform



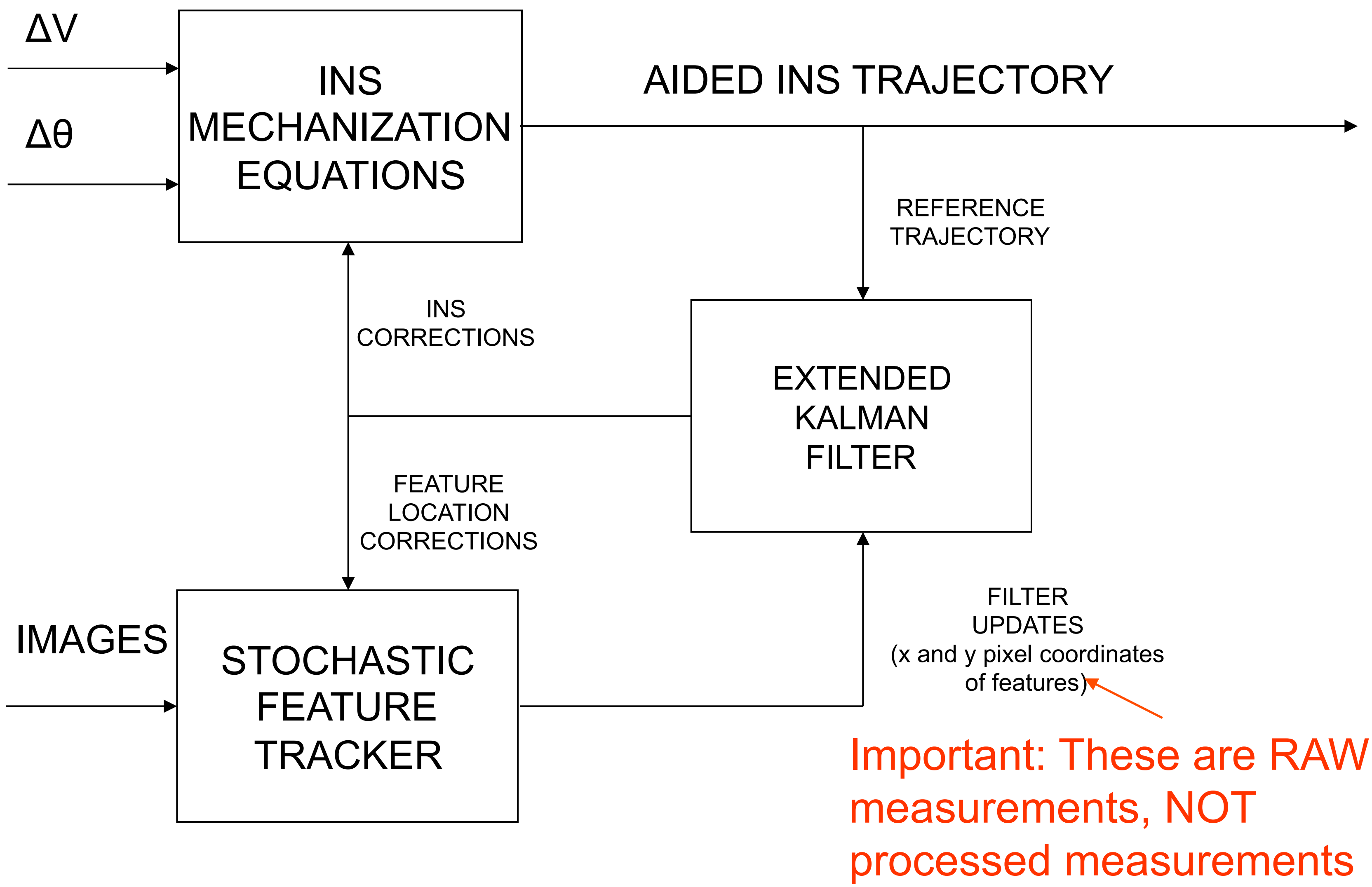
Statistical Feature Matching



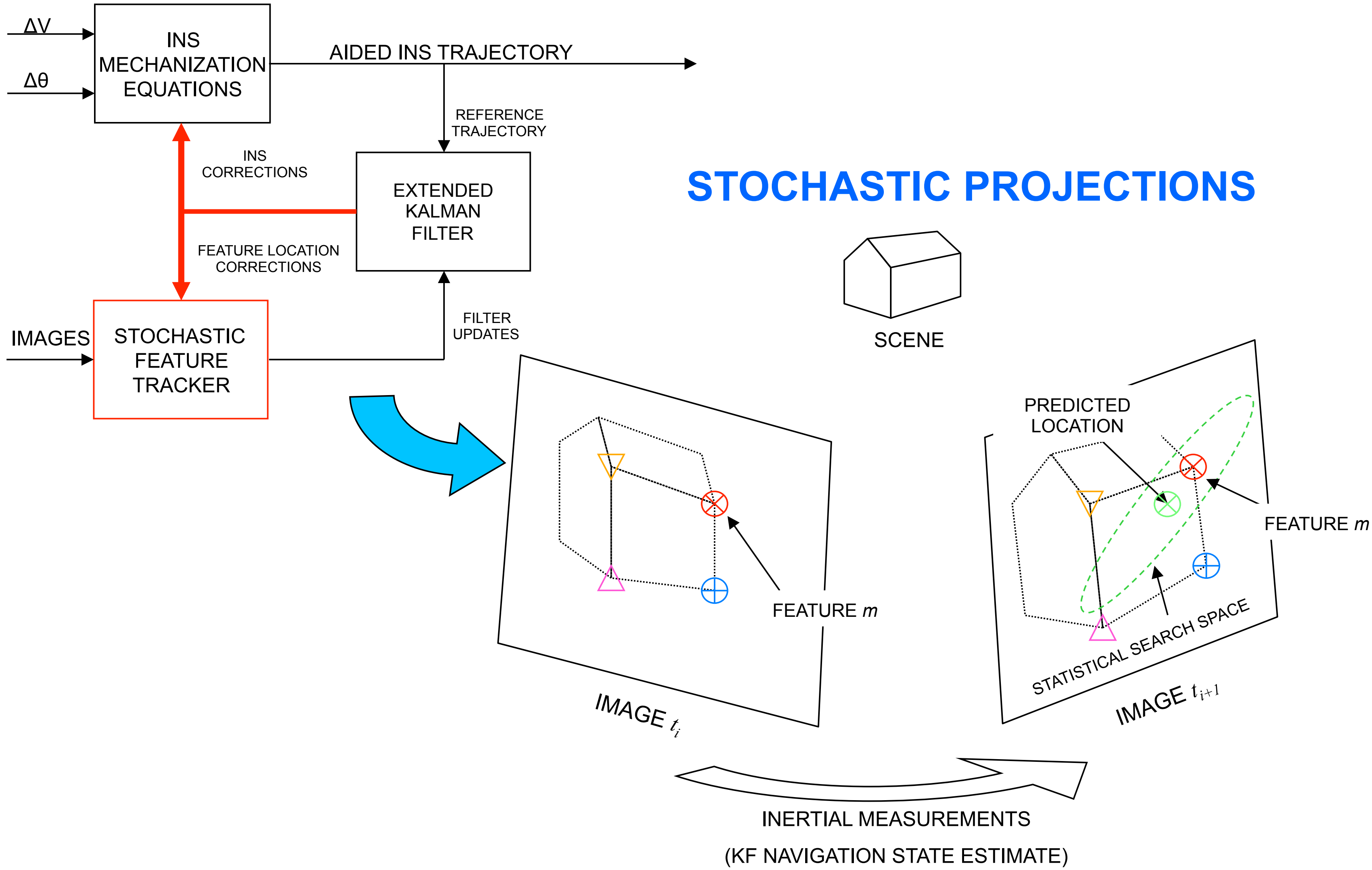
Estimate Trajectory Errors



Block Diagram



Key Word: Fusion



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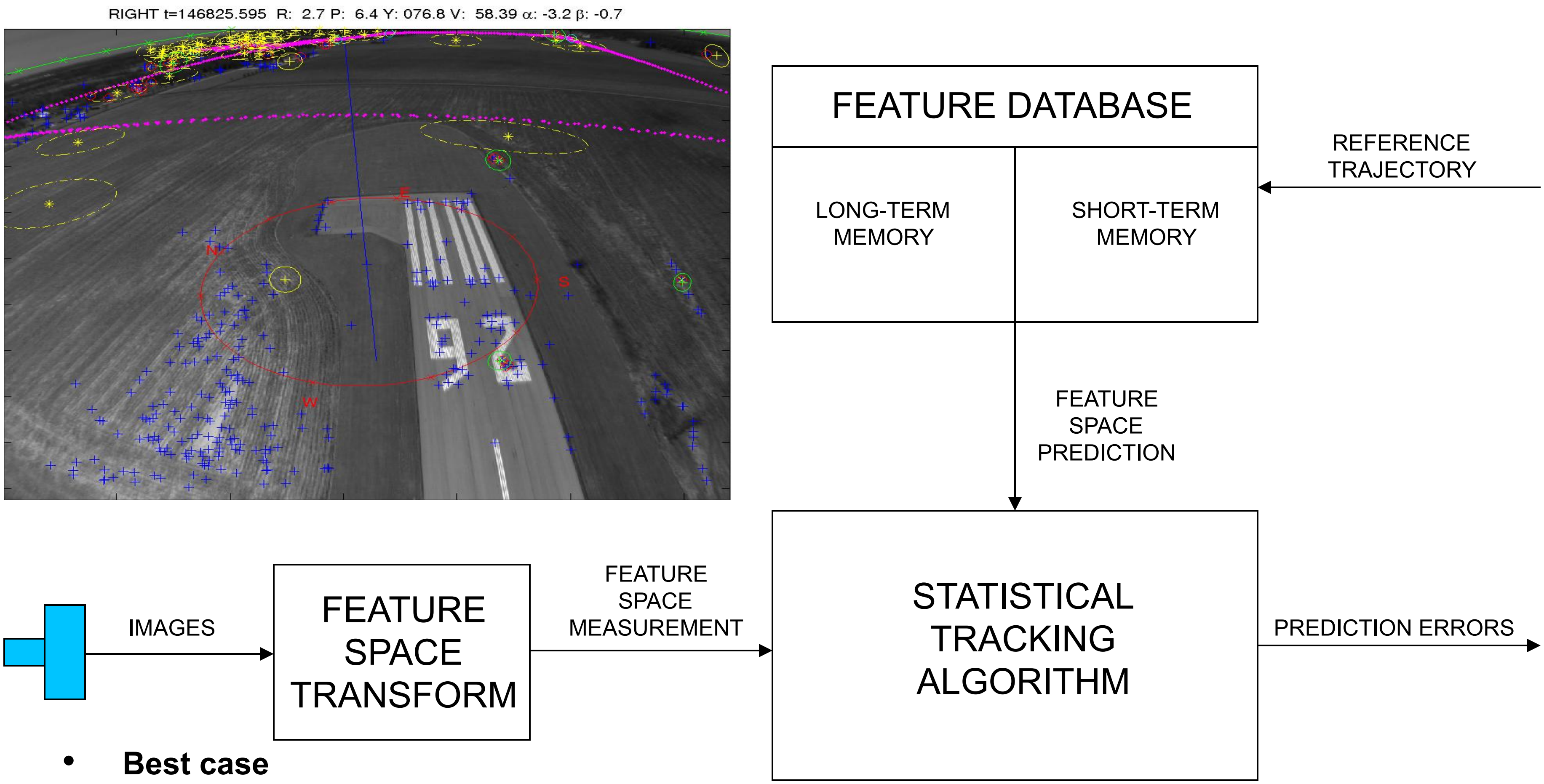
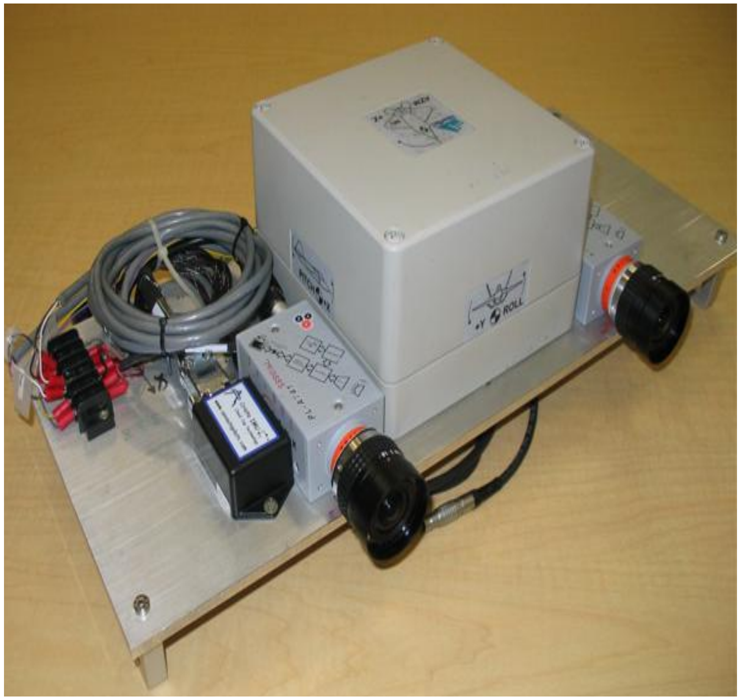
Stochastic Feature Tracker



- **Best case**
  - Track features which provide the best navigation information for as long as possible
  - Prefer features which are:
    - Strong and easily identified (to help maintain track)
    - Locally distinct in feature space (to minimize false matches)
    - Well-separated in image space (to maximize navigation state observability)

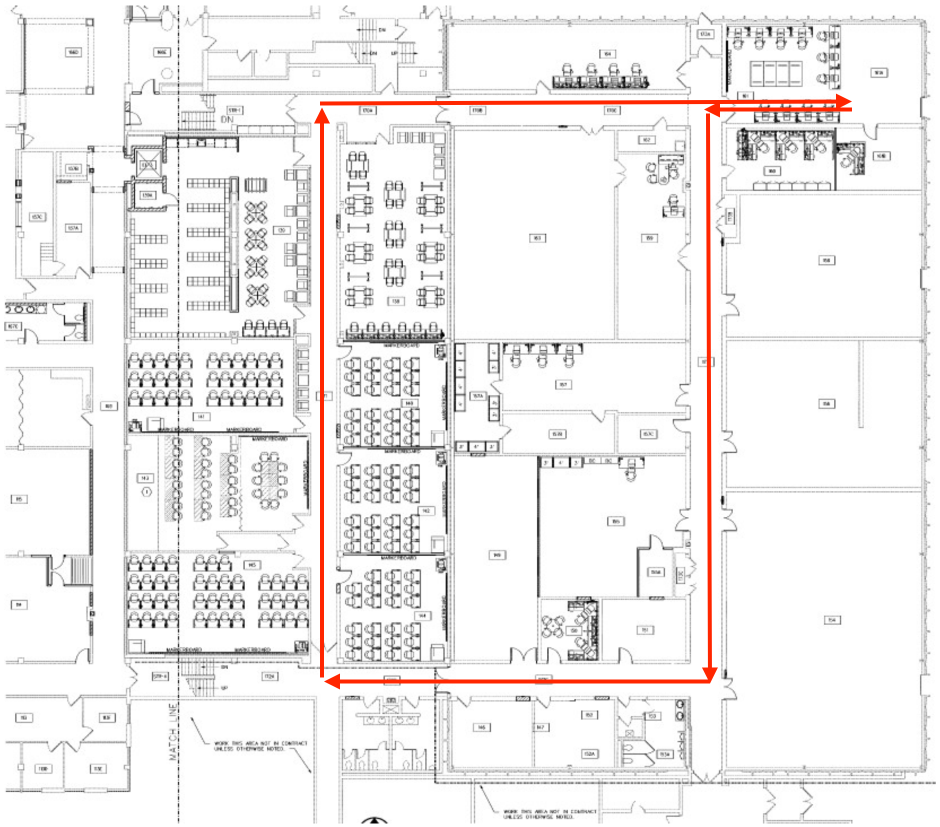
Experiment

- **Data collection system**
  - HG1700 IMU from Novatel Black Diamond System
    - 100 Hz measurements
  - Crista MEMS IMU
    - 100 Hz measurements
  - 2 CMOS digital cameras
    - Global shutter CMOS
    - Enables binocular measurements



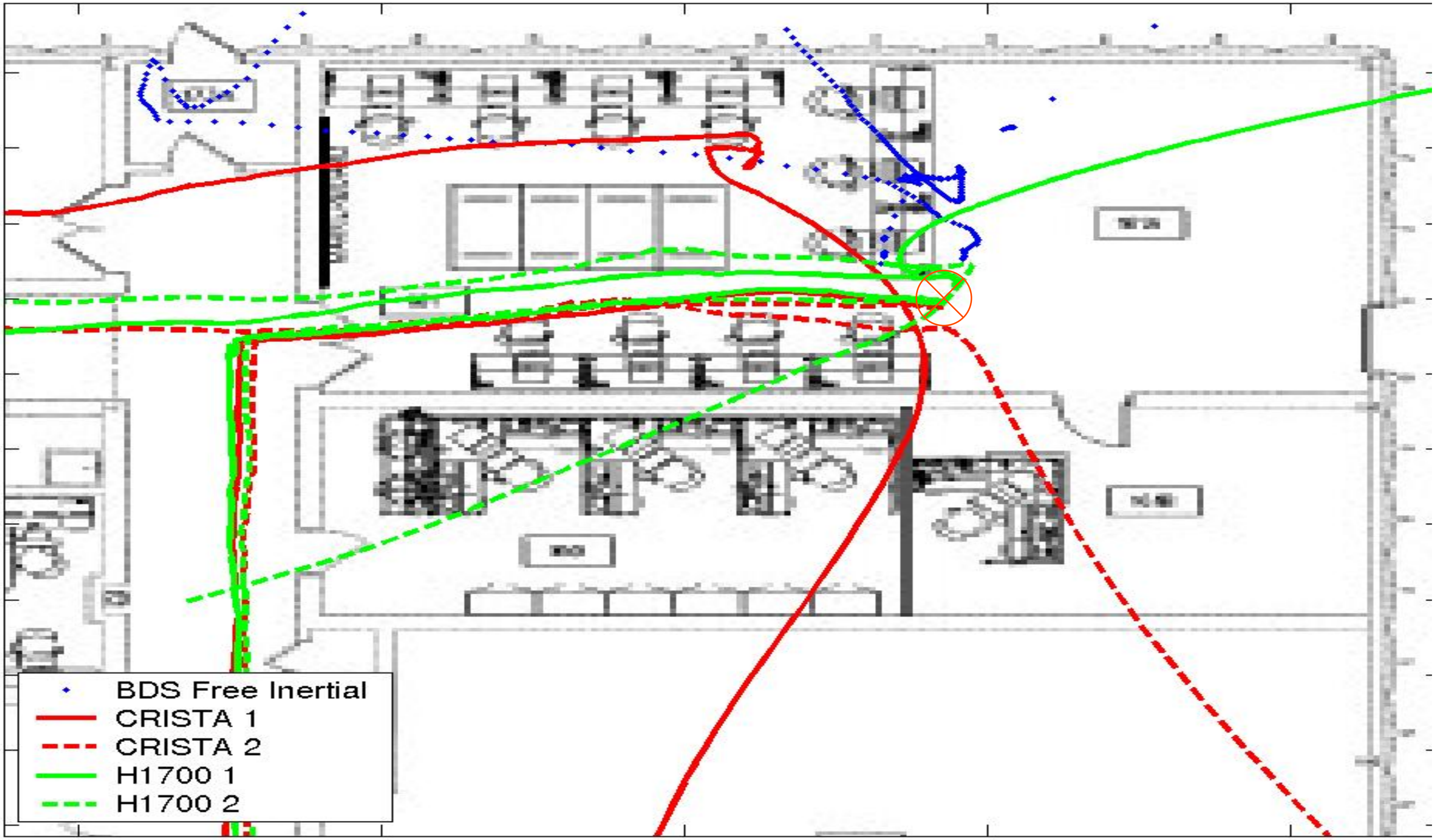
Indoor Profile

- **Conducted in the Advanced Navigation Technology Center**
- **5 minute alignment followed by 10 minute closed navigation path through hallways**
  - No “reused” landmarks
  - Tracked up to 10 landmarks at a time
- **GPS Unavailable**
- **Both Tactical and Consumer-grade inertial sensors**

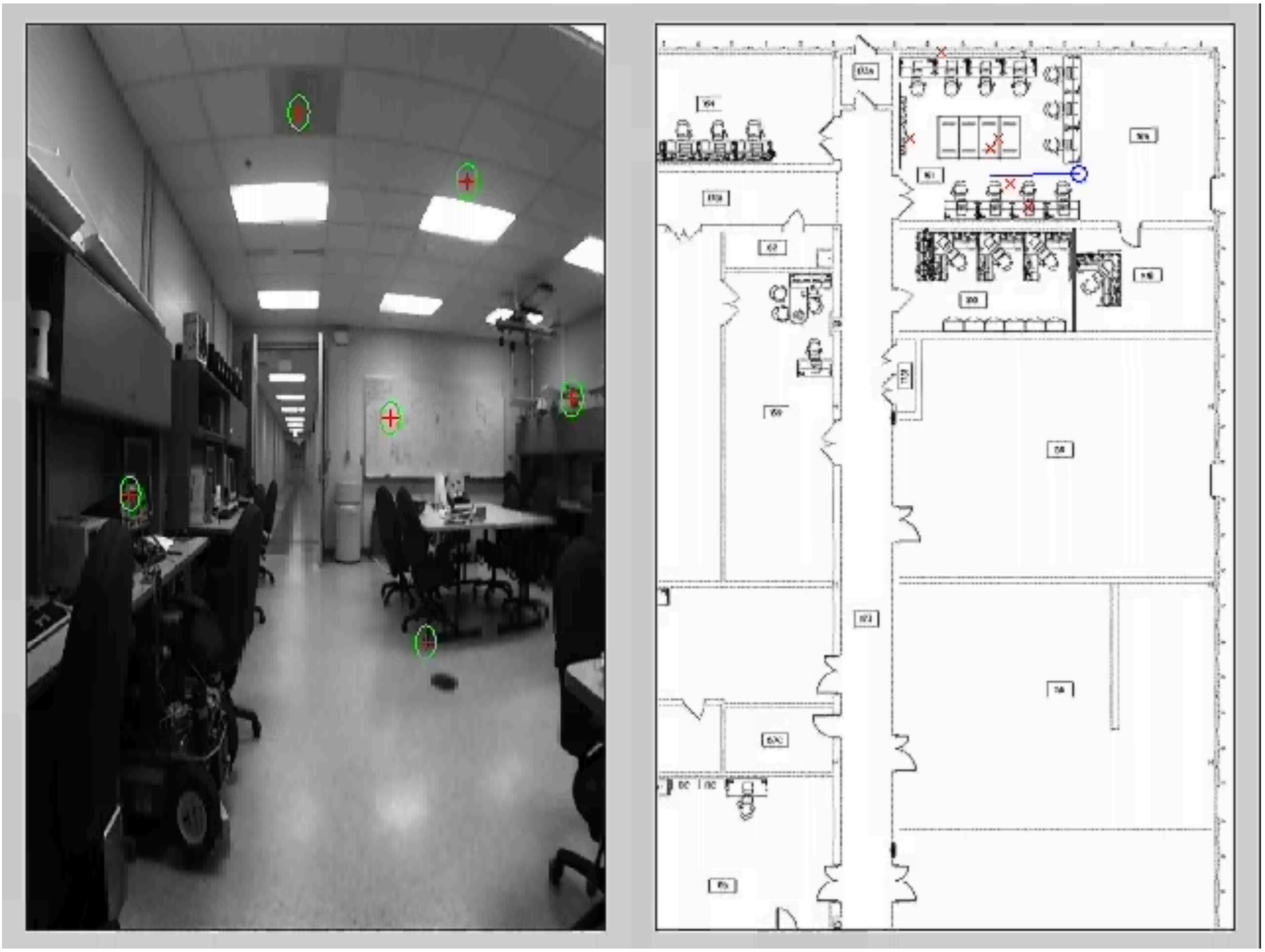


Indoor Profile

Indoor Profile



Video



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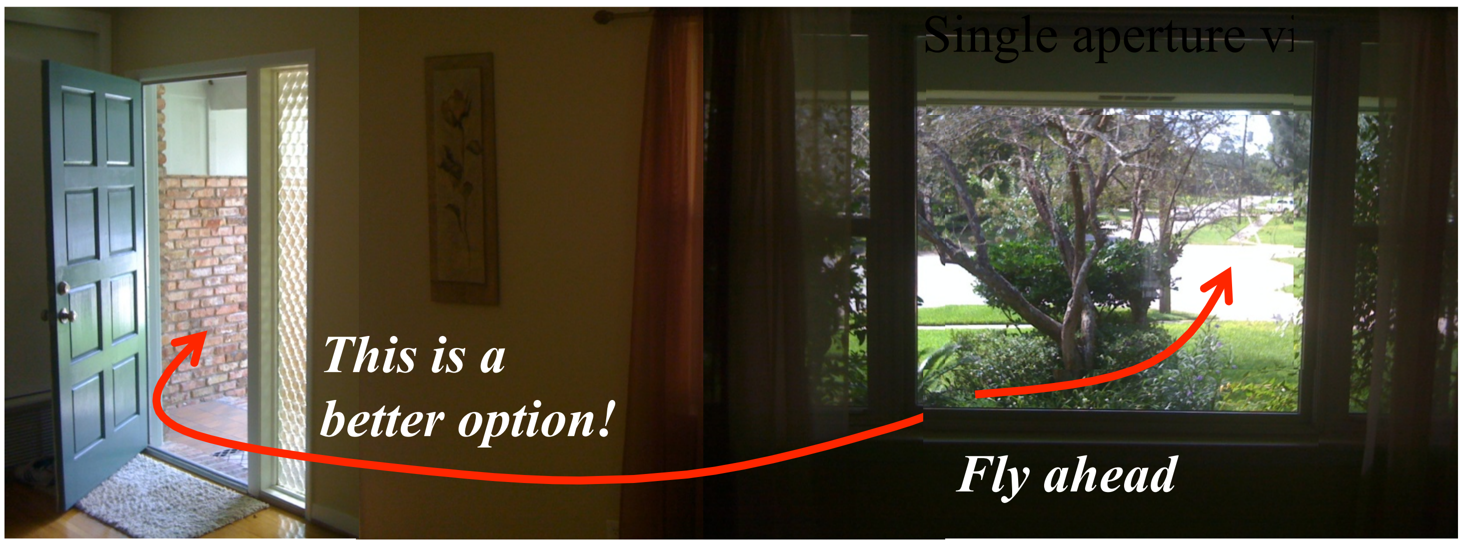
Motivation for Multi-Aperture Sensing

Biological sensors with wide ***field-of-regard***

Enhanced situation awareness, especially, in cluttered environments (urban canyons, indoors, forestry areas): ***look forward, backward, and to the sides***

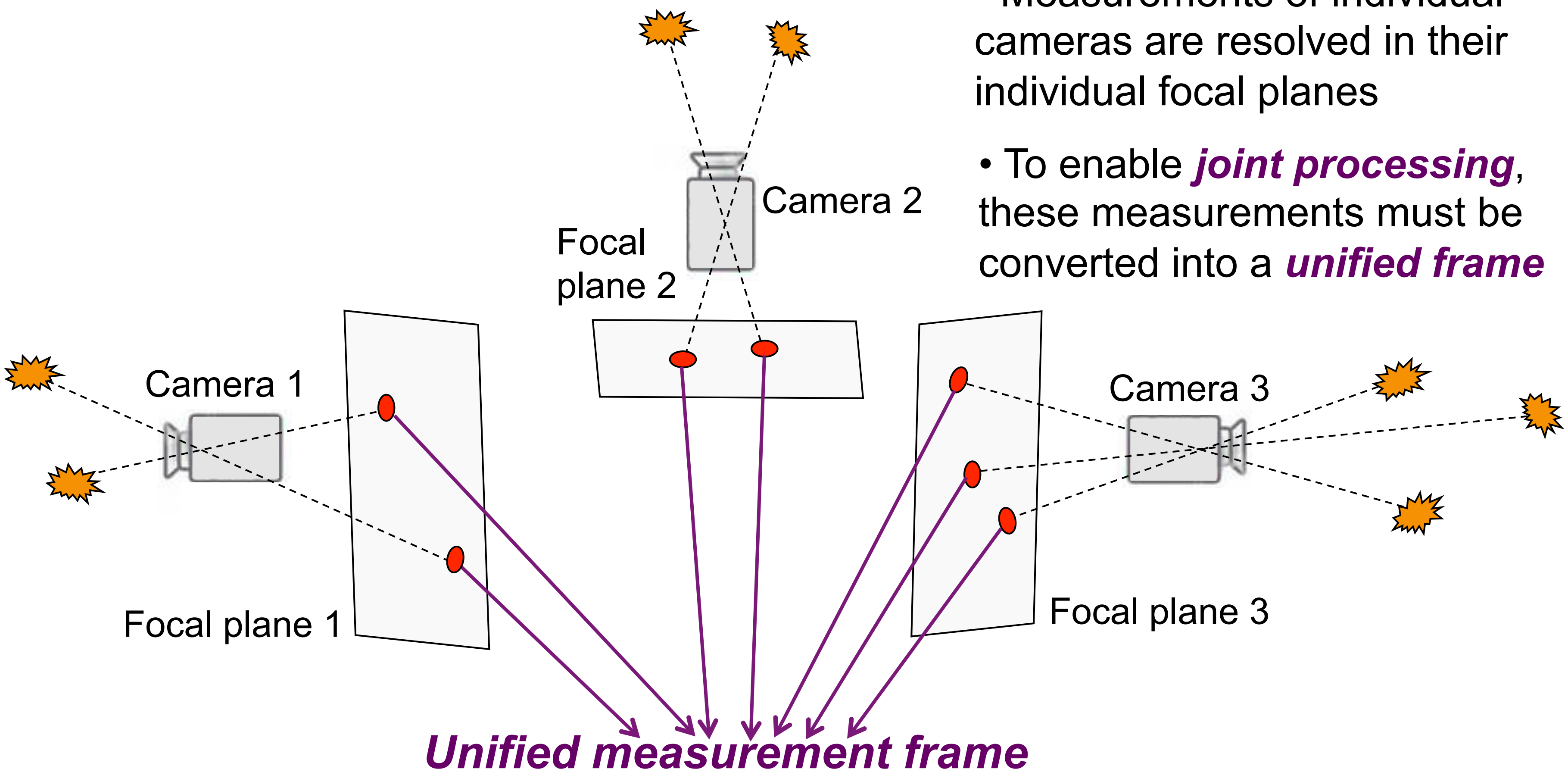
Multi-aperture view



What are the benefits for navigation?

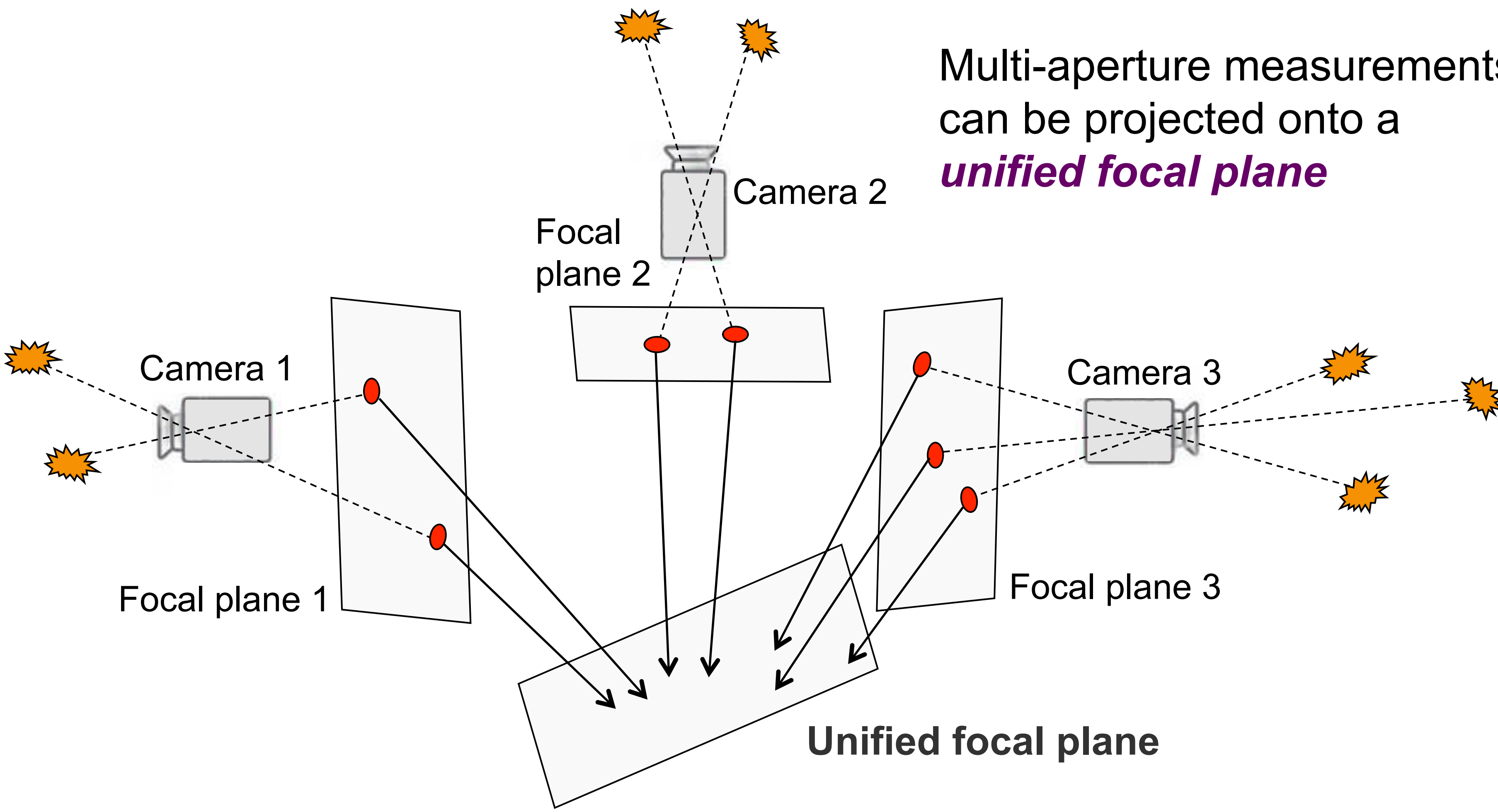
- Increased number of high-quality vision features
- Improved feature geometry (better DOPs)
- Improved range initialization capabilities

Representation of Measurements



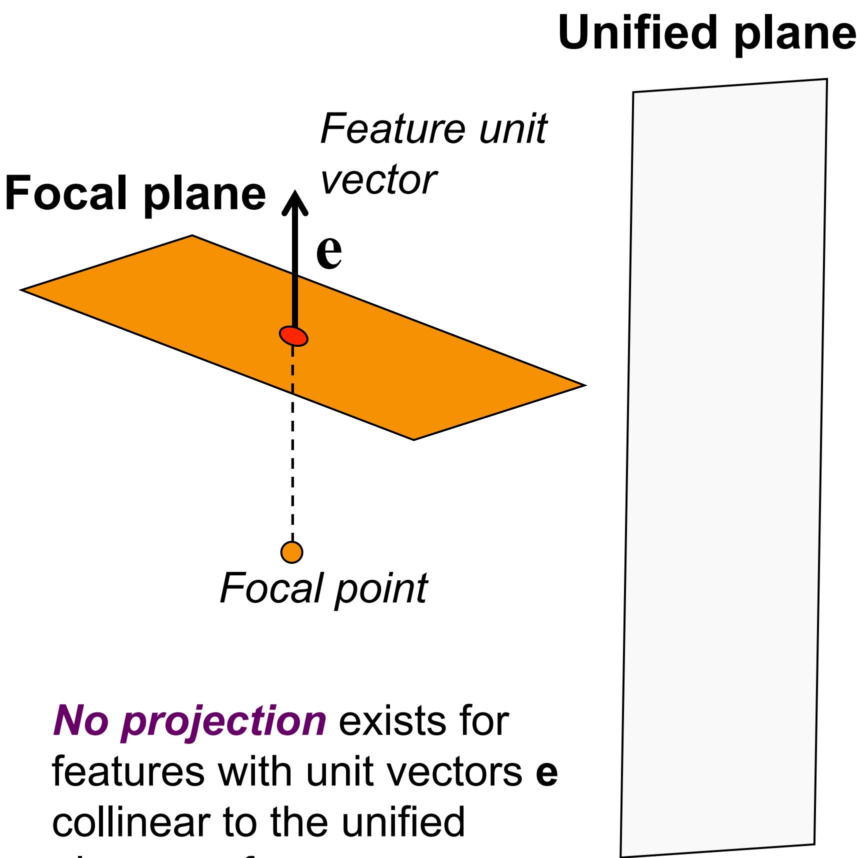
- Measurements of individual cameras are resolved in their individual focal planes
- To enable ***joint processing***, these measurements must be converted into a ***unified frame***

Focal Plane Representation



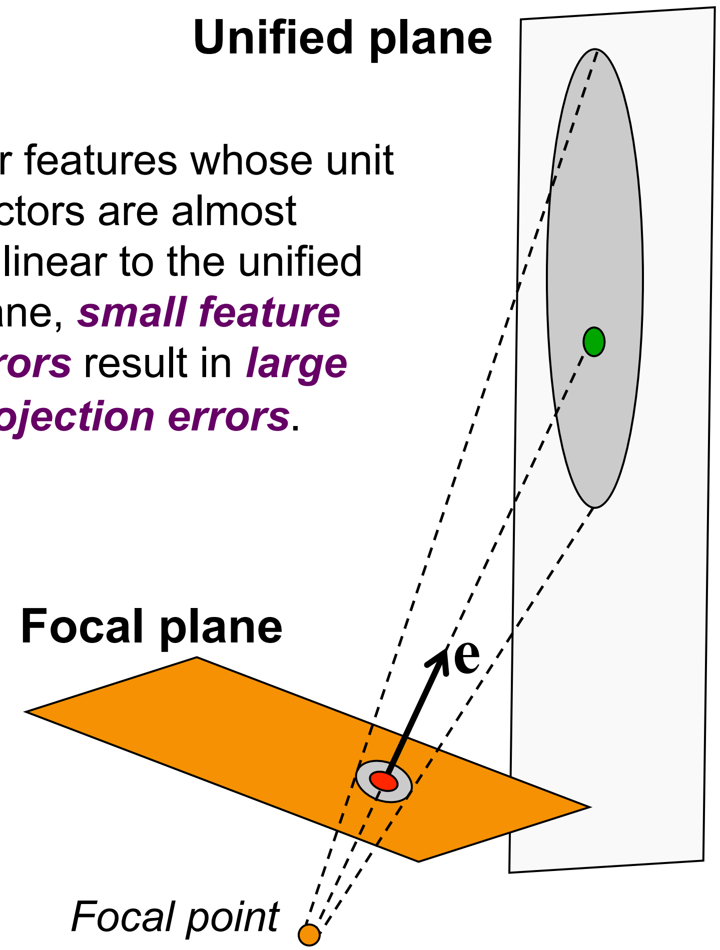
Multi-aperture measurements can be projected onto a ***unified focal plane***

Limitations of Traditional Focal Plane Representation



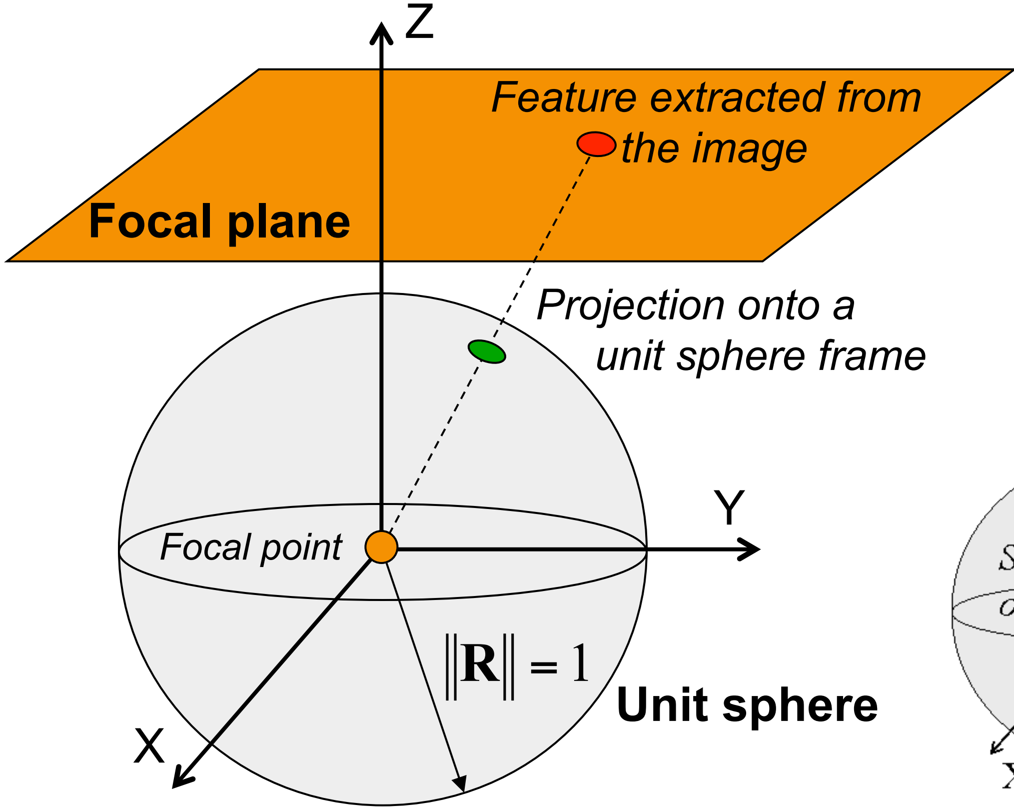
No projection exists for features with unit vectors **e** collinear to the unified planar surface.

For features whose unit vectors are almost collinear to the unified plane, ***small feature errors*** result in ***large projection errors***.

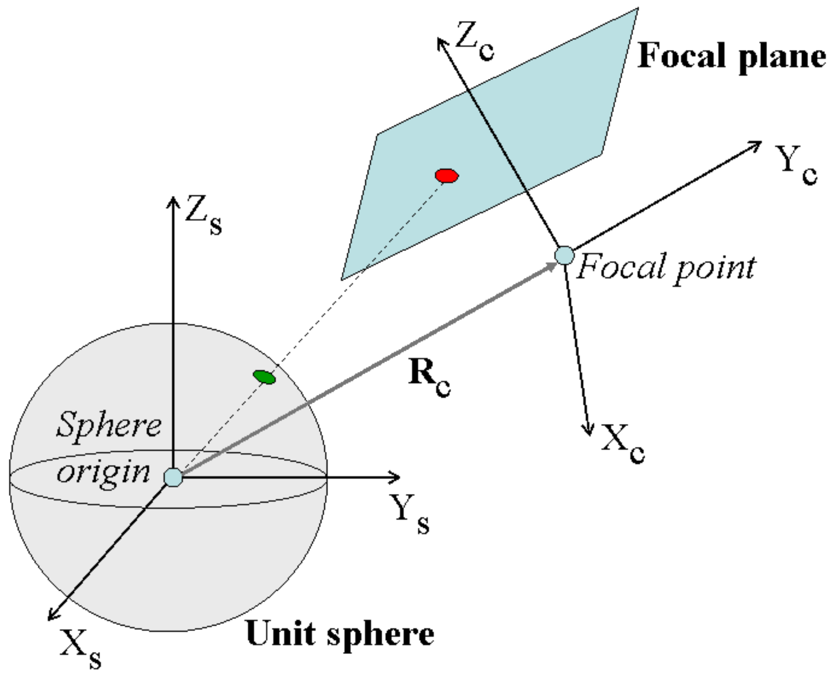


Unit Sphere Representation

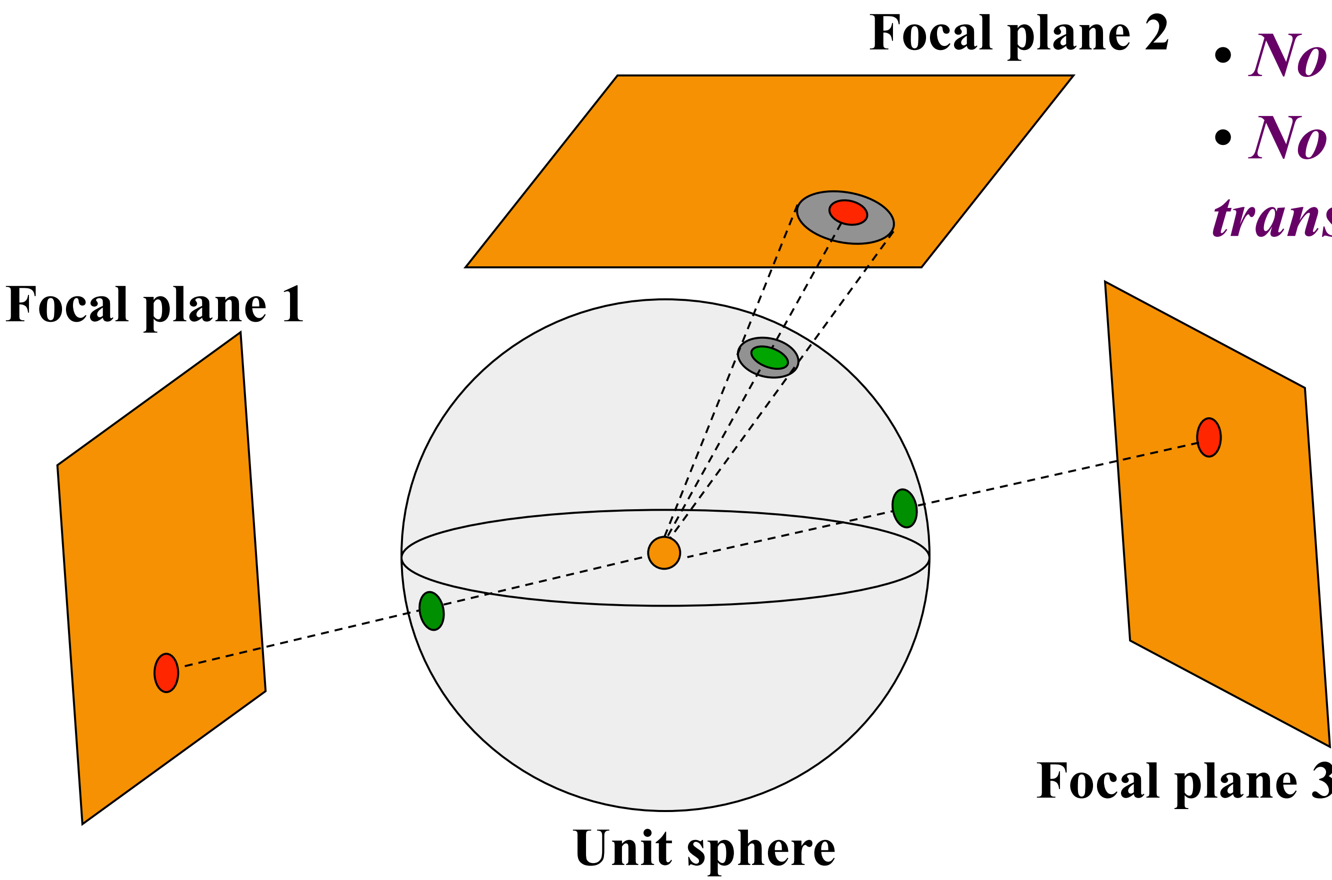
Features from multiple apertures are projected onto a sphere with the unit radius



Can be extended for cases where the camera focal point is not collocated with the origin of the sphere



Unit Sphere Representation

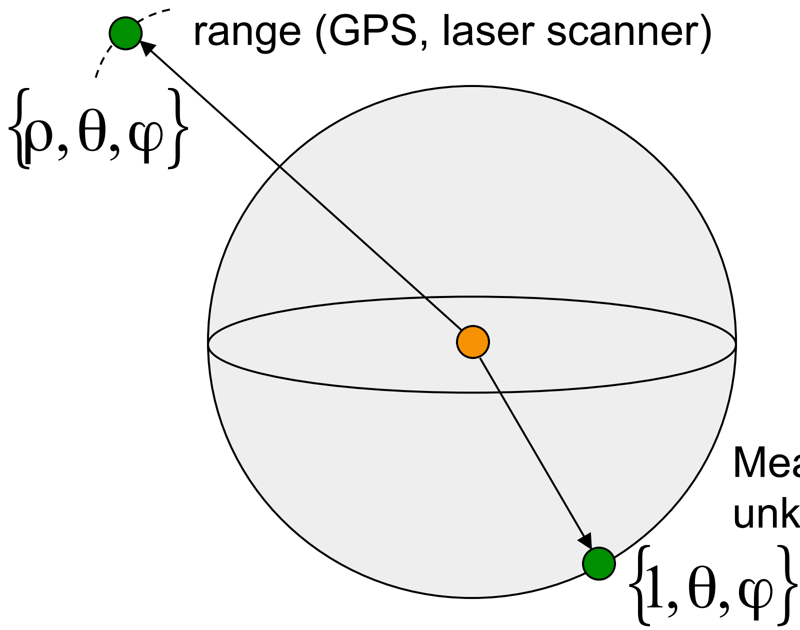


- *No singularity cases*
- *No small/large error transformations*

Unified Sphere Representation of Generic Multi-Sensor Fusion

The ***unit sphere*** frame also ***extends naturally*** into a ***generic multi-sensor fusion*** formulation

Unified sphere



- Represent ***navigation measurements*** as point features on a ***unified spherical surface***
- For a given set of features, their time history, and associated uncertainties, find ***optimal estimates of motion states*** (position, velocity, and attitude)

Motion Constraint Equations (1/3)

- **Motion constraint equations (i.e. relationships between feature parameters and motions states) have to be re-derived in the unit sphere frame to substitute conventional focal representations**

Focal plane representation:

$$f\left(\underbrace{\Delta\mathbf{R}, \Delta\mathbf{C}_b^N}_{\text{Camera motion between two images}}, \underbrace{\left\{x^{(j)}\right\}_{j=1,2}, \left\{y^{(j)}\right\}_{j=1,2}}_{\text{Feature coordinates (focal plane)}}, \underset{\text{Scale}}{z}\right) = 0$$

Camera motion between two images

Feature coordinates (focal plane)

Scale

Unit sphere representation:

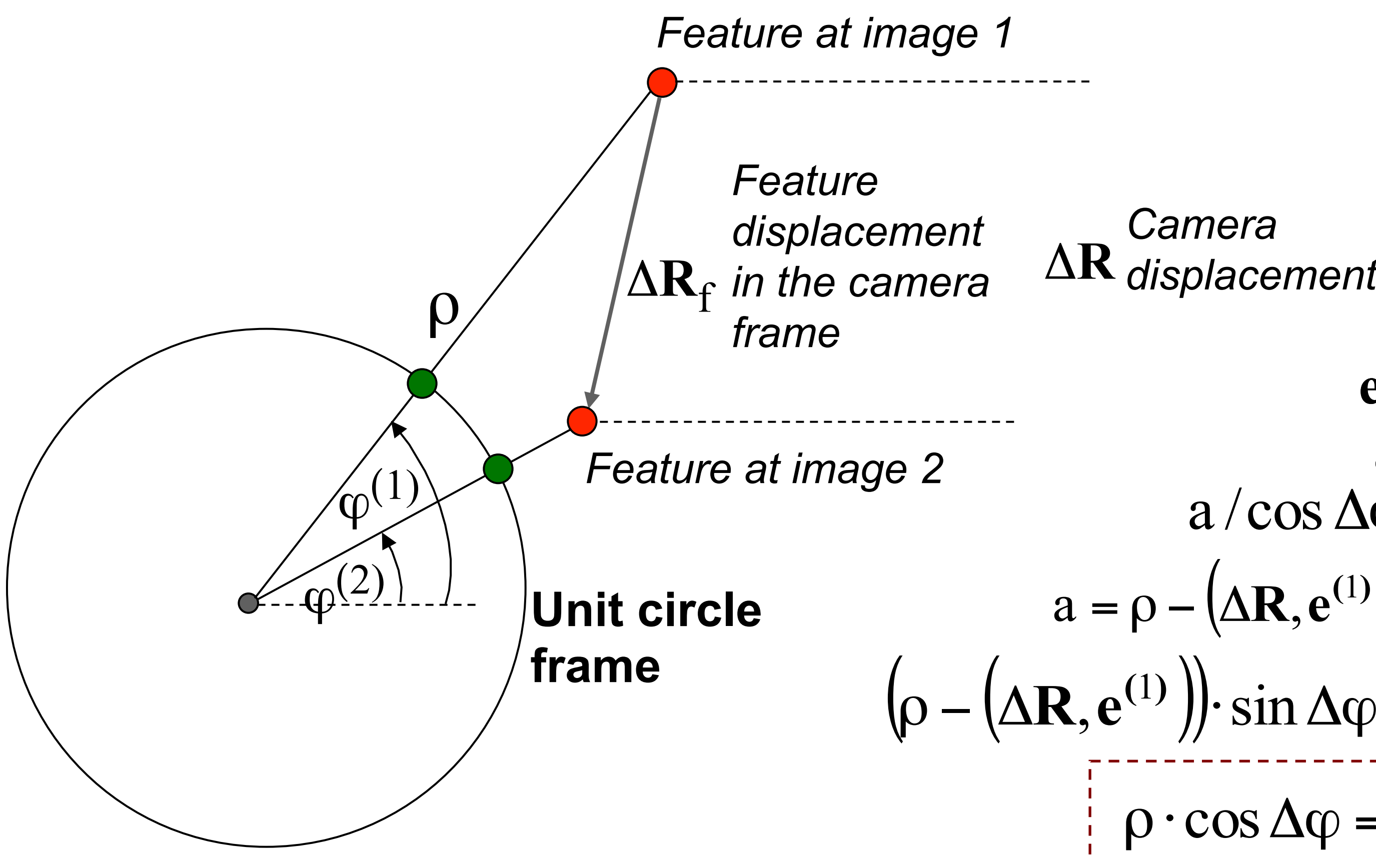
$$u\left(\Delta\mathbf{R}, \Delta\mathbf{C}_b^N, \underbrace{\left\{\theta^{(j)}\right\}_{j=1,2}, \left\{\varphi^{(j)}\right\}_{j=1,2}}_{\text{Feature spherical angles}}, \underset{\text{Range}}{\rho}\right) = 0$$

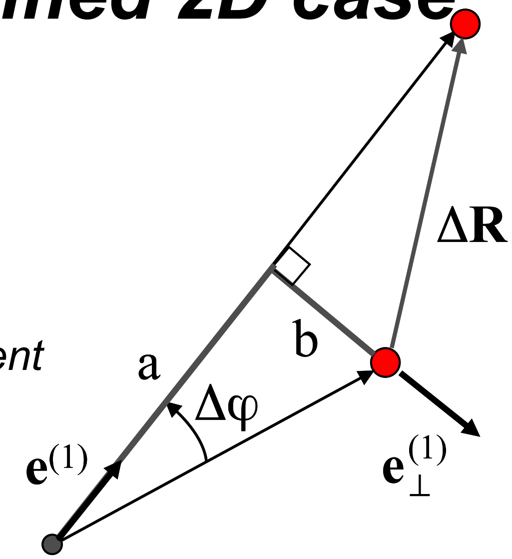
Feature spherical angles

Range

Motion Constraint Equations (2/3)

- **Translational motion only:** ***Simplified 2D case***





$$a / \cos\Delta\varphi = b / \sin\Delta\varphi$$

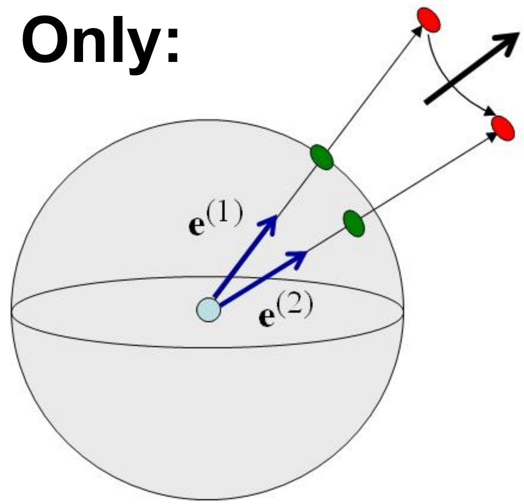
$$a = \rho - \left(\Delta\mathbf{R}, \mathbf{e}^{(1)}\right) \qquad b = -\left(\Delta\mathbf{R}, \mathbf{e}_{\perp}^{(1)}\right)$$

$$\left(\rho - \left(\Delta\mathbf{R}, \mathbf{e}^{(1)}\right)\right) \cdot \sin\Delta\varphi = -\left(\Delta\mathbf{R}, \mathbf{e}_{\perp}^{(1)}\right) \cdot \cos\Delta\varphi$$

$$\boxed{\rho \cdot \cos\Delta\varphi = -\left(\Delta\mathbf{R}, \mathbf{e}_{\perp}^{(2)}\right)}$$

Motion Constraint Equations (3/3)

- **Rotational Motion Only:**



$$\Delta C_b^N \cdot \mathbf{e}^{(2)} = \mathbf{e}^{(1)}$$

- **General Case**
  - 3D case, translational and rotational motion

$$\left(\mathbf{e}^{(2)}\right)^T \cdot \Delta C_N^b \cdot \mathbf{B} \cdot \Delta \mathbf{R} - \left(\mathbf{e}^{(1)}\right)^T \cdot \mathbf{B}^T \cdot \Delta C_b^N \cdot \mathbf{e}^{(2)} \cdot \rho^{(1)} = 0$$

$$\left(\mathbf{e}^{(2)}\right)^T \cdot \Delta C_N^b \cdot \mathbf{D} \cdot \Delta \mathbf{R} - \left(\mathbf{e}^{(2)}\right)^T \cdot \Delta C_N^b \cdot \mathbf{e}_\perp^{(1)} \cdot \rho^{(1)} = 0$$

where:

$$\mathbf{B} = \begin{bmatrix} 0 & -1 & 0 \\ 1 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix}, \quad \mathbf{D} = \begin{bmatrix} 0 & 0 & -\cos(\varphi^{(1)}) \\ 0 & 0 & -\sin(\varphi^{(1)}) \\ \cos(\varphi^{(1)}) & \sin(\varphi^{(1)}) & 0 \end{bmatrix}$$

Multi-Aperture/INS Data Fusion

Motion constraints

Non-linear measurement observables

$$\eta_p^{Kalman} = \begin{bmatrix} \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \mathbf{B} \cdot \Delta\tilde{\mathbf{R}}_{INS} - \left(\tilde{\mathbf{e}}_p^{(1)}\right)^T \cdot \mathbf{B}^T \cdot \Delta\tilde{\mathbf{C}}_b^N \cdot \tilde{\mathbf{e}}_p^{(2)} \cdot \hat{\rho}_p^{(1)} \\ \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \tilde{\mathbf{D}}_p \cdot \Delta\tilde{\mathbf{R}}_{INS} - \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \tilde{\mathbf{e}}_{\perp p}^{(1)} \cdot \hat{\rho}_p^{(1)} \end{bmatrix}, p = 1,\ldots,P$$

INS

Vision

Initial range estimate

Linearization

$$\eta_p^{Kalman} = \underbrace{\mathbf{H}_{p,\Delta\mathbf{R}}\delta\mathbf{R}_{INS} + \mathbf{H}_{p,\alpha}\delta\boldsymbol{\alpha}_{INS}}_{\textit{INS error states}} + \mathbf{H}_{p,f}\underbrace{\begin{bmatrix}\delta\varphi_p^{(1)} \\ \delta\theta_p^{(1)} \\ \delta\rho_p^{(1)}\end{bmatrix}}_{\textit{Feature error states}} + H_{p,\varepsilon}\underbrace{\begin{bmatrix}\delta\varphi_p^{(2)} \\ \delta\theta_p^{(2)}\end{bmatrix}}_{\textit{Measurement noise}}, p = 1,\ldots,P$$

Kalman filter

INS error states

Feature 1: feature error states

…

Feature N: feature error states

Range Initialization

Observe features from ***two different locations*** of the camera

↓

Measure the camera ***displacement and rotation*** with the ***INS***

↓

Estimate the range

↓

Update the Kalman filter ***state covariance*** to account for the ***correlation*** between ***range estimation errors*** and ***INS errors***

$$\left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \mathbf{B} \cdot \Delta\tilde{\mathbf{R}}_{INS} \approx \left(\tilde{\mathbf{e}}_p^{(1)}\right)^T \cdot \mathbf{B}^T \cdot \Delta\tilde{\mathbf{C}}_b^N \cdot \tilde{\mathbf{e}}_p^{(2)} \cdot \hat{\rho}_p^{(1)}$$

$$\left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \tilde{\mathbf{D}}_p \cdot \Delta\tilde{\mathbf{R}}_{INS} \approx \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \tilde{\mathbf{e}}_{\perp p}^{(1)} \cdot \hat{\rho}_p^{(1)}$$

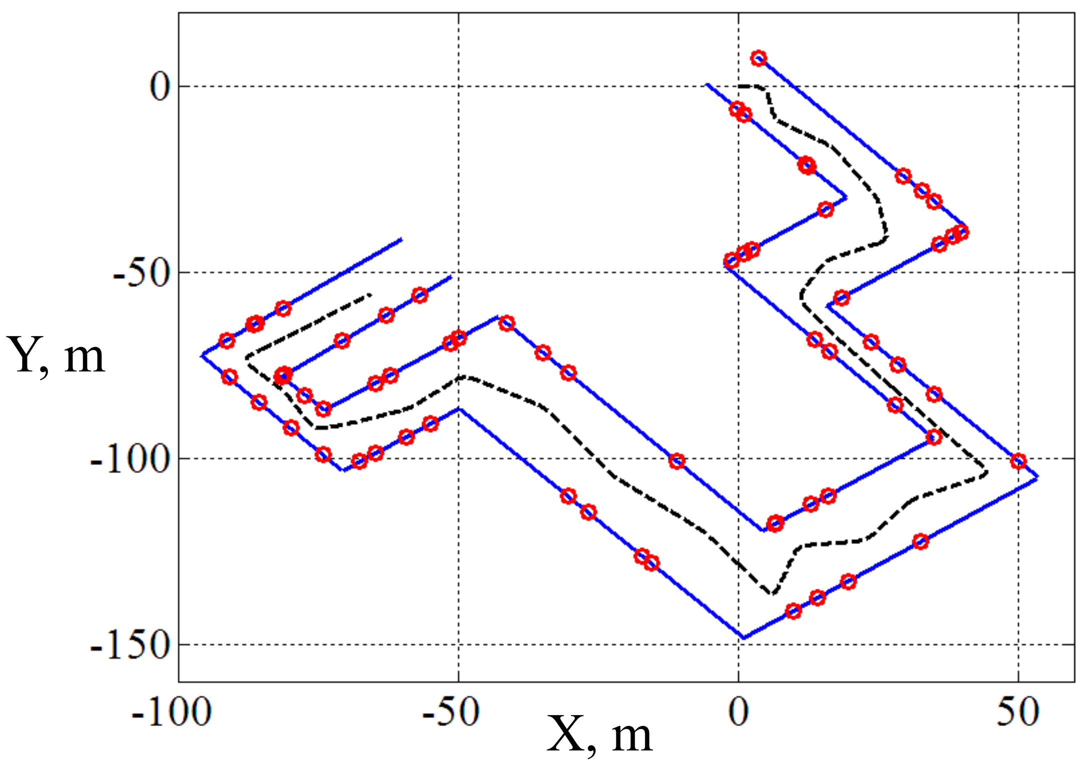
↓

$$\hat{\rho}_p^{(1)} = \left(\mathbf{H}_\rho^T \cdot \mathbf{H}_\rho\right)^{-1} \cdot \mathbf{H}_\rho^T \cdot \begin{bmatrix} \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \tilde{\mathbf{C}}_N^b \cdot \mathbf{B} \cdot \Delta\tilde{\mathbf{R}}_{INS} \\ \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \tilde{\mathbf{C}}_N^b \cdot \mathbf{D}_p \cdot \Delta\tilde{\mathbf{R}}_{INS} \end{bmatrix}$$

$$\mathbf{H}_\rho = \begin{bmatrix} \left(\tilde{\mathbf{e}}_p^{(1)}\right)^T \cdot \mathbf{B}^T \cdot \Delta\tilde{\mathbf{C}}_b^N \cdot \tilde{\mathbf{e}}_p^{(2)} \\ \left(\tilde{\mathbf{e}}_p^{(2)}\right)^T \cdot \Delta\tilde{\mathbf{C}}_N^b \cdot \tilde{\mathbf{e}}_{\perp p}^{(1)} \end{bmatrix}$$

Demonstration: Simulation

Simulated indoor environment



Inertial measurement unit:

Simulated Systron Donner MMQ-50:

Gyro drift: 50 deg/hr

Accel bias: 1 mg

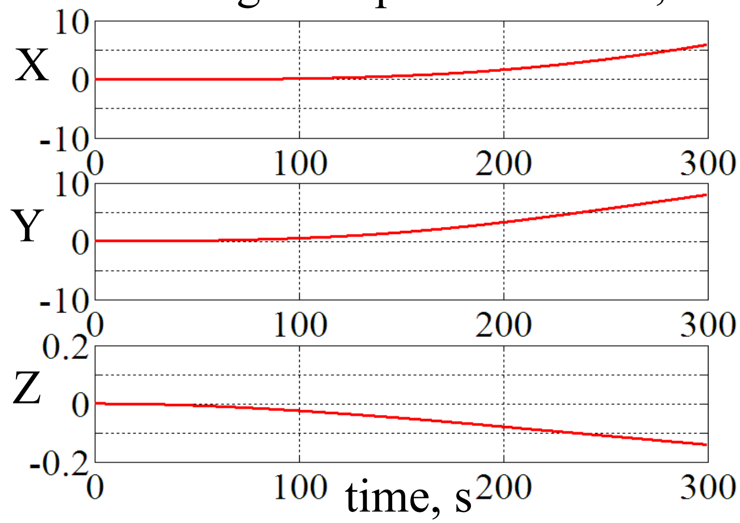
Video cameras:

Resolution: 640x480

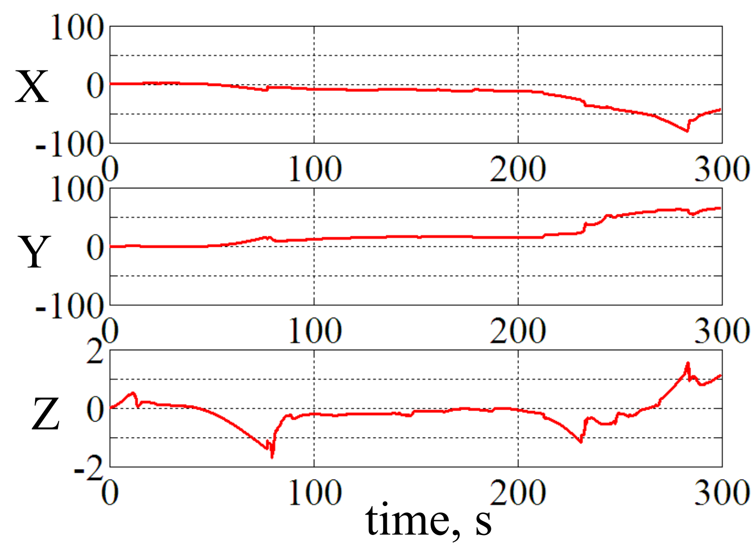
Filed of view: 40 deg by 30 deg

Simulation Results

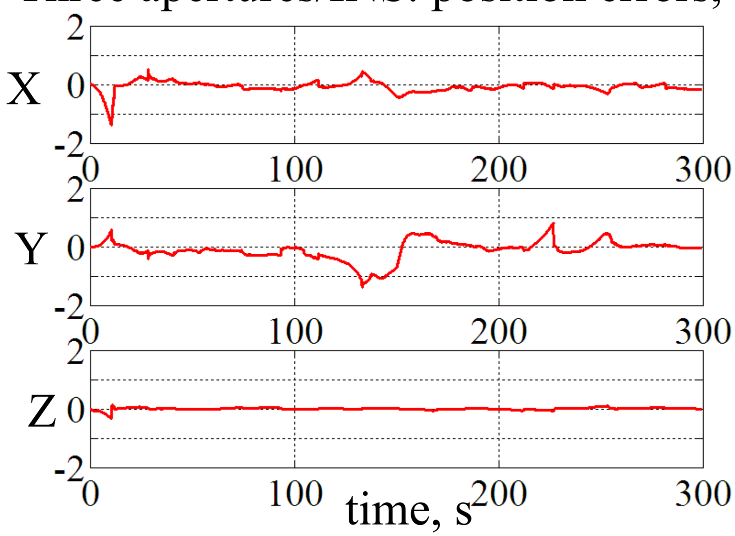
Free-running INS: position errors, km



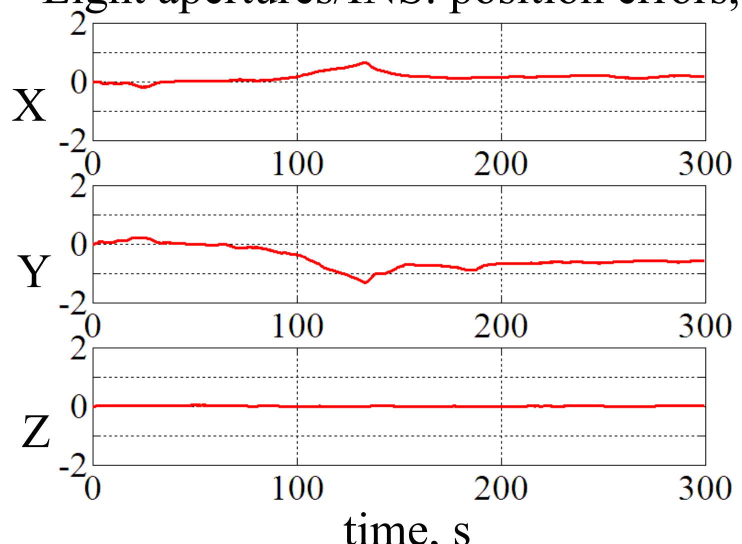
Single aperture/INS: position errors, m



Three apertures/INS: position errors, m



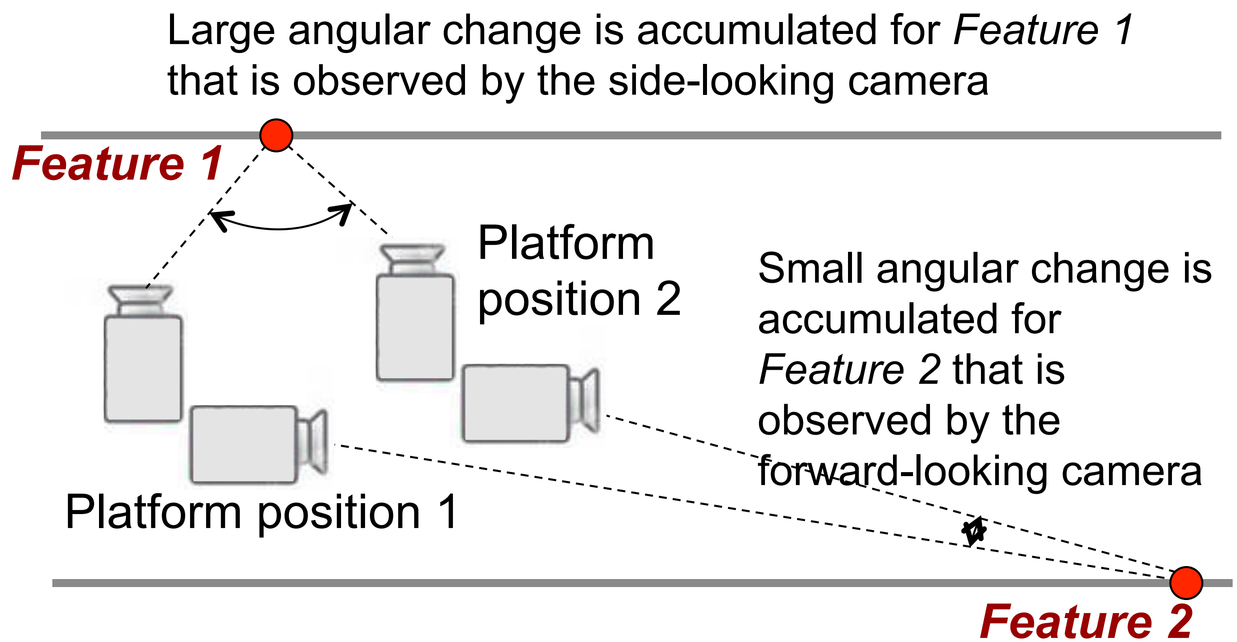
Eight apertures/INS: position errors, m



Advantages of Multi-Aperture Sensing

• For the simulation scenario implemented, ***two orders of magnitude error reduction*** is achieved with multi-aperture sensors (1 meter positioning errors) vs. the single aperture sensor (60 meter positioning error)

• Main reason: ***improved range initialization capabilities***



Feature 1 is initialized and then ***applied to correct inertial drift over a longer distance*** that is required to accumulate an angular change sufficient ***to initialize Feature 2***.

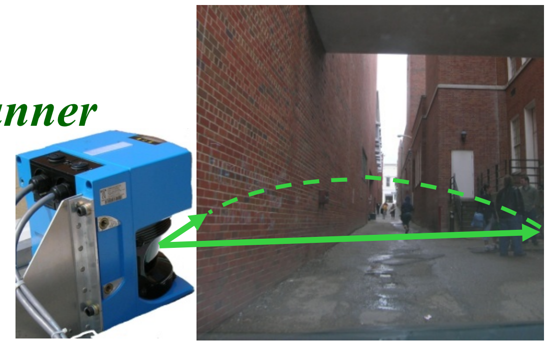
Outline

- **Motivation—why alternative navigation techniques?**
- **Image-aided INS**
  - Single aperture vision aiding
  - Multi-aperture vision aiding
- **Ladar-aided INS**
- **Multi-Sensor Fusion Techniques**

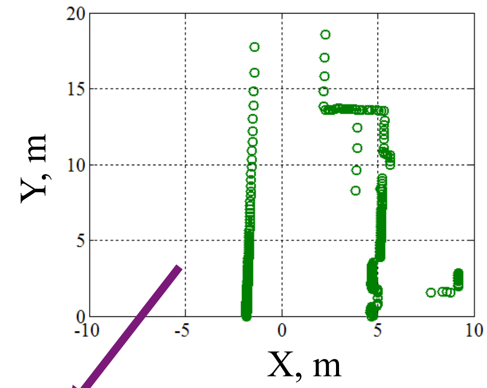
Laser Scanner Based Navigation
Generic Approach

2D scans

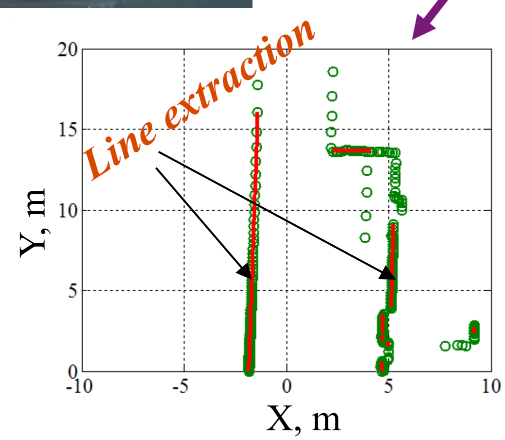
Laser Scanner



Scan



Feature extraction

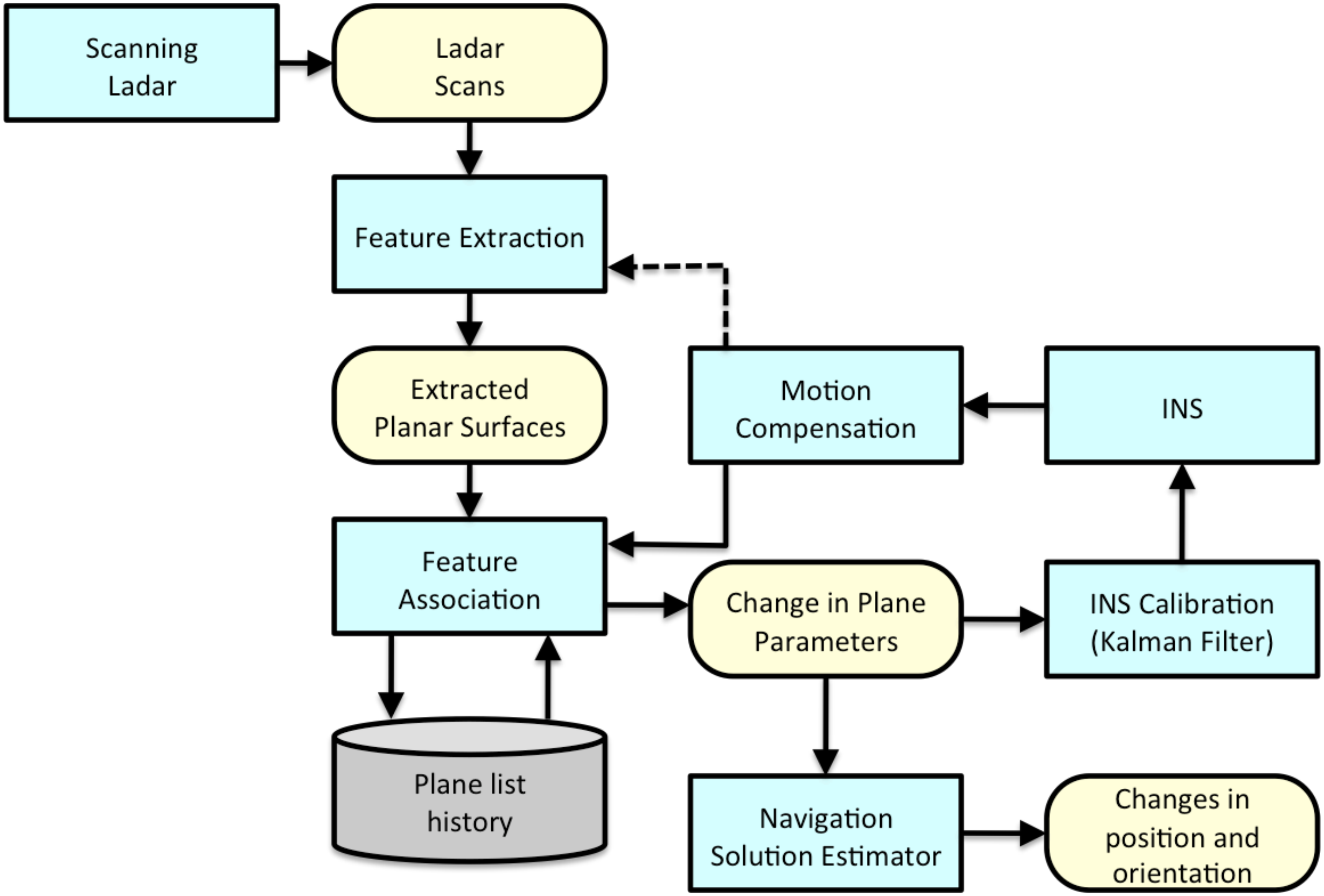


Navigation based on features extracted

Navigation of the lines

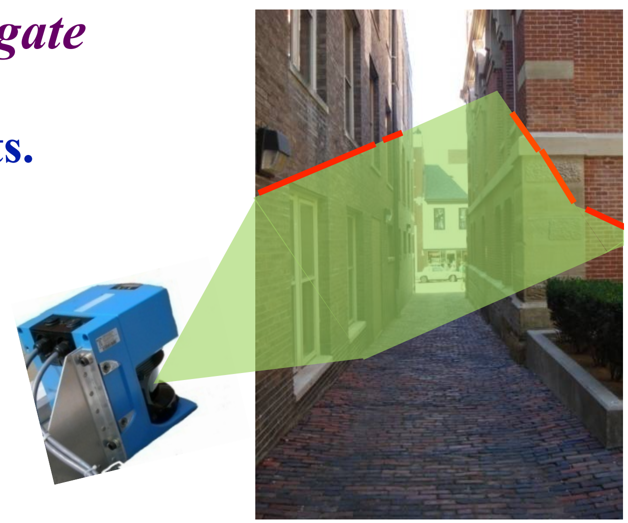
NOTE: Feature repeatability is a must

Main Steps of the Approach
Generic LADAR/INS Integration Approach



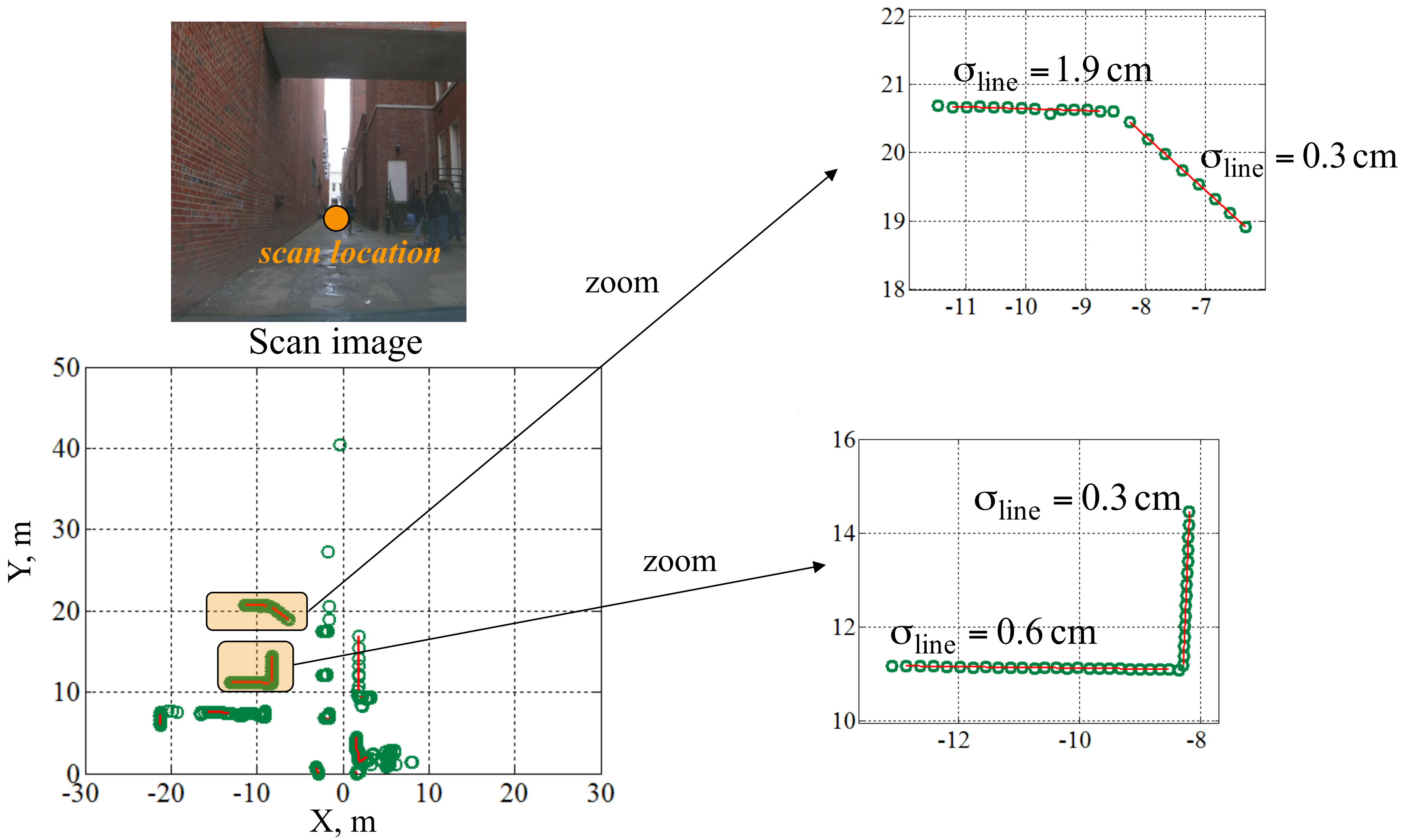
Laser Scanner Based Navigation
2D Case

Example



- ***Lines extracted*** **from laser scans are used to** ***navigate***
  - ***Why?***
    - **Lines are common in man made environments.**
    - **Lines are highly repeatable in multiple scans.**
    - **Lines can be easily extracted from a scan.**
  - ***How?***
    - **Lines are extracted from each scan using a Modified Split and Merge Algorithm.**
    - **Extracted lines are matched with coinciding lines from previous scans.**
    - **Changes in line parameters between scans are used to estimate position and orientation changes.**

Line Extraction Examples



Extension of 2D into 3D Navigation

***3D navigation* is based on *planar surfaces* vs. 2D line-based navigation**

Obtain an image of the environments

↓

Extract planar surfaces from the image

↓

Use plane parameters for the navigation

Why use planes to navigate?

***Planes* are *common* in *man made environments*.**

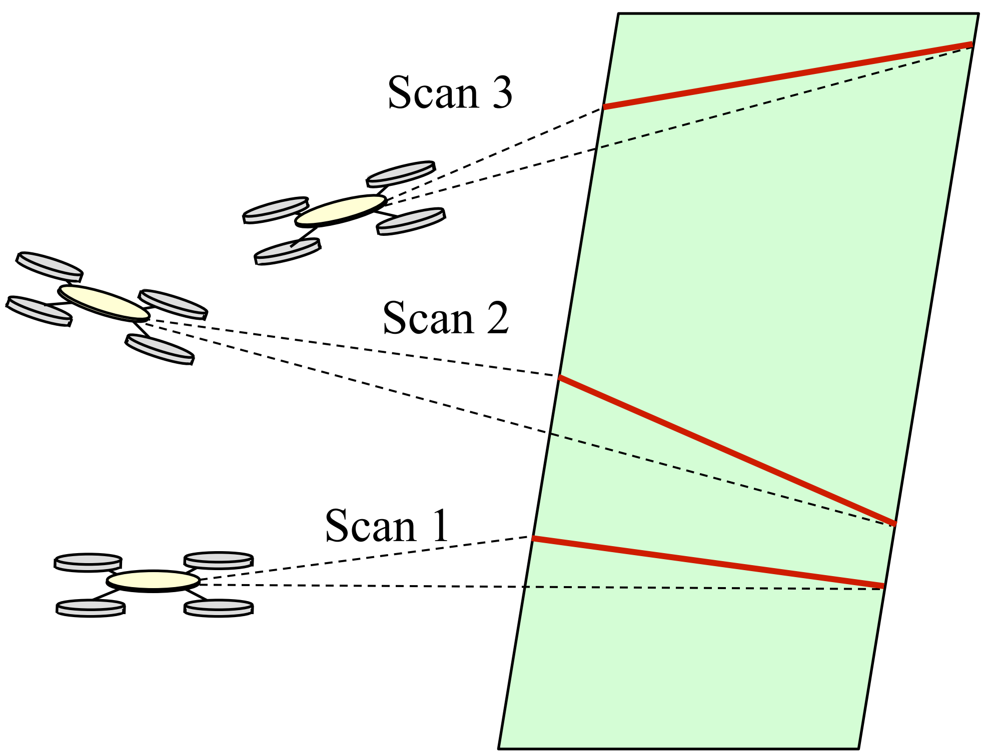
Indoor image

Outdoor image

***Planes* are *highly repeatable* from image to image.**

Plane Extraction

- ***Vehicle motion*** is ***exploited*** to ***observe*** the planar surface at three ***different "angles"***:
  - Both ***translational*** and ***rotational motion*** components are ***utilized***



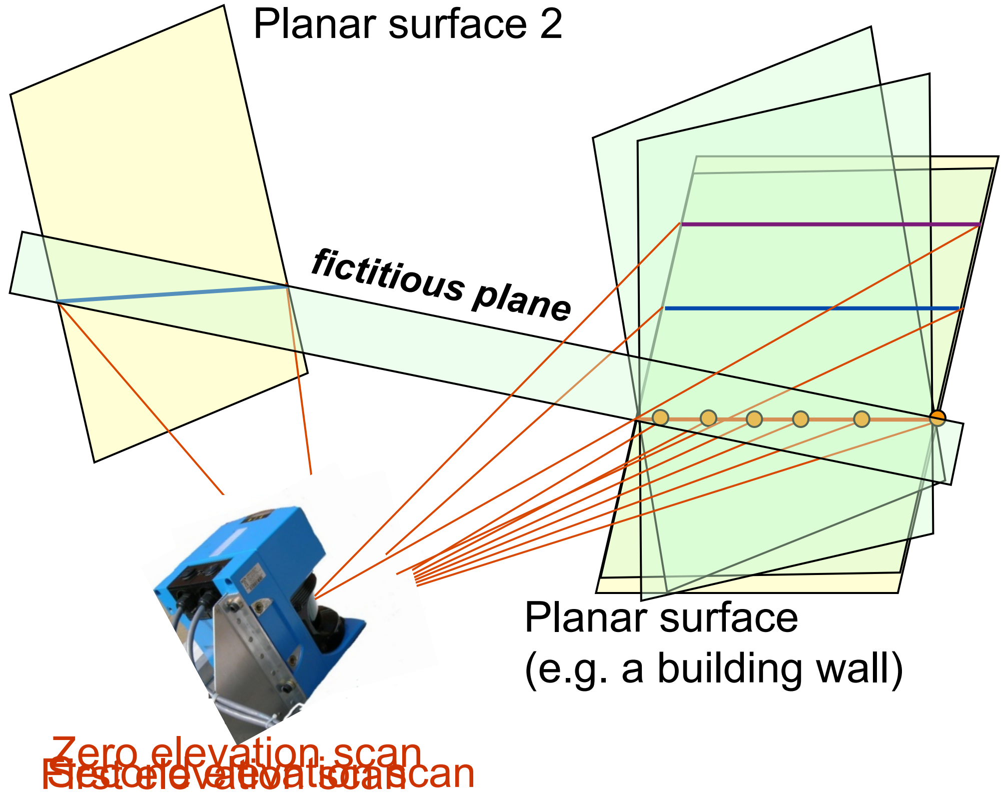
planar surface (e.g., building wall)

- ***Lines*** are ***extracted*** from ***2D scan images*** that ***correspond to different location and/or orientation*** of the laser scanner

- ***Inertial measurements*** (delta velocities and delta angles) are applied to ***reconstruct*** the laser ***motion between scans***

- ***Three lines*** are used to ***compute plane parameters***: two lines for the plane fit, third line to confirm the plane (removal of fictitious planes)

Plane Reconstruction

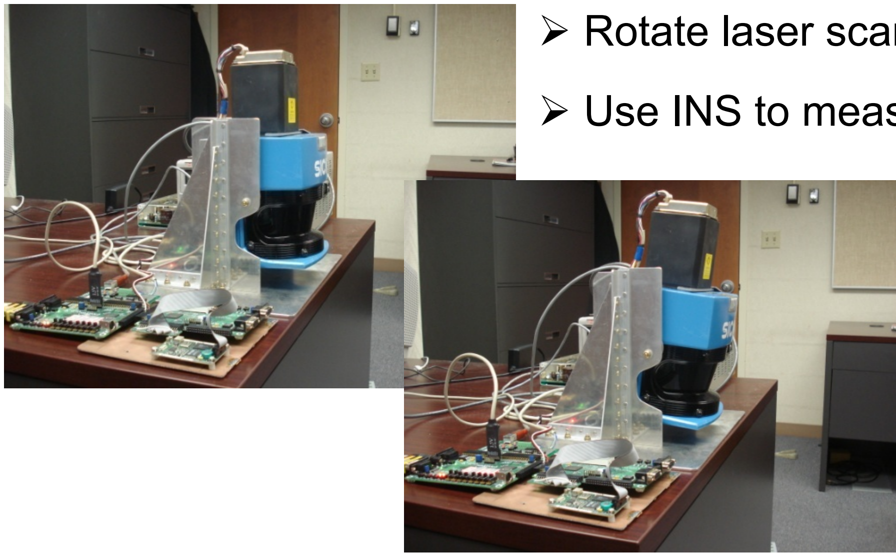


Only 3 elevation angles are required

3 elevation angles can be spanned in less than 1 s using e.g. a low-cost servo motor

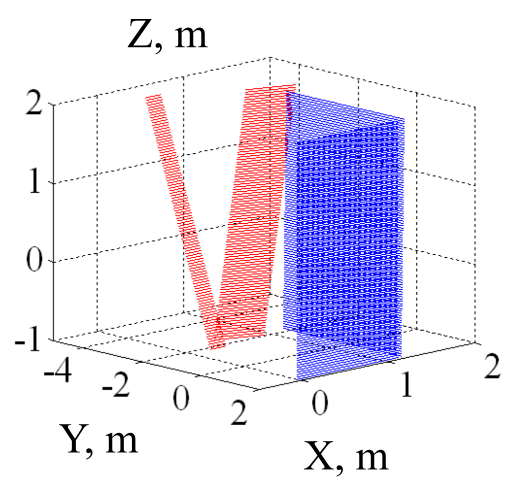
- **One line is insufficient for the plane reconstruction.**
- **Two lines can be applied to reconstruct the plane.**
- **Two line-based reconstruction is ambiguous.**
- **Third scan is used to resolve ambiguities.**
- **Complete plane reconstruction is performed.**

Plane Extraction Examples



- Rotate laser scanner within a limited elevation range (gimbals)
- Use INS to measure rotation angles

- Reconstruct planar 3D surfaces from multiple scans (3 scans at different elevation angles are sufficient)



Using Lines to Navigate (cont.)

- Geometrical Equation:

$$\rho_i - \rho_j = \cos(\alpha_i)x_u + \sin(\alpha_i)y_u$$

- Solved Using Weighted Least Squares Solution:

$$U = (H^T W H)^{-1}(H^T W M)$$

where:

$$U = \begin{bmatrix} x_u \\ y_u \end{bmatrix}$$

$$W = \begin{bmatrix} w_1 & 0 & \vdots & 0 & \\ 0 & w_2 & & & \\ \cdots & & \cdots & \cdots & \\ 0 & & \vdots & w_{n-1} & 0 \\ & & & 0 & w_n \end{bmatrix}$$

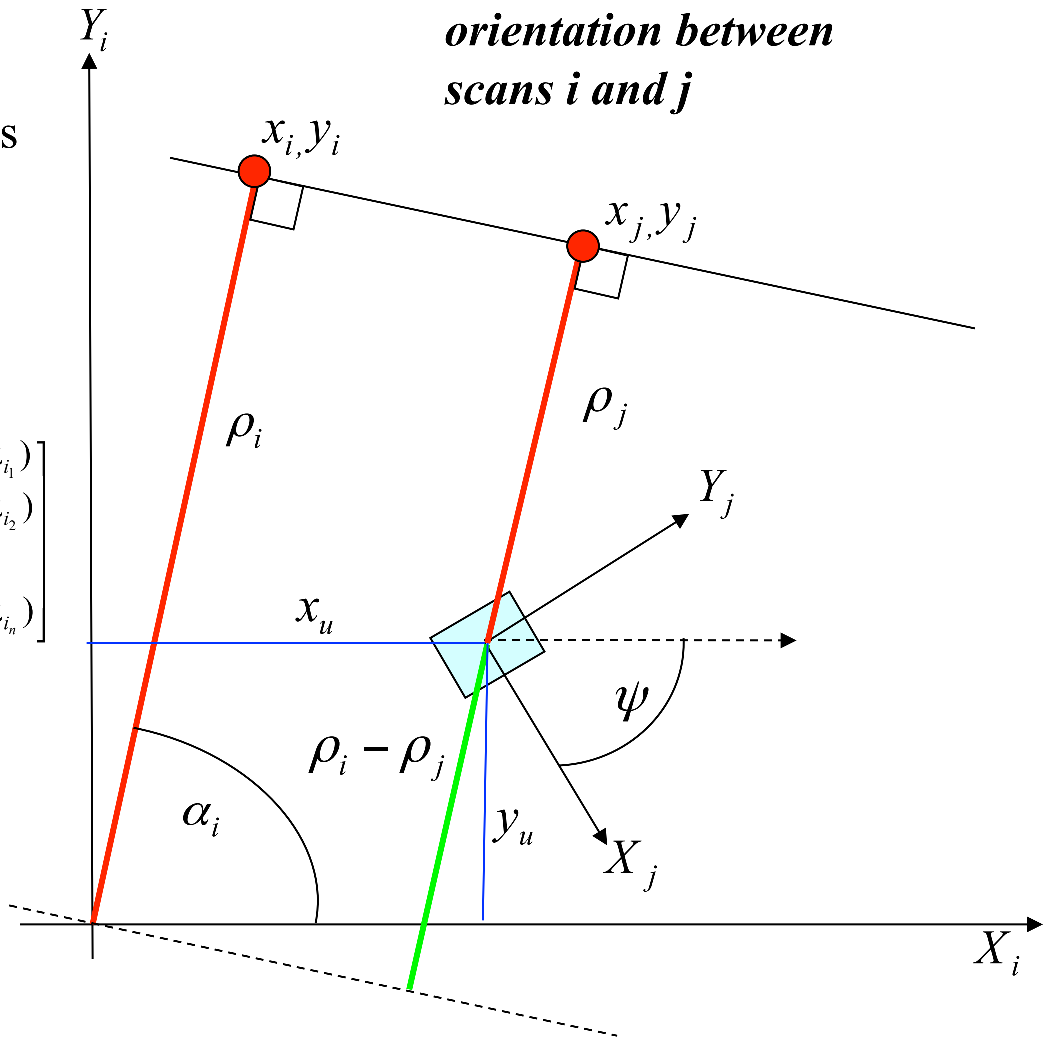
$$H = \begin{bmatrix} \cos(\alpha_{i_1}) & \sin(\alpha_{i_1}) \\ \cos(\alpha_{i_2}) & \sin(\alpha_{i_2}) \\ \cdots & \\ \cos(\alpha_{i_n}) & \sin(\alpha_{i_n}) \end{bmatrix}$$

$$M = \begin{bmatrix} (\rho_{i_1} - \rho_{j_1}) \\ (\rho_{i_2} - \rho_{j_2}) \\ \cdots \\ (\rho_{i_n} - \rho_{j_n}) \end{bmatrix}$$

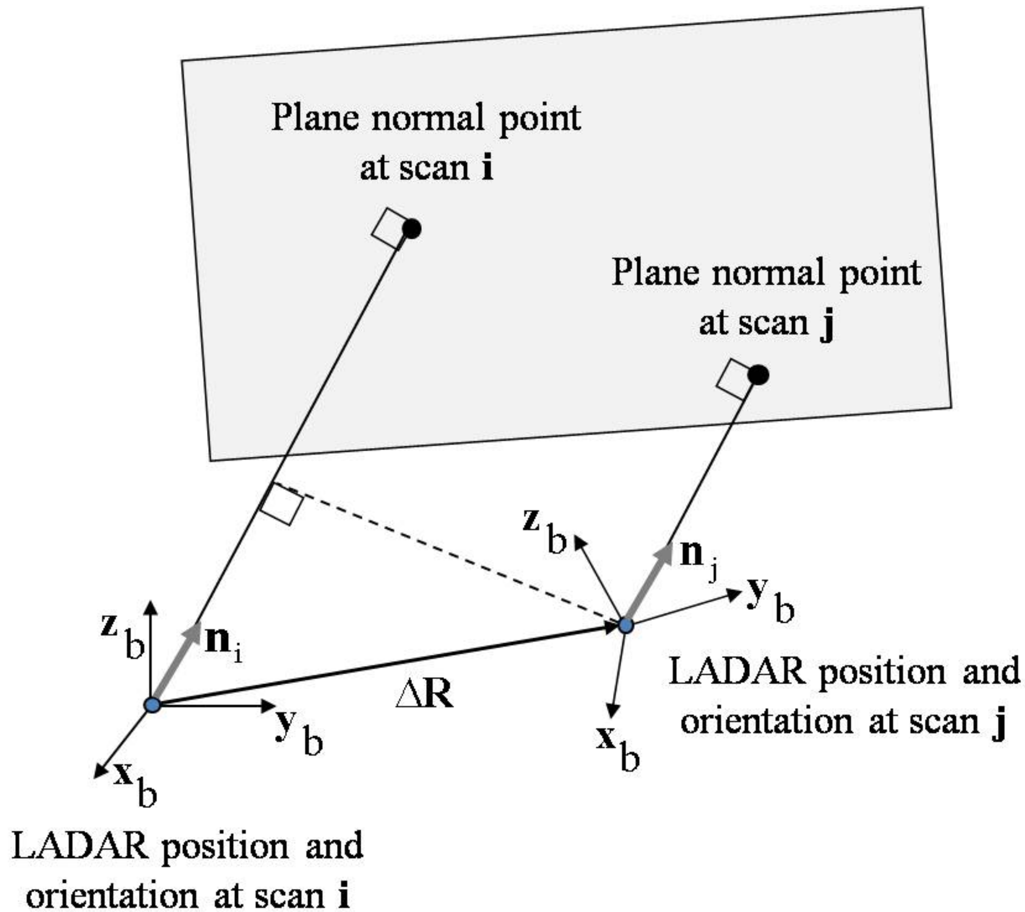
w's are based on line covariances

- Need at least 2 lines to find x_u, y_u and ψ

relative position and orientation between scans i and j



Using Planes to Navigate



At least three non-collinear planes are required.

$$\left(\Delta \mathbf{R}, \mathbf{n}_i\right) = \rho_i - \rho_j$$

$$\Delta \mathbf{C}_{b_i}^{b_j} \cdot \mathbf{n}_i = \mathbf{n}_j \quad \Rightarrow \quad \Delta \mathbf{R}, \Delta \mathbf{C}_{b_i}^{b_j}$$

where:

$\mathbf{n}_{i\,(j)}$ is the plane normal vector with vector components defined at the LADAR body frame at scan **i** (**j**)

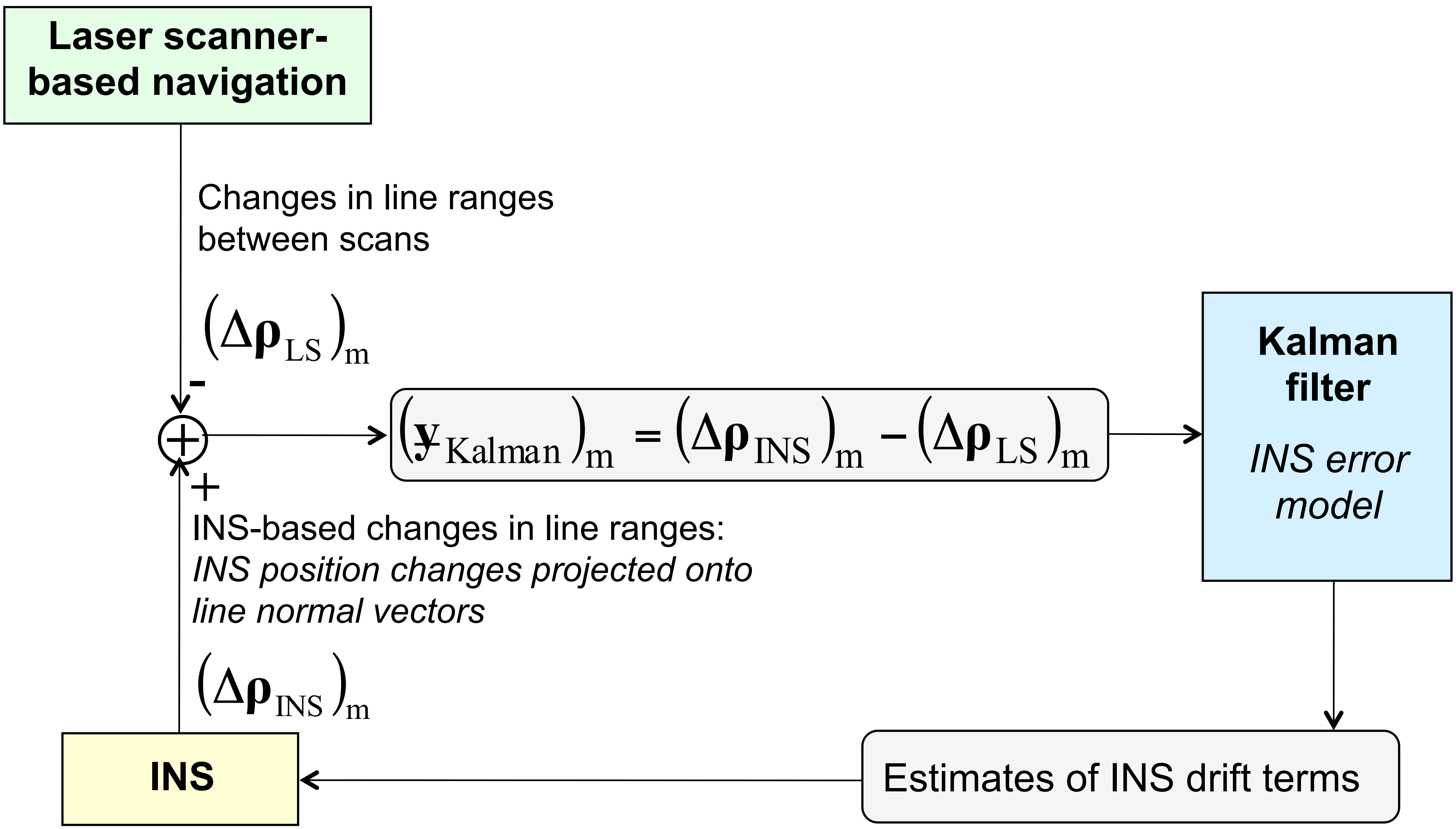
$\rho_{i(j)}$ is the distance to the plane at scan **i** (**j**)

$\Delta \mathbf{C}_{b_i}^{b_j}$ is the change in direction cosine matrix that defines the LADAR body frame rotation between scans **i** and **j**

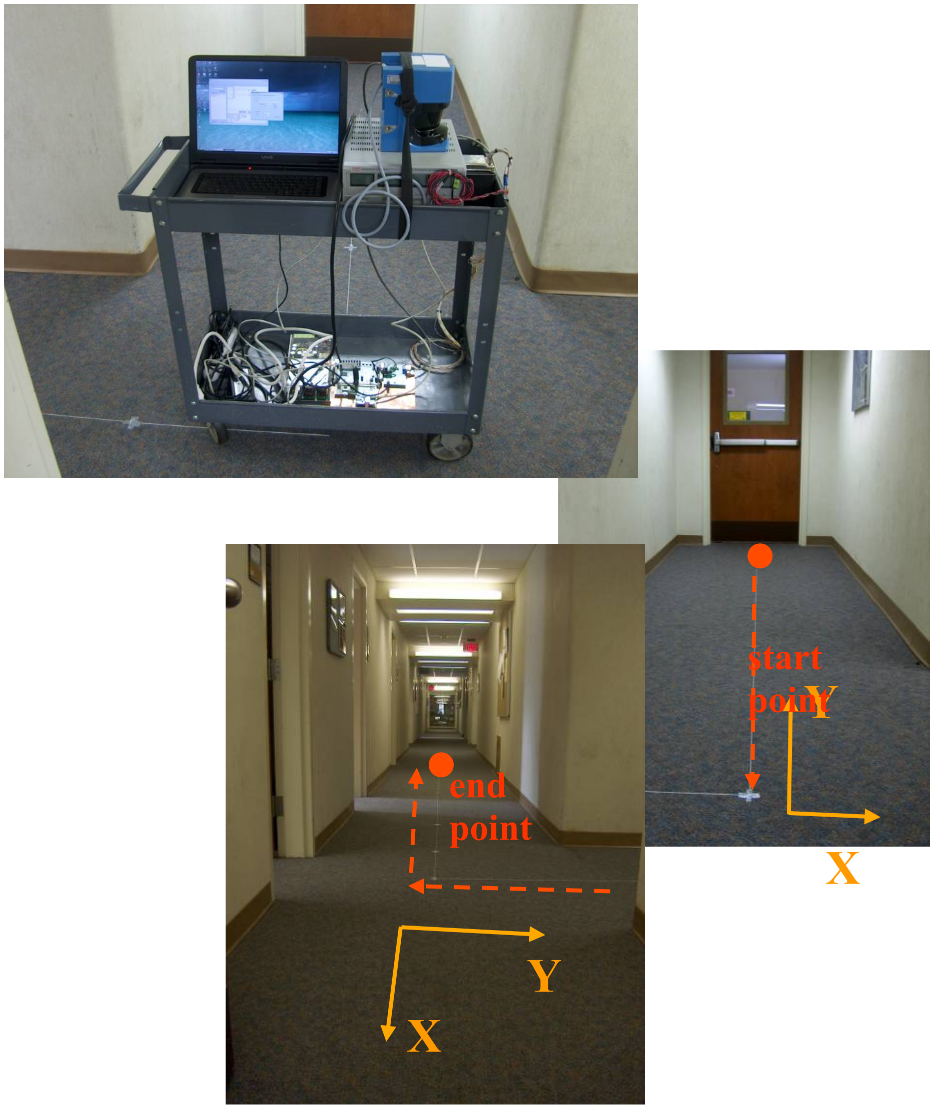
Change* in the perceived *location* of the *plane normal point between scans* is used to estimate the *change in position and orientation.

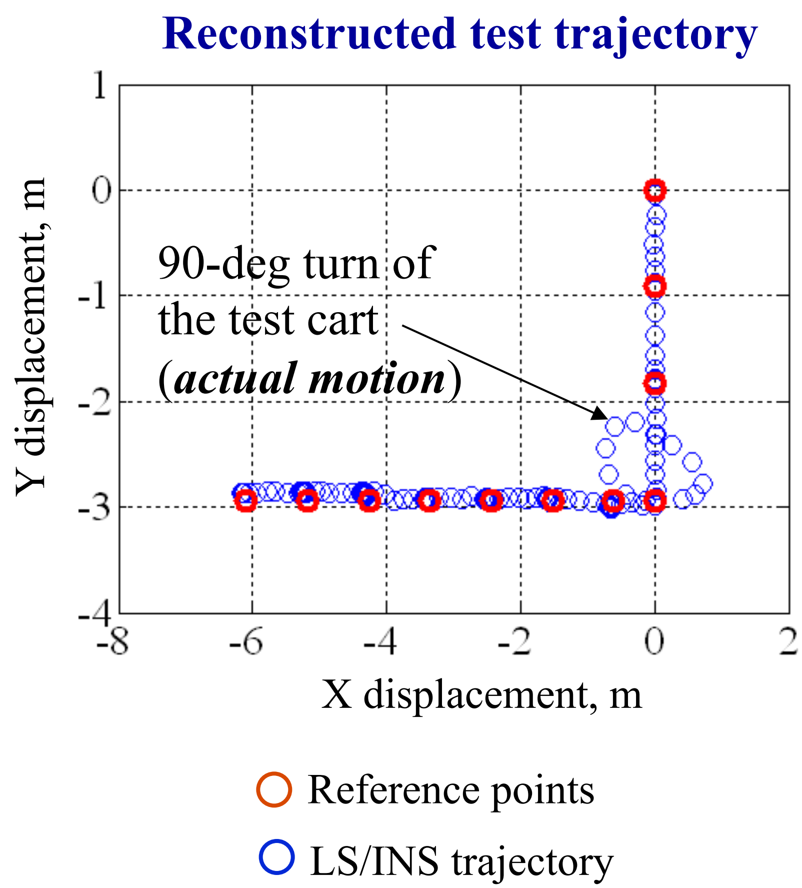
NOTE: Planar surfaces are assumed stationary.

Kalman Filter Design

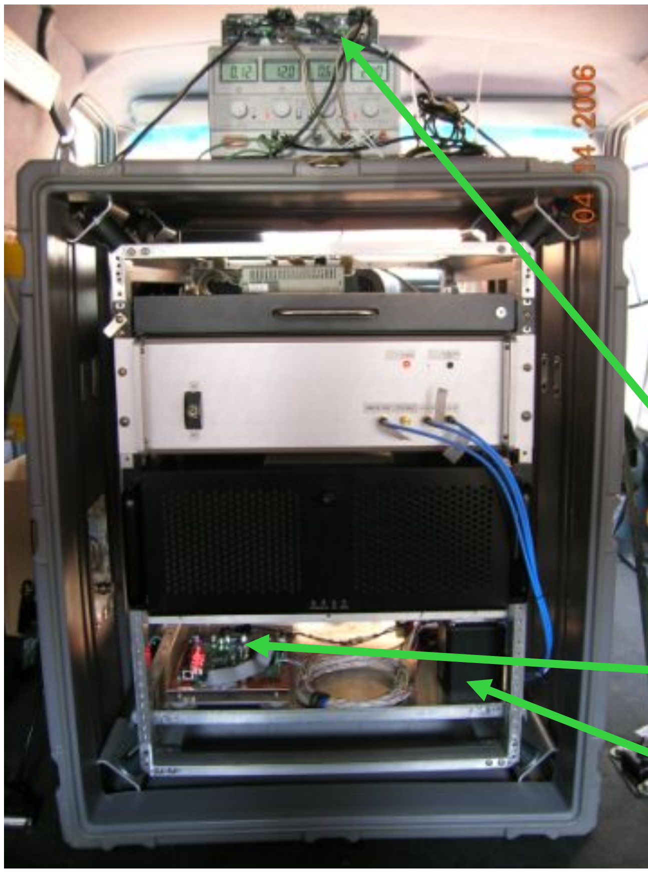


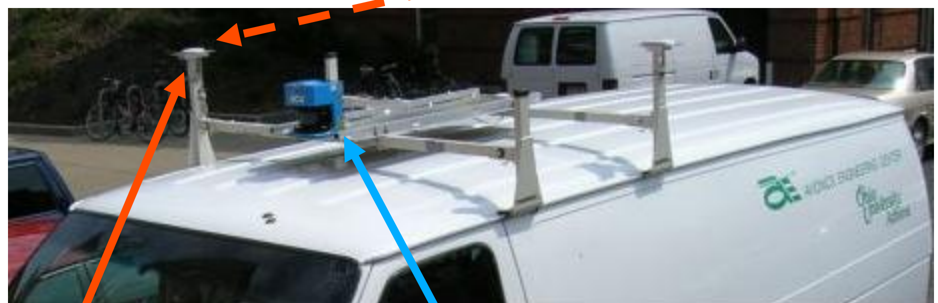
Performance Demonstration
Indoor Test





Urban Outdoor Test Setup





NovAtel L1/L2 pinwheel antenna

GPS antenna

Laser scanner

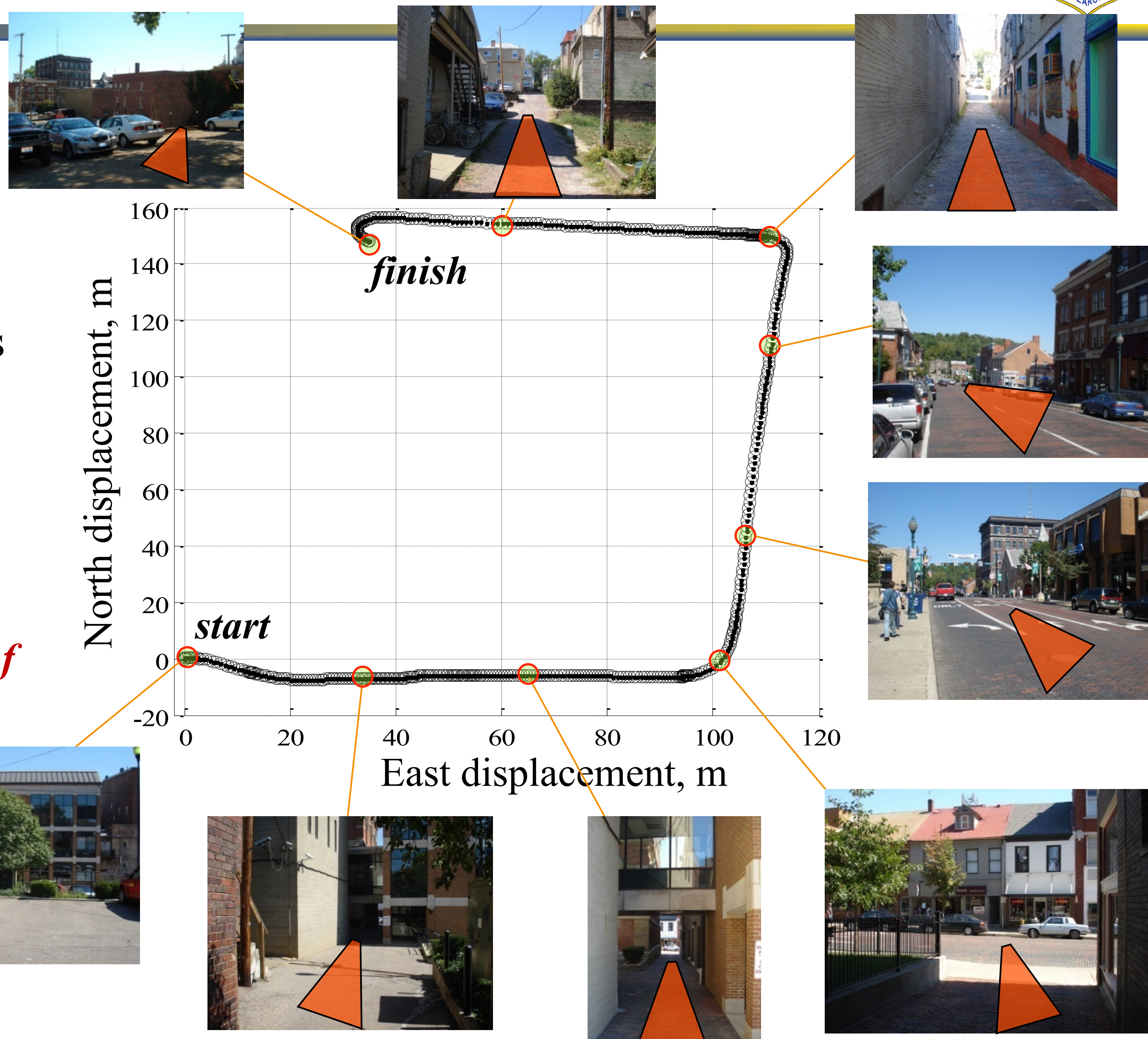
NovAtel OEM-4 GPS receiver

LS/Inertial synchronization and data collection board

Inertial Measurement Unit

Outdoor Test

Vehicle trajectory is reconstructed from integrated Ladar/ Inertial data



red segment of vehicle path

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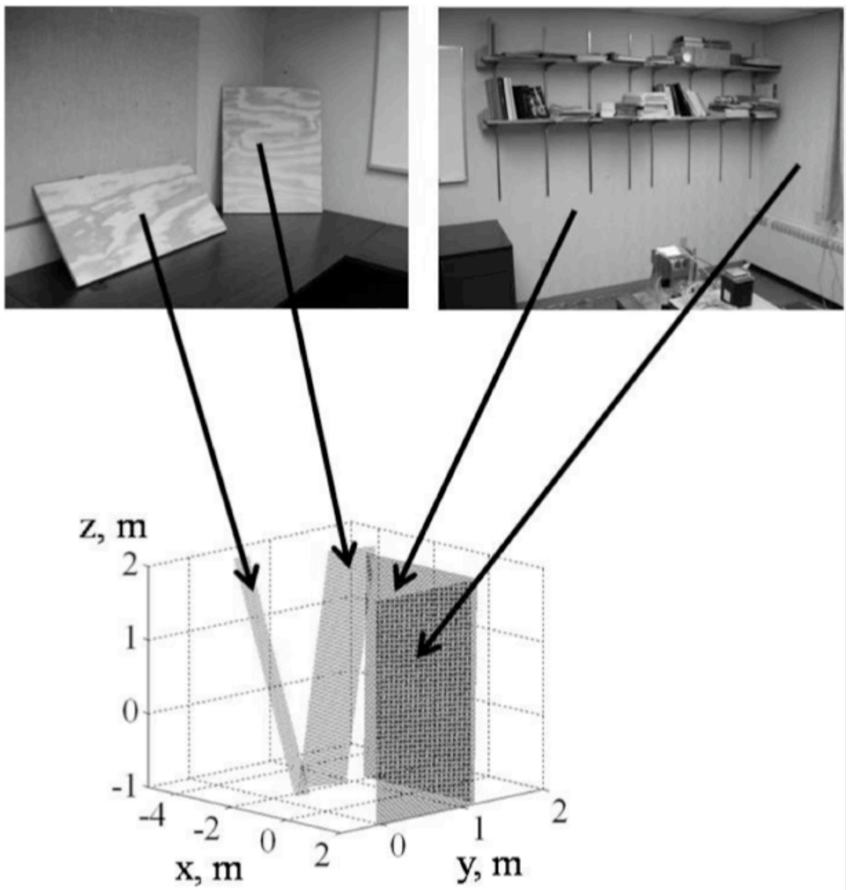
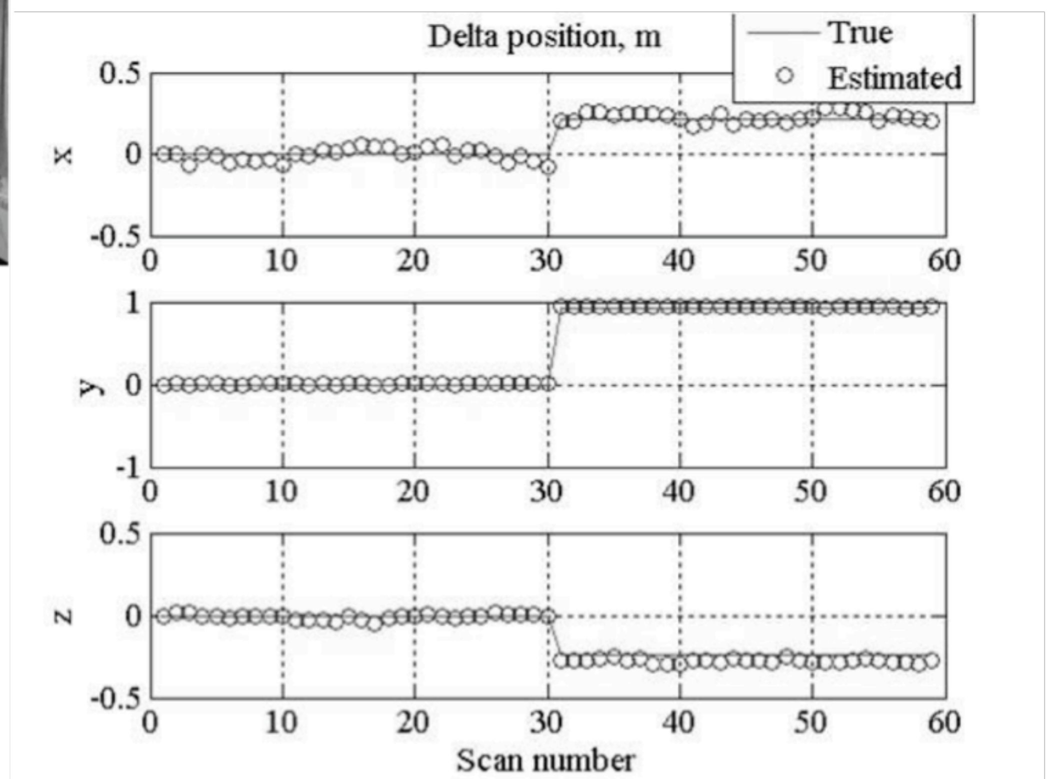
3D Trajectory Reconstruction





Questions?

Navigation in GPS Denied Environments:

Feature-Aided Inertial Systems