

Distributed Vision-Aided Cooperative Navigation Based on Three-View Geometry

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Introduction

- A group of cooperative platforms is considered
 - Required to autonomously perform different missions
 - Navigation is an essential capability
- Dead reckoning \ inertial navigation errors have to be compensated
 - External sensors (e.g.: GPS, camera, range sensor)
 - Additional information (e.g.: DTM)
- What happens if GPS is unavailable or unreliable?
- This work:
 - Vision-based approach for cooperative navigation
 - Each platform is equipped only with: INS, single camera
 - No additional sensors or a priori information is required
 - Except for initial navigation solution and camera calibration parameters

Previous Work

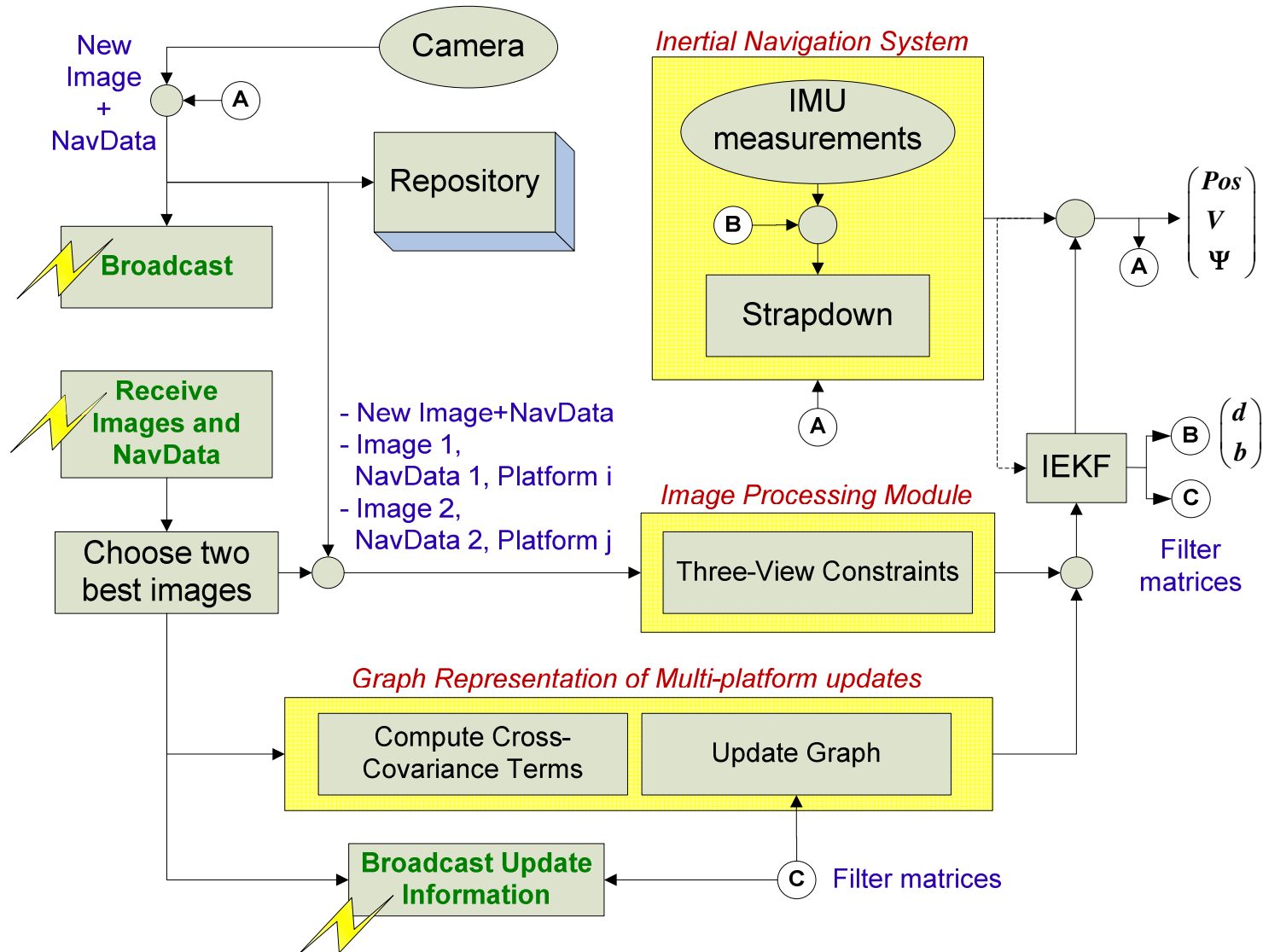
- [Use some robots as landmarks](#): “Cooperative Positioning with Multiple Robots”, Kurazume R. et al., 1994
- [Relative pose measurements between pairs of robots](#): “Distributed Multirobot Localization”, Roumeliotis S.I. and Bekey G.A., 2002
- [Direct & indirect encounters between pairs of robots, nonlinear optimization](#): “Multiple Relative Pose Graphs for Robust Cooperative Mapping”, Kim B. et al., 2010
- [Vision-aided navigation based on three-view geometry](#): “Mosaic Aided Navigation: Tools, Methods and Results”, Indelman V. et al., 2010
- [Consistent information fusion](#): “Consistent Cooperative Localization”, Bahr A. et al., 2009

Concept

- Navigation update whenever the same scene is observed by three views
 - Possibly captured by different platforms
 - Not necessarily at the same time
 - The camera is not required to be aimed towards other platforms (in contrast to relative pose measurements)

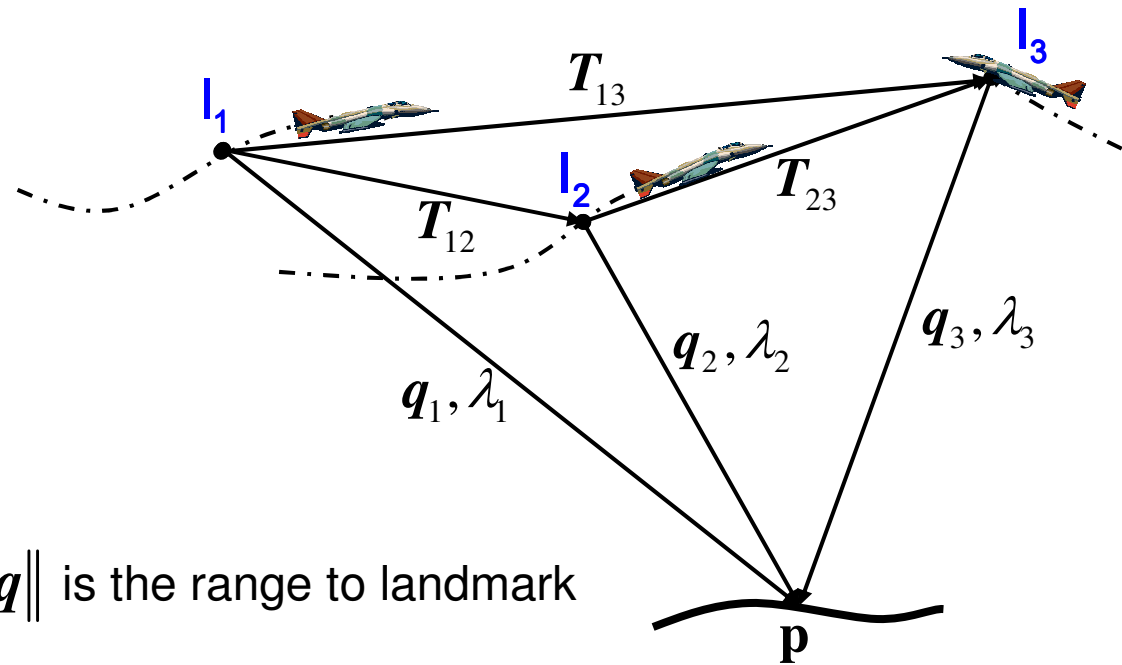
- Setup
 - Each platform is equipped with its own
 - INS, Camera
 - Perhaps, additional sensors or a-priori information
 - All\some platforms maintain a repository of stored images associated with navigation information
 - The platforms are able to exchange navigation and imagery data
 - Each platform maintains a local graph, required for correlation calculation

Overview



Three-view Constraints

- Each image may be captured by a different platform
- The images are not necessarily captured at the same time
- Images are stored in repositories and retrieved upon demand



- p - static landmark
- q - line of sight (LOS)
- λ - scale parameter, s.t. $\|\lambda q\|$ is the range to landmark
- T_{ij} - translation from i to j

Three-view Constraints (cont.)

$$\mathbf{q}_1^T (\mathbf{T}_{12} \times \mathbf{q}_2) = 0$$

$$\mathbf{q}_2^T (\mathbf{T}_{23} \times \mathbf{q}_3) = 0$$

$$(\mathbf{q}_2 \times \mathbf{q}_1)^T (\mathbf{q}_3 \times \mathbf{T}_{23}) = (\mathbf{q}_1 \times \mathbf{T}_{12})^T (\mathbf{q}_3 \times \mathbf{q}_2)$$

- First two equations – epipolar constraints
- Third equation – relates between the magnitudes of \mathbf{T}_{12} and \mathbf{T}_{23}
- Reformulating:

$$\begin{aligned} \Rightarrow \quad & \begin{bmatrix} \mathbf{g}^T \end{bmatrix}_{1 \times 3} \mathbf{T}_{12} = 0 \\ & \begin{bmatrix} \mathbf{f}^T \end{bmatrix}_{1 \times 3} \mathbf{T}_{23} = 0 \\ & \begin{bmatrix} \mathbf{u}^T \end{bmatrix}_{1 \times 3} \mathbf{T}_{23} = \begin{bmatrix} \mathbf{w}^T \end{bmatrix}_{1 \times 3} \mathbf{T}_{12} \end{aligned} \quad \text{where} \quad \begin{aligned} \mathbf{g} &= \mathbf{g}(\mathbf{q}_1, \mathbf{q}_2) \\ \mathbf{f} &= \mathbf{f}(\mathbf{q}_2, \mathbf{q}_3) \\ \mathbf{u} &= \mathbf{u}(\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3) \\ \mathbf{w} &= \mathbf{w}(\mathbf{q}_1, \mathbf{q}_2, \mathbf{q}_3) \end{aligned}$$

Three-view Constraints (cont.)

- Multiple features

- Matching pairs between 1st and 2nd view
- Matching pairs between 2nd and 3rd view
- Matching triplets between the three views

$$\left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2} \right\}_{i=1}^{N_{12}}$$

$$\left\{ \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\}_{i=1}^{N_{23}}$$

$$\left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\}_{i=1}^{N_{123}}$$

$$\left[\mathbf{u}_i^T \right]_{1 \times 3} \mathbf{T}_{23} = \left[\mathbf{w}_i^T \right]_{1 \times 3} \mathbf{T}_{12} \quad i = 1, \dots, N_{123}$$

$$\left[\mathbf{f}_j^T \right]_{1 \times 3} \mathbf{T}_{23} = \mathbf{0} \quad j = 1, \dots, N_{23}$$

$$\left[\mathbf{g}_k^T \right]_{1 \times 3} \mathbf{T}_{12} = \mathbf{0} \quad k = 1, \dots, N_{12}$$



$$\begin{bmatrix} U \\ F \\ 0 \end{bmatrix}_{N \times 3} \mathbf{T}_{23} = \begin{bmatrix} W \\ 0 \\ G \end{bmatrix}_{N \times 3} \mathbf{T}_{12}$$

$$N = N_{123} + N_{12} + N_{23}$$

Fusion with Navigation using Implicit Extended Kalman Filter (IEKF)

- Residual Measurement

$$\mathbf{z} \equiv \begin{bmatrix} U \\ F \\ 0 \end{bmatrix}_{N \times 3} \mathbf{T}_{23} - \begin{bmatrix} W \\ 0 \\ G \end{bmatrix}_{N \times 3} \mathbf{T}_{12}$$

- Recall

- All original LOS vectors are expressed in camera system of the appropriate view
- $\mathbf{T}_{23}, \mathbf{T}_{12}$ are functions of $\mathbf{Pos}_3, \mathbf{Pos}_2, \mathbf{Pos}_1$

$$\mathbf{Pos}_i \equiv \mathbf{Pos}_i(t_i)$$



$$\mathbf{z} = \mathbf{h} \left(\mathbf{Pos}_3, \Psi_3, \mathbf{Pos}_2, \Psi_2, \mathbf{Pos}_1, \Psi_1, \left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\} \right)$$

Fusion with Navigation using IEKF (cont.)

- State vector definition:
$$\mathbf{X} = \left[\Delta \mathbf{P}^T \quad \Delta \mathbf{V}^T \quad \Delta \boldsymbol{\Psi}^T \quad \mathbf{d}^T \quad \mathbf{b}^T \right]^T$$

- Inertial navigation error of the i -th platform:
$$\mathbf{X}_i(t_b) = \Phi_{t_a \rightarrow t_b}^i \mathbf{X}_i(t_a) + \boldsymbol{\omega}_{t_a \rightarrow t_b}^i$$

- Linearization of \mathbf{z}

$$\begin{aligned} \mathbf{z} &= \mathbf{h} \left(\mathbf{Pos}_3, \boldsymbol{\Psi}_3, \mathbf{Pos}_2, \boldsymbol{\Psi}_2, \mathbf{Pos}_1, \boldsymbol{\Psi}_1, \left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\} \right) \\ &\cong H_3 \mathbf{X}_{\text{III}}(t_3) + H_2 \mathbf{X}_{\text{II}}(t_2) + H_1 \mathbf{X}_{\text{I}}(t_1) + D\mathbf{v} + H.O.T. \end{aligned}$$

- $\mathbf{X}_{\text{III}}(t_3), \mathbf{X}_{\text{II}}(t_2), \mathbf{X}_{\text{I}}(t_1)$ represent navigation errors of different platforms at different time instances.
 - **None of these are known a-priori**
 - **Can be correlated**
- Theoretically, all the participating platforms can be updated

Fusion with Navigation (cont.)

- The measurement update step involves cross-covariance terms

- E.g., if only platform III is updated: $K = P_{X_{III}(t_3)z(t_3,t_2,t_1)} P_{z(t_3,t_2,t_1)}^{-1}$

- with

$$P_{X(t_3)z(t_3,t_2,t_1)} = P_3 H_3^T + P_{32} H_2^T + P_{31} H_1^T$$

$$P_{z(t_3,t_2,t_1)} = H_3 P_3 H_3^T + \begin{bmatrix} H_2 & H_1 \end{bmatrix} \begin{bmatrix} P_2 & P_{21} \\ P_{21}^T & P_1 \end{bmatrix} \begin{bmatrix} H_2 & H_1 \end{bmatrix}^T + DRD^T$$

- where

$$P_{ij} \equiv E \left[\tilde{X}_i(t_i) \tilde{X}_j^T(t_j) \right]$$

- Maintaining all the possible cross-covariance terms – impractical
 - In contrast to relative pose measurements
- Therefore: either neglect, or [calculate upon-demand](#)

Explicit Calculation of Cross-covariance terms - Concept

- Algorithm:
 - More details: “Graph-based Distributed Cooperative Navigation”, Indelman V., et al., ICRA 2011
 - Allows updating only one platform

- Concept:
 1. Store covariance and cross-covariance terms from **all the past** three-view measurement updates
 2. Express $\tilde{\mathbf{X}}_i(t_i)$ and $\tilde{\mathbf{X}}_j(t_j)$ according to the history of MP measurement updates
 3. Calculate $\mathbf{E} \left[\tilde{\mathbf{X}}_i(t_i) \tilde{\mathbf{X}}_j^T(t_j) \right]$ based on expressions from step 2.

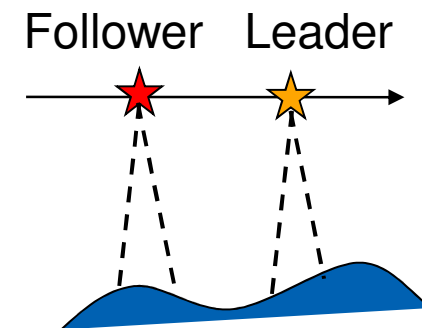
- Automation of the above for general scenarios using graph representation

Simulation Results – Leader-Follower Scenario

- 2 platforms: **Leader, Follower**
 - Leader is equipped with a better IMU
 - Initial navigation errors and IMU errors:

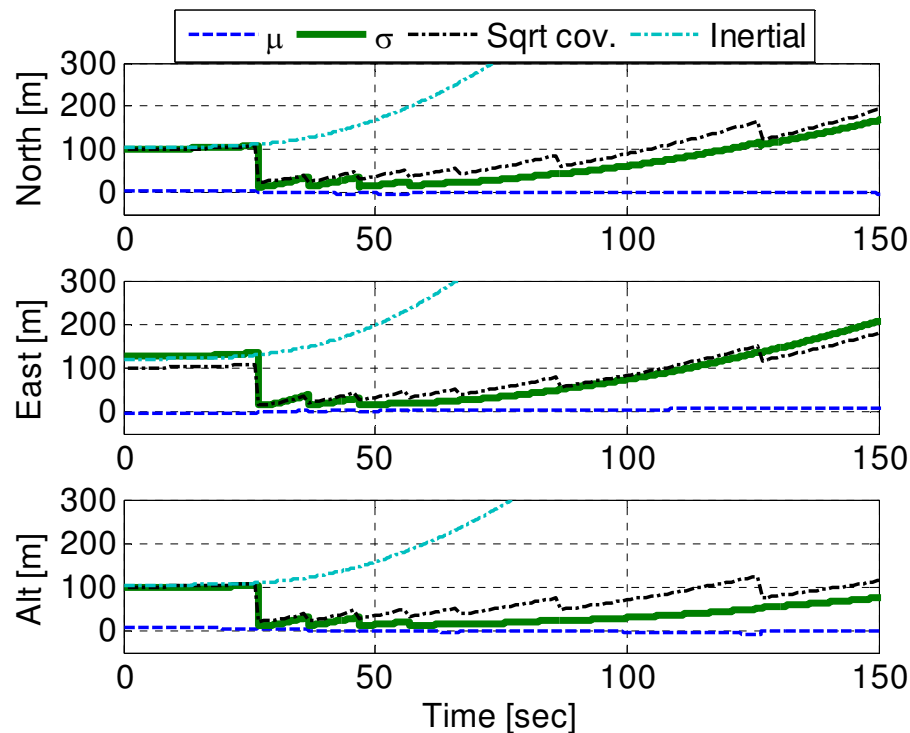
Parameter	Description	Leader	Follower	Units
$\Delta \mathbf{P}$	Initial position error (1σ)	$(10, 10, 10)^T$	$(100, 100, 100)^T$	m
$\Delta \mathbf{V}$	Initial velocity error (1σ)	$(0.1, 0.1, 0.1)^T$	$(0.3, 0.3, 0.3)^T$	m/s
$\Delta \Psi$	Initial attitude error (1σ)	$(0.1, 0.1, 0.1)^T$	$(0.1, 0.1, 0.1)^T$	deg
\mathbf{d}	IMU drift (1σ)	$(1, 1, 1)^T$	$(10, 10, 10)^T$	deg/hr
\mathbf{b}	IMU bias (1σ)	$(1, 1, 1)^T$	$(10, 10, 10)^T$	mg

- Trajectory: Straight and level, north heading flight
 - Velocity: 100 m/s
 - Leader is 2000 m ahead (20 second delay)
 - Height above ground level: 2000 ± 200 m
- Follower is updated every 10 seconds
- Leader is not updated (inertial navigation)
- Synthetic imagery

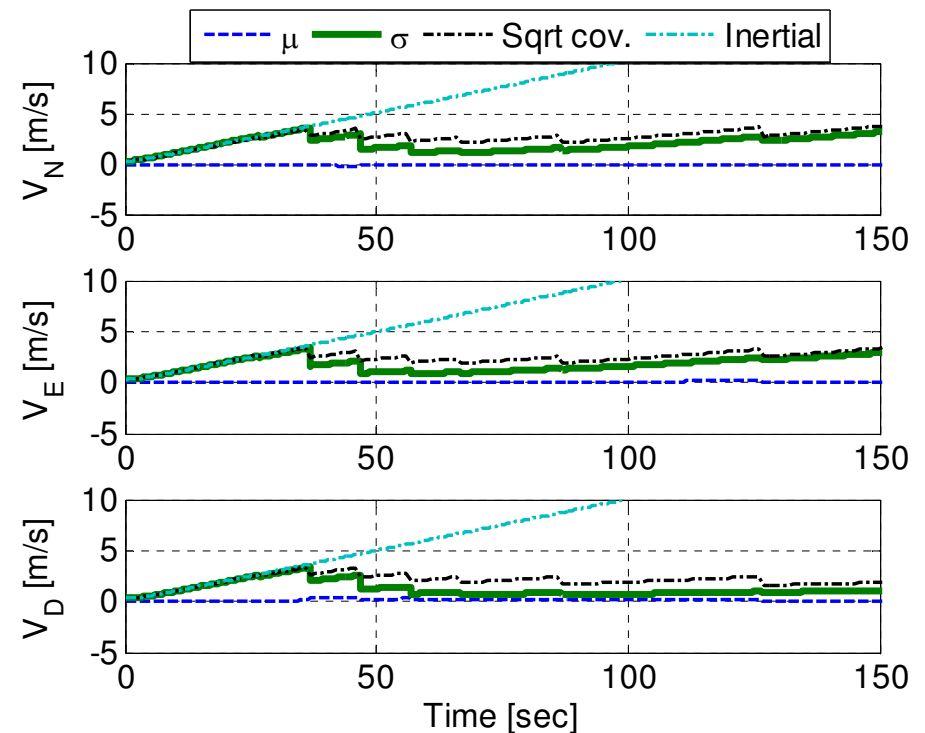


Simulation Results – Leader-Follower Scenario (cont.)

Monte Carlo results (1000 runs): **Follower's navigation errors**



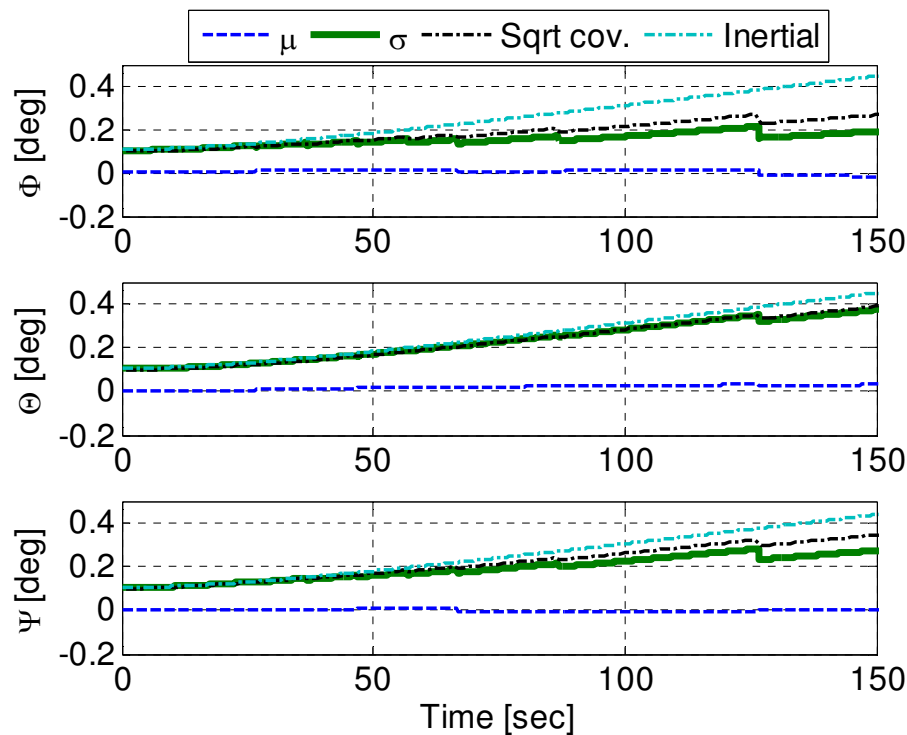
Position errors



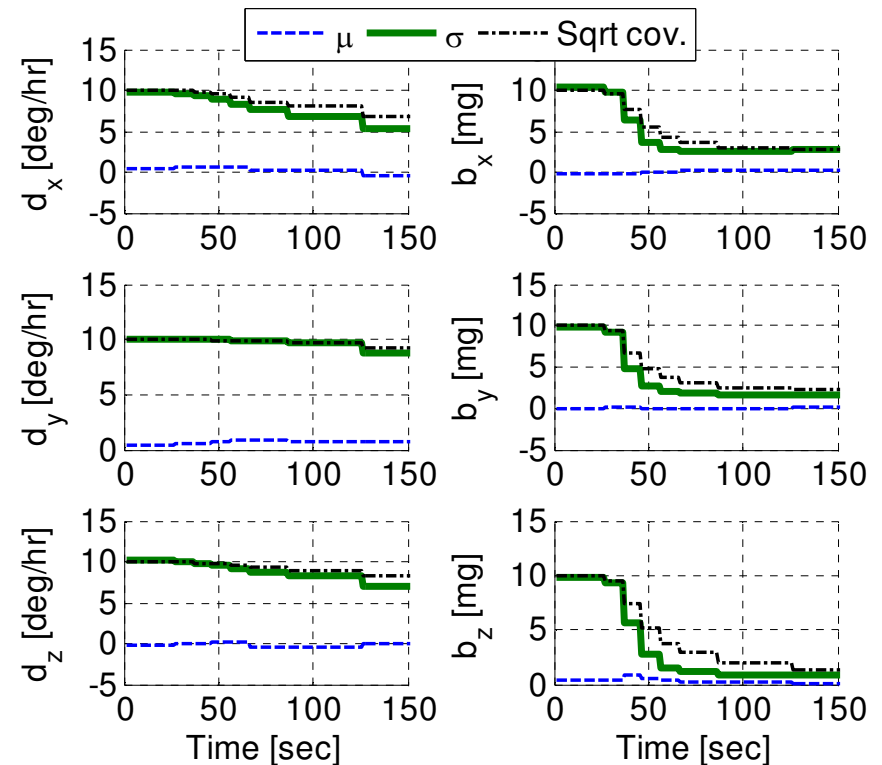
Velocity errors

Simulation Results – Leader-Follower Scenario (cont.)

Monte Carlo results (1000 runs): **Follower's navigation errors**



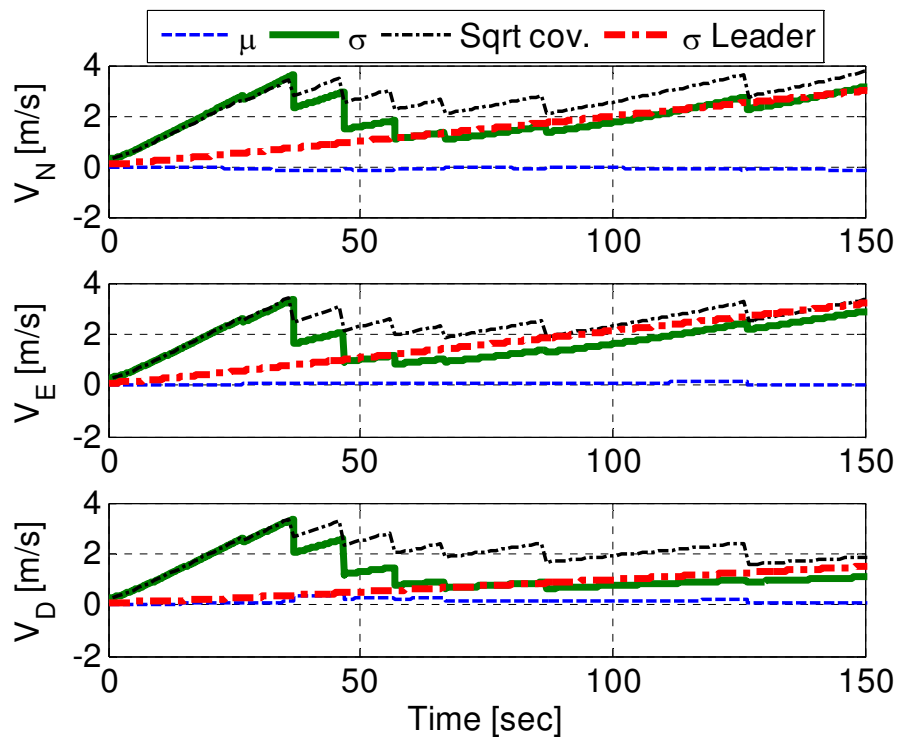
Euler angle errors



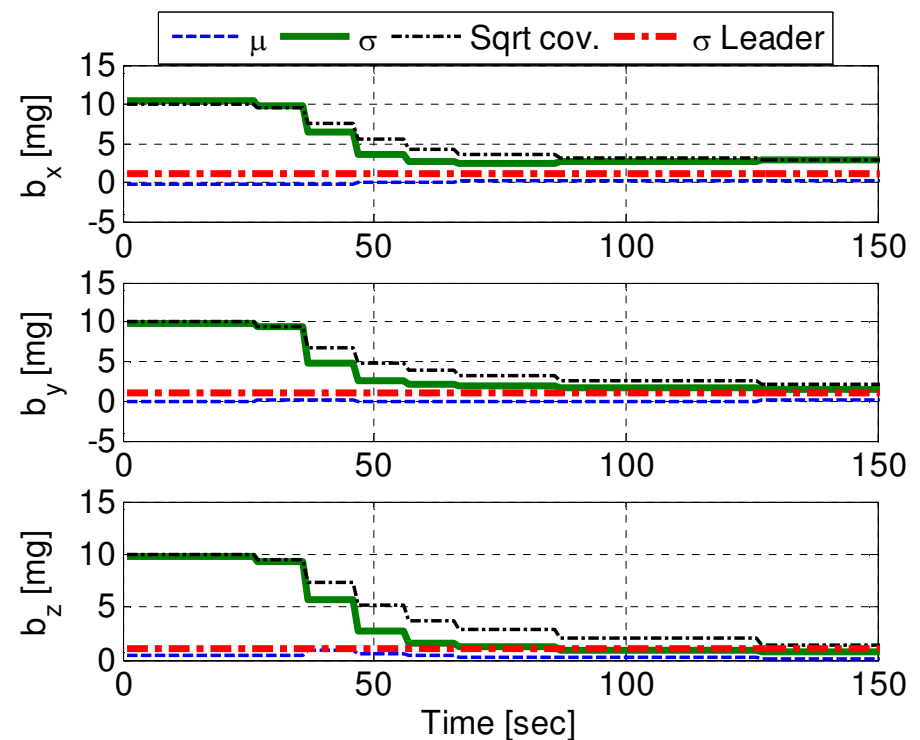
Drift and bias estimation errors

Simulation Results – Leader-Follower Scenario

Monte Carlo results (1000 runs): **Follower's** vs. **Leader's** navigation errors



Velocity errors



Bias estimation errors

Experiment Results – Pattern Holding Scenario

- Experiment Setup
 - An IMU and a camera were mounted on top of a ground vehicle
 - IMU\INS: Xsens MTi-G
 - Camera: Axis 207MW
- IMU data and captured images were stored and synchronized
 - IMU data @ 100Hz
 - Imagery data @ 15Hz
- The method was applied in two modes:
 - ♦ Multi-platform update
 - × Self update (all images from the same platform)



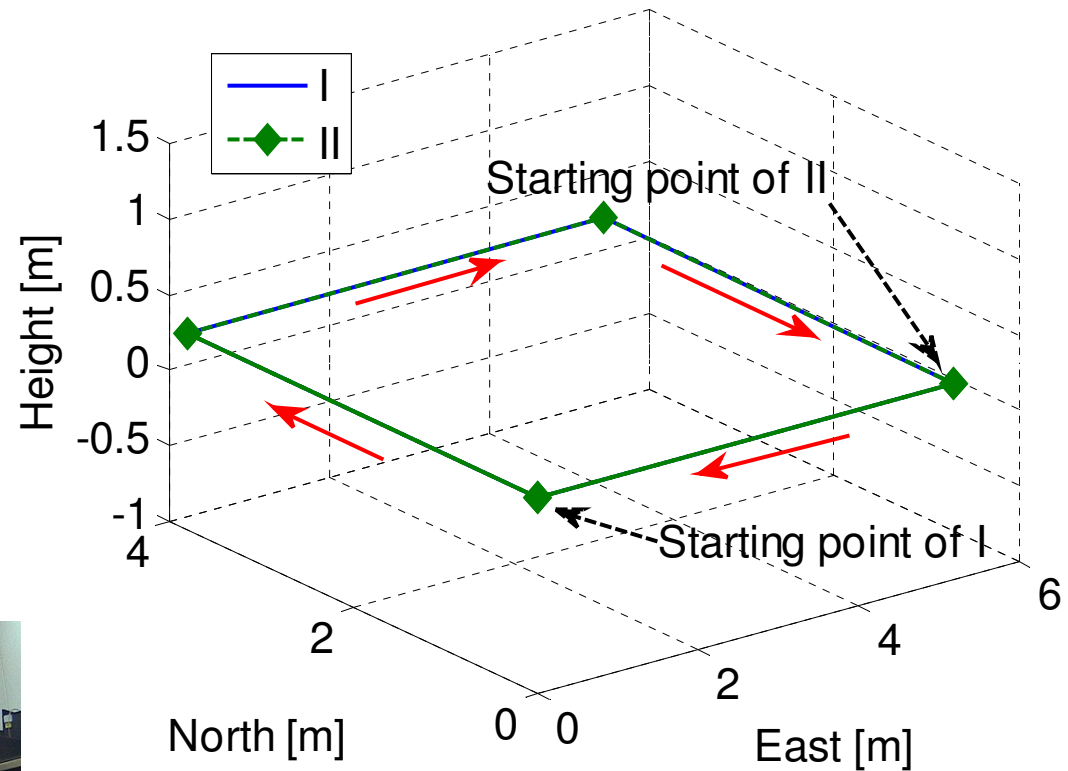
Experiment Results – Pattern Holding Scenario (cont.)

- Two different trajectories
- IMU and camera were turned off in between



Two platforms with identical hardware (camera + IMU)

Recorded imagery



Experiment Results – Pattern Holding Scenario (cont.)

Example



Image 1



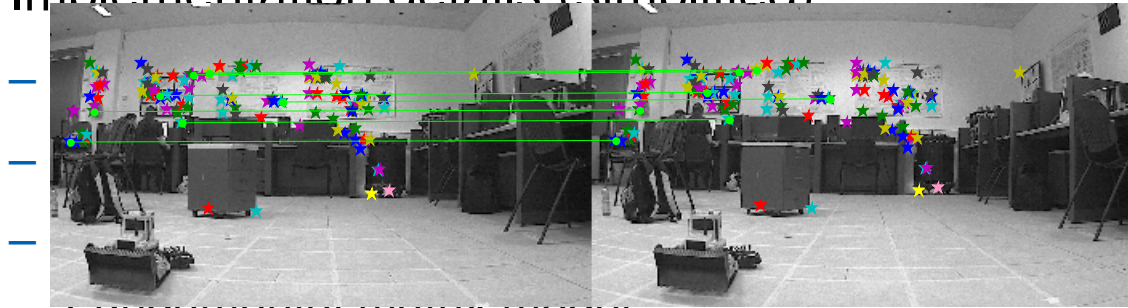
Image 2



Image 3

Matching Triplets

Implementation details (simplified)



- The Fundamental matrix is not required elsewhere

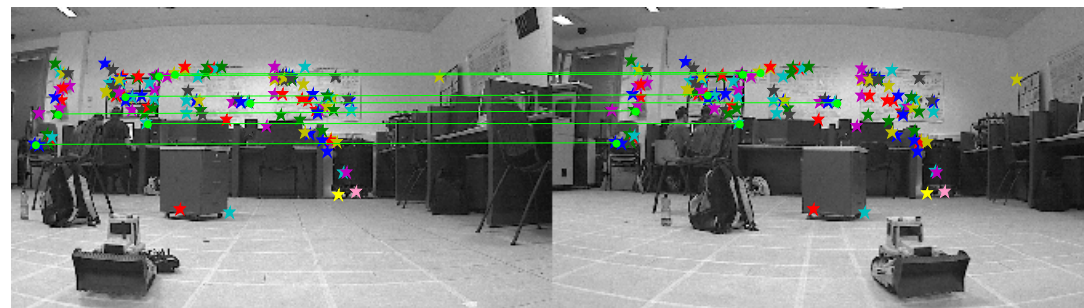


Image 2

Image 3

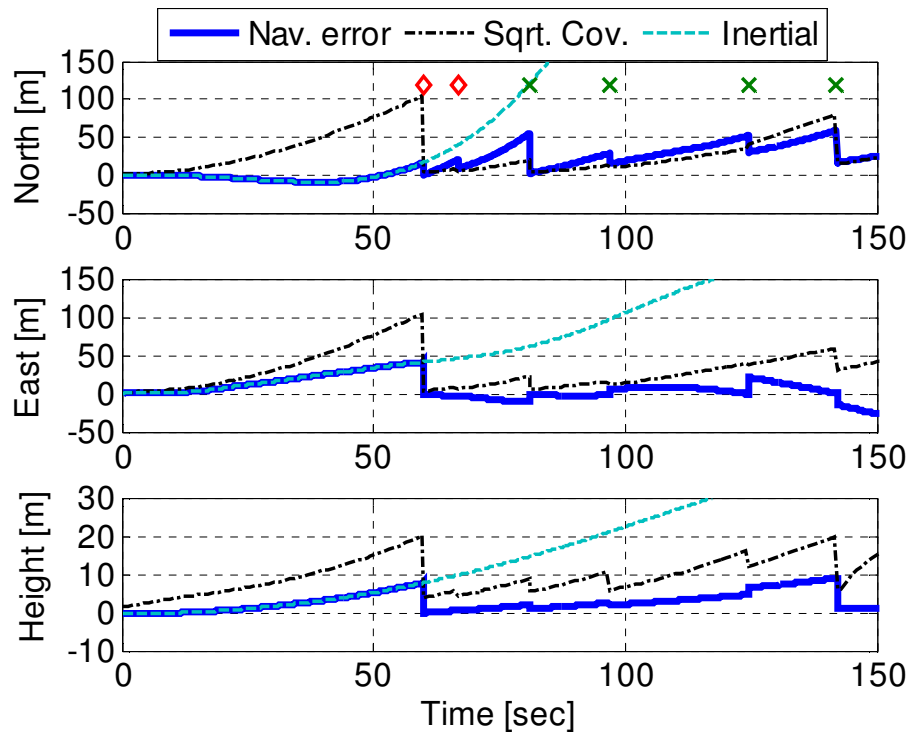


$$\left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\}_{i=1}^{N_{123}}, \left\{ \mathbf{q}_{1_i}^{C_1}, \mathbf{q}_{2_i}^{C_2} \right\}_{i=1}^{N_{12}}, \left\{ \mathbf{q}_{2_i}^{C_2}, \mathbf{q}_{3_i}^{C_3} \right\}_{i=1}^{N_{23}}$$

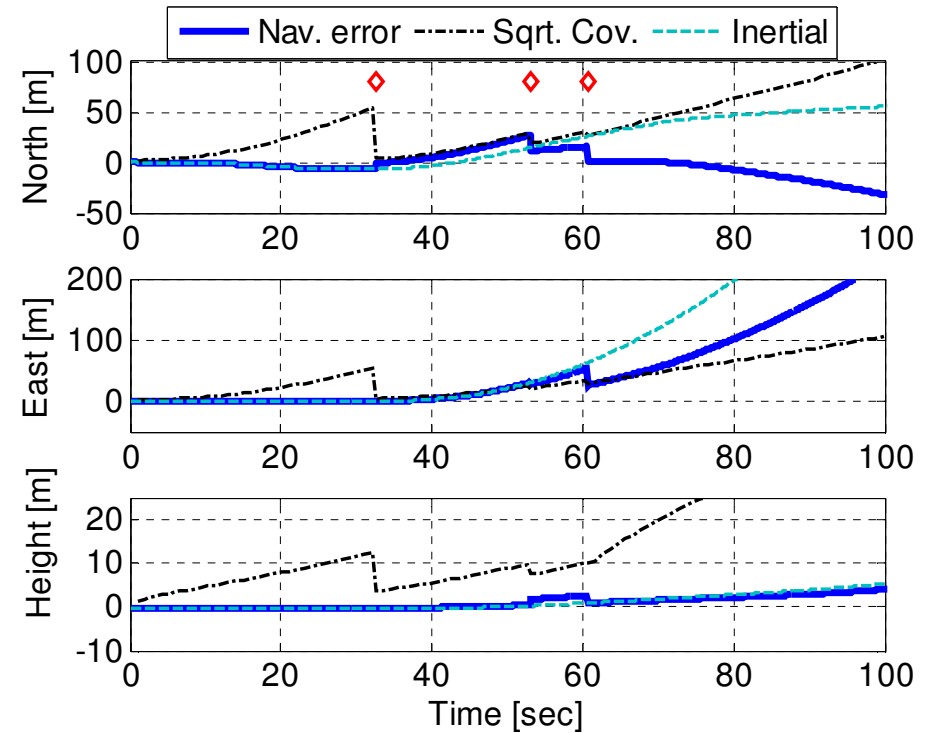
Experiment Results – Pattern Holding Scenario (cont.)

- ◇ Multi platform update
- × Self update

Position errors



Platform I



Platform II

Conclusions

- Distributed cooperative navigation aiding
 - Three-view constraints are formulated whenever the same scene is observed by several platforms
 - The camera is no more required to be aimed towards other platforms (as in relative pose measurements)
 - Range sensor is not required
 - The views are not necessarily captured at the same time
 - Allows reduction of navigation errors in some platforms based on other platforms in the group
 - Including position and velocity errors in all axes