Self Localization in Multi-Robotic Experimental Platforms

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For presentation at

International Symposium on Resilient Control Systems

Idaho Falls, ID

Aug. 10 – 12, 2010

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Sensors in Control Systems

- Uncertain Environments
- Sensors Enrich System's Knowledge
- Limitations of Single Sensor
- Multiple Sensors:
  - Complementary, Redundant, Diverse, Timely Information
- Sensor Fusion: The theory, techniques and tools which are used for integrating data from multiple sensory sources, or information generated from any source of data into a common, coherent representational format

Multi-Sensor Fusion: Commercial Applications

- **Biomedical Applications**

  Diagnostic assistance, fusion of medical images

- **Health Monitoring**

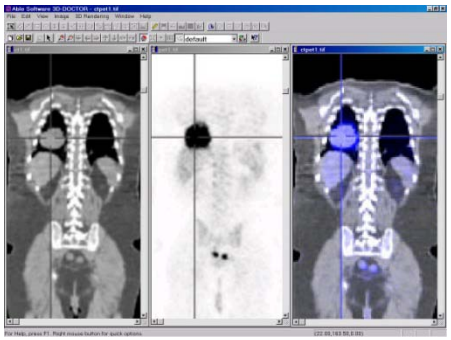
  Smart Structures, Machines, Diagnosis, Prognosis

- **Environment Monitoring**

  Habitat Monitoring, Traffic Monitoring

- **Industrial Applications**

  Robotics, Manufacturing Automation



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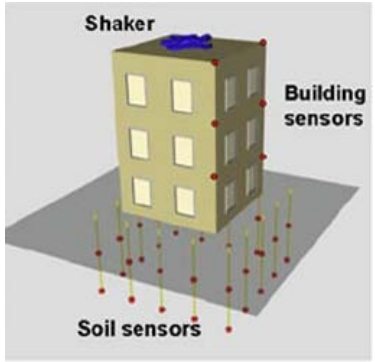

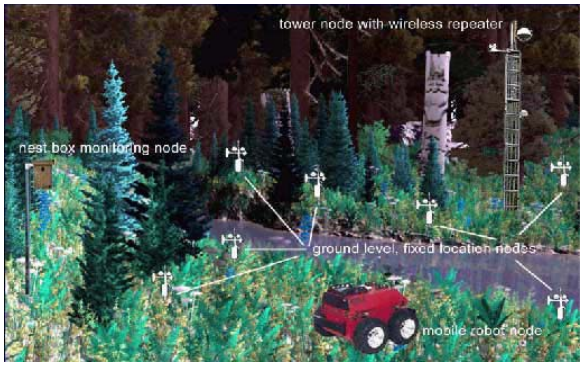

Source: www.cs.ucla.edu/~jessicaf/

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Multi-Sensor Fusion: Military Applications

- **Battlefield Operations**

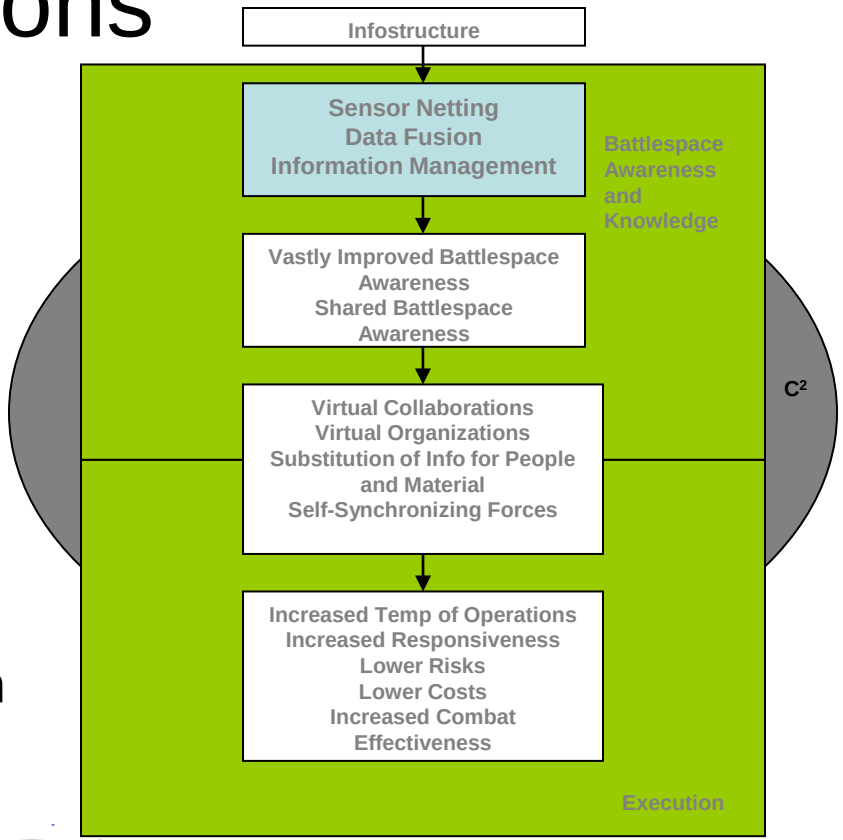
  Detection, Tracking, Identifying and Locating Targets

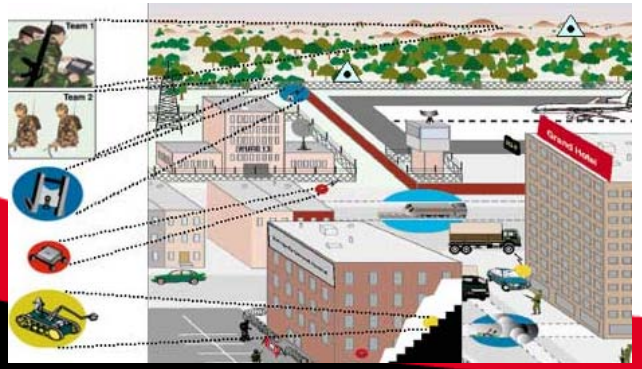
- **Situation Awareness**

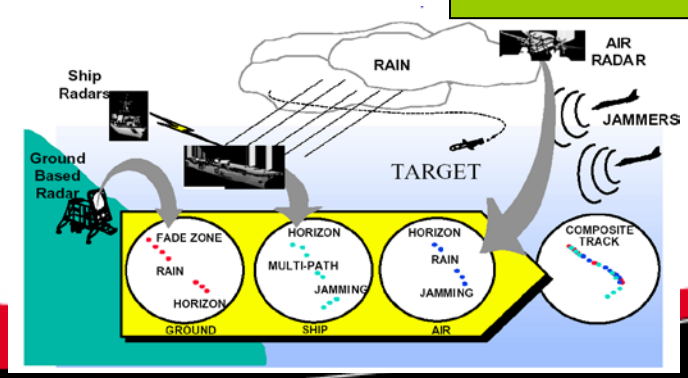
  Web of Human and Non-Human Sources, Information Superiority

- **Network Centric Warfare**

  Linkage between Sensors, Decision Makers and Armaments



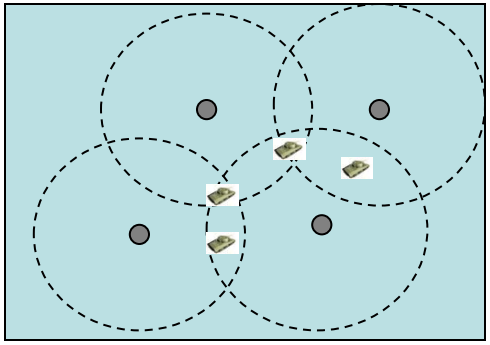




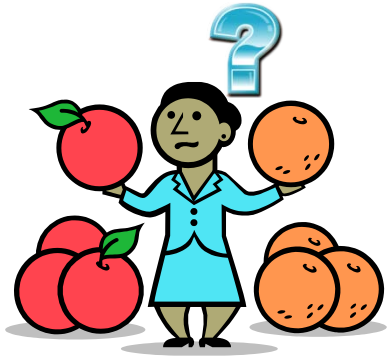
Source: http://www.dod.mil/nii/NCW/ncw_0801.pdf

Issues and Challenges

- Sensor Uncertainty: Noise, Ambiguity, Spuriousness
- Data Association

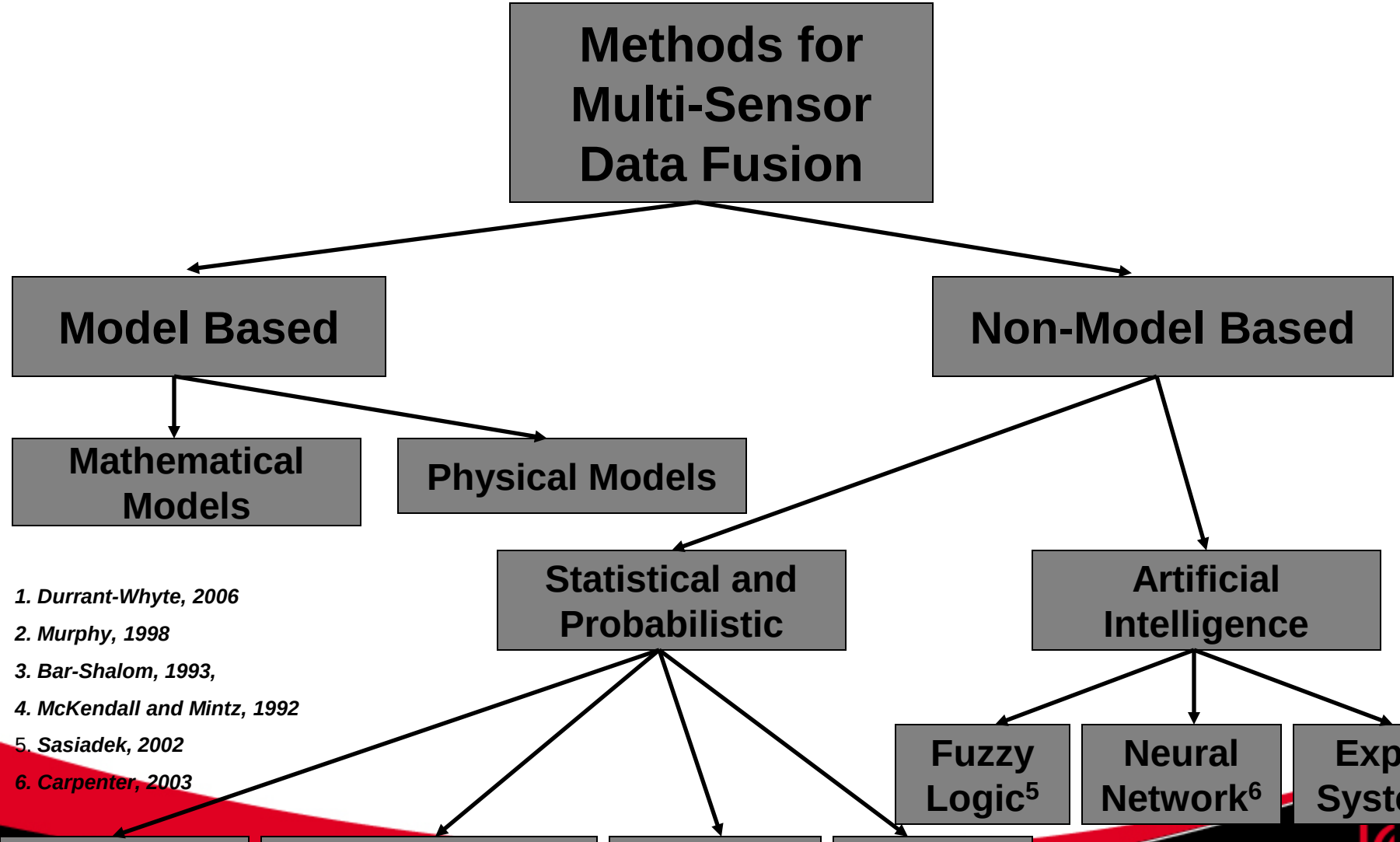


- Sensor Selection: Optimization of Resources



- Complexity and Synergism: Numerous Sources

Sensor Fusion Algorithms



1. Durrant-Whyte, 2006

2. Murphy, 1998

3. Bar-Shalom, 1993,

4. McKendall and Mintz, 1992

5. *Sasiadek, 2002*

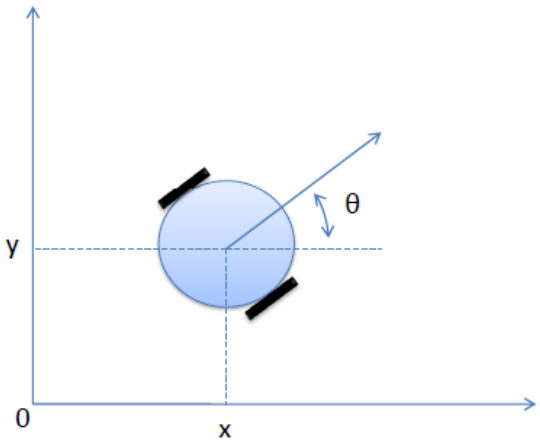
6. Carpenter, 2003

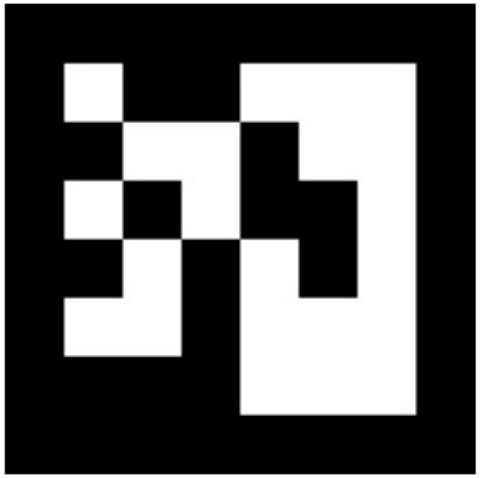
Data Fusion Applied to Self-Localization in Multi-Robot Experiments

- Self – localization
  - Where am I? Obtain one's own positional estimate
    - Important for robot control and navigation algorithms
- Multi-robot scenarios
  - Where am I?
  - Where are others?
  - Needed for control and coordination algorithms

Localization methods

- Self-localization
  - Obtaining positional estimate (x, y, θ)
  - Approaches: GPS, Radio – acoustic ranging, centralized sensing system such as vision
- Centralized vision system
  - Uses patterns
    - Provides both state and IDs
  - Not scalable
  - Practical implementation issues





ARTAG Marker

Localization Methods

	Pattern	Non-Pattern
Position (x, y):	Direct measurement (Pattern recognition)	Direct measurement (Blob extraction)
Bearing (θ):	Direct measurement (Pattern recognition)	Estimation (Kalman filter)
ID:	Direct measurement (Pattern recognition)	Data Association (in distributed manner)
Computation mode:	Centralized	Decentralized

Self-localization in Single Robot Scenario

State of the robot:

$$X_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix}$$

$$F = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$$

Dynamics Equation:

$$X_k = f(X_{k-1}, U_k, W)$$

$$= FX_{k-1} + B_{k-1}U_k + W$$

$$B_{k-1} = \begin{bmatrix} T_s \times cos(\theta_{k-1}) & 0 \\ T_s \times sin(\theta_{k-1}) & 0 \\ 0 & -T_s \end{bmatrix}$$

$$H = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{bmatrix}$$

Observation equation:

$$Z_k = h(X_k, V) = HX_k + V$$

$$U_k = \begin{bmatrix} v_k \\ \omega_k \end{bmatrix}$$

Extended Kalman Filter for the Estimation

Prediction Equations:

$$\hat{X}_{k|k-1} = F\hat{X}_{k-1|k-1} + B_{k-1}U_k$$

$$P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q$$

Update Equations:

$$K_k = P_{k|k-1}H^T(HP_{k|k-1}H^T + R)^{-1}$$

$$\hat{X}_{k|k} = \hat{X}_{k|k-1} + K_k(Z_k - H\hat{X}_{k|k-1})$$

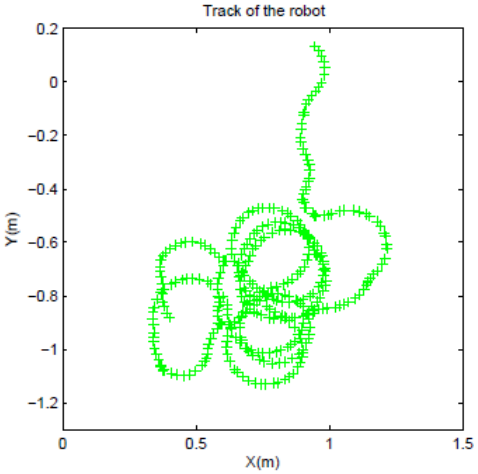
$$P_{k|k} = (I - K_k H)P_{k|k-1}$$

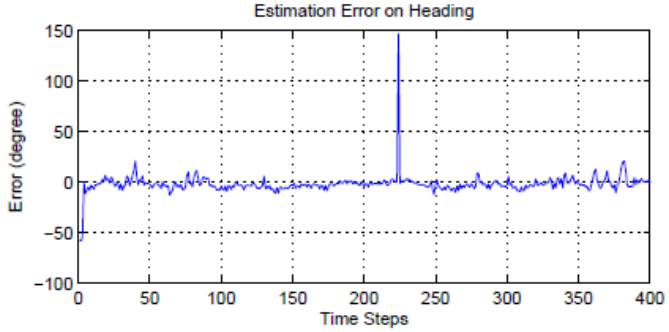
where $Z_k - H\hat{X}_{k|k-1}$ is called measurement reidual, A_k is Jacobian matrix of partial derivative of f with respect to X

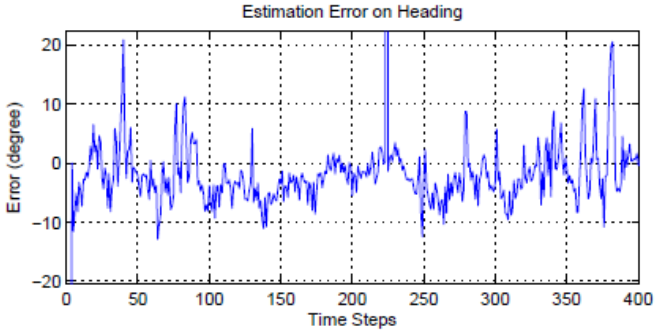
$$A_{[i,j]} = \frac{\partial f_{[i]}}{\partial X_{[j]}}(X_{k-1}, U_k, 0) \qquad A_k = \begin{bmatrix} 1 & 0 & -v_k \times T_s \times sin(\theta_{k-1}) \\ 0 & 1 & v_k \times T_s \times cos(\theta_{k-1}) \\ 0 & 0 & 1 \end{bmatrix}$$

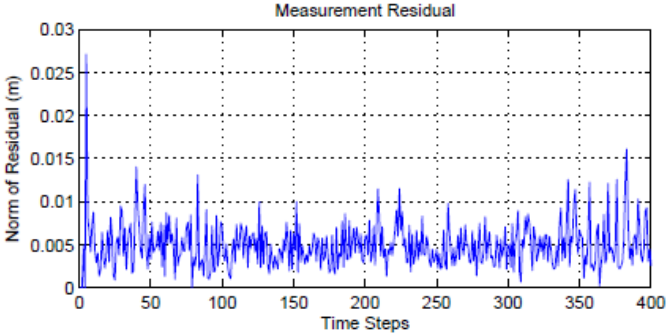
Single Robot Experiment

- Robot motion is random
- Bearing estimation converges quickly







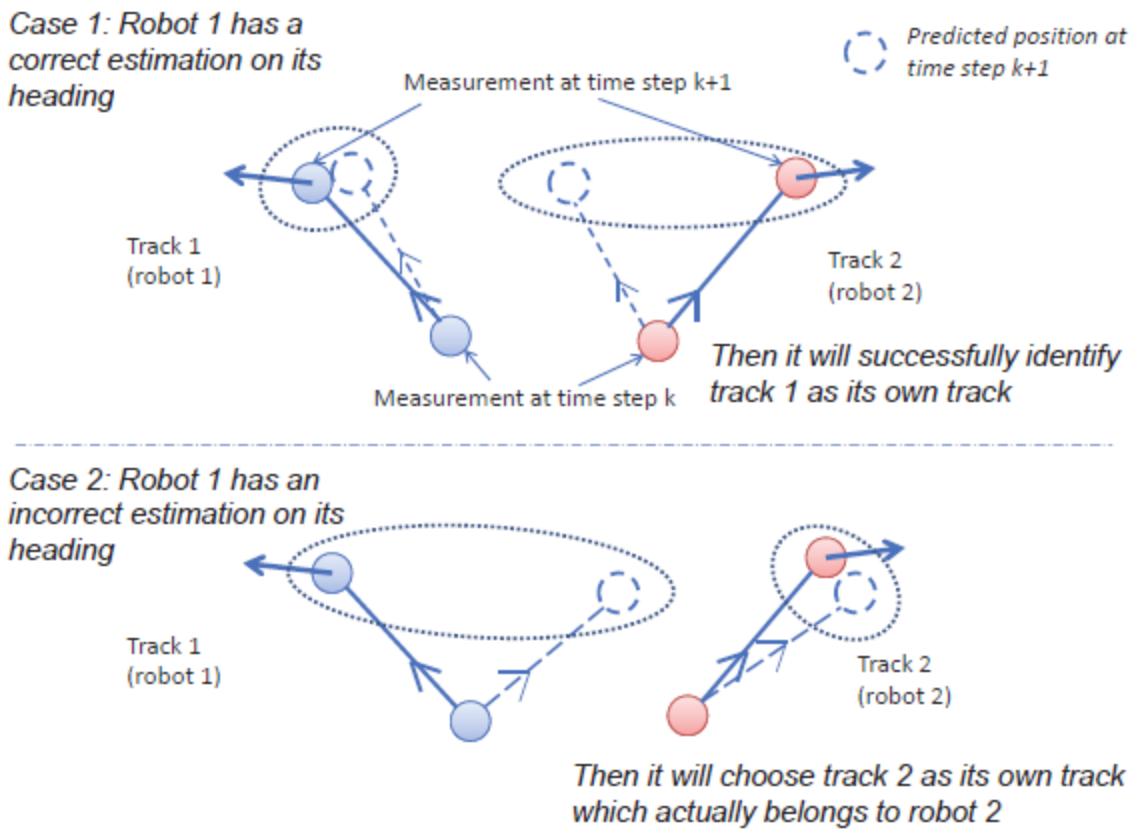


Multi-robot scenario

- All robots look alike to a vision camera
- Camera provides a bunch of points corresponding to positions, no IDs
- Hence, the challenge is two stage: i) data identification and ii) estimation
- Solution:
  - First identify the data, i.e., tag them
  - Then use the EKF based method for estimation
- Turns out, its not so easy

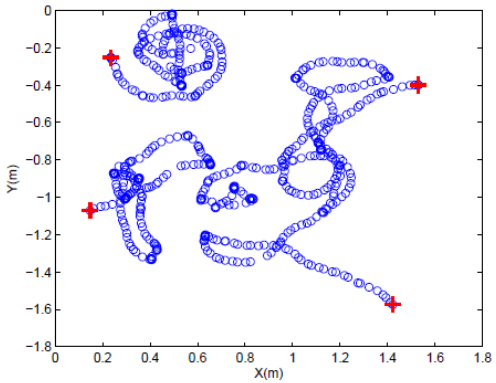
Multi-Robot Scenario

- Identification of data requires a good estimate of bearing
- Estimation of bearing requires identified data

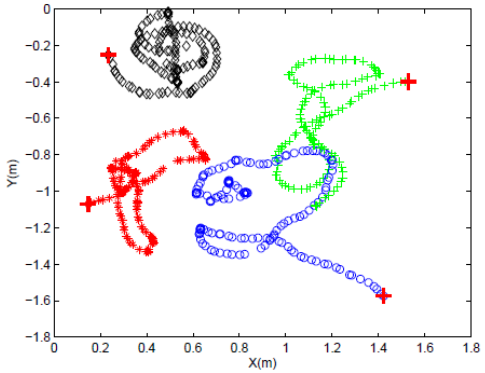


Proposed Approach

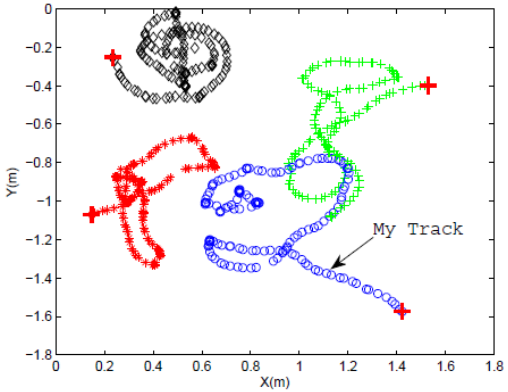
- Generate all potential tracks from the data
- Identify the robot's own track from among these candidates
- Once the track is identified, associate the incoming data in a step-wise basis.



Initial data received in one robot after 150 timestep



Generate all potential tracks (Nearest Neighbor).



Identify its own track (by comparing Measurement Residual).

Proposed Approach

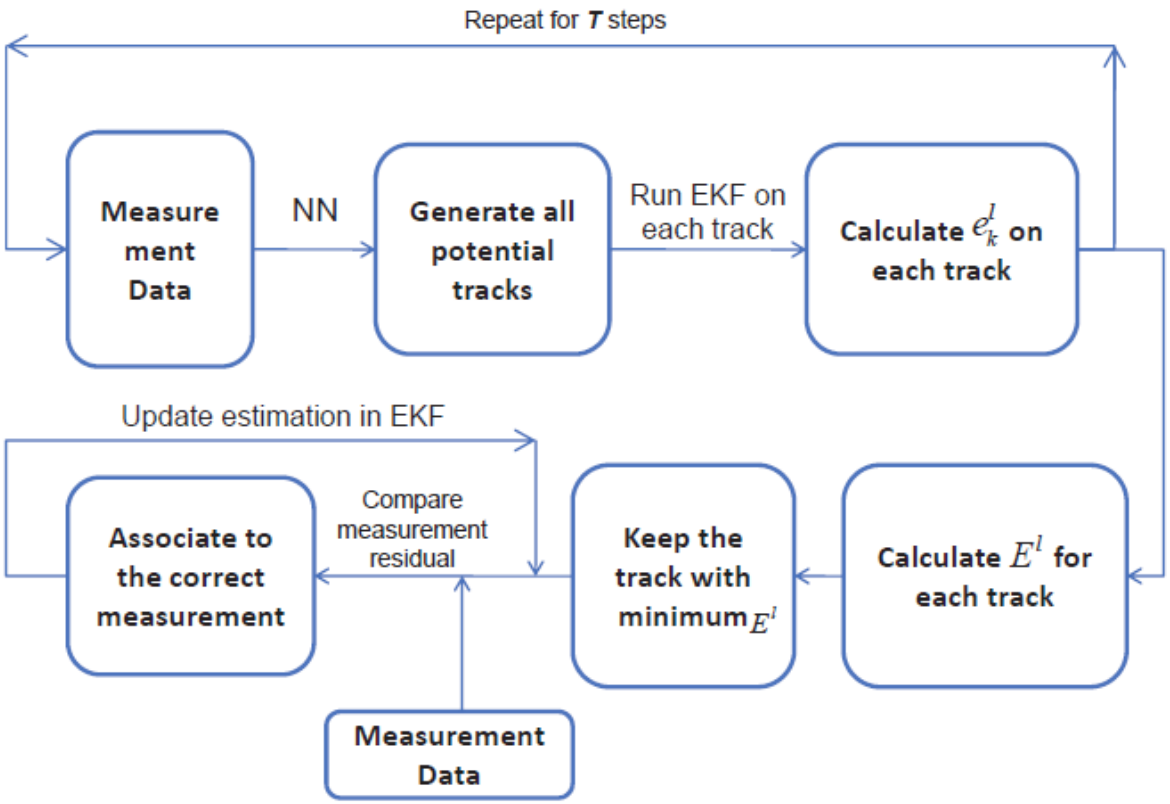
- Generation of all potential tracks:
  - Nearest neighbor algorithm $Correlation(Z_k, Z_{k-1}) = \|Z_k - Z_{k-1}\|$
- Identification of the robot's own track:
  - Use a robot's control input as a unique information
  - For each potential track calculate average measurement residual

$$E^l = \frac{1}{T - T_0} \sum_{k=T_0}^{T} e_k^l$$

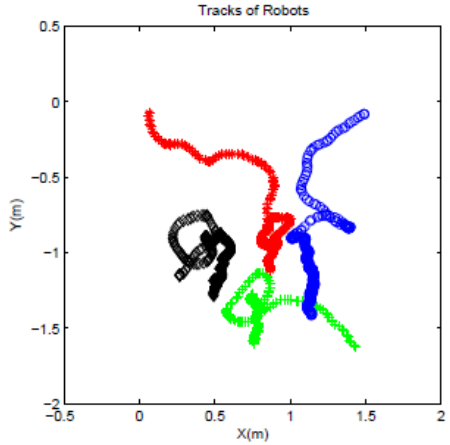
$$e_k^l = \| \mathbf{Z}_k^l - \mathbf{H}\hat{\mathbf{X}}_{k|k-1}^l \|$$

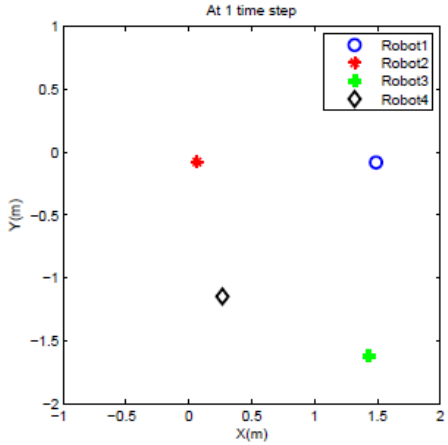
- Data association and state estimation:
  - Once track is identified, state estimation error converges
  - Data association for future measurements can be carried out in stepwise fashion.

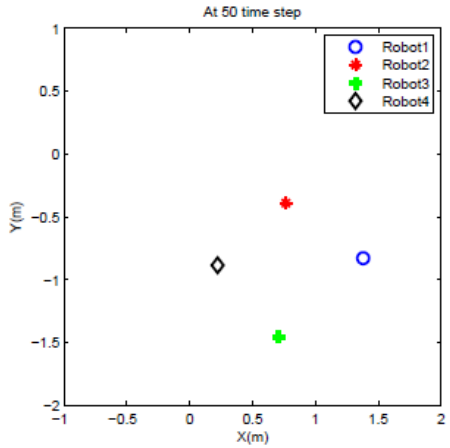
Proposed Approach

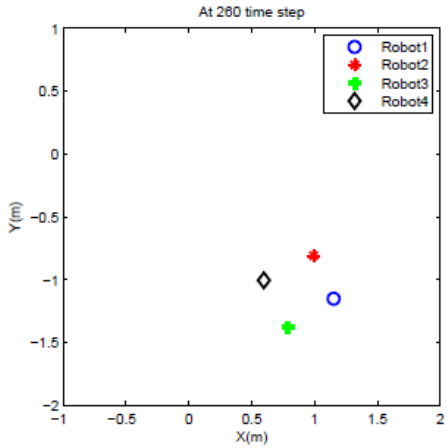


Experimental Results

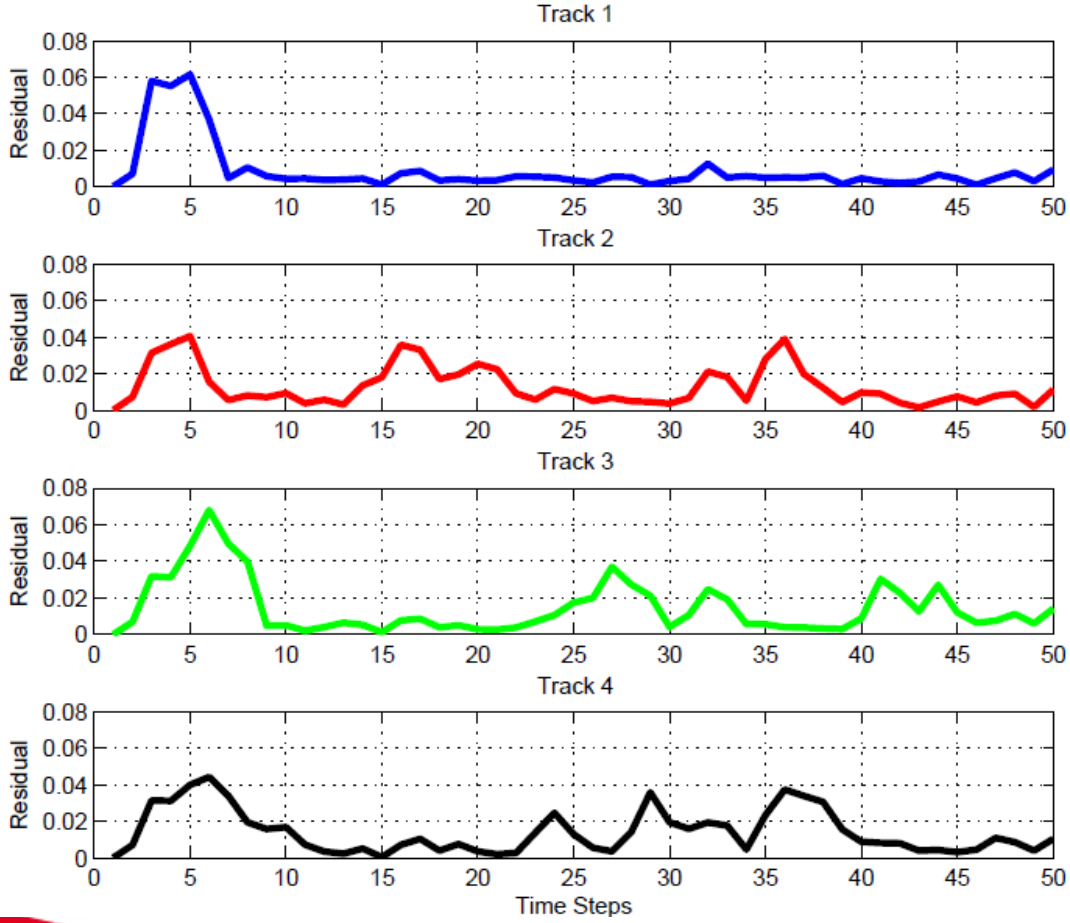








Results: Measurement Residuals



Robot 1

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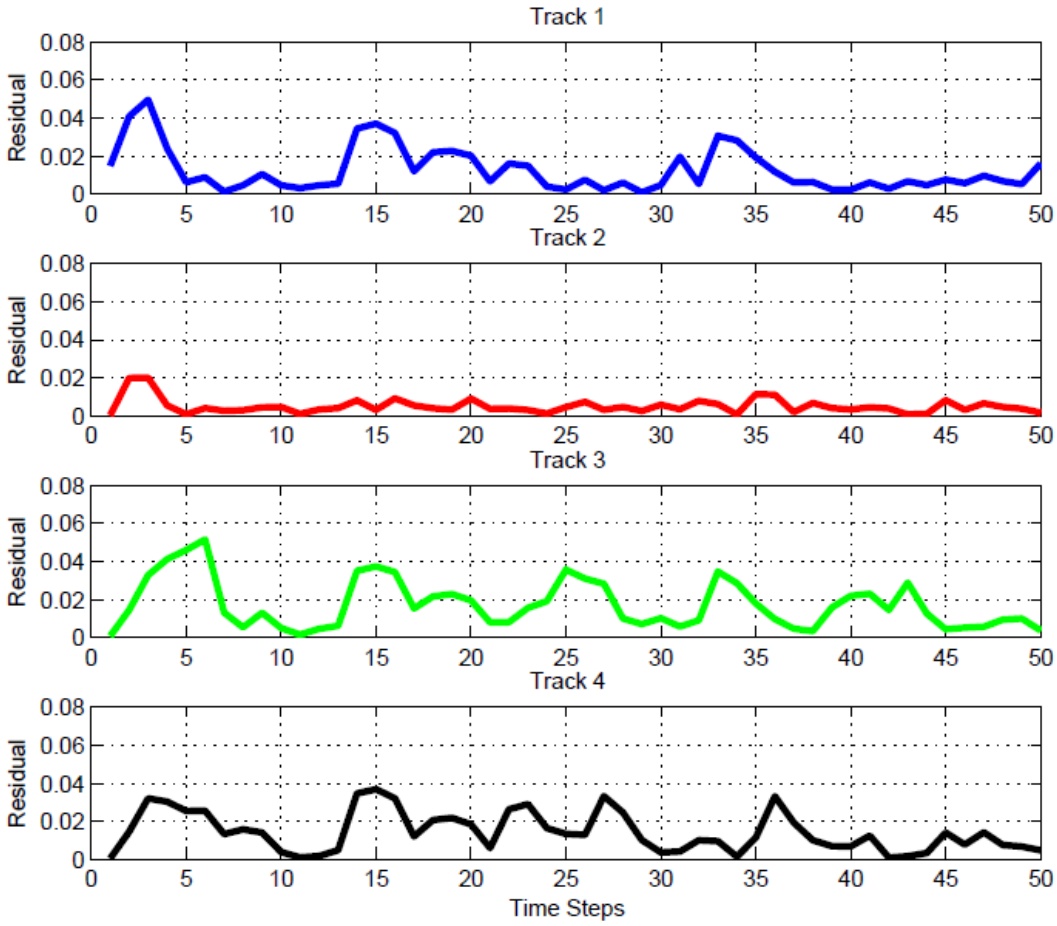
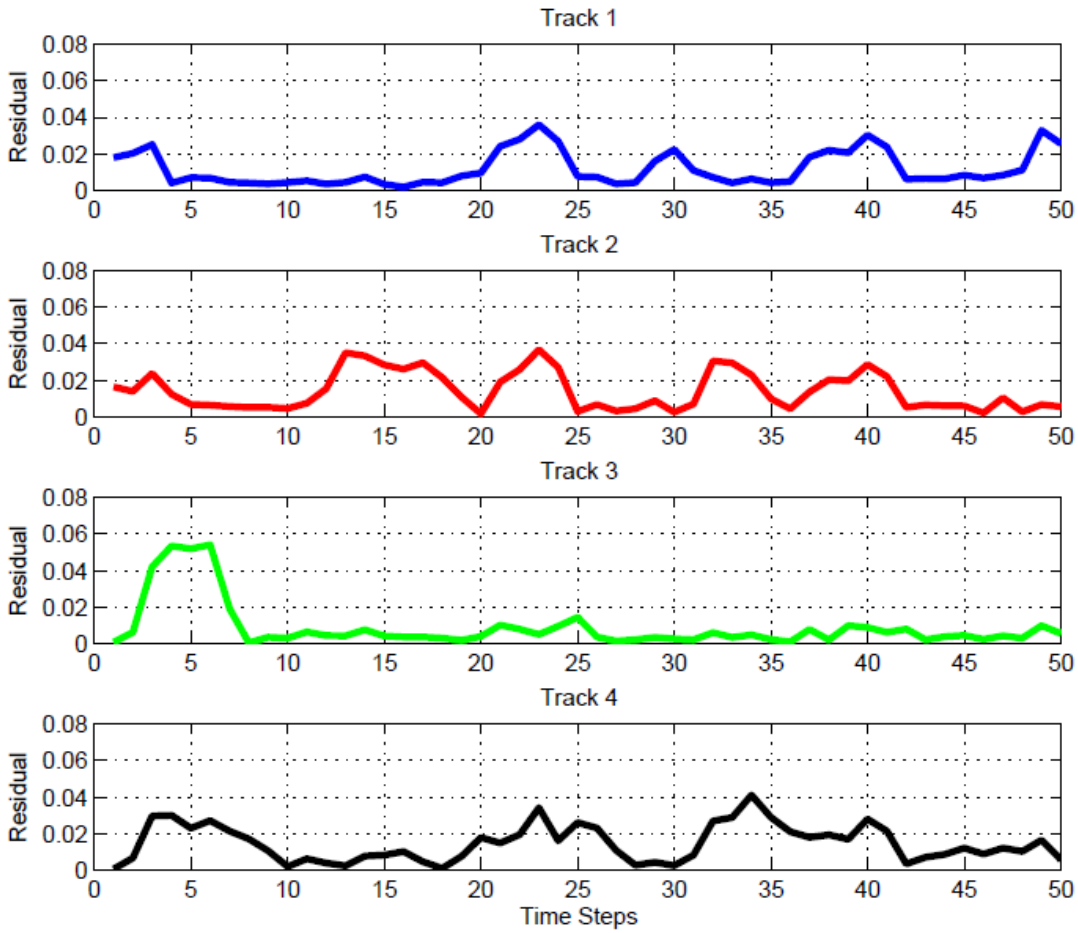
Results: Measurement Residuals



Robot 2

Results: Measurement Residuals



Robot 3

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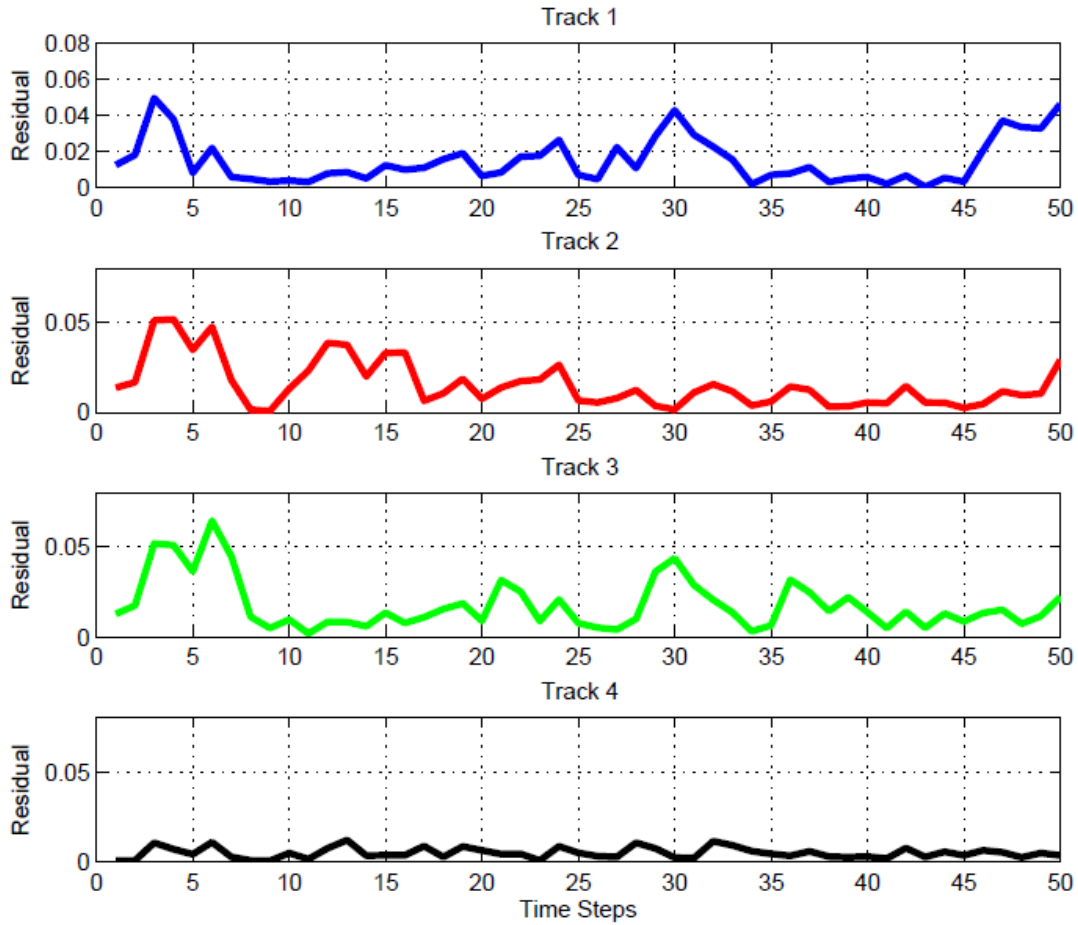
Results: Measurement Residuals



Robot 4

Summary

- Implemented self-localization technique for multi-robot experimental testbeds based on data fusion
- The technique fuses control signals with measurements to obtain a metric called measurement residual for identification
- Eliminates traditional use of patterns to carry out self-locations