Self Localization in Multi-Robotic Experimental Platforms

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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

Source: http://www.ablesw.com/3d-doctor/regist.html
Source: www.cs.ucla.edu/~jessicaf/
Source: http://www.wes-tech.com/manuf1.jpg
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.plansys.com](http://www.plansys.com)
Issues and Challenges

- Sensor Uncertainty: Noise, Ambiguity, Spuriousness
- Data Association
- Sensor Selection: Optimization of Resources
- Complexity and Synergism: Numerous Sources
Sensor Fusion Algorithms

Methods for Multi-Sensor Data Fusion

Model Based
- Mathematical Models
  - Physical Models
    - Statistical and Probabilistic
      - Artificial Intelligence
        - Fuzzy Logic
        - Neural Networks
        - Expert Systems
  - Bayesian Technique
  - Dempster-Shafer Technique
  - Kalman Filter
  - Robust Fusion

Non-Model Based

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 \((x, y, \theta)\)
  – 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
## Localization Methods

<table>
<thead>
<tr>
<th></th>
<th>Pattern</th>
<th>Non-Pattern</th>
</tr>
</thead>
<tbody>
<tr>
<td>Position (x, y):</td>
<td>Direct measurement</td>
<td>Direct measurement</td>
</tr>
<tr>
<td></td>
<td>(Pattern recognition)</td>
<td>(Blob extraction)</td>
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<tr>
<td>Bearing (θ):</td>
<td>Direct measurement</td>
<td>Estimation</td>
</tr>
<tr>
<td></td>
<td>(Pattern recognition)</td>
<td>(Kalman filter)</td>
</tr>
<tr>
<td>ID:</td>
<td>Direct measurement</td>
<td>Data Association</td>
</tr>
<tr>
<td></td>
<td>(Pattern recognition)</td>
<td>(in distributed manner)</td>
</tr>
<tr>
<td>Computation mode:</td>
<td>Centralized</td>
<td>Decentralized</td>
</tr>
</tbody>
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Self-localization in Single Robot Scenario

State of the robot:

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

Dynamics Equation:

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

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

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

Observation equation:

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

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

$$U_k = \begin{bmatrix} v_k \\ \omega_k \end{bmatrix}$$
Extended Kalman Filter for the Estimation

Prediction Equations:

\[ \dot{X}_{k|k-1} = F \hat{X}_{k-1|k-1} + B_{k-1} U_k \]
\[ P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + Q \]

where \( Z_k - H \dot{X}_{k|k-1} \) is called measurement residual, \( A_k \) is Jacobian matrix of partial derivative of \( f \) with respect to \( X \)

Update Equations:

\[ K_k = P_{k|k-1} H^T (HP_{k|k-1}H^T + R)^{-1} \]
\[ \dot{X}_{k|k} = \dot{X}_{k|k-1} + K_k (Z_k - H \dot{X}_{k|k-1}) \]
\[ P_{k|k} = (I - K_k H) P_{k|k-1} \]
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

\[ \text{Correlation}(Z_k, Z_{k-1}) = \| Z_k - Z_{k-1} \| \]

• 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

\[ E^i = \frac{1}{T - T_0} \sum_{k=T_0}^{T} e^i_k \]

\[ e^i_k = \| Z^i_k - H\hat{X}^i_{k|k-1} \| \]

• 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
Results: Measurement Residuals

Robot 2
Results: Measurement Residuals

Robot 3
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