Wireless Sensor Networks: Robust Estimation and Real-Time Control

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July 20, 2007
How can we build a reliable system using unreliable components?

Wireless sensor network-based control system
- Estimation: Multi-target tracking (MTT)
- Control: Pursuit evasion game (PEG)

Our method
- System-level approach
- Multiple layers of data fusion
- Robust and efficient algorithms

First demonstration of MTT using WSN
Wireless Sensor Networks (WSN)

Sensor Node (a.k.a. Mote):

Ad-hoc Wireless Network:
WSN: Applications

- Environment / Structure Monitoring
- Event / Fault Detection
- Home / Office Automation
- Healthcare
- Industrial Automation
Reality Check

Forecast: $8B WSN market in 2007

Source: InStat/MDR 11/2003 (Wireless); Wireless Data Research Group 2003; InStat/MDR 7/2004 (Handsets)
Motivation: Cost reduction

- More than 85% reduction in cost compared to wired systems (case study by Emerson)
- SCADA (Supervisory Control And Data Acquisition)

Killer application (?)

A typical industrial facility:
- 40+ years old
- $10B infrastructure
Industrial Automation (2)

- Reliability is the number one issue
  - Robust estimation
  - Real-time control
- Robust estimation
  - Estimation of parameters of interest from noisy measurements with high fidelity in the presence of unreliable communication
- Real-time control
  - Necessary for mission-critical systems
Outline

- Wireless sensor networks (WSN)
- Motivating application
  - Demonstration from the final experiment of the DARPA funded NEST (Network Embedded Systems Technology) project
- Real-time hierarchical control system
- Bayesian framework for multi-target tracking problems
- Markov chain Monte Carlo data association (MCMCDA)
- Current and future work
NEST Final Experiment:
557 nodes network deployed (Summer 2005)
Goal

- Track an unknown number of human targets
- Dispatch pursuers to capture them

First demonstration of MTT using WSN!
Closing the Loop in Sensor Networks: Multi-Target Tracking and Pursuit Evasion Games

NEST Final Experiment
August 30, 2005

EECS, UC Berkeley
Outline

- Wireless sensor networks (WSN)
- Motivating application
- **Real-time hierarchical control system**
- Bayesian framework for multi-target tracking problems
- Markov chain Monte Carlo data association (MCMCDA)
- Current and future work
Challenges

- Each sensor node is resource constrained
  - Limited processing power, storage capacity, communication bandwidth, and energy (if battery-powered)

- Measurement inconsistency
  - Noise, False alarms

- Communication unreliability
  - Transmission failure, Delay

- Can we build a system that works under
  - 90% delayed packets?
  - 50% packet loss?
LochNess*: A Real-Time Sensor Network-Based Control System

Hierarchical architecture for real-time operation

Multiple layers of data fusion for robustness and to reduce communication load

* LochNess (Large-scale “On-time” Collaborative Heterogeneous Networked Embedded SystemS).

[Oh, Schenato, Chen, Sastry, PIEEE, 2007]

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“Naive” Multi-Sensor Fusion for Binary Sensors

Idea: Compute likelihood assuming there is a single object

- Partition the sensing region into non-overlapping cells
- Compute likelihood based on measurements, detection probabilities, and false alarm probabilities
- E.g., $P(y_1, y_2 \mid x \in S_1)$, $P(y_1, y_2 \mid x \in S_3)$

$x = $ position of an object
$y_1 = $ sensor 1’s measurement
$y_2 = $ sensor 2’s measurement
Multi-Sensor Fusion for Binary Sensors

detection

likelihood

threshold

clustering
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- **Bayesian framework for multi-target tracking problems**
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Multi-Target Tracking (MTT) Problem

**Given**
- Multiple dynamics and measurement models
- Sensor and clutter (false alarms) models
- Target appearance and disappearance models
- Set of noisy unlabeled observations $Y$

**Find**
- Number of targets
- States of all targets

**Requires solutions to both**
- Data association
- State estimation
Solution space $\Omega$ is a collection of all partitions of $Y$.

Posterior $P(\omega|Y)$ can be used to estimate parameters in multi-target tracking ($\omega \in \Omega$).
Two Popular Approaches to Data Association Problem

- **MAP (maximum a posteriori):**
  - Find $\omega^* = \arg\max P(\omega|Y)$
  - Multiple hypothesis tracker (MHT) [Reid, 79; Kurien, 90]

- **MMSE (minimum mean square error):**
  - Given a function $X: \Omega \rightarrow \mathbb{R}^n$, estimate $E(X|Y)$
  - Joint probabilistic data association (JPDA) [Bar-Shalom & Fortmann, 88]

- **Complexity of either approach is NP-hard [Collins & Uhlmann, 92; Poore, 95]**
  - JPDA: #P-complete (no known deterministic approximation algorithm)
Previous Work:
Multi-Target Tracking in Sensor Networks

- Most algorithms are designed to track a single target
- Traditional – computationally intensive
  - JPDA [Bar-Shalom, Fortmann 1988]
  - MHT [Reid 1979; Chong, Mori, Chang 1990]
- Classification-based – multiple single-target tracking
  - Classification [Li et al., 2002; Shin et al., 2003; Liu et al., 2004; Arora et al., 2004]
- Heuristics – not robust
  - Nearest neighbor filter [Brooks et al., 2004; Liu et al., 2003]
- No general algorithm suited to sensor networks
Outline

- Wireless sensor networks (WSN)
- Motivating application
- Real-time hierarchical control system
- Bayesian framework for multi-target tracking problems
- Markov chain Monte Carlo data association (MCMCDA)
  - Special Case: Fixed number of targets
  - General Case: Unknown number of targets
- Current and future work
Optimal Bayesian Filter for MTT

Assumption: Fixed number $K$ of targets

$$X_t = (X_t^1, X_t^2, \ldots, X_t^K)$$
For each $k$

\[ P(X_{t-1}^k | y_{1:t-1}) \rightarrow P(X_t^k | y_{1:t-1}) \rightarrow P(X_t^k | y_{1:t}) \]

Prediction

Measurement Update

Example: JPDA

\[ P(X_t | y_{1:t}) \approx \prod_{k=1}^{K} P(X_t^k | y_{1:t}) \]

Measurement Validation

\[ y_t \]
$\hat{P}^k(Y_t^j | y_{1:t-1})$: measurement density for target $k$
Measurement $y_t^j$ is validated for target $k$, if and only if

$$\hat{P}^k(y_t^j | y_{1:t-1}) \geq \delta^k,$$
Feasible joint association event is a matching in $G$, i.e., a subset $M \subset E$ such that no two edges in $M$ share a vertex. Let $\Omega$ be a set of all feasible joint association events.

Posterior of $\omega \in \Omega$ given observations:

$$
\hat{P}(\omega | Y_{1:t}) = \frac{1}{Z} \lambda_f^{N-|\omega|} p_d^{\omega} (1 - p_d)^{K-|\omega|} \prod_{(u,v) \in \omega} \hat{P}^v(u | y_{1:t-1}),
$$

where $Z$ is a normalizing constant.
Measurement Update

Let $\Omega$ be a set of all feasible joint association events.

\[
\hat{P}(X^k_t|y_{1:t}) = \sum_{\omega \in \Omega} \hat{P}(X^k_t|\omega, y_{1:t}) \hat{P}(\omega|y_{1:t})
\]  

\[
= \sum_{j=0}^{N} \hat{P}(X^k_t|\omega_{jk}, y_{1:t}) \underbrace{P(\omega_{jk}|Y_{1:t})}_\text{single target tracking} \underbrace{\beta_{jk}}_\text{association probability}
\]  

where $\omega_{jk}$ denotes the event $\{\omega \in \Omega : \omega \ni (j, k)\}$, i.e., $j$-th observations in $Y_t$ is from $k$-th target.

Hence, the computation of $\hat{P}(X^k_t|y_{1:t})$ reduces to the computation of $\beta_{jk}$ (association probability), where

\[
\beta_{jk} = \hat{P}(\omega_{jk}|y_{1:t}) = \sum_{\omega: (j, k) \in \omega} \hat{P}(\omega|y_{1:t}).
\]
The exact computation of $\beta_{jk}$ (association probability) is NP-hard [Collins, Uhlmann, 1992] and there is no known deterministic approximation algorithm.
Markov Chain Monte Carlo Data Association (MCMCDA)

- Approximates association probabilities ($\beta_{jk}$)
- Based on the Markov chain Monte Carlo (MCMC) technique

Markov chain Monte Carlo (MCMC)

- A general method to generate samples from a complex distribution
- Used when we cannot sample directly from a target distribution
Markov Chain Monte Carlo (MCMC)

- Construct a Markov chain over $\Omega$
- Start with some initial state $\omega_1 \in \Omega$

Note: MCMC does not enumerate all states
Markov Chain Monte Carlo (MCMC)

- Propose a new state $\omega' \sim q(\omega_n, \omega')$
  
  $q(\omega_n, \omega')$ = probability of proposing $\omega_n$ when the chain is in $\omega'$

- Accept the proposal with probability

  $A = \min \left( 1, \frac{\pi(\omega')q(\omega', \omega_n)}{\pi(\omega_n)q(\omega_n, \omega')} \right)$  
  
  where $\pi(\omega) = P(\omega|y_{1:t})$

- If accepted,

  $$\omega_{n+1} = \omega'$$

- If not accepted,

  $$\omega_{n+1} = \omega_n$$
Repeat for $N_{mc}$ steps

By the ergodic theorem, the Markov chain converges to its stationary distribution $\pi(\omega) = P(\omega|y_{1:t})$
Propose a new state $\omega' \sim q(\omega_n, \omega')$

$q: \Omega \times 2^\Omega \rightarrow [0,1]$, proposal distribution $q(\omega_n, \omega') = \text{probability of proposing } \omega' \text{ when the chain is in } \omega_n$

$q(\omega_n, \omega')$: choose $e \in E$ uniformly at random
Theorem: Let $N$ be the number of measurements, $0 < \epsilon_1, \epsilon_2 \leq 1$, and $0 < \eta < .5$. Then, with at most

$$N_{mc} = O\left(\epsilon_1^{-2}\epsilon_2^{-1} \log \eta^{-1} N (N \log N + \log(\epsilon_1^{-1}\epsilon_2^{-1}))\right)$$

samples, MCMCDA finds estimates $\hat{\beta}_{jk}$ for $\beta_{jk}$ with probability at least $1 - \eta$, such that, for $\beta_{jk} \geq \epsilon_2$,

$$(1 - \epsilon_1) \leq \frac{\hat{\beta}_{jk}}{\beta_{jk}} \leq (1 + \epsilon_1).$$

First data association algorithm with guaranteed error bounds!
Generalized MCMCDA

(a) Observations $Y$
(b) An example of a partition $\omega$ of $Y$

Solution space $\Omega$ is a collection of all partitions of $Y$

Posterior $P(\omega|Y)$ can be used to estimate parameters in multi-target tracking ($\omega \in \Omega$)

No assumption on the number of targets
Propose a new state \( \omega' \sim q(\omega_n, \omega') \)

- \( q: \Omega \times 2^\Omega \to [0,1] \), proposal distribution \( q(\omega_n, \omega') = \text{probability of proposing } \omega' \text{ when the chain is in } \omega_n \)

- \( q(\omega_n, \omega') \) is determined by 8 moves:
Simulation: Setup

Assumptions
- Independent transmission failure model is assumed
- Independent communication delay model is assumed
Simulation Results

Robustness against Transmission Failure

- Each single-hop transmission fails with probability (transmission failure rate)
- **Tolerates up to 50% lost-to-total packet ratio**
Simulation Results

Robustness against Communication Delay

- Each single-hop transmission gets delayed with probability (communication delay rate)
- Tolerates up to 90% delayed-to-total packet ratio
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**Multi-Agent Coordination Algorithm**

**Input:**
- Pursers and evaders
  - Positions/velocities
  - Error estimates
  - Input constraints

**Goal:**
- Minimize time-to-capture of “farthest” evader

**Approach:**
- Compute expected time-to-capture for each pursuer-evader pair
- Find assignment based on time-to-capture matrix
- **Robust minimum time control (MTC)**
Summary

- How can we build a reliable system using unreliable wireless sensor networks?

- A reliable system can be built using
  - Spatio-temporal correlation
  - Sound mathematical frameworks
  - Robust and efficient algorithms
  - Carefully designed system-level architecture

- First demonstration of MTT using WSN

- First polynomial-time approximation algorithm for data association problems
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- Current and future work
Current Work

Air Traffic Control*

Networking
Control
Inference

Distributed Networked Control Systems / Swarms

* [Oh, Hwang, and Sastry, Journal of Guidance, Control, and Dynamics (to appear)]
Current Work

Heterogeneous Sensor Networks

Networking

Control

Inference

Low-bandwidth, high-bandwidth, & mobile sensors
Vision

- Wireless sensing and control networks will be everywhere
  - Killer applications: Industrial automation, healthcare
  - Strong drive by semiconductor manufacturers
  - HW/SW technology for WSN is getting matured

- WSN will enable
  - Pervasive / ubiquitous computing
  - The Internet of things

- What will happen once they are everywhere?
## Back-of-the-Envelope Calculation

<table>
<thead>
<tr>
<th><strong>WSN</strong></th>
<th><strong>Internet</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td>10 active motes / sec / km²</td>
<td>(7 million new pages per day)</td>
</tr>
<tr>
<td>x 1 packet / active mote</td>
<td>80 pages / sec</td>
</tr>
<tr>
<td>x 1 byte (data) / packet</td>
<td>x 1000 words / page</td>
</tr>
<tr>
<td>x $7.5 \times 10^6$ km² (Assuming only 5% of land equipped with WSN; Earth’s land = $150\times10^6$ km²)</td>
<td>x 7 characters / words</td>
</tr>
<tr>
<td>= 75 Mbytes / sec</td>
<td>x 2 bytes / character</td>
</tr>
<tr>
<td></td>
<td>= 1 Mbytes / sec</td>
</tr>
</tbody>
</table>

**It requires about 75 Googles to handle WSN data !!!**

- Inference, control, and networking will be the most challenging problems
Open Problems

1. Inference and networking
2. Complexity
   - Time
   - Space
   - Communication cost
3. Control and networking
   - Communication, Topology
4. Statistical learning
   - Computation, Sensor fusion
5. Security and privacy