Control of sensor with unknown clutter and detection profile using Multi-Bernoulli filter

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Introduction

Object estimation and Random Finite Sets

Cardinality Balanced-MeMBer filter

Sensor control

Simulation Results
Introduction

Problem Statement

- Sensor/Sensors
- Unknown number of moving objects
- One-step ahead sensor control
- Goal: Receiving the best measurements
Introduction
Problem Statement

Sensor control problem features:

- Stochastic control process
- Control values $\rightarrow$ sensing parameters
- The goal is to maximize $\rightarrow$ measurements

Object estimation problem

Sensor control problem components:

- Object estimation
- Optimal decision making
Bayes filter

\[
\int p_{k-1}(x_{k-1} | z_{1:k-1}) f_{k|k-1}(x_k | x_{k-1}) \, dx_{k-1} = \int g_k(z_k | x_k) p_{k|k-1}(x_k | z_{1:k-1}) \, dx_k
\]

**Objective**: Jointly estimate the number & states of object
**Object estimation and Random Finite Sets**

**Random Finite Sets**

- **New approach:** Reconceptualise as a finite **set-valued** filtering problem
  - Multi-object **state & observation** represented by **finite sets**
  - Bayesian framework treats **state/observation** as **random variables**

**Example:** Bernoulli RFS, multi-Bernoulli RFS, Poisson RFS, i.i.d. cluster RFS
Adaptive CB-MeMBer filter
Bernoulli RFS

Multi-Bernoulli RFS
Union of $M$ independent Bernoulli RFSs
Completely characterized by the set of parameter pairs

$$\{(r^i, p^i)\}^M_{i=1}$$
Existence Probability $\rightarrow$ Density
Standard CB-MeMBer filter

Approximate predicted/posterior RFSs by Multi-Bernoulli RFSs

Valid for low clutter rate & high probability of detection

More useful than PHD filters in practical implementations.
Adaptive CB-MeMBer filter

Problem:
- **Clutter intensity**: unknown and non-homogeneous
- **Probability of detection profile**: unknown

Solution:
Accommodate an unknown and non-homogeneous clutter intensity as a **hybrid space**

\[
\tilde{X} = X^{(0)} \cup X^{(1)}
\]

Propagate probability of detection as an **augmented state**

\[
X^{(\Delta)} = [0,1]
\]
Adaptive CB-MeMBer filter

Prediction

... \rightarrow \{(r_{k-1}^{(i)}, p_{k-1}^{(i)})\}_{i=1}^{M_{k-1}} \text{prediction} \rightarrow \{(r_{k|k-1}^{(i)}, p_{k|k-1}^{(i)(u)}(a,x))\}_{i=1}^{M_{k|k-1}} \text{update} \rightarrow \{(r_{k}^{(i)}, p_{k}^{(i)(u)}(a,x))\}_{i=1}^{M_k} \rightarrow ...

\textbf{Union} of two multi-Bernoulli parameter sets:

- \textbf{Surviving} objects
- \textbf{Birth} objects

propagates hybrid space and augmented state according to:

- \textit{Single object transition density}
- \textit{Probability of survival}

Robust Multi-Bernoulli filtering
[B.-T. Vo et. al. 2013]
Adaptive CB-MeMBer filter

**Update**

... → \( \{(r_k^{(i)}, p_k^{(i)})\}_{i=1}^{M_{k-1}} \) **prediction** \( \{(r_k^{(i)}(u), p_k^{(i)}(a,x))\}_{i=1}^{M_{k|k-1}} \) **update** \( \{(r_k^{(i)}, p_k^{(i)}(a,x))\}_{i=1}^{M_k} \) ...

Union of two multi-Bernoulli parameter sets:

- **Legacy** (missed-detection) tracks
- **Measurement-corrected** tracks

Propagates hybrid space and augmented state according to:

- **Single object measurement likelihood**

Robust Multi-Bernoulli filtering
[B.-T. Vo et. al. 2013]
Adaptive Sensor Control
Overview

Sensor(s) states

- Information state at each time step: multi-object posterior pdf
  \[ \pi(X_k|Z_{1:k}, u_{0:k-1}) \]
- Action/control at each time step:
  \[ u_k \in U_k \]

Objective function

- Reward/Cost function associated with each action
Adaptive Sensor Control
Sensor Control-Algorithm

Initialization ➔ Prediction ➔ Update for $U_k$

- Pre-estimation
- Synthetic Measurements
- Update for $U$
- Objective function

Update According to desired Sensor position
Adaptive Sensor Control
State estimation and Objective function

State estimation methods:
- JPDAF
- PHD-based
- Standard multi-Bernoulli
- Adaptive multi-Bernoulli

Objective function:
- Rènyi divergence
  - $\pi_1^\alpha(x)$ & $\pi_0^{1-\alpha}(x)$
  - Expectation of an error over all possible updated multi-object states:

$$s_k = \arg\min_{s \in \mathcal{S}} \mathbb{E}_{X_{k-1},X_k} \left[ \mathcal{J}(X_{k-1}, s, X_k) \right]$$
Adaptive Sensor Control

Objective function

Where:

$$\mathcal{J}(s) = \eta_{|X|} \sigma^2_{|X|}(s) + \eta_x \sigma^2_x(s) + \eta_\lambda \sigma^2_\lambda(s)$$

$$\hat{\sigma}^2_{|X|}(s) = \sum_{i=1}^{M_k} \left[ r_k^{(i)(1)} \left(1 - r_k^{(i)(1)}\right) \right]$$

$$\hat{\sigma}^2_x(s) = \sum_{i=1}^{M_k} \left[ r_k^{(i)(1)} \hat{\sigma}^2_{x,i} \right] / \sum_{i=1}^{M_k} r_k^{(i)(1)}$$

$$\hat{\sigma}^2_\lambda(s) = \sum_{i=1}^{M_k} \left[ r_k^{(i)(0)} \sum_{j=1}^{L_k^{(i)(0)}} \left\{ r_{\lambda,k}^{(i,j)} \left(1 - r_{\lambda,k}^{(i,j)}\right) \right\} \right]$$

And:

$$\hat{\sigma}^2_{x,i} = \sum_{j=1}^{L_k^{(i)(1)}} \left[ w_k^{(i,j)(1)} \left(x_k^{(i,j)(1)}\right)^2 - (w_k^{(i,j)(1)} x_k^{(i,j)(1)})^2 \right] \quad , \quad \eta_{|X|} + \eta_x + \eta_\lambda = 1$$
Simulation Results
Case study

A controllable sensor
17 candidate placements

Range & Bearing measurements.
Simulation Results
Results

![Graph showing Simulation Results](image-url)
Simulation Results

Results

![Graph showing simulation results]
Simulation Results
Results

![Graph showing simulation results comparison between Adaptive MB with sensor control and MB sensor control with fixed parameters. The graph plots statistical mean of cardinality estimation over time. The red line represents the Adaptive MB with sensor control, the green dashed line represents the MB sensor control with fixed parameters, and the black line represents the true values. The graph shows the performance over time, highlighting the differences in estimation accuracy between the two control methods.](image-url)
**Conclusion**

- High accurate in cardinality estimation compare to the state of art methods
- High accurate in state estimation compare to the state of art methods
- Robustness
Thanks for your attention.
Please forward your questions
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