Multi-Sensor Multi-Scan Radar Sensing of Multiple Extended Targets

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Motivation: Tracking filter (1/2)

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$$
\begin{tikzcd}
 & & \Psi_t \arrow[d, "\text{Observation model}"'] \\
 & & f(\Psi_t \mid \tilde{\Phi}_t) \arrow[d] \\
f(\tilde{\Phi}_{t-1}) \arrow[r, "\text{Dynamical model}"] & f(\tilde{\Phi}_t \mid \tilde{\Phi}_{t-1}) \arrow[r] & f(\tilde{\Phi}_t \mid \Psi_t) \arrow[ll, bend left, "t \leftarrow t+1"]
\end{tikzcd}
$$

Figure: Typical tracking filter.

Motivation: Tracking filter (1/2)

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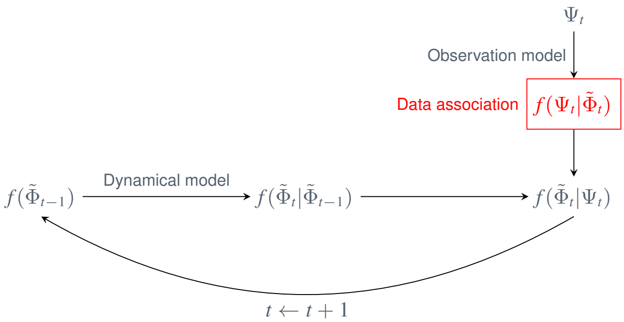

Figure: Typical tracking filter.

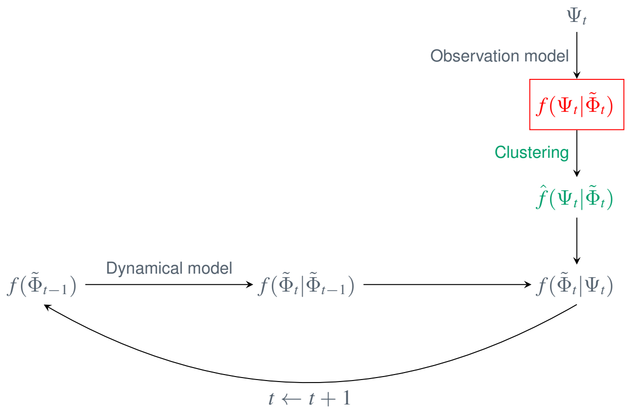

Figure: Typical filter for tracking multiple extended targets: clustering is used to only consider a subset of data association hypotheses in the likelihood.

[1] Karl Granström, Maryam Fatemi, and Lennart Svensson. *Poisson Multi-Bernoulli Mixture Conjugate Prior for Multiple Extended Target Filtering*. IEEE Trans. Aerosp. Electron. Syst., 56(1):208-225, 2020

Motivation: Clustering example (1/4)

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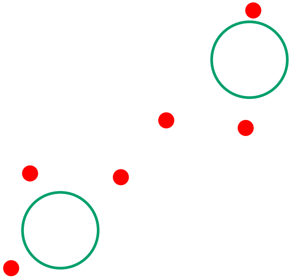

Figure: Observation.

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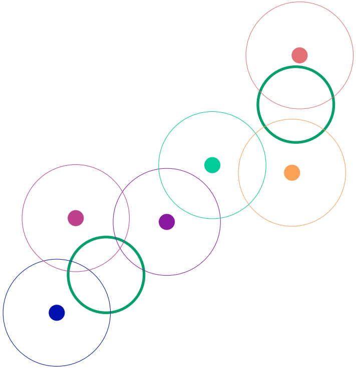

Figure: Distance based clustering: low radius.

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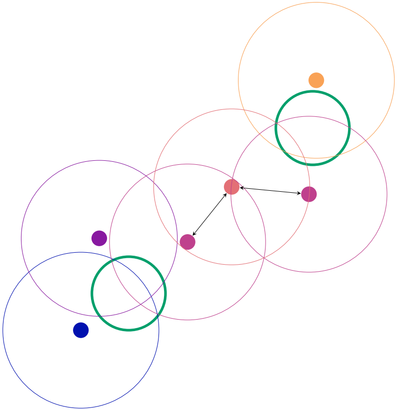

Figure: Distance based clustering: medium radius.

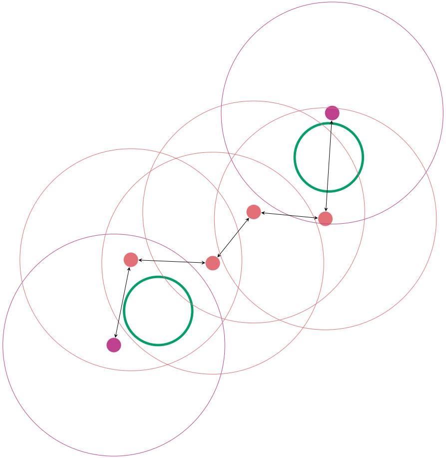

Figure: Distance based clustering: large radius.

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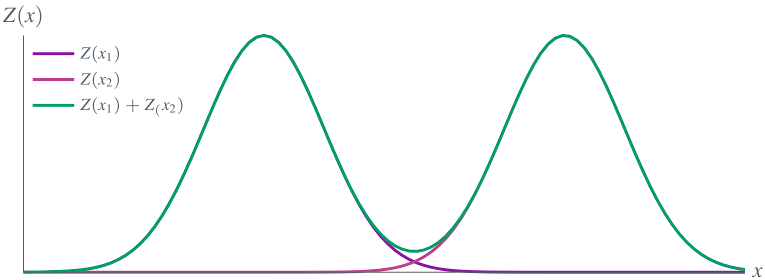

Figure: Well-separated targets.

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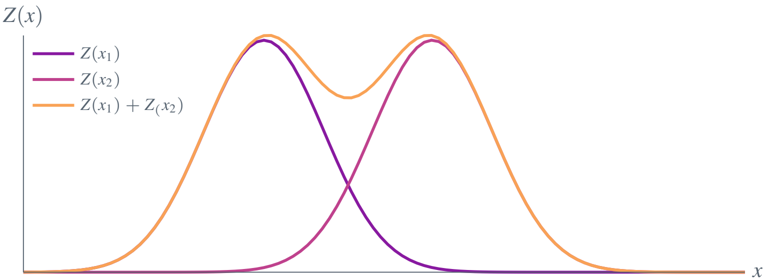

Figure: Separable targets.

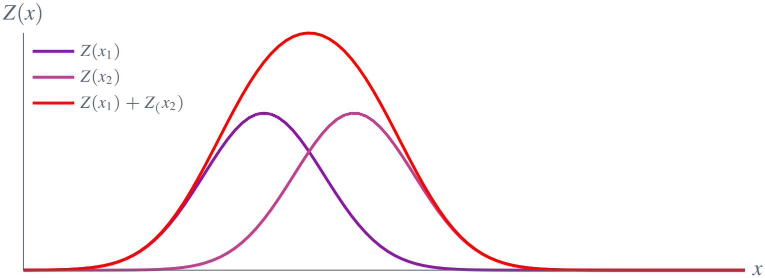

Figure: Non-separable targets.

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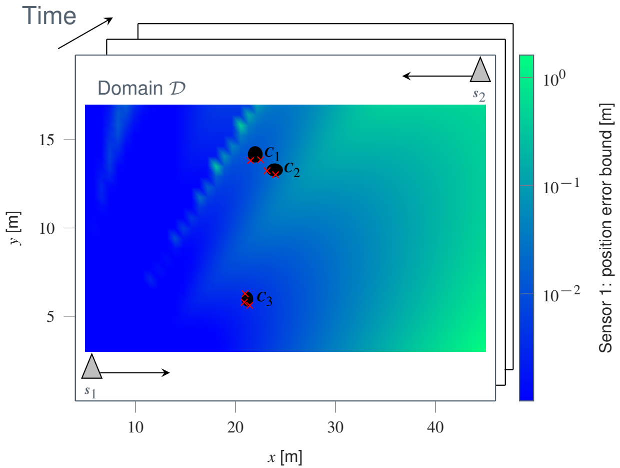

Figure: Illustration of scenario with two sensors and three extended targets.

Measurement process

- Targets: $\tilde{\Phi} = \{\boldsymbol{C}_1, \ldots, \boldsymbol{C}_L\}$ for $\boldsymbol{C}_l = (\boldsymbol{c}_l, \boldsymbol{E}_l)$.
- Measurement model: $\boldsymbol{z}_{k,i}(\boldsymbol{C}) = \boldsymbol{v}_i + \boldsymbol{\varepsilon}_{k,i}(\boldsymbol{v}_i)$, $\boldsymbol{v}_i = \boldsymbol{c} + \boldsymbol{\varepsilon}_i^{\mathrm{E}}$.
- Measurement process: $\Psi_k = \{\boldsymbol{z}_{k,i}(\boldsymbol{C}_l)\}_{l,i} \bigcup \Psi_k^{\mathrm{c}}$.
- Aggregated observations: $\Psi = \bigcup_{k=1}^{K} \Psi_k$.

Assume $\Psi_k|\tilde{\Phi}$ is Poisson with intensity

$$Z^{(k)}_{\tilde{\Phi},\lambda^c}(\boldsymbol{\xi}) = \lambda^c + \sum_{l=1}^{L} \eta_k(\boldsymbol{\xi}|\boldsymbol{C}_l) \tag{1}$$

where $\eta_k(\boldsymbol{\xi}|\boldsymbol{C}_l) = \tilde{\rho}_k(\boldsymbol{C}_l)\mathcal{K}_{\tilde{\boldsymbol{\Sigma}}_k(\boldsymbol{C}_l)}(\boldsymbol{\xi} - \boldsymbol{c}_l)$ and

$$\mathcal{K}_{\boldsymbol{\Sigma}}(\boldsymbol{\xi} - \boldsymbol{c}) = \frac{\exp\left(-\frac{1}{2}(\boldsymbol{\xi} - \boldsymbol{c})^T\boldsymbol{\Sigma}^{-1}(\boldsymbol{\xi} - \boldsymbol{c})\right)}{\sqrt{(2\pi)^d|\boldsymbol{\Sigma}|}}. \tag{2}$$

We call this a doubly inhomogeneous-generalized shot noise Cox process (DI-GSNCP).

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The model parameters are $\theta = (\tilde{\Phi}, \lambda, \lambda^c)$ and, up to a constant, the posterior is $\Pi(\theta|\Psi) = \prod_{k=1}^{K} \Pi_{\text{likelihood}}(\Psi_k|\tilde{\Phi}, \lambda^c)\Pi_{\text{prior}}(\tilde{\Phi}, \lambda, \lambda^c)$. Using the Poisson assumption, the observed likelihood is

$$\Pi_{\text{likelihood}}(\Psi_k|\tilde{\Phi}, \lambda^c) = \exp((1-\lambda^c)|\mathcal{D}| - \sum_{l=1}^{L} \tilde{\rho}_k(\boldsymbol{c}_l)) \prod_{m_k=1}^{M_k} Z^{(k)}_{\tilde{\Phi}, \lambda^c}(\boldsymbol{p}_{k,m_k}). \tag{3}$$

The prior is proportional to

$$\Pi_{\text{prior}}(\tilde{\Phi}, \lambda, \lambda^c) = \lambda^L \mathbb{1}_{\mathbb{R}_+}(\lambda)\mathbb{1}_{\mathbb{R}_+}(\lambda^c) \prod_{l=1}^{L} \Pi_E(\boldsymbol{\Sigma}_l^E) \prod_{\substack{j=1 \\ j\neq l}}^{L} \mathbb{1}_{\mathbb{R}_+}(\|\boldsymbol{c}_l - \boldsymbol{c}_j\| - R) \tag{4}$$

where $\mathbb{1}_A(x)$ is the indicator function which equals 1 if $x \in A$ and 0 otherwise, Π_E is the extent prior density, and we have assumed uniform priors on the cluster center and clutter intensities.

- Using Markov chain Monte Carlo (MCMC), a Markov chain $\theta_0, \theta_1, \dots$ is constructed as follows: given the previous configuration in the Markov chain, i.e., θ_{i-1}, a possible new configuration of model parameters is sampled as $\theta^* \sim \mathcal{Q}_{(\theta_{i-1})}(\cdot)$ from a predefined transition density. We define the acceptance probability function $\alpha(\theta_{i-1}, \theta^*) = \min\left\{1, \frac{\Pi(\theta^* \,|\, \Psi)}{\Pi(\theta_{i-1} \,|\, \Psi)}\right\}$ and sample $U \sim \text{Unif}(0, 1)$. If $U < \alpha(\theta_{i-1}, \theta^*)$ set $\theta_i = \theta^*$, otherwise let $\theta_i = \theta_{i-1}$.

- In this work, the parameters in θ are updated sequentially. Firstly, the driving process $\tilde{\Phi}$ is updated followed by an update of λ and λ^c. We define the transition density for updating the driving process as a birth-death-move proposal: with probability p_m a move is taken, with probability $(1 - p_m)p_b(\theta_{i-1})$ a birth is proposed, and with probability $(1 - p_m)(1 - p_b(\theta_{i-1}))$ a death is proposed.

- We define a scenario with two sensors scanning over 6 time epochs. The spatial domain is $\mathcal{D} = [0, 50] \times [0, 20] \times [0, 10]\ m^3$ and we assume extent prior as $e_{l,1}, e_{l,2}, e_{l,3} \sim$ Unif$(1, 1.5)$ and $e_{l,4}, e_{l,5}, e_{l,6} \sim$ Unif$(-0.5, 0.5)$. Moreover, we let $R = 8\ m$, $\lambda = \frac{20}{|\mathcal{D}|}$, and $\lambda^c = \frac{35}{|\mathcal{D}|}$.
- Baselines: Oracle and DBSCAN.
- Performance metric: Optimal sub-pattern assignment (OSPA) metric with pair-wise metric defined by the Gaussian Wasserstein distance.

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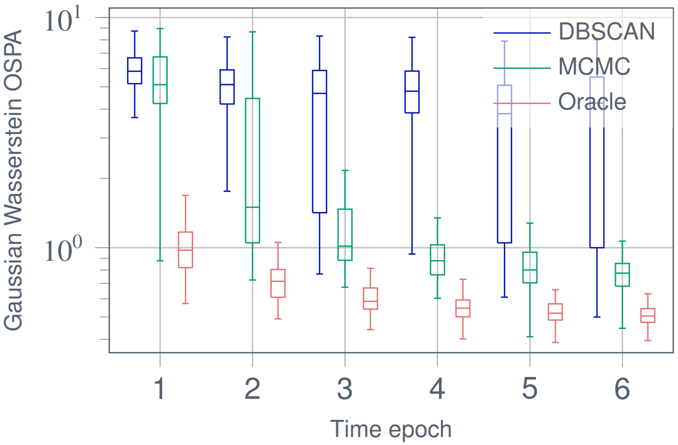
Sensing accuracy



- A methodology for target state estimation in multi-sensor multi-scan multiple extended target sensing scenarios is developed. The method is based on parametrizing the target states through a DI-GSNCP taking spatial properties of multiple sensors into account and using a model jump MCMC algorithm to estimate the parameters.
- The method scales only **linearly** in the number of measurements, effectively estimating the target states without requiring data association.
- Numerical experiments demonstrate the benefits over spatial proximity based clustering in **high clutter** scenarios with **closely spaced targets**.
- In future work, we aim to generalize the method to: (i) non-linear measurement models, (ii) moving targets, (iii) inter-cluster interactions.

Thank you for listening!

Questions?