

Message Passing for Sensor Fusion

Multi-Target Tracking, Multi-Modal Sensors and the Registration Problem

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Outline

- Introduction
- Problem Definition
- UDRC Phase 2 Work
- Vector-type vs. Set-type MTT
- Message Passing for Tracking
- Factor Graphs & Sum-Product Algorithm
- Graph Stretching
- Implementation
- Results
- Future Work

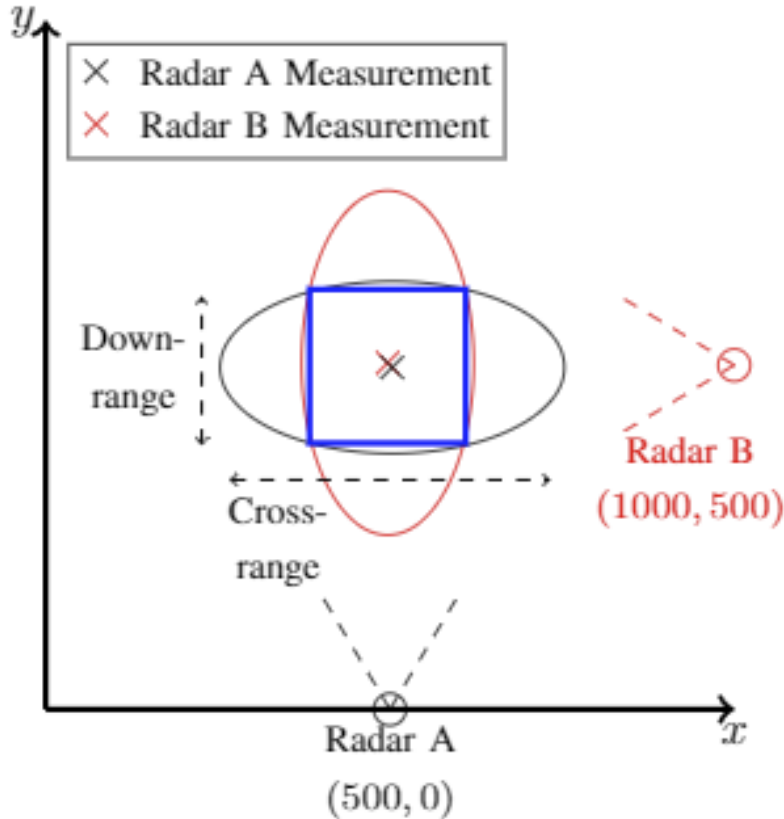
Introduction

- Sensor platforms becoming more complex with multi-modal sensor suites available to operators.
- Multi-modal multi-sensor Fusion incorporates contextual information, improves tracking accuracy, and potentially increases tracking update rate.
- Many systems developed with commercial-off-the-shelf (COTS) sensors and not specifically designed for fusion purposes: they have different
 - coordinate space representations;
 - frames of reference;
 - sampling and communication protocols;
 - ...

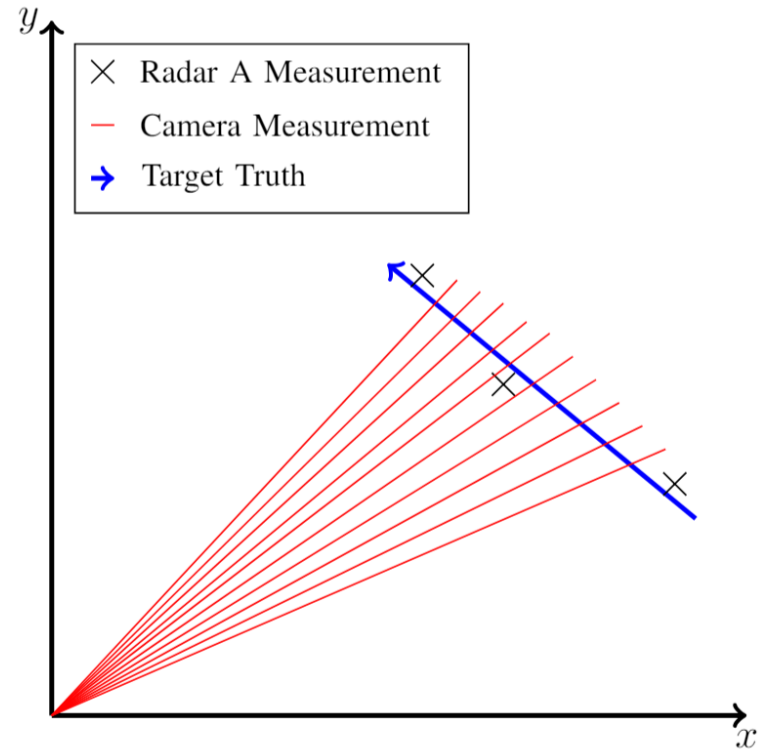
Introduction

- Projecting information to a common reference frame correctly is very important:
 - Do my measurements all correlate?
 - How many targets do I see?
- Sensor bias and errors can put a lot of extra burden on operators, especially in complex scenarios.

Problem Definition

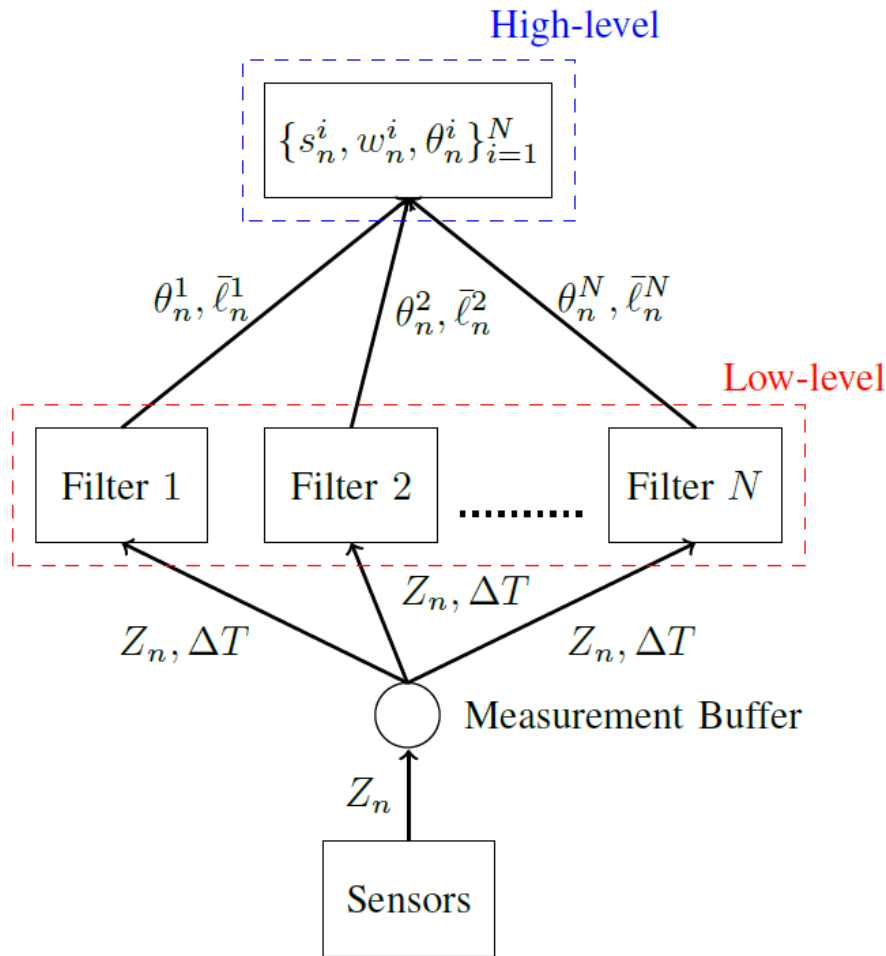


Cross-range
uncertainty reduction



Spatio-temporal
uncertainty reduction

UDRC Phase 2 Work: RFS Based Approaches



Types of MTT

Vector-type MTT	Set-type MTT
Multiple Hypothesis Tracking (MHT)	Probability Hypothesis Density Filter (PHD)
Joint Probabilistic Data Association (JPDA)	Cardinalized Probability Hypothesis Density Filter (CPHD)
Joint Integrated Probabilistic Data Association (JIPDA)	Generalized Labelled Multi-Bernoulli Filter (GLMB)
Belief Propagation (BP)	Belief Propagation (BP)

- State/measurement representations
- Data association
- Track management
- Computational efficiency/trade-offs

Data Association

	Target	1	2	3	4
Meas.					
1			X		
2					X
3				X	
4		X			

- Classical approaches – Munkres, Auction,...
- Newer MP approach - SPADA

Message Passing Introduction

- Many of previously shown MTT methods have high complexity.
- Lower complexity can be achieved by using message passing (Belief Propagation, sum-product algorithm (SPA)).
- SPA provides a principled approximation of Bayesian inference.
- Flexibility between performance and efficiency.
- Can be directly applied to non-linear, non-Gaussian scenarios.

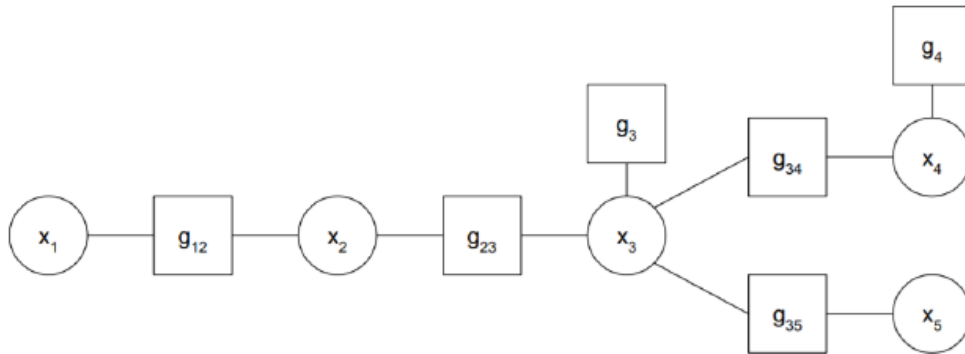
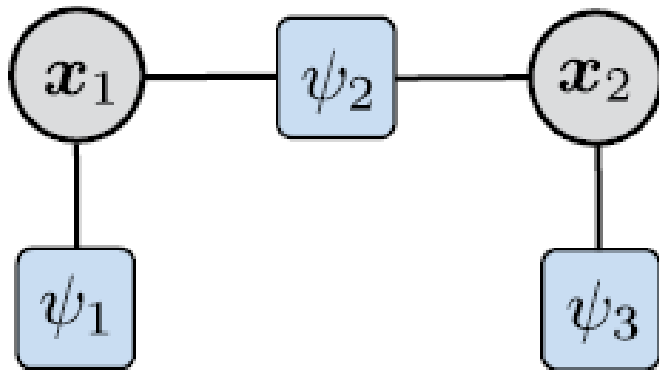
Message Passing Intro

- Further advantages
 - Inclusion of SPADA resolves data association efficiently
 - Generalises previous methods such as JPDA
 - Scalable to scenarios with large numbers of targets and sensors
- Follows all of the traditional assumptions used in MTT
 - At most, one measurement is associated to one target
 - Poisson clutter model
 - Measurements independent across time
 - ...

Relation to JPDA/JIPDA

- Classical approaches to MTT propagate a marginal pdf separately for each target (joint pdf approximated by product of these marginals).
- JPDA – fixed, known number of targets
- JIPDA – time-varying, unknown number of targets
- Scales exponentially in scenarios with closely-spaced targets, overcome with SPADA.
- Message passing methods include binary indicators for each target, based on probability of existence.

Factor Graphs & SPA



Joint pdf representation

$$f(\mathbf{x}|\mathbf{z}) \propto \prod_l \psi_l(\mathbf{x}^{(l)}).$$

Message Passing operations

$$\zeta_{\psi_l \rightarrow x_i}(\mathbf{x}_i) = \int \psi_l(\mathbf{x}^{(l)}) \prod_{i' \in \mathcal{V}_l \setminus \{i\}} \eta_{x_{i'} \rightarrow \psi_l}(\mathbf{x}_{i'}) d\mathbf{x}_{\sim i}.$$

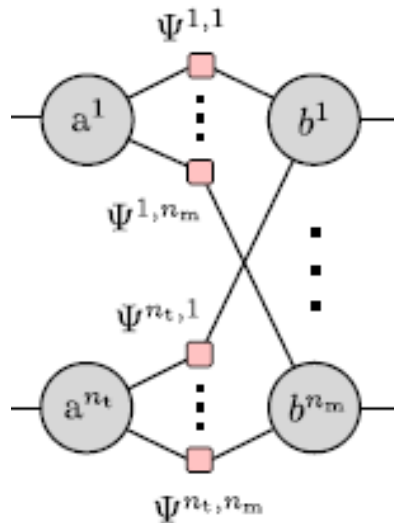
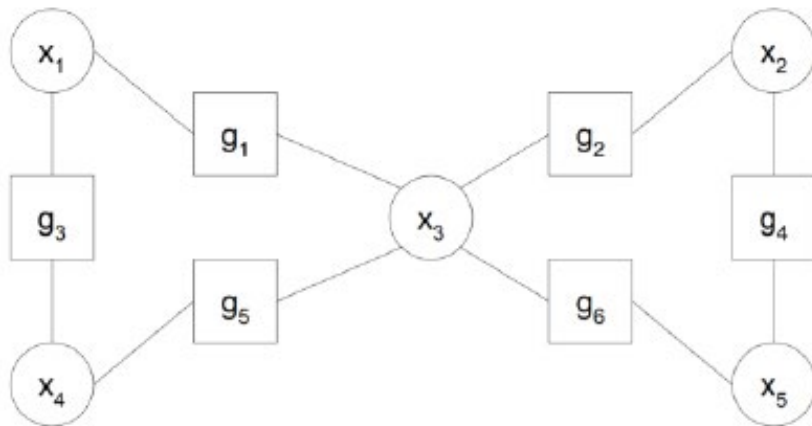
$$\eta_{x_i \rightarrow \psi_l}(\mathbf{x}_i) = \prod_{l' \in \mathcal{F}_i \setminus \{l\}} \zeta_{\psi_{l'} \rightarrow x_i}(\mathbf{x}_i).$$

Belief computation

$$\tilde{f}(\mathbf{x}_i) = C_i \prod_{l \in \mathcal{F}_i} \zeta_{\psi_l \rightarrow x_i}(\mathbf{x}_i)$$

[1] F. Kschischang, B. Frey and H.-A. Loeliger, "Factor graphs and the sum-product algorithm", IEEE Transactions on Information Theory, vol.47, no.2, pp. 498-519, 2001

Factor Graphs & SPA



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Factor Graph Stretching

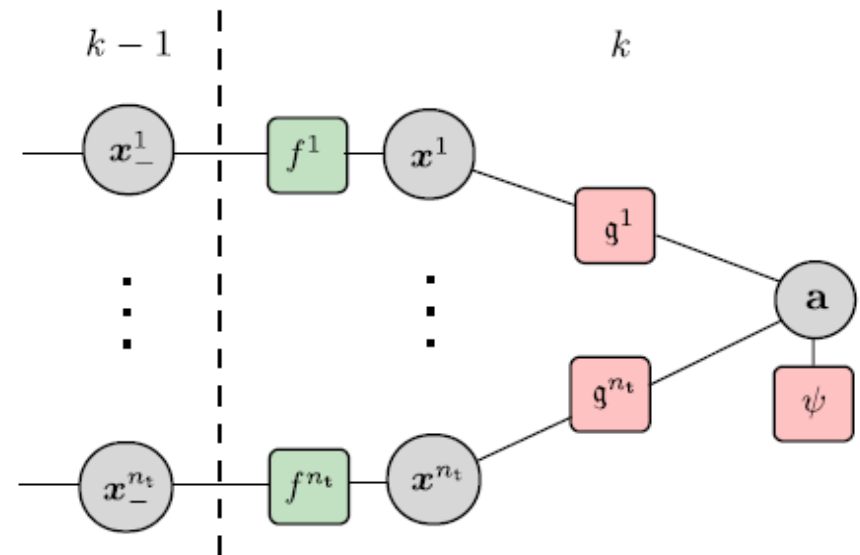
- Stretching (opening) is useful tool for adjusting factor graphs
- Introduces more (latent, random) variables into the graph
- New variables depend deterministically on variables already in the graph
- Certain factor nodes are then stretched into a larger number of factor nodes
- Variable nodes connected to new factor nodes will likely have lower dimensionality
- Messages being passed also likely to be lower dimensional

Factor Graph Stretching

- Typical prediction and update scales exponentially with the number of targets
- Firstly introduce the association vector \mathbf{a} giving new factorisation

$$f(\mathbf{x}_{1:k}, \mathbf{a}_{1:k} | \mathbf{z}_{1:k}) \propto \prod_{k'=1}^k \left(\prod_{i=1}^{n_t} f(\mathbf{x}_{k'}^{(i)} | \mathbf{x}_{k'-1}^{(i)}) \right) \prod_{s=1}^{n_s} \psi(\mathbf{a}_{k',s})$$

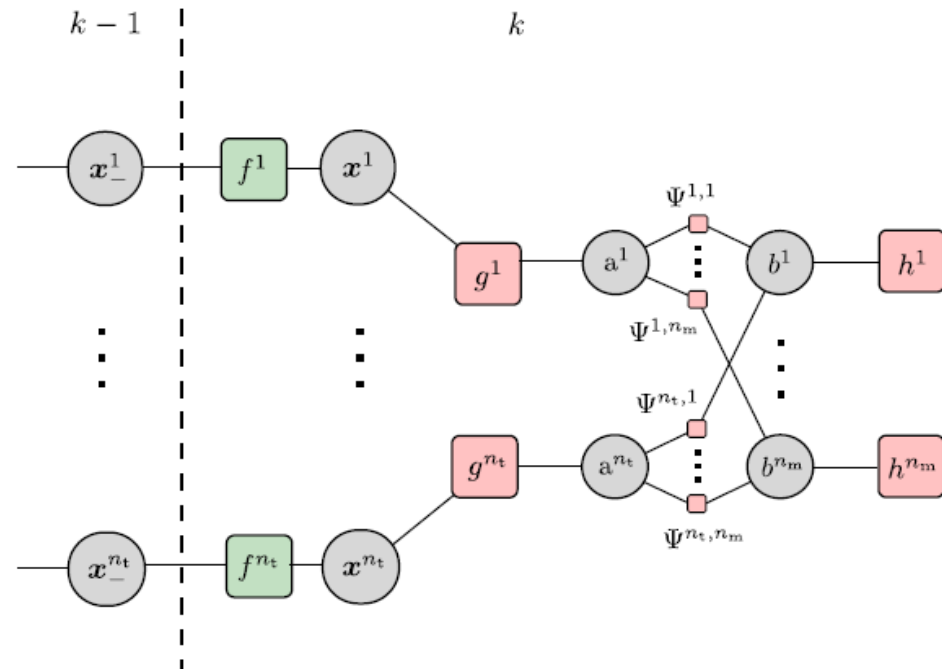
$$\times \prod_{i=1}^{n_t} \mathfrak{g}(\mathbf{x}_{k'}^{(i)}, \mathbf{a}_{k',s}^{(i)}; \mathbf{z}_{k',s})$$



Factor Graph Stretching

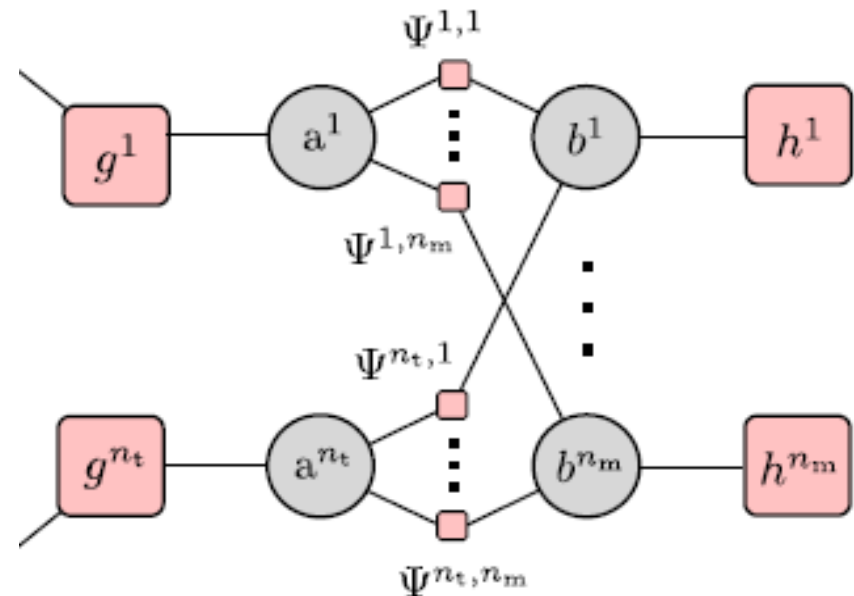
- Now introduce the association vector \mathbf{b} which carries the same information as \mathbf{a} but in a different form

$$\begin{aligned}
 & f(\mathbf{x}_{1:k}, \mathbf{a}_{1:k}, \mathbf{b}_{1:k} \mid \mathbf{z}_{1:k}) \\
 & \propto \prod_{k'=1}^k \left(\prod_{i'=1}^{n_t} f(\mathbf{x}_{k'}^{(i')} \mid \mathbf{x}_{k'-1}^{(i')}) \right) \prod_{s=1}^{n_s} \left(\prod_{i=1}^{n_t} g(\mathbf{x}_{k',s}^{(i)}, \mathbf{a}_{k',s}^{(i)}; \mathbf{z}_{k',s}) \right) \\
 & \times \prod_{m'=1}^{m_{k',s}} \Psi_{i,m'}(\mathbf{a}_{k',s}^{(i)}, \mathbf{b}_{k',s}^{(m')}) \prod_{m=1}^{m_{k',s}} h(\mathbf{b}_{k',s}^{(m)}; \mathbf{z}_{k',s}^{(m)})
 \end{aligned}$$



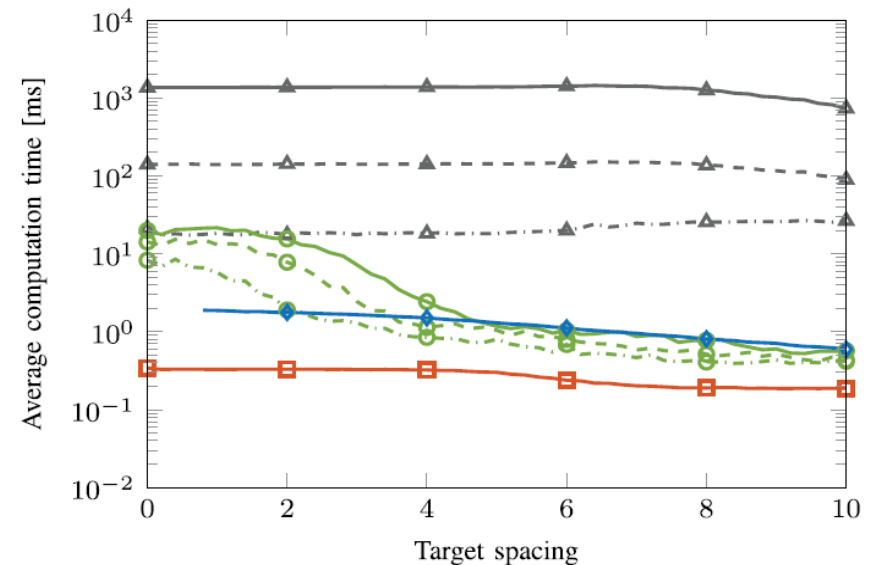
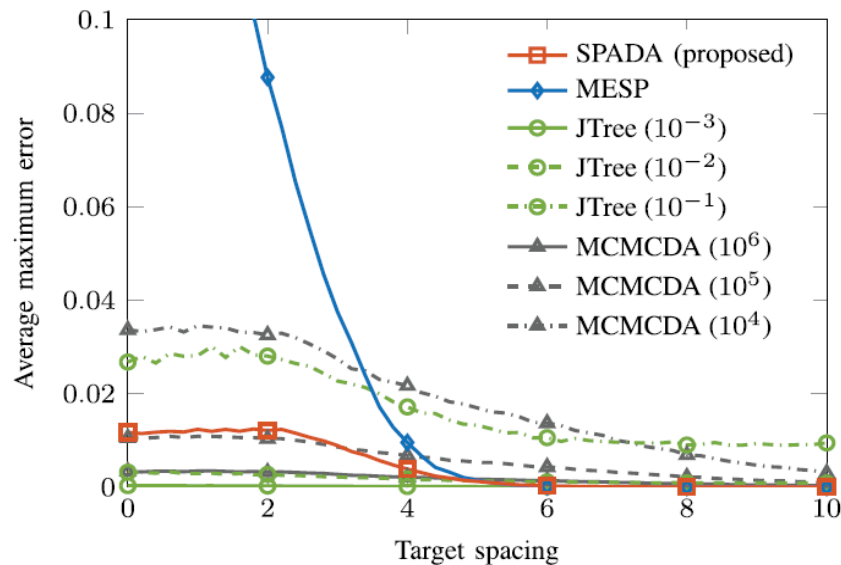
Factor Graph Stretching

- Loopy SPA applied to calculate **approximations** of the marginals
- Messages only passed forward in time
- Arrive at **SPADA** function
- Solves convex optimisation problem – converges to global optimum
- Number of iterations required to meet convergence criterion is bounded



Factor Graph Stretching

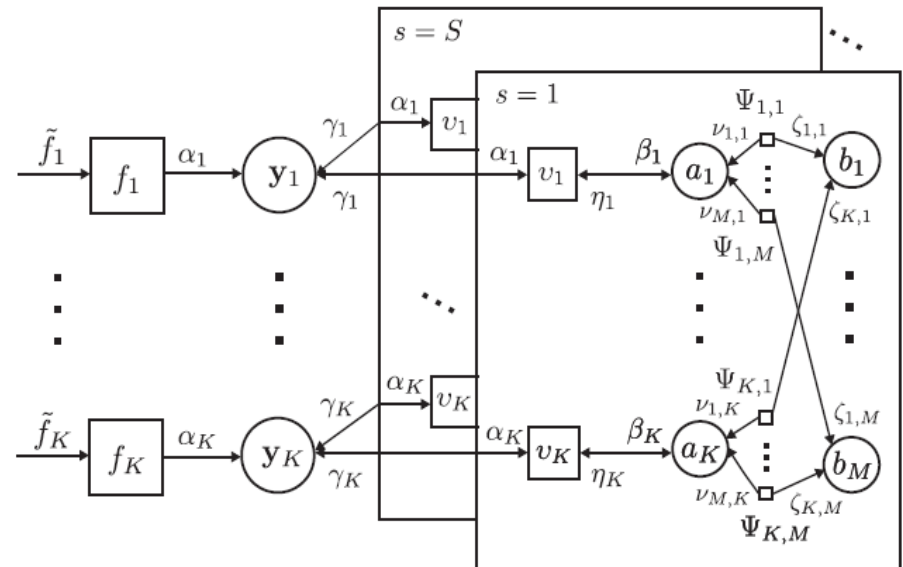
- Sum-Product Algorithm for Data Association (SPADA) proven to be orders of magnitude faster than Junction Tree and MCMC-DA.
- Accuracy comparable to MCMC-DA with 10^5 steps.



[1] J. Williams and R. Lau, "Approximate evaluation of marginal association probabilities with belief propagation", IEEE Transactions on Aerospace and Electronic Systems, vol. 50, no. 4, pp. 2942 – 2959, 2014.

Particle BP Implementation

- Particle BP to allow for non-linear, non-Gaussian models
- Multi-sensor tracking built into formulation
- Each target represented by N particles with existence indicator

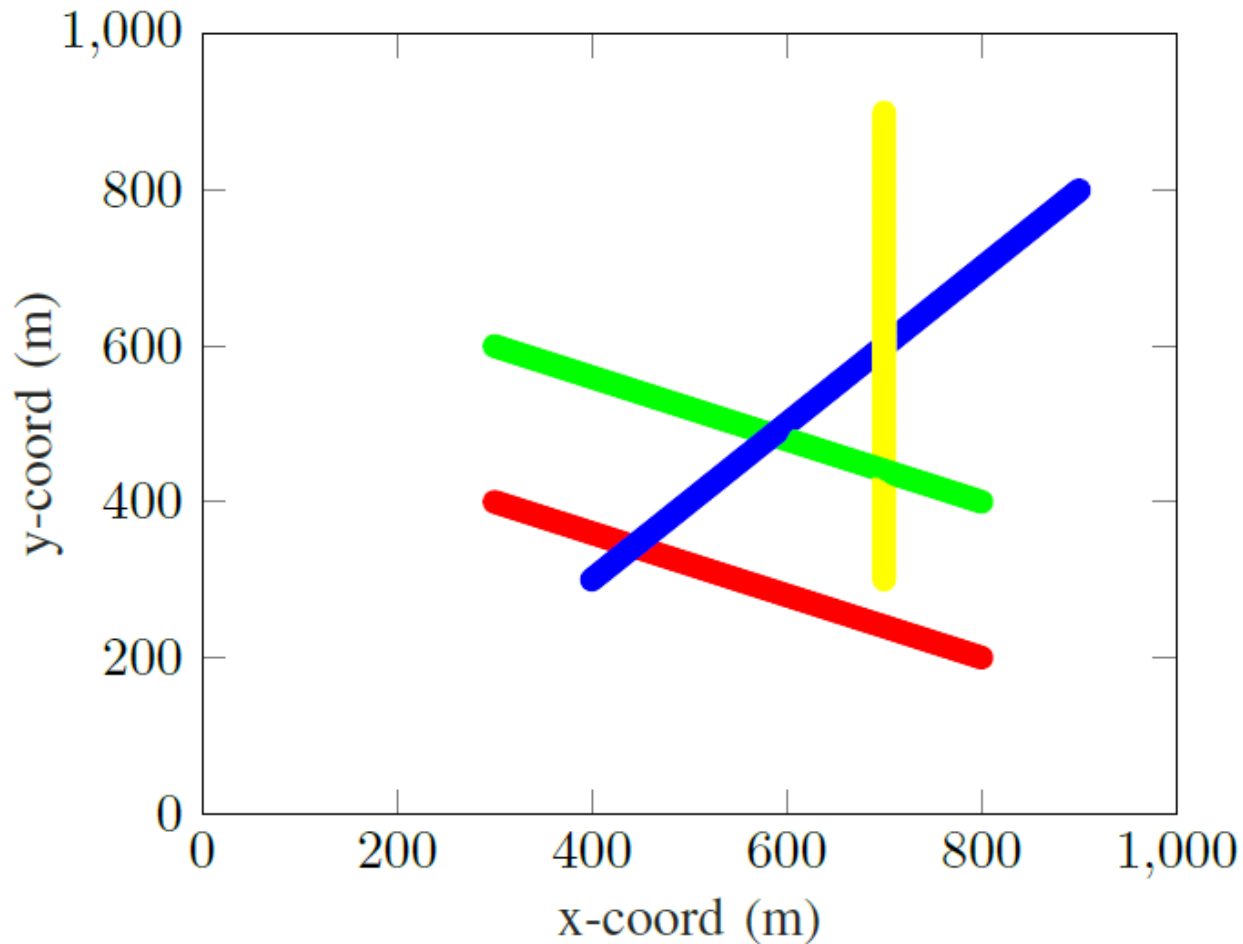


[1] F. Meyer, P. Braca, P. Willett and F. Hlawatsch, "A Scalable Algorithm for Tracking an Unknown Number of Targets Using Multiple Sensors", IEEE Transactions on Signal Processing, vol. 65, no.13, pp. 3478 – 3493, 2017

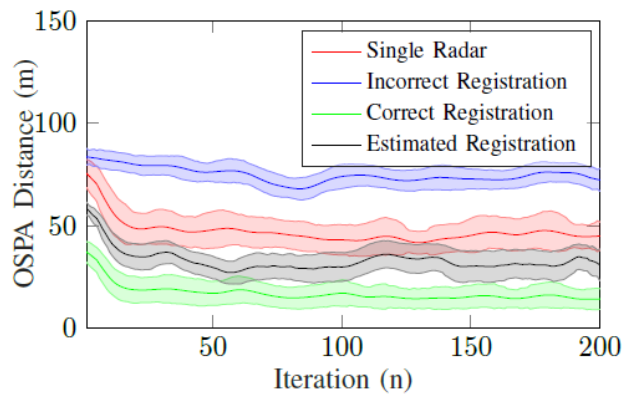
Particle BP Implementation

- No high-dimensional or computationally expensive operations.
- Most low-level operations are simple multiplications.
- No complex matrix inversions or decompositions as required in other MTT algorithms.
- Track management explicit in implementation as each target has unique ID.

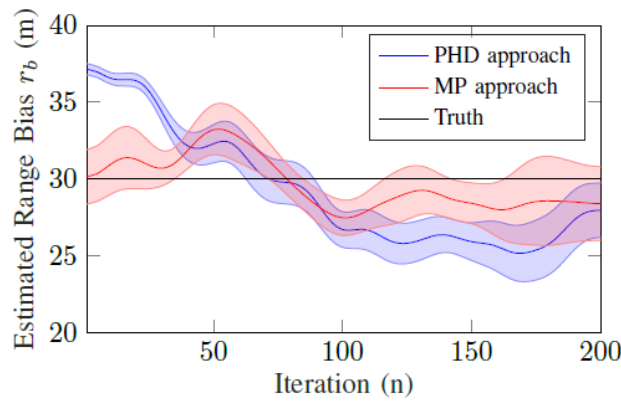
UDRC Phase 3 Work: Simulations/Results



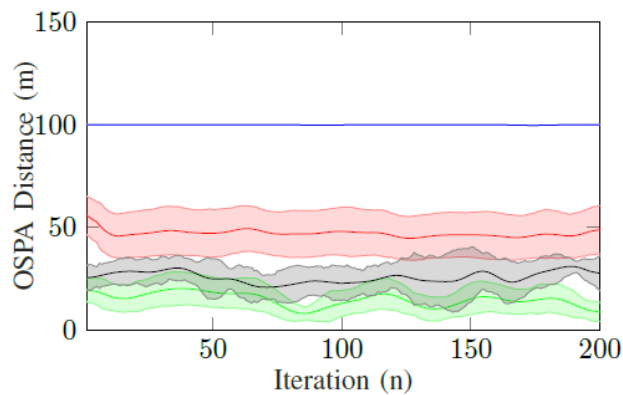
UDRC Phase 3 Work: Simulations/Results



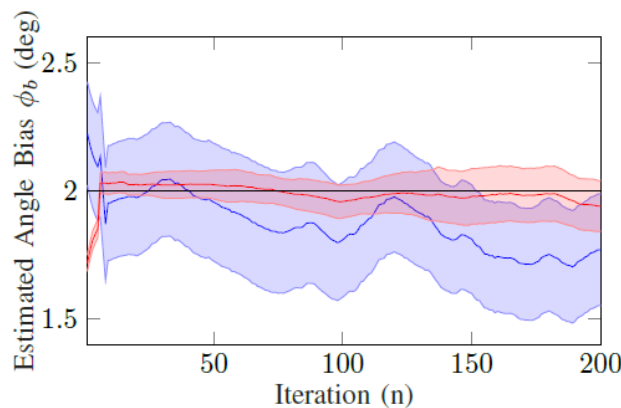
(a) PHD approach



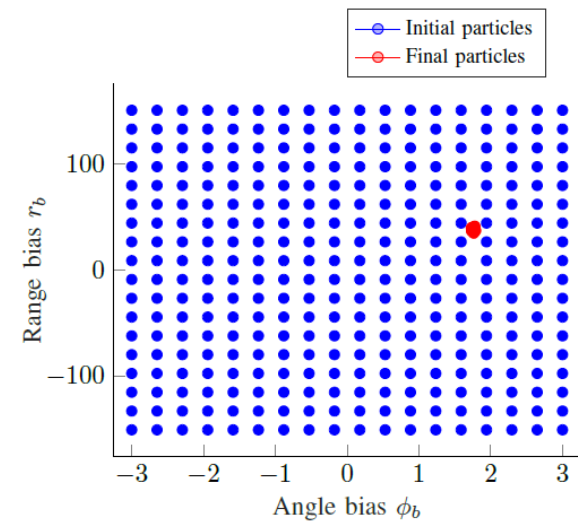
(a) Range τ_b estimation



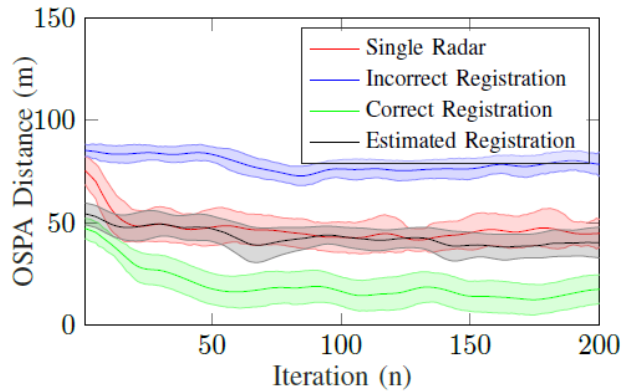
(b) MP approach



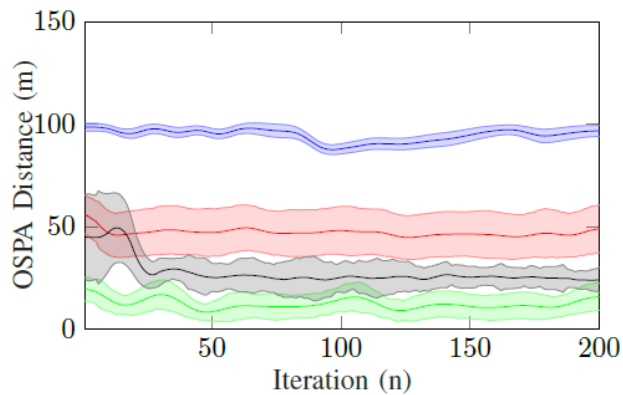
(b) Angle ϕ_b estimation



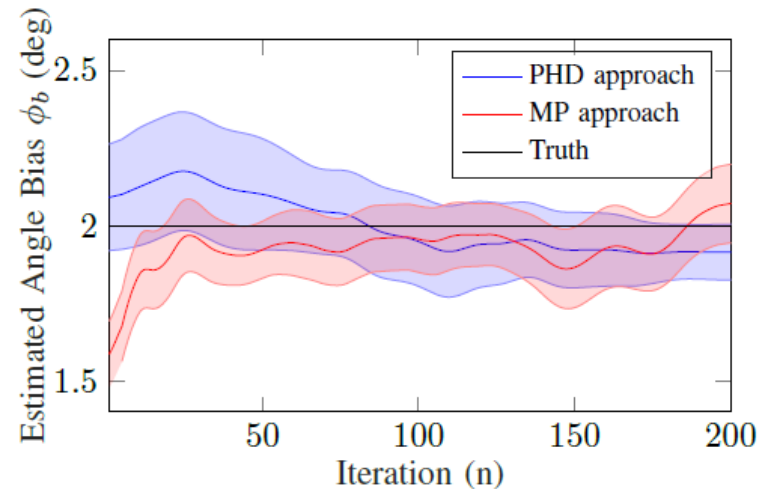
UDRC Phase 3 Work: Simulations/Results



(a) PHD approach



(b) MP approach



Conclusions

- Homogeneous sensors (2 radars, separated)
 - Tracking accuracy improved by 3% over set-type implementation
 - 1.39x slower
- Heterogeneous sensors (radar + camera, co-located)
 - Tracking accuracy improved by 16% over set-type implementation
 - 1.27x slower
- Shows importance of having correct registration

Future Work

- Full draft for submission to IEEE Transactions on Signal Processing
- Native message passing approach to tracking and registration
- Investigate scalability with larger numbers of sensors/targets
- Thesis submission – Jan 2020

Questions?