The Fast Product Multi-Sensor Labeled Multi-Bernoulli Filter

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Motivation

- Goal for multi-object multi-sensor tracking:
  - Realtime capable
  - small bandwith during data transmission
  - Safety: sensor order independent result

Prototype autoELF of project UNICARagil

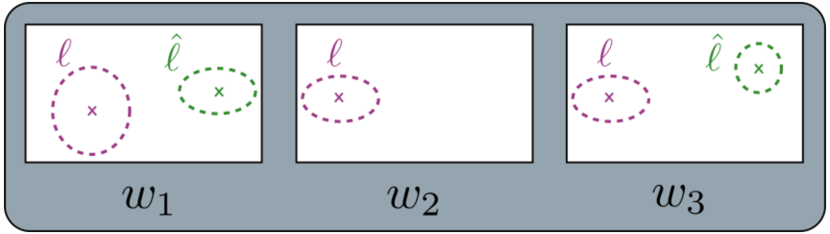
Infrastructure based sensors

Random Finite Sets

- Random Finite Sets (RFSs) provide a useful mathematical basis for multi-object tracking
- Well known filters are:

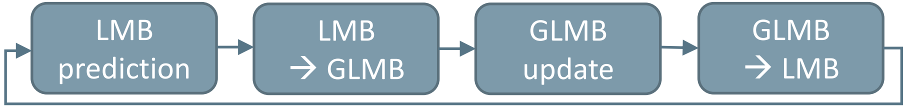
The Generalized Labeled Multi-Bernoulli Filter [1]

- Density is described by **many hypotheses** containing
  - spatial densities of tracks
  - data association information



The Labeled Multi-Bernoulli Filter [2]

- Efficient approximation of the GLMB filter



- Density is described **only** by
  - Existence probability of tracks
  - Spatial density of tracks

[1] B.-T Vo, B.-N. Vo, „Labeled random finite sets and multi-object conjugate priors", Transactions on Signal Processing, vol. 61, pp. 5952-5967, 2013
[2] S. Reuter, B.-T Vo, B.-N. Vo , K. Dietmayer, „The labeled multi-Bernoulli filter", Transactions on Signal Processing, vol. 62, pp. 3246-3260, 2014

Centralized Multi-Sensor Multi-Object Tracking System Architectures

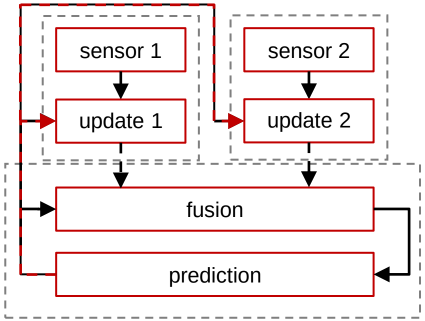
Multi-Sensor Update

- Computationally demanding due to NP-hard truncation
- Inflexible and hard to extend
- Parallelization not possible

Iterated Corrector (IC) Update

- Computationally manageable
- Approximations lead to sensor order dependent results
- Easy to extend
- Parallelization not possible

Bayes Parallel Combination Rule (BPCR)



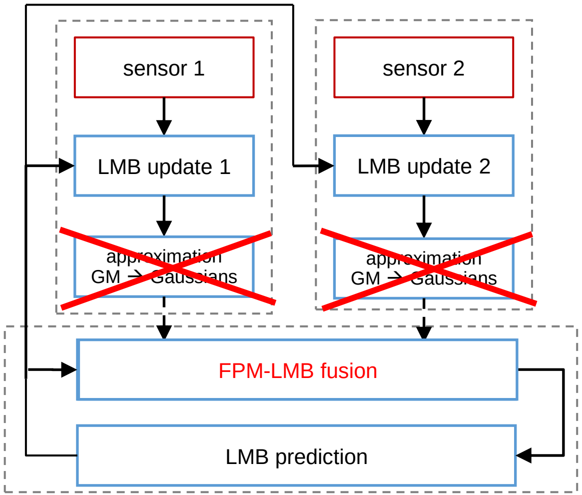
- Computationally manageable
- Separate update for each sensor
  → Reduces complexity
  → Robust behaviour
- Flexible and extendable
- Parallelization possible

Approaches based on the Bayes Parallel Combination Rule

Product Multi-Sensor LMB (PM-LMB) filter [3]

- Fusion of :
  → Many GLMB hypotheses
  → Spatial density
- Transmission of GLMB densities

Fast Product Multi-Sensor LMB (FPM-LMB) filter



- Fusion of:
  → Existence probability
  → Spatial density
- ~~Approximation Gaussian Mixtures to Gaussians necessary~~
- Transmission of LMB densities

[3] M. Herrmann, T.Luchterhand, C. Hermann , M. Buchholz, „The product multi-sensor labeled multi-Bernoulli filter", 26st International Conference on Information Fusion, to be published, 2023
[4] S.C. Robertson, C.E. Daalen, and J.A. du Preez, „Efficient approximations of the multi-sensor labelled multi-Bernoulli filter", Signal Processing, vol. 199, pp. 1-30, 2022

The Parallel Update Labeled Multi-Bernoulli filter [4]

- Division of spatial distributions is necessary

prior spatial distribution

$$p^{(\ell)}(x) = \frac{1}{\eta_Z^{(\ell)}} \left(p_+^{(\ell)}(x)\right)^{1-V} \underbrace{\prod_{s=1}^{V}}_{} p^{(s,\ell)}(x)$$

fused multi-sensor
posterior spatial distribution

normalization constant

product over
all V sensors

single-sensor posterior spatial distribution

- Problem: Solution for Division of Gaussian Mixtures (GMs) is not trivial

➢ The PU-LMB solution: Approximation of single-sensor posteriors as Gaussians → information loss

[4] S.C. Robertson, C.E. Daalen, and J.A. du Preez, „Efficient approximations of the multi-sensor labelled multi-Bernoulli filter“, Signal Processing, vol. 199, pp. 1-30, 2022

The Fast Product Multi-Sensor Labeled Multi Bernoulli Filter

- **Idea:** Application of the BPCR (similar to the PM-LMB filter [3]) to a reformulation of the fused posterior density of the PU-LMB filter [4]

- Calculation of the fused posterior spatial density is done via the Information Matrix Fusion (IMF) formulas

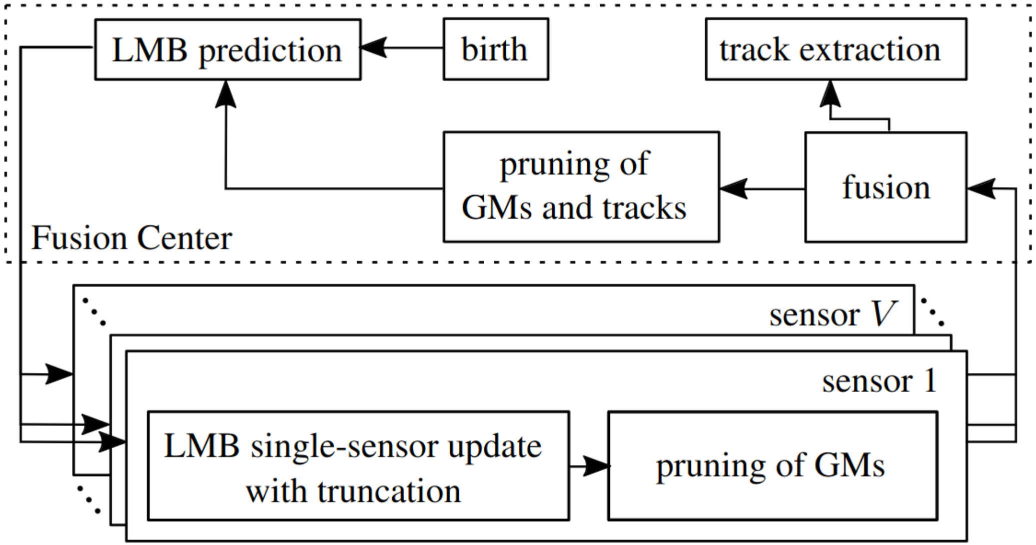
- Mean and covariance of the GM components are equivalent to the result of the optimal multi-sensor GLMB update

- Calculation of the fused existence probability is done using the PU-LMB [4] formula

[3] M. Herrmann, T.Luchterhand, C. Hermann , M. Buchholz, „The product multi-sensor labeled multi-Bernoulli filter", 26st International Conference on Information Fusion, to be published, 2023
[4] S.C. Robertson, C.E. Daalen, and J.A. du Preez, „Efficient approximations of the multi-sensor labelled multi-Bernoulli filter“, Signal Processing, vol. 199, pp. 1-30, 2022

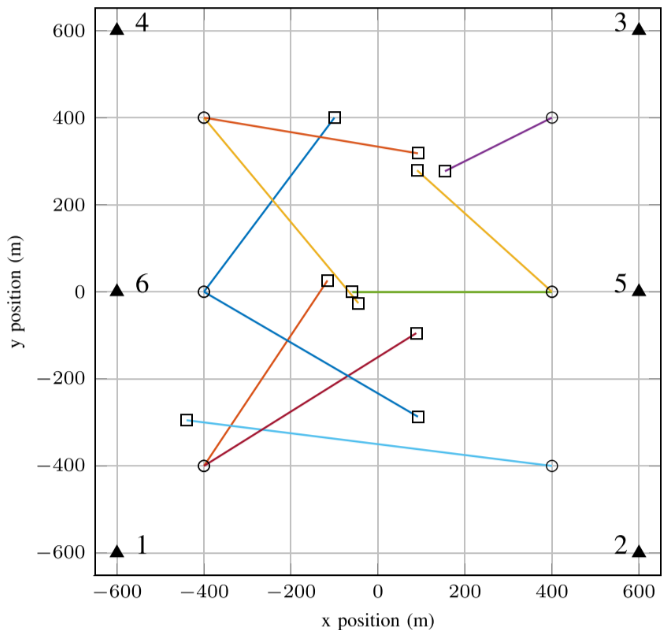
The Fast Product Multi-Sensor Labeled Multi Bernoulli Filter - Overview

- Truncation is done during the single-sensor update using the Murty ranked assignement algorithm
- Pruning of GMs means removing GM components with low weight
- Pruning of tracks means removing tracks with an existence probability below a certain threshold



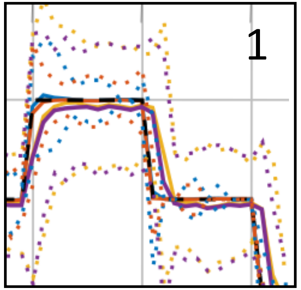
Evaluation

- 100 Monte Carlo runs of 100s duration
- A max. number of 10 point targets arise during the simulation
- Static birth model
- 2 or 6 synchronous sensors measure the position
  - $f = 1\ \mathrm{Hz}$
  - $\sigma = 0.6m$
  - $\lambda_c = 7$
- Evaluation using the Optimal Sub-Pattern Assignement (OSPA) and OSPA^2 metric
- Two different scenarios:
  - Linear scenario ($p_D = 0.67$)
  - Linear scenario with severe sensor failure ($p_D = 0.9$)

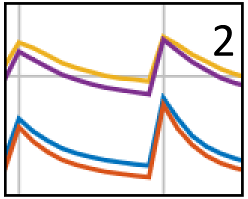


Evaluation
Results of the Linear scenario

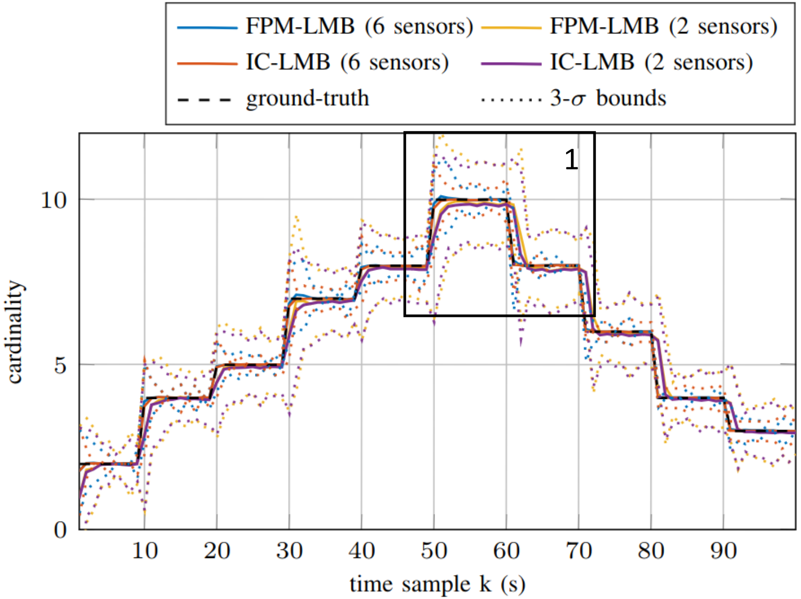
- FPM-LMB shows similar behaviour to IC-LMB filter

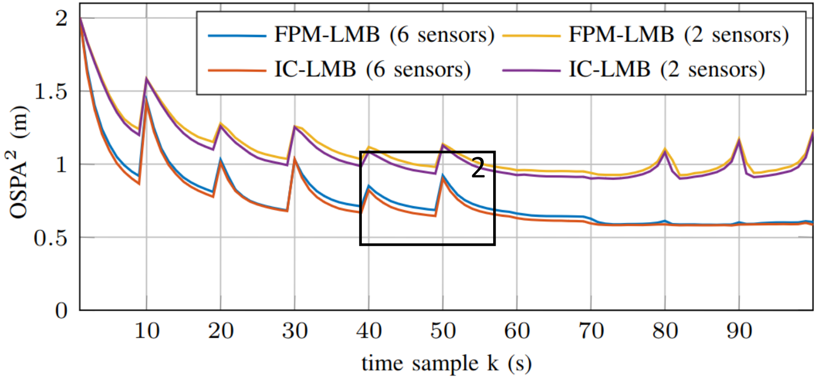


- FPM-LMB filter sometimes tends overestimate the cardinality and also tends to label switches when tracks are born



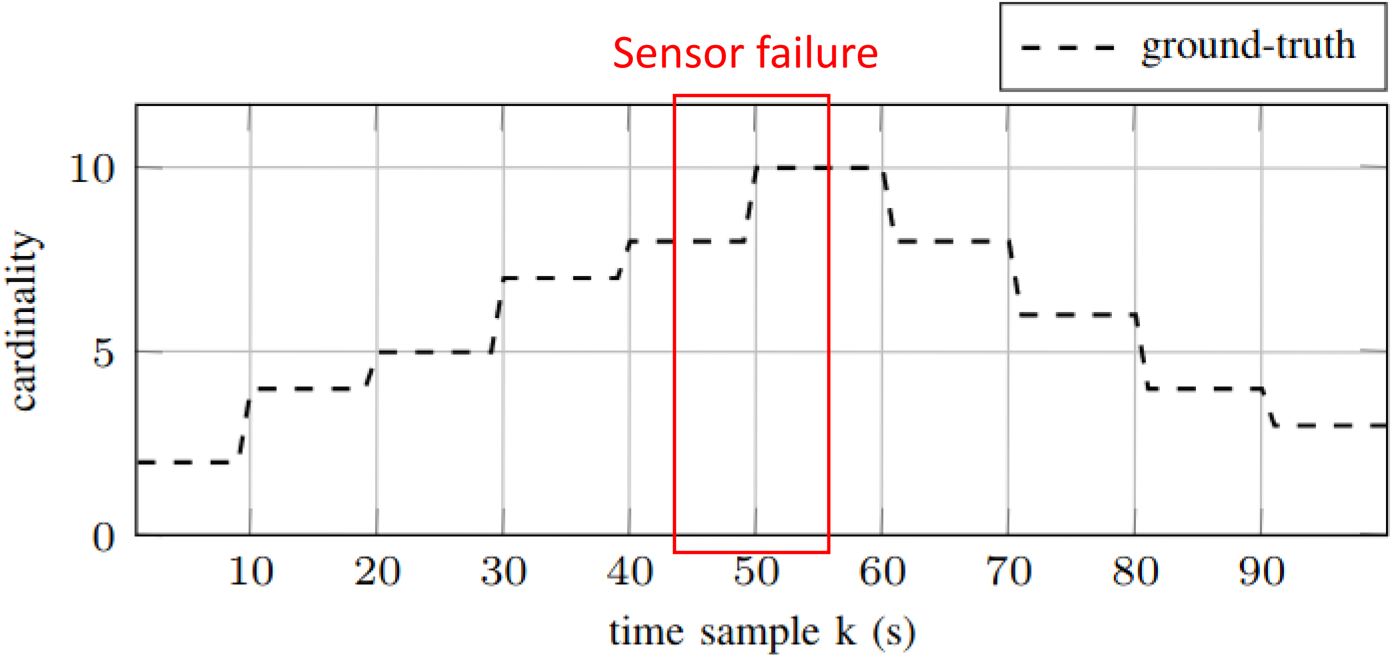
→ adaptive birth could solve this issue





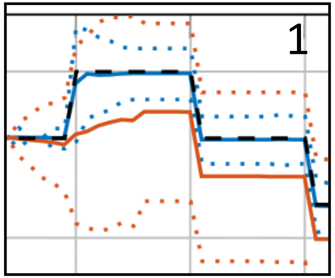
Evaluation
Linear scenario with severe sensor failure

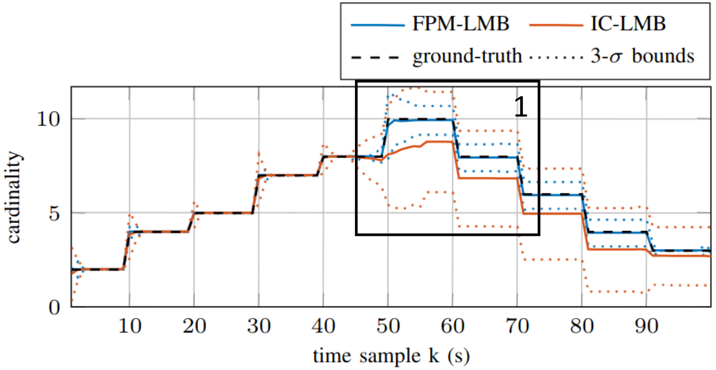
- 2 of the 6 sensors do not provide any detections during 44s < k < 56s
- IC-LMB: the first 2 sensors fail

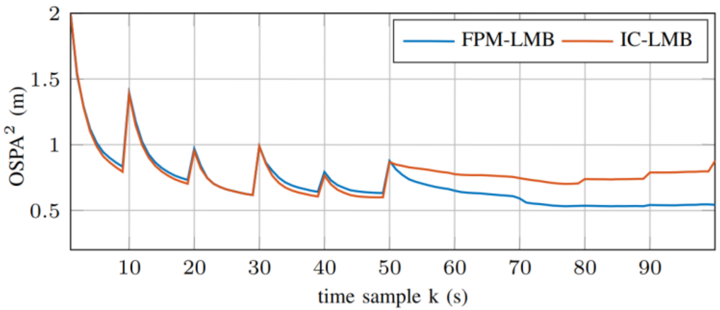


Evaluation
Results of the Linear scenario with severe sensor failure

- FPM-LMB filter outperforms the IC-LMB filter during the sensor failure and after because of the expected robust behaviour







Evaluation

- Computation time savings of the FPM-LMB filter relative to the IC-LMB filter (MATLAB implementation on an AMD RYZEN 7 3800X processor)

Scenario	Two Sensors	Six Sensors
Linear scenario	-22.33%	-41.89%
Linear scenario with severe sensor failure	-	-43.41%

➢ FPM-LMB filter outperforms the IC-LMB filter with respect to computation time

Summary

The FPM-LMB filter

- Enables the fusion of LMB densities using GMs
- Performs similarly to the IC-LMB filter with respect to tracking results
- Outperforms the IC-LMB filter in more challenging situations like sensor failure
  → robust behaviour
- Shows a lower computation time

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Thank you very much for your attention!

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