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Track Classification for Random Finite Set Based Multi-Sensor Multi-Object Tracking

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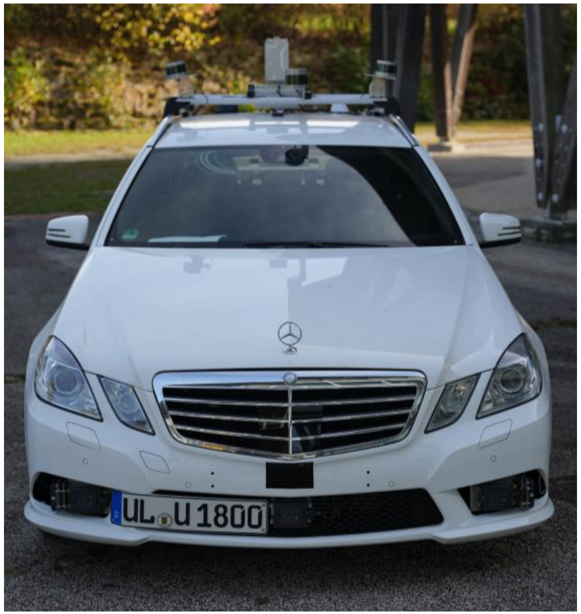
Track Classification for Random Finite Set Based Multi-Sensor Multi-Object Tracking

Combined SDF and MFI Conference 2023

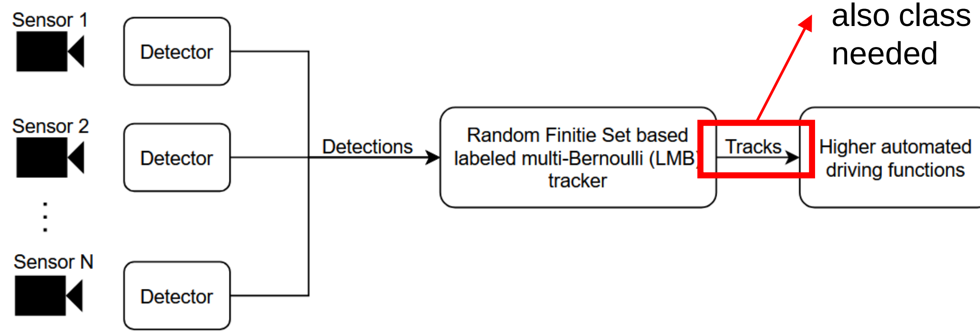
Alexander Scheible

Institute for Measurement, Control and Microtechnology

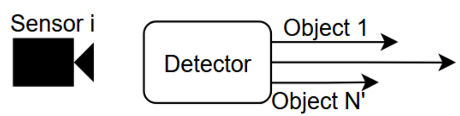
Automated Driving Car



Tracking Setup



Not only kinematic, but also class information needed



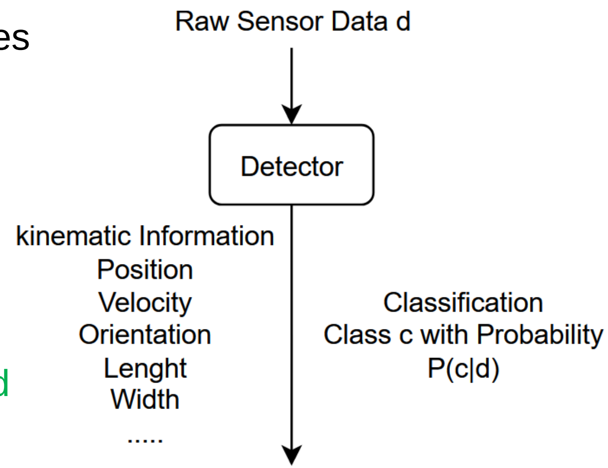
Object j with
- Pos X
- Pos Y
- Rotation about Z
- ...
- Classification

→ Why not use this class information for Track Classification?

Existing Approaches for Track Classification

Implicit Method [1, 2]

- Use only the kinematic features which are used by the (kinematic) tracker
- Allow a full Bayesian problem formulation often with a multi-model approach
- + mathematically closed
- + profitable for the tracker and classification
- - computational demanding
- - characteristic kinematic Model for every Class



Explicit Method [3]

- Use external provided class information, e.g., by the detector
- On-top classification based on a existing tracker
- - Can not use the classification information inside the tracker
- + computational cheap
- + Classification not limited to kinematic properties

Combine the explicit method with a random finite-set tracker / LMB

[1] B. T. Vo and B. N. Vo, “Tracking, identification, and classification with random finite sets,” Defense, Security, and Sensing, vol. 8745, p. 87450D, 2013.
[2] W. Yang, Z. Wang, Y. Fu, X. Pan, and X. Li, “Joint detection, tracking and classification of a manoeuvring target in the finite set statistics framework,” IET Signal Processing, vol. 9, no. 1, pp. 10–20, 2015.
[3] S. Haag, B. Duraisamy, W. Koch, and J. Dickmann, “Classification assisted tracking for autonomous driving domain,” in IEEE Sensor Data Fusion: Trends, Solutions, Applications, 2018, pp. 1–8.

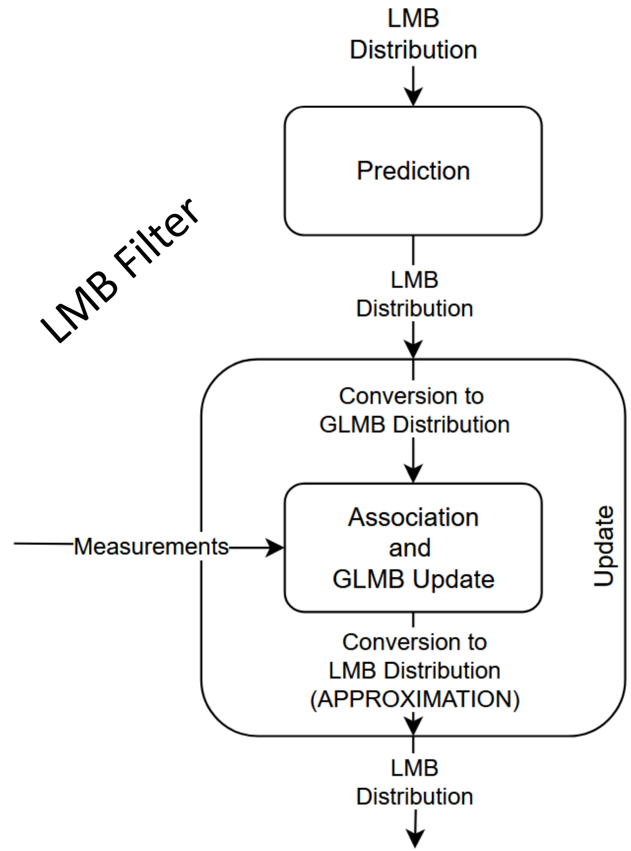
Random Finite-Set Based Multi-Object Tracking with the Labeled Multi-Bernoulli Filter

- Joint estimation of the number and state of the objects with a random finite-set

- Labeled multi-Bernoulli (LMB) filter [4]: approximation of the generalized labeled multi-Bernoulli (GLMB) filter

- Important for this work:

  Unambigious association between track and measurement during the update



[4] S. Reuter, B.-T. Vo, B.-N. Vo, and K. Dietmayer, "The labeled multi-bernoulli filter," IEEE Transactions on Signal Processing, vol. 62, no. 12, pp. 3246–3260, 2014.

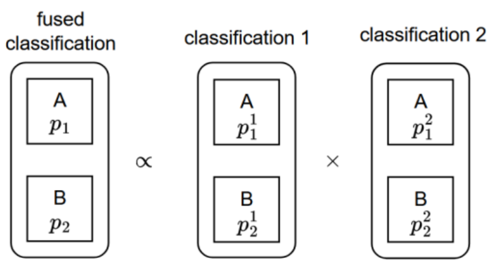
Combining Classification

Classification in form of a a-posteriori probability $P(c|d)$ for class c and input data d

Based on Bayes [5]

- *Product Rule* ⊗ If inputs are conditional independent of the class,

then



$$P(c|d_1,\ldots,d_n) \propto P(c)^{1-n} \prod_{i=1}^{n} P(c|d_i)$$

- *Sum Rule* ⊞ more robust

$$P(c|d_1,\ldots,d_n) \propto (1-n)P(c) + \sum_{i=1}^{n} P(c|d_i)$$

[5] J. Kittler, M. Hatef, R. Duin, and J. Matas, “On combining classifiers,” IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 20, no. 3, pp. 226–239, 1998.

Based on Subjective Logic [6, 7]

- Second order probability with $c \sim \mathrm{Cat}(p),$ $p \sim \mathrm{Dir}(\alpha).$

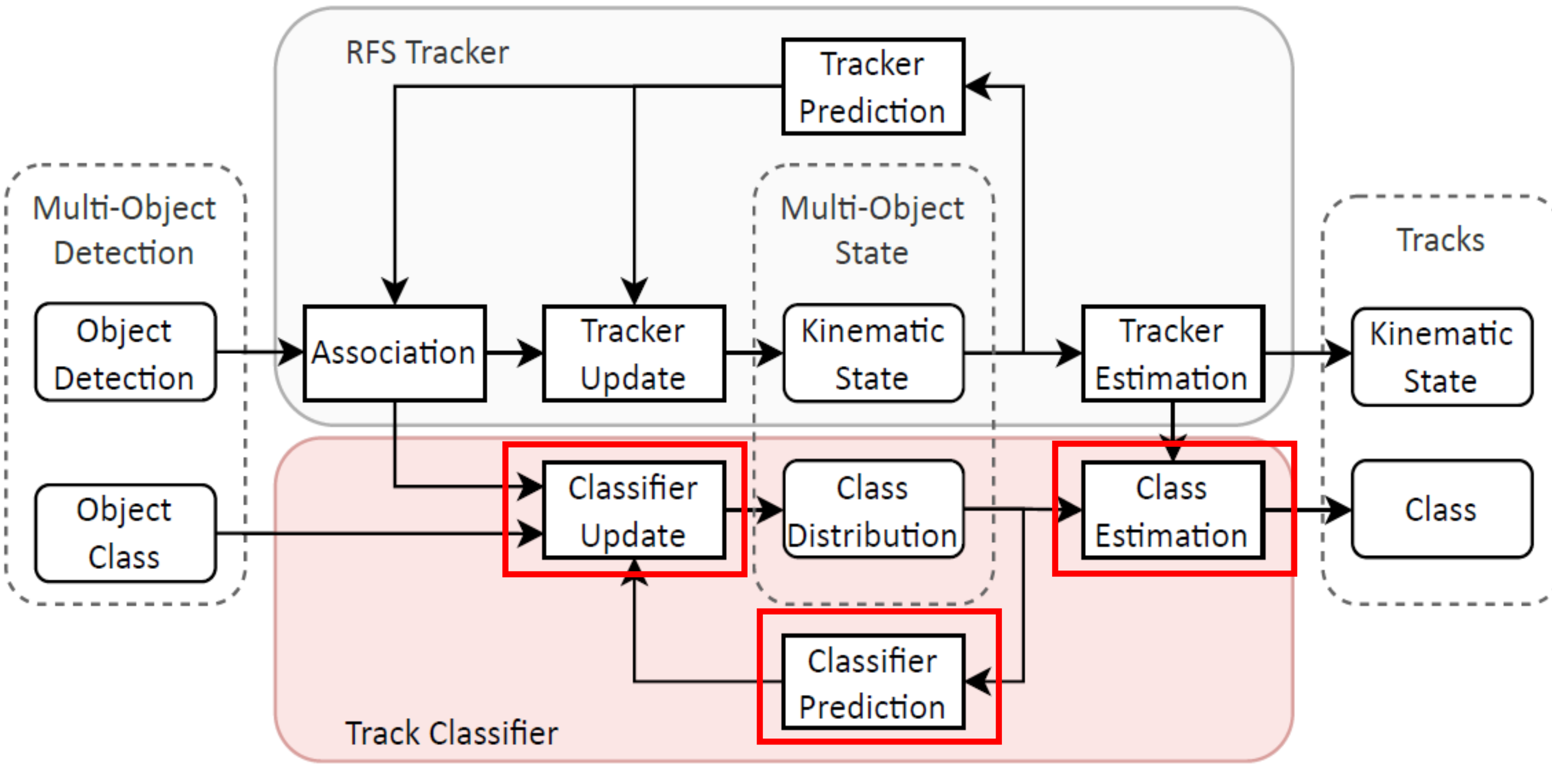
- Paper [6] uses external classification info of the form $\boxed{f(d|c)}$ for the update

Difficult to estimate

→ Presentation of a fusion operator for the a-posteriori Probability $P(c|d)$

[6]] L. Kaplan, M. Sensoy, S. Chakraborty, and G. De Mel, “Partial observable update for subjective logic and its application for trust estimation,” Information Fusion, vol. 26, pp. 66–83, 2015.
[7] A. Josang, Subjective Logic. Cham: Springer International Publishing, 2016.

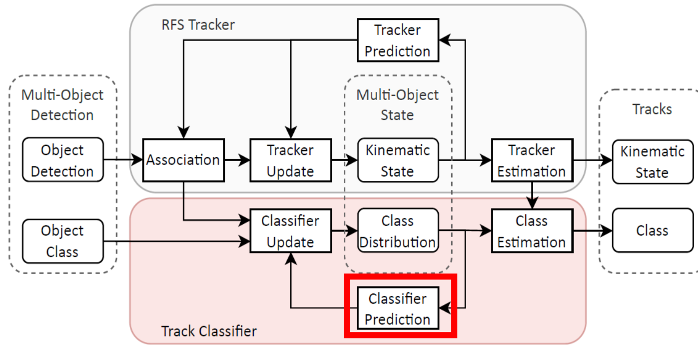
Framework for Track Classifacation with RFS based Trackers



Classifier Prediction

Discount old knowledge

Model Class changes



Bayes Method

- Weigthed average between old estimation and uniform distribution:

predicted estimation · old estimation · uniform distribution

$$\begin{pmatrix} \text{A} \\ p_1^+ \\ \text{B} \\ p_2^+ \end{pmatrix} = \delta \begin{pmatrix} \text{A} \\ p_1 \\ \text{B} \\ p_2 \end{pmatrix} + (1-\delta) \begin{pmatrix} \text{A} \\ 1/2 \\ \text{B} \\ 1/2 \end{pmatrix}$$

$$P(c_{+,i}) = \delta P(c_i) + (1-\delta)\frac{1}{|\mathbb{C}|}$$

- General: Markov Transition

Subjective Logic Method

- Use the trust discount [7] operator, i.e., $c \sim \mathrm{Cat}(p)$, $p \sim \mathrm{Dir}(\alpha)$

then approx.

predicted estimation · old estimation

$$\begin{pmatrix} \text{A} \\ \alpha_1^+ \\ \text{B} \\ \alpha_2^+ \end{pmatrix} = \delta \begin{pmatrix} \text{A} \\ \alpha_1 \\ \text{B} \\ \alpha_2 \end{pmatrix}$$

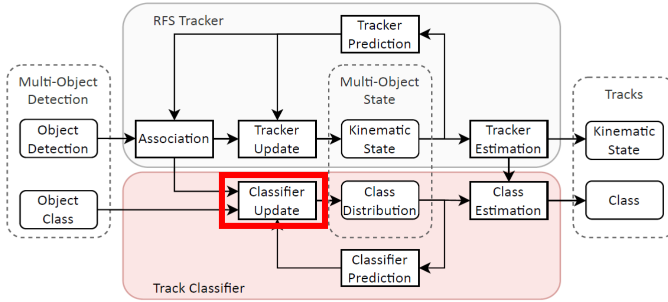
$$\alpha_+ = \delta\alpha$$

[7] A. Josang, Subjective Logic. Cham: Springer International Publishing, 2016.

Classifier Update

Update of one track with

the associated measurement



i-th standard basis vector

Prior
$c \sim \mathrm{Cat}(p),$
$p \sim \mathrm{Dir}(\alpha).$

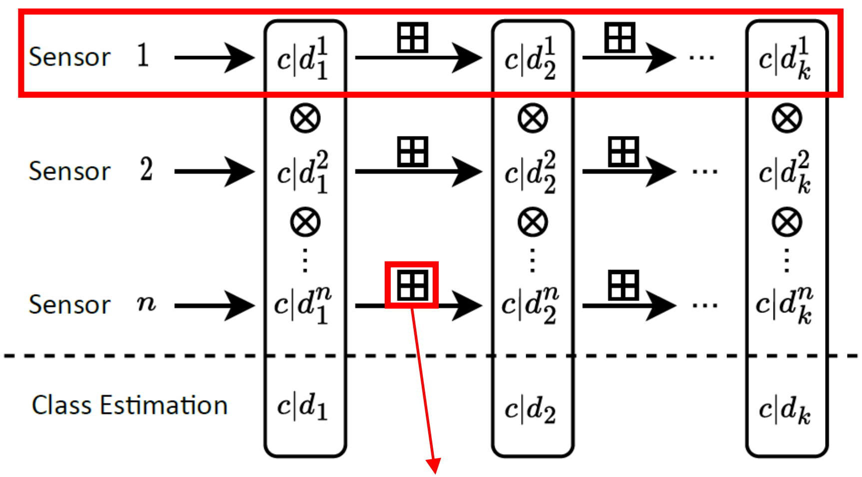
Bayes Method

Sum rule to combine estimations of the same sensor of different time steps

Subjective Logic Method

If $P(c_i|d) = 1$ for some i,
then $p|c_i \sim \mathrm{Dir}(\alpha + \boxed{e_i})$

→ The measured class is certain



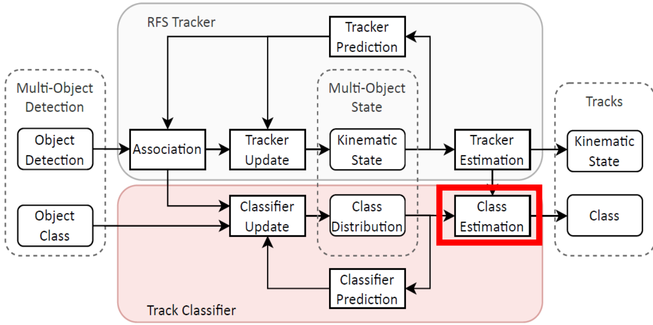
Sum Rule

But in general $P(c_i|d) = l_i \in [0,1]$, → The measured class is uncertain
so $p|d \sim \sum_i l_i \, \mathrm{Dir}(\alpha + e_i)$

Reduce growing number of mixtures with a moment matching approach → Paper

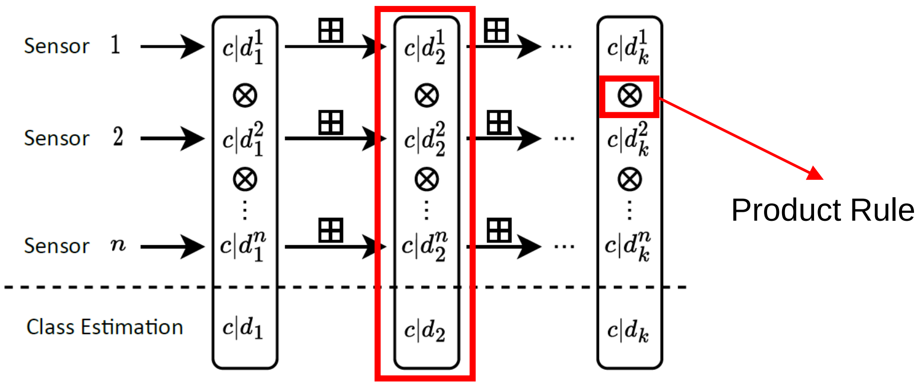
Classifier Estimation

Get a single class for each track



Bayes Method

- Combine estimations of all sensors with the product rule



- Return the most probable class

$$\hat{c} = \arg\max_{c_i} \; P(c_i | d_1, \ldots, d_k)$$

Subjective Logic Method

- Marginalize p out
- Return the most probable class

$$\hat{c} = \arg\max_{c_k} \; P(c_k|\alpha) = \arg\max_{c_k} \; \frac{\alpha_k}{S}$$

Evaluation General

- 5 classes: Car, Bike, Pedestrian, Truck, Unknown
- Classes do not change in time
- Performance averaged over the track age
- Classification performance evaluated with the weighted averaged F1-Score
- Association to ground truth
  - Use association computed by the the GOSPA [8] (a multi-object tracking) metric

[8] A. S. Rahmathullah, A. F. Garcia-Fernandez, and L. Svensson, “Generalized optimal sub-pattern assignment metric,” in IEEE International Conference on Information Fusion, 2017, pp. 1–8.

Evalutation Scenario Set-Up

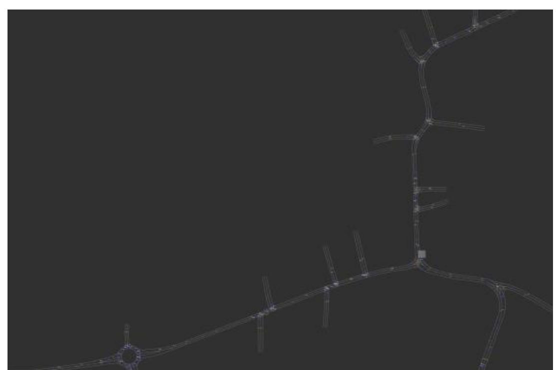
Simulation
Single Object Tracking

- Association given – no tracking needed
- Simulated detector with classification output as a sample from a Dirichlet Distribution with Parameter:

$$\alpha_i^D = \begin{cases} h(\text{igh}) & \text{True Class} = c_i \\ l(\text{ow}) & \text{else.} \end{cases}$$

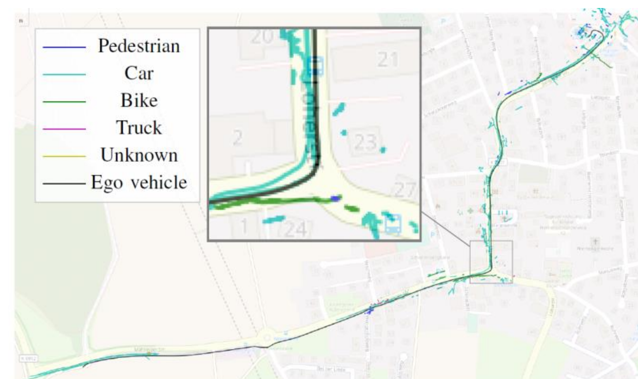
Simulation
Multi-Object Tracking

- Software-in-the Loop (SIL) simulator to simulate the automated vehicle
- Simulate detector output with fixed probilities

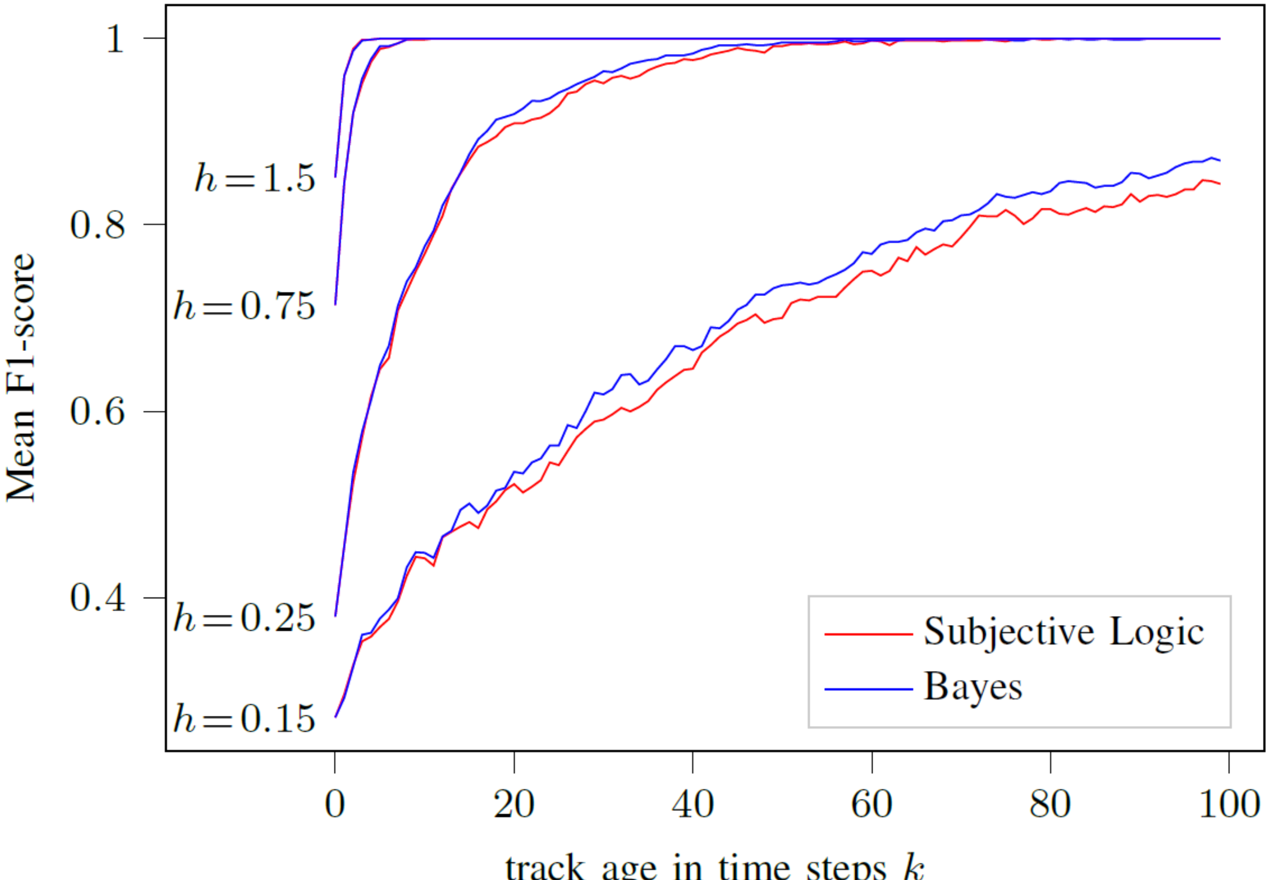


Real-World
Multi-Object Tracking

- Automated car with one LiDAR sensor and three RADAR sensors
- Manual labeled ground-truth for the estimated tracks



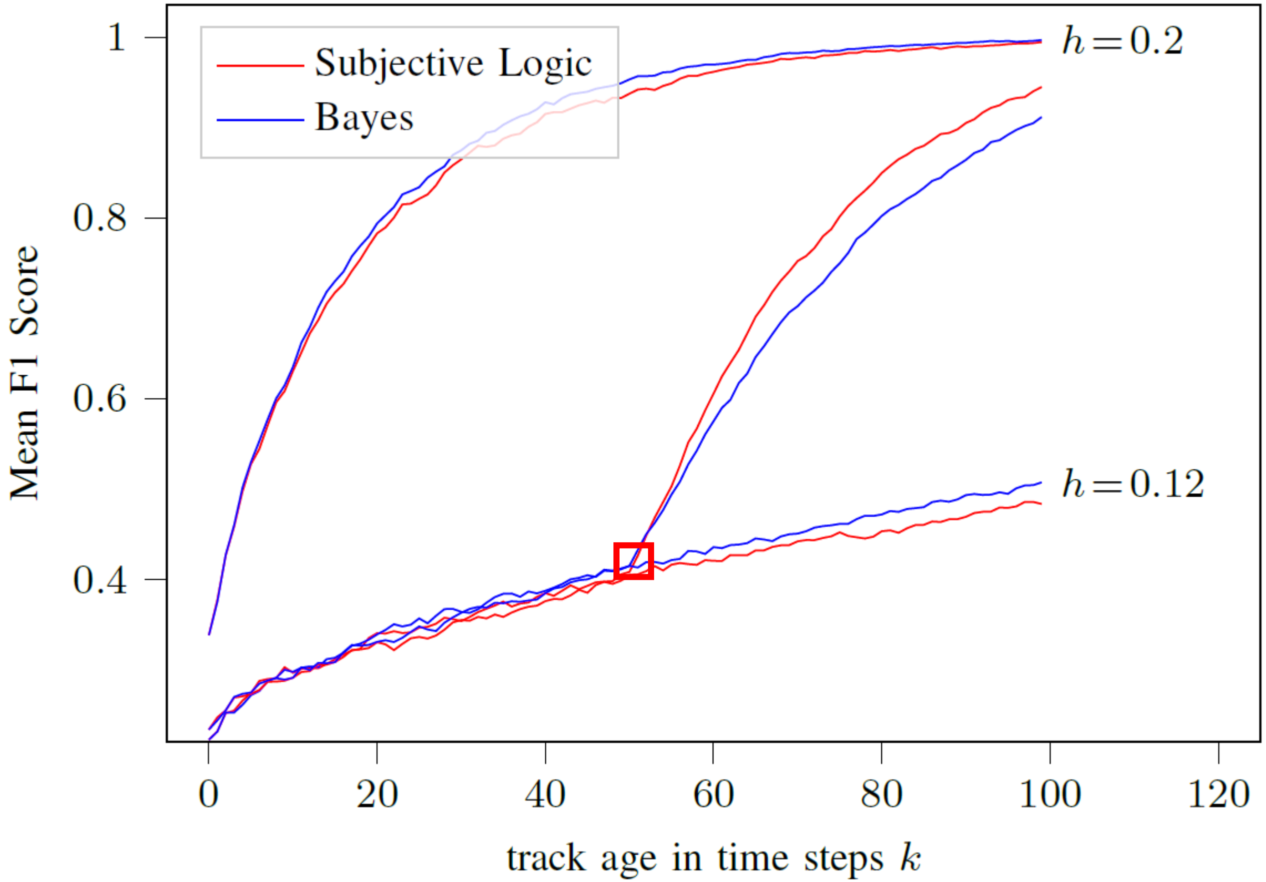
Single-Object Tracking
Varying Detector Qualities



Key Points

- Fusion enhances the classification performance
- As expected in ideal settings: Bayes method superior
- But small difference with good detectors

Single-Object Tracking
Switching Detector Quality



Key Points

- At time step 50: change in the detector performance
- Subjective Logic method better in the non-ideal setting
  → more robust

Conclusion

- Framework for explicit track classification for random finite-set based tracker
  - computational cheap track classification
  - works with different trackers

- Presentation and comparison of different classification fusion methods

- All fusion methods enhance the classification performance compared to the detector