FORSCHUNGSINITIATIVE
KO-FAS

Road User Tracking at Intersections Using a Classifying Multiple-Model PHD Filter

Verfolgen des Kreuzungsverkehrs mit einem klassifizierenden Multi-Modell PHD Filter

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Supported by:
Federal Ministry of Economics and Technology
on the basis of a decision by the German Bundestag

Benefit of Intersection Perception

Overview

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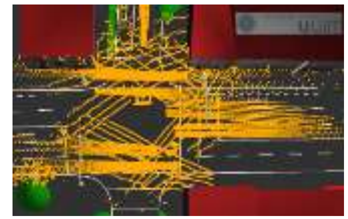
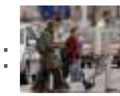
Cameras

C:  P: 

• • •

Laserscanners



C:  P: 

B:  T: 

Z_k 3D position, orientation, extend, class probabilities, and related uncertainties Z_k

Multi-Class, Multi-Sensor Tracking and Classification Using a Multiple-Model PHD Filter

X_k

Classified Tracks of Road Users

Dempster-Shafer Theory of Evidence

- Frame of discernment:

$$\Omega = \{B, C, P, T\}$$

- Express level of correctness α by discounting

$$m^{\alpha}(A) = \begin{cases} \alpha m(A), & A \neq \emptyset \\ 1 - \alpha + \alpha m(\Omega), & A = \Omega \end{cases}$$

- Fusion of BBAs

$$m_{1 \oplus 2}(A) = m_1(A) \oplus m_2(A)$$

- Pignistic transformation

$$BetP_m(A) = \sum_{B \subseteq \Omega} \frac{|A \cap B|}{|B|} m(B)$$




Basic Belief Assignments (BBA) for Track Classification

Measurement Features:

$$m_k^{z_j}(B) = p_k^{z_j}(B|M)$$
$$m_k^{z_j}(C) = p_k^{z_j}(C|M)$$
$$m_k^{z_j}(P) = p_k^{z_j}(P|M)$$
$$m_k^{z_j}(T) = p_k^{z_j}(T|M)$$

update of track BBA:

$$m_+^{(i)} = m_-^{(i)} \oplus \left(m_k^{z_j}\right)^{p_{LP}}$$

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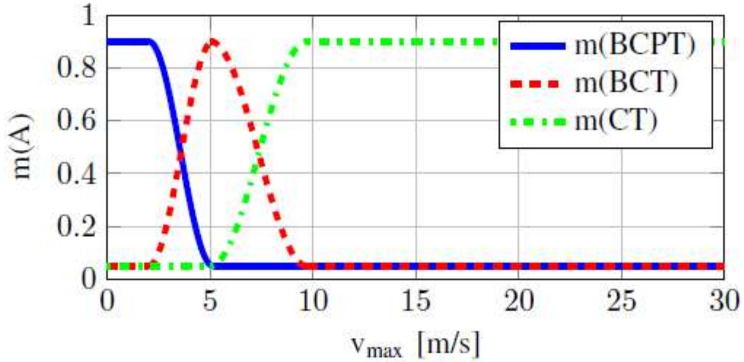
Track Features:



update of track BBA:

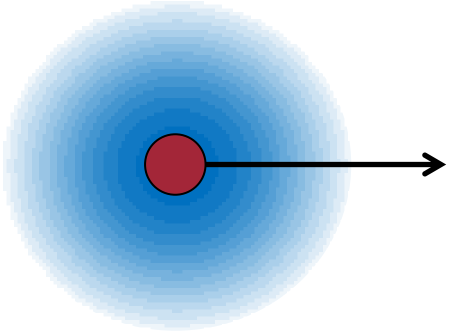
$$m_+^{(i)} = m_-^{(i)} \oplus \left(m_{v_{max},k}^{i}\right)^{p_{LP}}$$

$$T_{k|k-1}^{(i)} = \begin{bmatrix} BetP_m(P)^{(i)} & BetP_m(BCT)^{(i)} \\ BetP_m(P)^{(i)} & BetP_m(BCT)^{(i)} \end{bmatrix} = \begin{bmatrix} p(P)^{(i)} & p(BCT)^{(i)} \\ p(P)^{(i)} & p(BCT)^{(i)} \end{bmatrix}$$

Motion Models

linear **c**onstant **v**elocity (LCV)

$$\begin{bmatrix} x_{LCV} \\ y_{LCV} \\ z_{LCV} \\ \dot{x}_{LCV} \\ \dot{y}_{LCV} \\ \phi_{LCV} \end{bmatrix}$$



to track pedestrians (P)

$$T^{(i)}_{k|k-1} = \begin{bmatrix} p(P)^{(i)} & p(BCT)^{(i)} \\ p(P)^{(i)} & p(BCT)^{(i)} \end{bmatrix}$$

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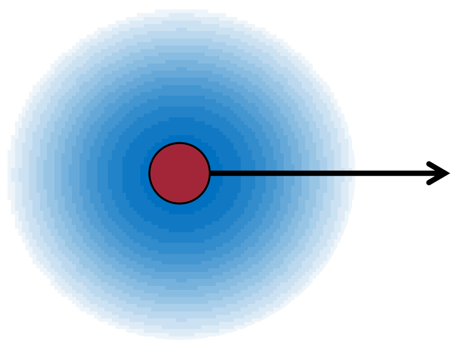
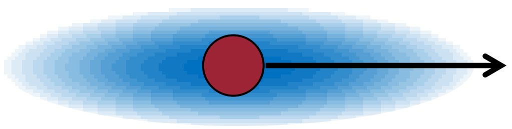


to track pedestrians (P)

single track **c**onstant **v**elocity (SCV)

$$\begin{bmatrix} x_{SCV} \\ y_{SCV} \\ z_{SCV} \\ |v_{SCV}| \\ \phi_{SCV} \\ \dot{\phi}_{SCV} \end{bmatrix}$$



to track bikes, cars, trucks (BCT)

$$T^{(i)}_{k|k-1} = \begin{bmatrix} p(P)^{(i)} & p(BCT)^{(i)} \\ p(P)^{(i)} & p(BCT)^{(i)} \end{bmatrix}$$

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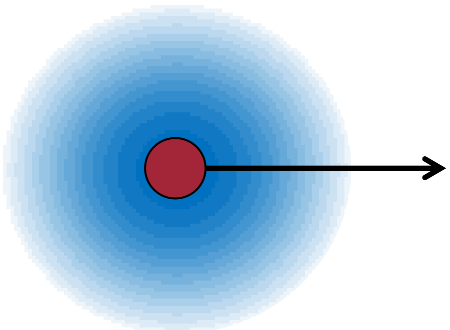

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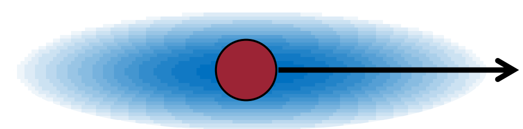

to track bikes, cars, trucks (BCT)

Unscented Transformation

$$T^{(i)}_{k|k-1} = \begin{bmatrix} p(P)^{(i)} & p(BCT)^{(i)} \\ p(P)^{(i)} & p(BCT)^{(i)} \end{bmatrix}$$

Using Multiple Models and Class BBAs in PHD Filtering

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- Extension of the multi-object state:

$$\ddot{X} = \{\ddot{\mathrm{x}}_1, \ldots, \ddot{\mathrm{x}}_M\} = \{(\mathrm{x}_1, o_1), \ldots, (\mathrm{x}_M, o_M)\}$$

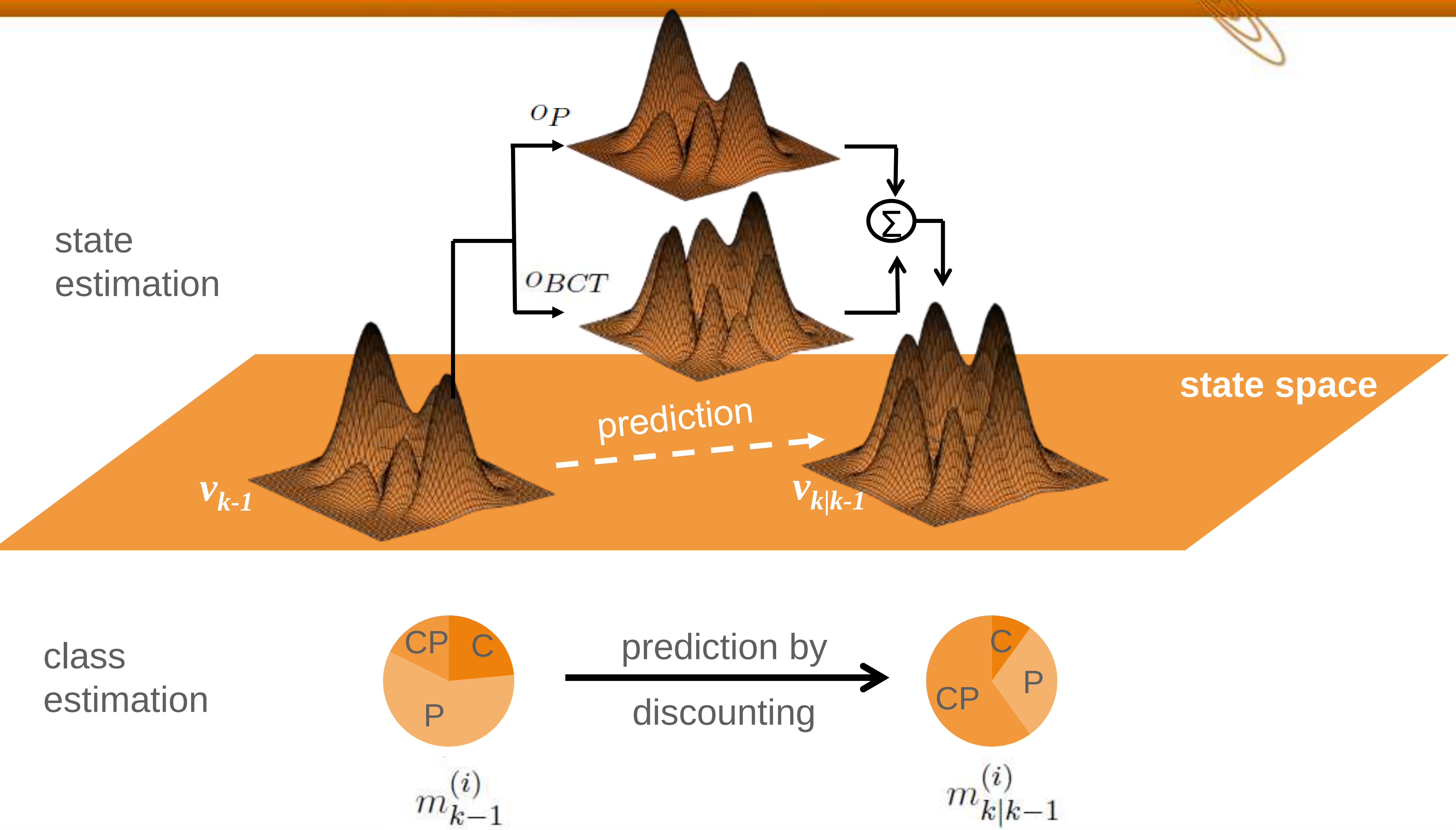
- Model modes represent the motion characteristics of the different object classes

- No explicit data association step in PHD-filters
  - ☑ Costly data association methods (JIPDA, Auction, …) not required
  - ✘ Missing association of measurement based class probabilities and tracks

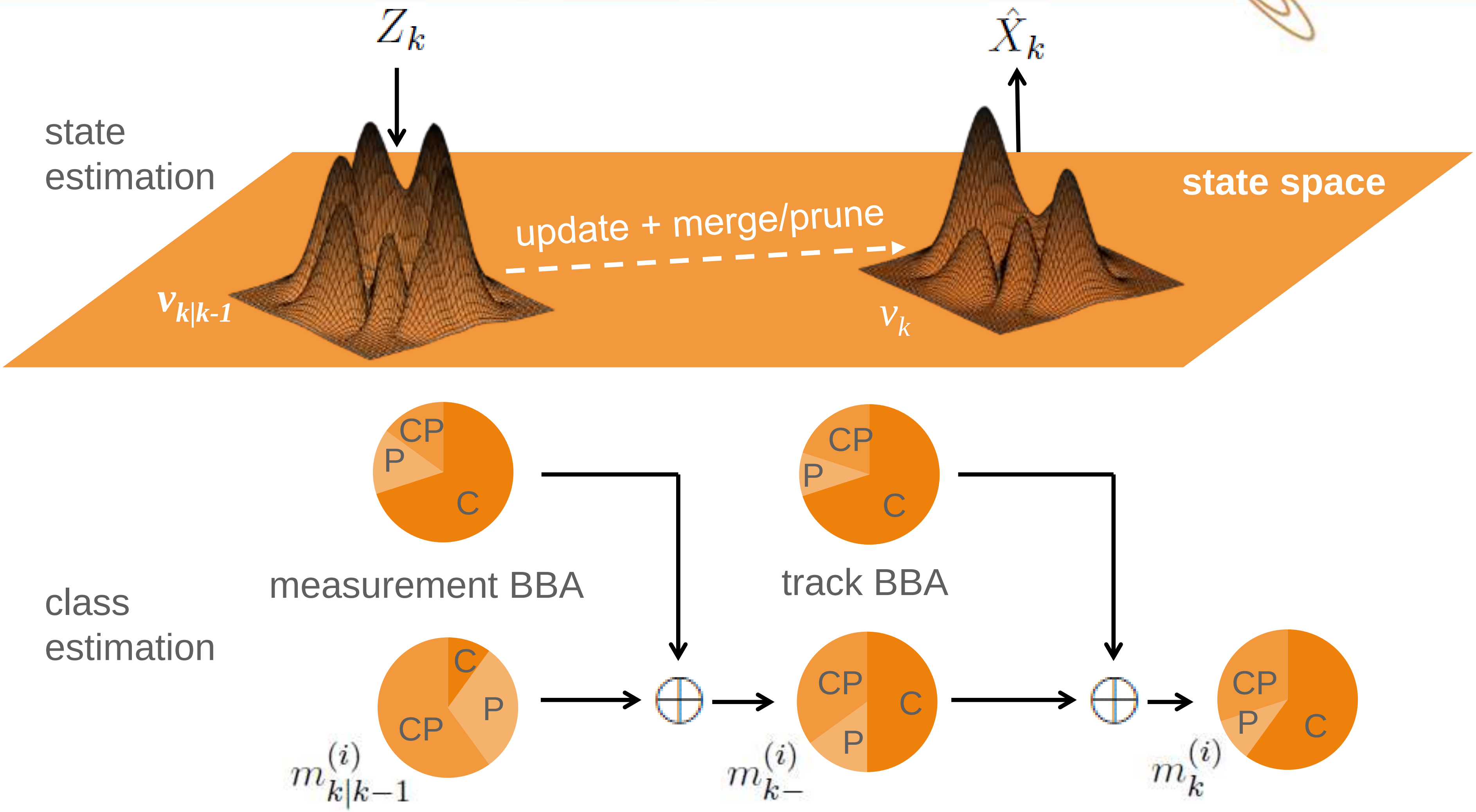
→ Each Gaussian additionally holds its class BBA

$$\left\{w^{(i)}, \mathcal{N}\left(x, \mu^{(i)}, P^{(i)}\right), m^{(i)}\right\}$$

Gaussian Mixture Multiple-Model PHD Filter Prediction



Gaussian Mixture Multiple-Model PHD Filter Update



Gaussian Mixture Multiple-Model PHD Prediction

Single-model a priori PHD:

$$v_{k|k-1}(\mathbf{x}) = \sum_{i=1}^{J_{k|k-1}} w_{k|k-1}^{(i)} \mathcal{N}\left(\mathbf{x}; \mathbf{m}_{k|k-1}^{(i)}, P_{k|k-1}^{(i)}\right)$$

Multiple-model a priori PHD:

$$v_{k|k-1}(\ddot{\mathbf{x}}) = \sum_{o'} \sum_{i=1}^{J_{k|k-1}(o')} w_{k|k-1}^{(i)}(o|o') \mathcal{N}\left(\mathbf{x}; \mathbf{m}_{k|k-1}^{(i)}(o|o'), P_{k|k-1}^{(i)}(o|o')\right)$$

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$$w_{k|k-1}^{(i)}(o|o') = p_{S,k|k-1}(o') t_{k|k-1}^{(i)}(o|o') w_{k-1}^{(i)}(o')$$

Gaussian Mixture Multiple-Model PHD Prediction

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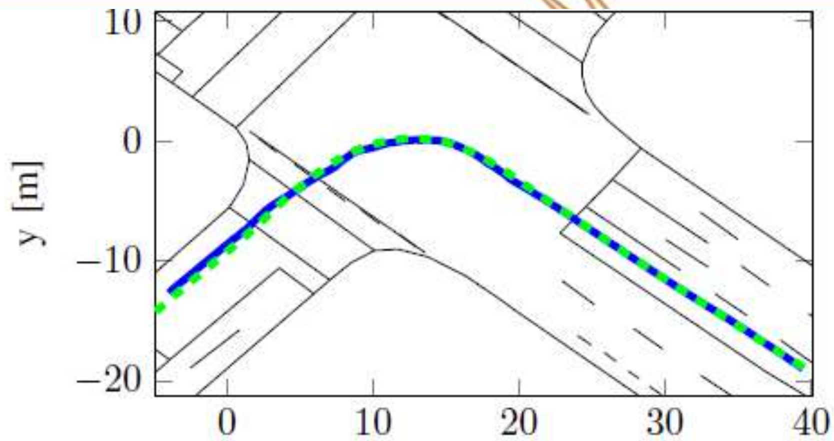
Video Road User Tracking

Absolute Error to Reference Data of Vehicles

- Left turning vehicle

  Route Mean Square Error (E):

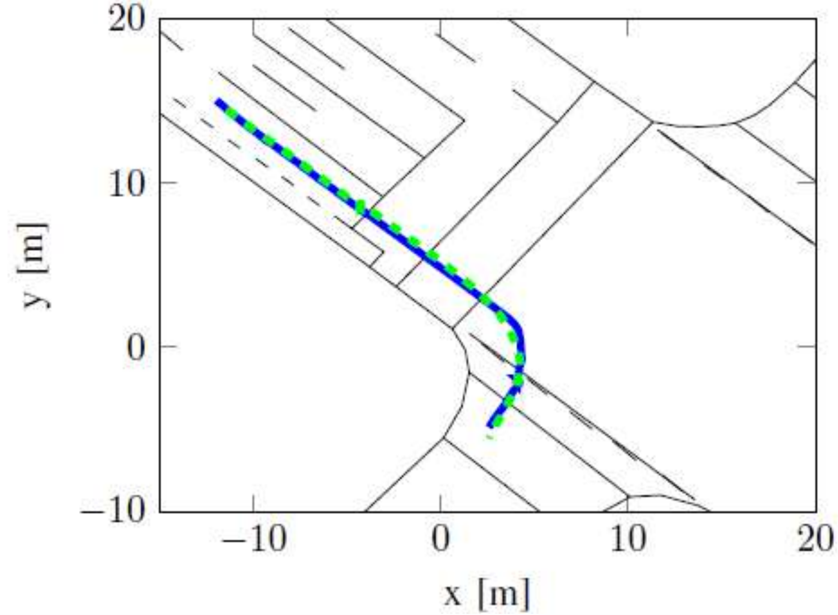
E_x[m]	E_y[m]	E_Φ[°]	$E_{\|v\|}$[m/s]
0.85	0.56	2.54	0.87



- Right turning vehicle

  Route Mean Square Error (E):

E_x[m]	E_y[m]	E_Φ[°]	$E_{\|v\|}$[m/s]
0.21	0.30	2.27	0.57



Conclusion

- Tracking using a classifying multiple-model PHD filter
  - One filter to track multiple object classes
  - Robust against incorrect classification
  - Estimation of objects class probabilities
  - Adaption of transition matrix based on track BBA

- Results
  - Persistent tracking and reliable classification of road users
  - Low RMSE of estimated object states to RTK-GPS data of vehicles

Questions?

Visit Our Live-Demo Tomorrow

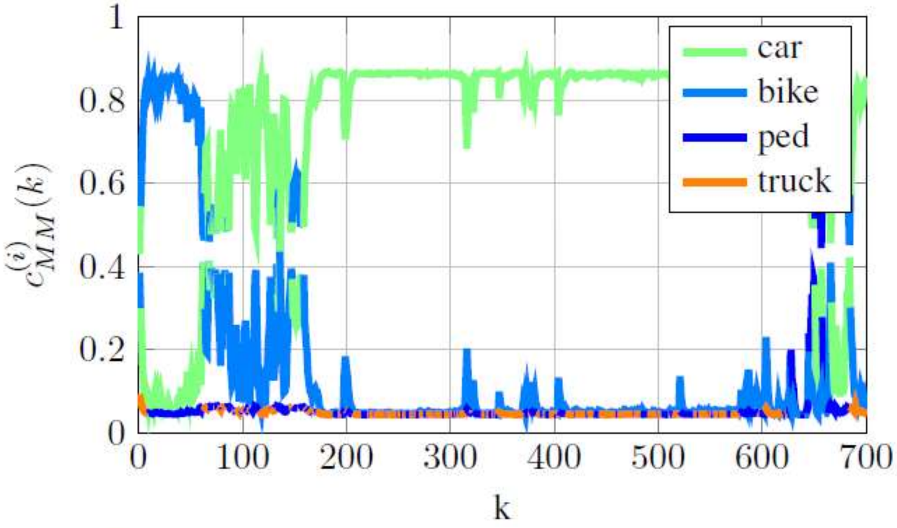
Bundesministerium für Wirtschaft und Technologie

The highly innovative activities of the Ko-FAS research initiative are supported with funds from the German Federal Ministry of Economics and Technology.

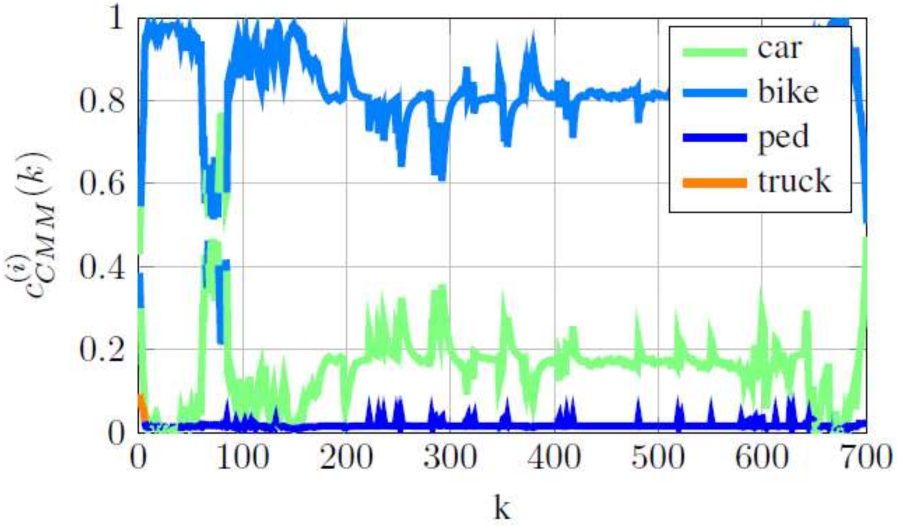
Benefit of Track Features

Three most likely classes of a bike track

- MMPHD filter without track features is unable to classify the bike correctly



- CMMPHD filter with track features estimates correct object class



Overview of Tracking and Classification Results