interactIVe

Accident avoidance by active intervention for Intelligent Vehicles

Models and Filters for camera-based Multi-target Tracking

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interactIVe Summer School

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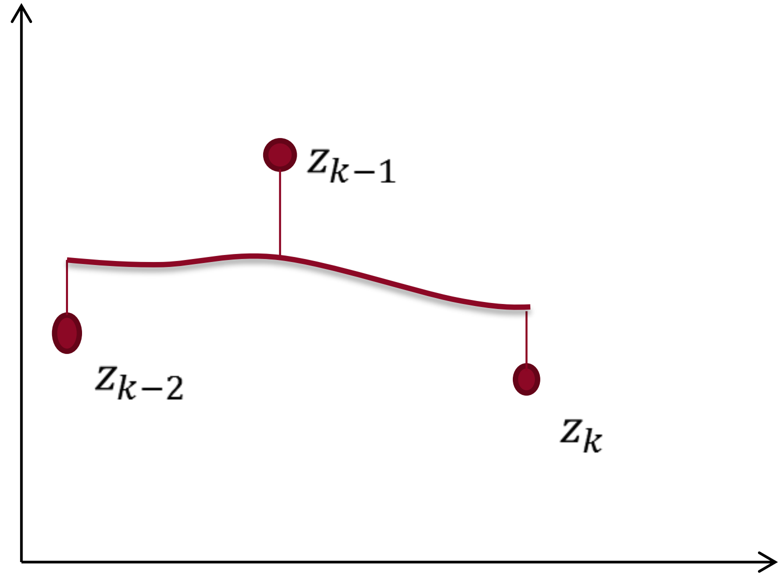
Outline: Contents of the Presentation

- From detection to tracking
- Overview over camera based multi-target tracking systems
- Association of measurements to tracks
- Filters for different tracking systems
    - Kalman Filter
    - EKF, UKF
    - Particle Filter
    - IMM Filter
- Models for camera-based tracking
    - 3D backprojection measurement model
    - Lane tracking models
    - Traffic sign tracking model
    - Pedestrian tracking model
    - Vehicle tracking models

From Detection to Tracking

Objective

- Follow objects over time
- Filter object trajectories
- Reduce failures and noise



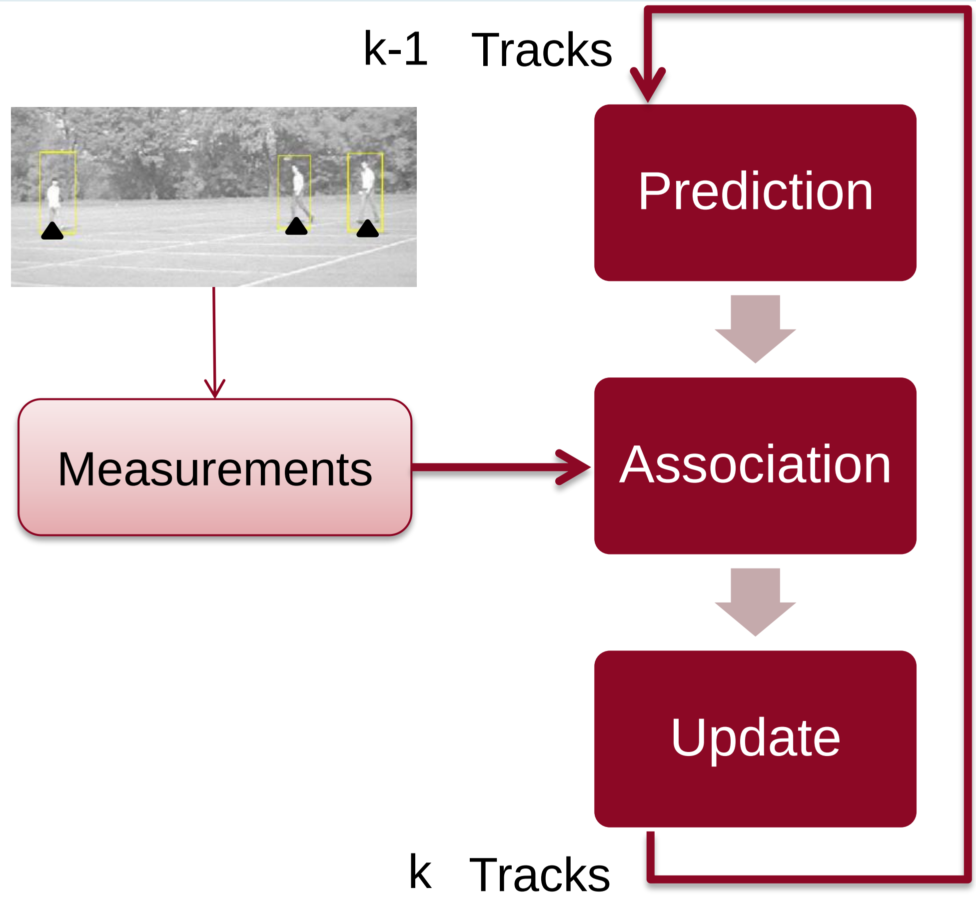
Structure of a camera-based Tracking System

Camera → Single frame recognition → Tracking and Fusion → Postprocessing

- Input
  - Single frame recognition
  - Noisy
  - No temporal connection
- Output
  - Object lists („Track Lists")
  - Estimated object states

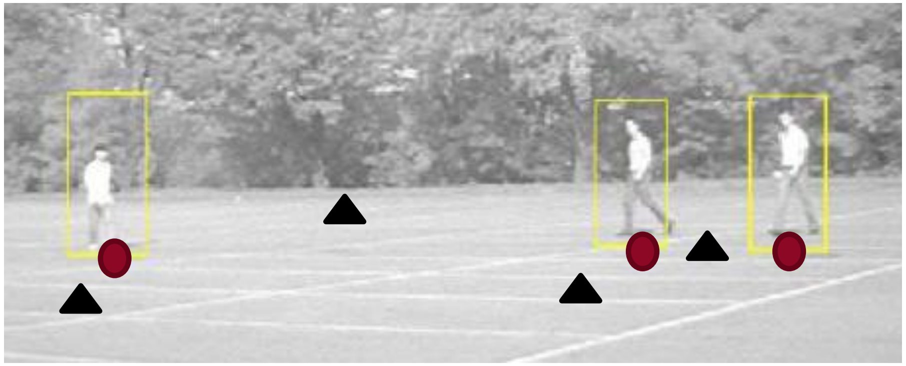
Structure of a camera-based Tracking System

- System
  - Measurement association
  - Creation and deletion of tracks
  - Filter interaction
- Filtering
  - Requires modeling of the object motion and the measurement process
  - Motion extraction
  - Noise reduction



Association of Tracks to Measurements

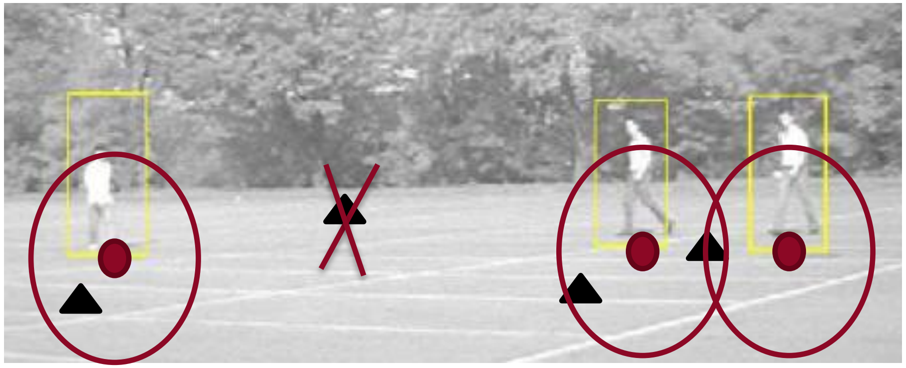
- Input for classic tracking filters is a temporal list of measurement readings
- The measurements must be assigned to each filter / filter element



Association of Tracks to Measurements

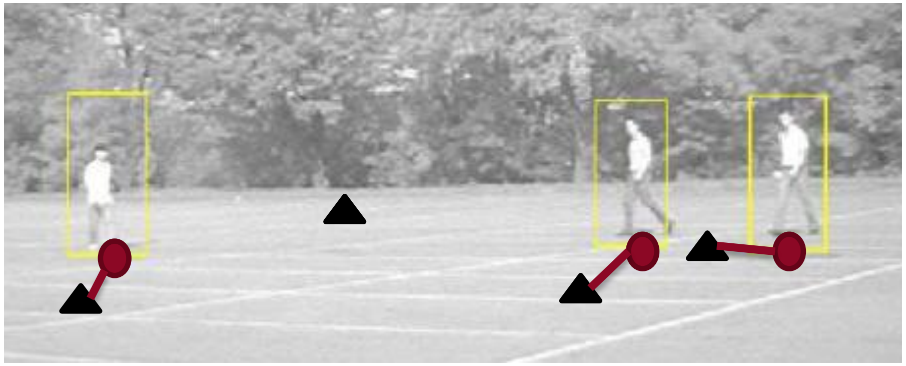
- Gating can be used to reduce the number of feasible association sets

- The expected / predicted measurement innovation covariance can be used to determine the association area (KF)



Association of Tracks to Measurements

- Assign measurements to tracks based on the postition / velocity / size
  - Evaluate least overall distance / highest probability of the association set
  - Hard associations
    - Assign one measurement to one track
    - E.g. Global nearest neighbour / HM
  - Soft associations
    - Assign all measurements in the environment with a certain probability
    - E.g. PDA, JPDA and extensions
  - Association based on a delayed decision
    - Maintain a set of association hypothesis
    - E.g. MHT and extensions
- Association using image cues
  - Association based on feature similarity
  - E.g. comparison of descriptor vectors used for interest point tracking



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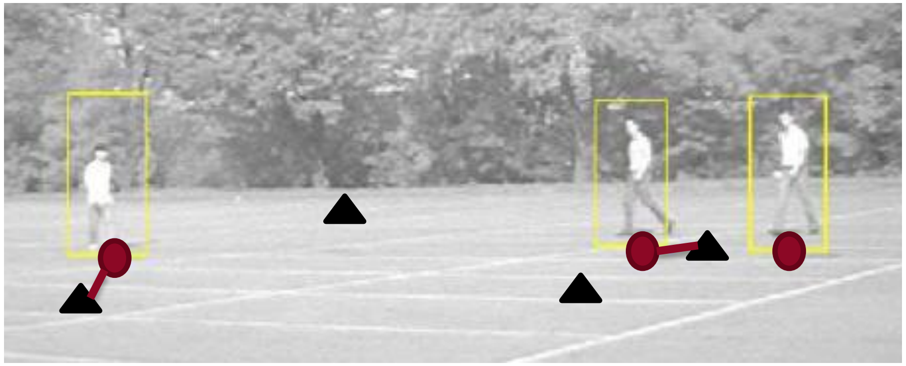


Filter Model

Objective

- Filter a set of temporal measurement readings (z)
- Extract object state information (x)

Model

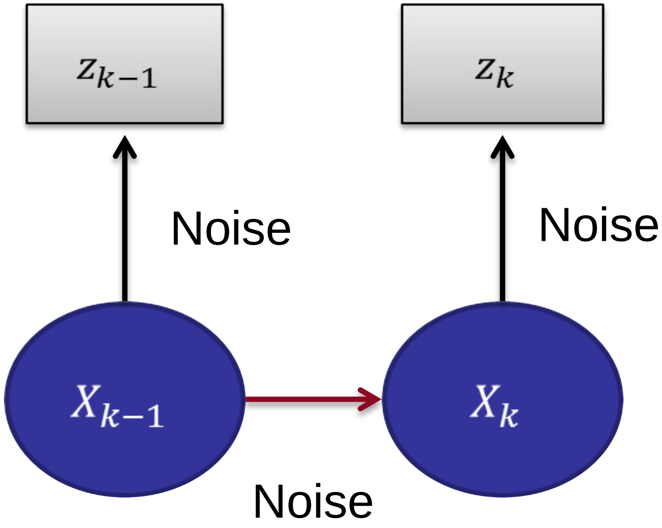
- Object evolves according to a stochastic markov process

$$p(x_k|x_{k-1}, \dots, x_1) = p(x_k|x_{k-1})$$

- Stochastic measurement process

Solution

- Use a recursive Bayesian filter to estimate the probability density of x conditioned on all measurements
- Extract x



Find $p(x_k|Z_k)$

Tracking Filters for Linear Systems

- Kalman Filter
  - Linear system and measurement model
  - Normally distributed system and measurement noise
  - Normally distributed state pdf
  - Estimates mean and covariance

$$\mathbf{x}_k = \mathbf{F}_{k-1}\mathbf{x}_{k-1} + \mathbf{B}_{k-1}\mathbf{u}_{k-1} + \mathbf{q}_{k-1}$$
$$\mathbf{y}_k = \mathbf{H}_k\mathbf{x}_k + \mathbf{r}_k$$

Normally distributed random variable

$$\begin{aligned}
\hat{\mathbf{x}}_{k|k-1} &= \mathbf{F}_{k-1}\hat{\mathbf{x}}_{k-1|k-1} + \mathbf{B}_{k-1}\mathbf{u}_{k-1}\\
\hat{\mathbf{P}}_{k|k-1} &= \mathbf{F}_{k-1}\hat{\mathbf{P}}_{k-1|k-1}\mathbf{F}_{k-1}^T + \mathbf{Q}_{k-1}\\
\hat{\mathbf{y}}_k &= \mathbf{H}_k\hat{\mathbf{x}}\\
\hat{\mathbf{S}}_k &= \mathbf{H}_k\hat{\mathbf{P}}_{k|k-1}\mathbf{H}_k^T + \mathbf{R}_k,\\
\mathbf{K}_k &= \hat{\mathbf{P}}_{k|k-1}\mathbf{H}_k^T\hat{\mathbf{S}}_k^{-1}\\
\hat{\mathbf{x}}_{k|k} &= \hat{\mathbf{x}}_{k|k-1} + \mathbf{K}_k(\mathbf{y}_k - \hat{\mathbf{y}}_k)\\
\hat{\mathbf{P}}_{k|k} &= (\mathbf{I} - \mathbf{K}_k\mathbf{H}_k)\hat{\mathbf{P}}_{k|k-1}
\end{aligned}$$

Tracking Filters for Linear Systems

- Fixed Gain Kalman Filter
  - Simplification of the Kalman filter for constant noise and system matrices
  - Steady state gain is used to map measurement deviations to the state space
  - No propagation of the covariance matrix necessary
- Alpha-beta Filter
  - Simplified KF with constant velocity model
  - Simplified parameterization
  - No covariance propagation
- Alpha-beta-gamma Filter
  - Simplified KF with constant acceleration model
  - Simplified parameterization
  - No covariance propagation

Tracking Filters for Linear Systems

- Alpha-beta filter

$$p_t = p_{t-1} + v\,dt$$

$$\begin{bmatrix} \hat{p}_{k|k-1} \\ \hat{v}_{k|k-1} \end{bmatrix} = \begin{bmatrix} 1 & dt \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{p}_{k-1|k-1} \\ \hat{v}_{k-1|k-1} \end{bmatrix}$$

$$\begin{bmatrix} \hat{p}_{k|k} \\ \hat{v}_{k|k} \end{bmatrix} = \begin{bmatrix} \hat{p}_{k|k-1} \\ \hat{v}_{k|k-1} \end{bmatrix} + \begin{bmatrix} \alpha(p - \hat{p}_{k|k-1}) \\ \frac{\beta}{dt}(p - \hat{p}_{k|k-1}) \end{bmatrix}$$

- Alpha-beta-gamma filter

$$p_t = p_{t-1} + v\,dt + \frac{1}{2} a dt^2$$

$$\begin{bmatrix} \hat{p}_{k|k-1} \\ \hat{v}_{k|k-1} \\ \hat{a}_{k|k-1} \end{bmatrix} = \begin{bmatrix} 1 & dt & \frac{1}{2}dt^2 \\ 0 & 1 & dt \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \hat{p}_{k-1|k-1} \\ \hat{v}_{k-1|k-1} \\ \hat{a}_{k-1|k-1} \end{bmatrix}$$

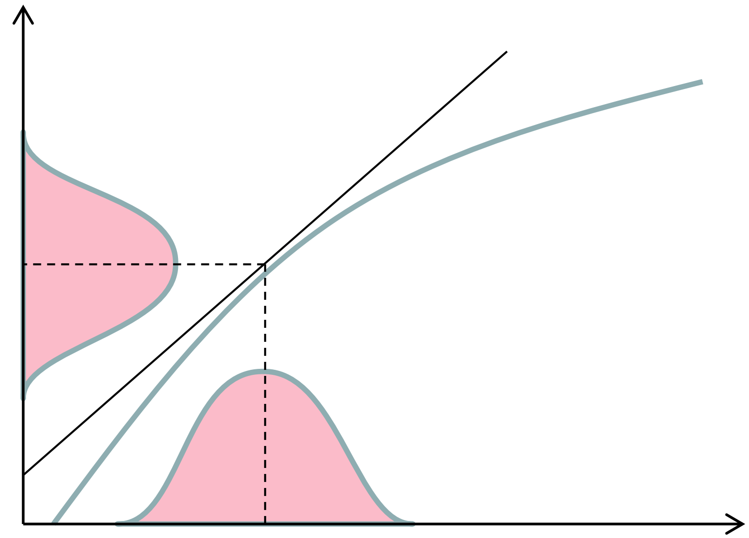
$$\begin{bmatrix} \hat{p}_{k|k} \\ \hat{v}_{k|k} \\ \hat{a}_{k|k} \end{bmatrix} = \begin{bmatrix} \hat{p}_{k|k-1} \\ \hat{v}_{k|k-1} \\ \hat{a}_{k|k-1} \end{bmatrix} + \begin{bmatrix} \alpha(p - \hat{p}_{k|k-1}) \\ \frac{\beta}{dt}(p - \hat{p}_{k|k-1}) \\ \frac{\gamma}{2dt^2}(p - \hat{p}_{k|k-1}) \end{bmatrix}$$

4 to 6 lines of code and the filter is ready

Tracking Filters for Nonlinear Systems

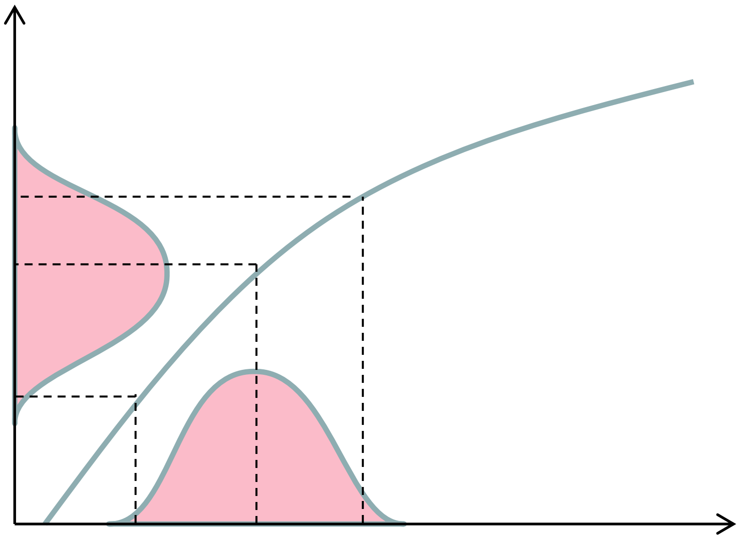
Extended Kalman filter

- Normally distributed state and noise pdfs
- Linearizes system and measurement equations around the mean estimate
- A relinearization around the estimate can be used to improve the results



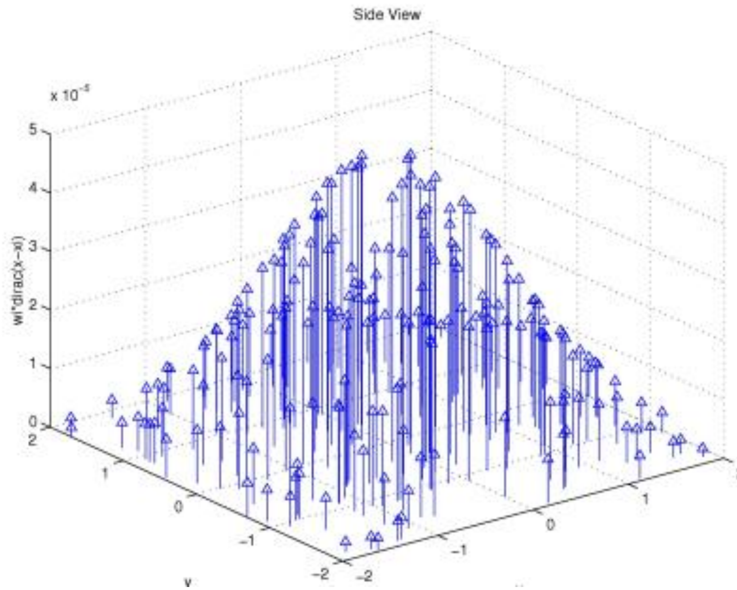
Tracking Filters for Nonlinear Systems

- Unscented Kalman filter
  - Normally distributed state and noise pdfs
  - Propagates a small set of sigma points through the nonlinear function
  - Better Covariance estimates
  - Higher calculation effort (except for special forms)



Tracking Filters for Nonlinear Systems

- Particle filter
  - General Bayesian filter
  - Approximates the probability densities using a number of weighted points in the state space
  - Can be used for all kinds of system and noise models
  - Can be computationally expensive



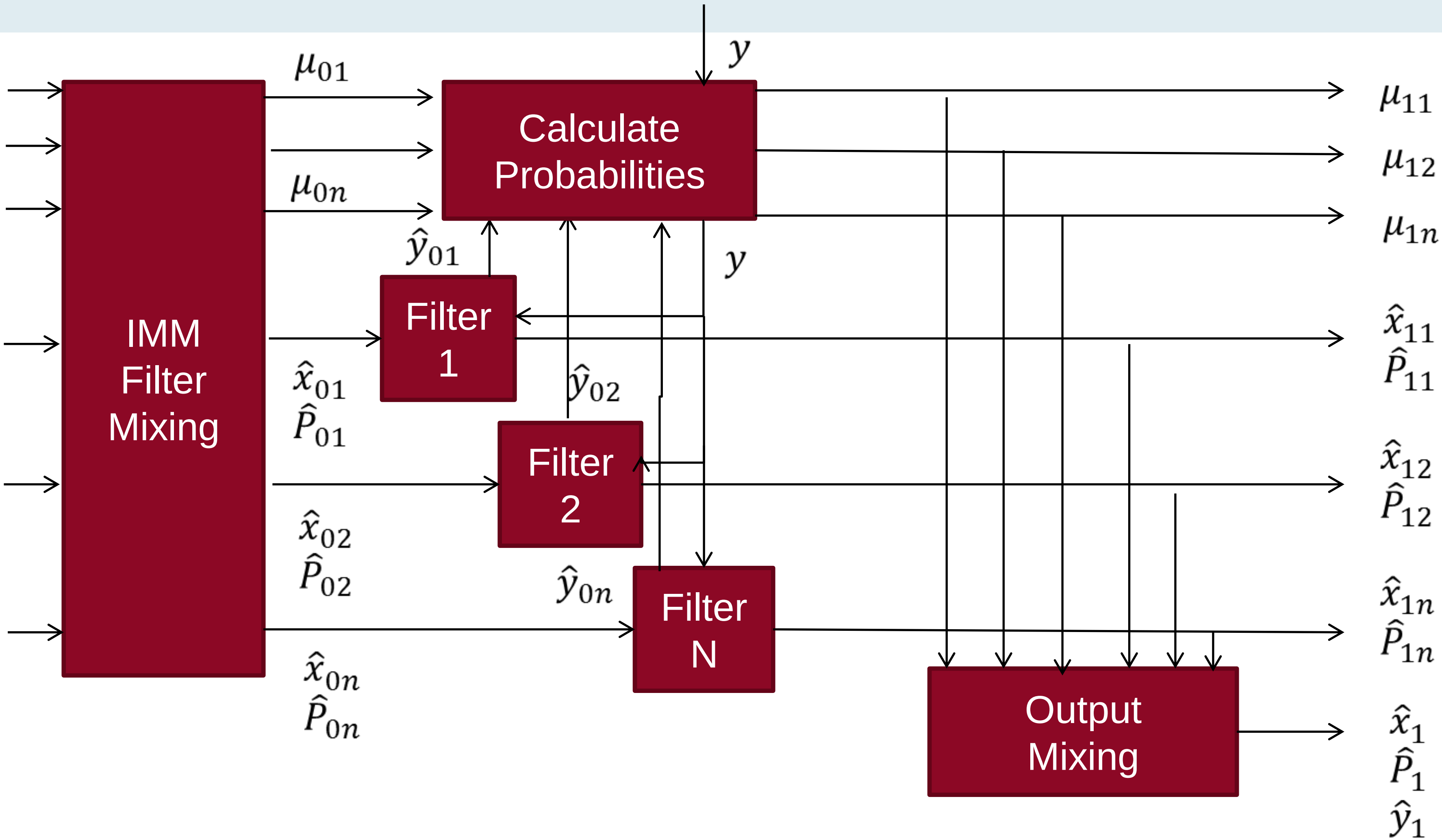
- Further Alternatives
  - GMM filters, Rao blackwellized Kalman filters, …)

Coupling of Several Hypotheses
The Interacting Multiple Model Filter

- Interacting Multiple Model Filter (IMM-Filter)
  - Filter bank of filters with different properties
  - Automatic probabilistic mode change

- Can be used for:
  - Dynamic system noise adaption for maneuver situations
  - Model switching to switch to less complex models
    - E.g. switching from a constant acceleration to a constant velocity model
  - Model switching to avoid observability problems
  - Data fusion to fuse sensors with a small probability for false readings
  - High filter performance and robustness

Coupling of Several Hypotheses
The Interacting Multiple Model Filter



Models for Camera Appliciations

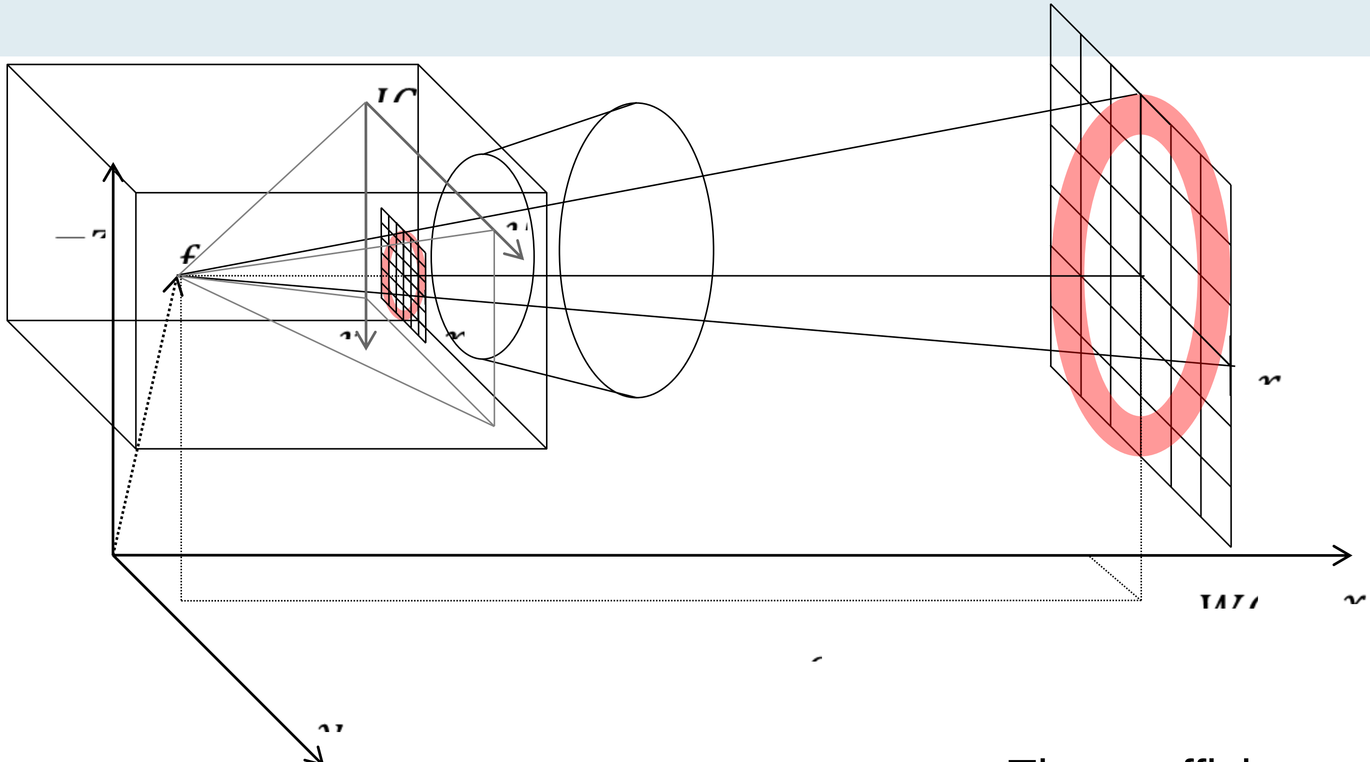
- 2D Models
  - Image plane motion
  - Often constant velocity or constant acceleration model
  - No direct relation to real world motion
  - Simple and fast
- 3D models
  - World motion model Object specific
    - Object type is known
  - Ego motion compensation
    - velocity and yaw rate data
  - Projective measurement model
    - Requires camera calibration data

3D Measurement Model
Relation between 3D World and 2D Image Coordinates

- In a monocular camera, the distance information is lost
- For distance reconstruction, some constraints are needed
  - Observed movement of stationary(!) points and ego motion estimation (Slam) or use of sensor ego motion information
  - Size observations and size constraints of objects
  - Ground plane assumption
- Otherwise, the distance is unobservable!

- For vehicles, camera pitch should be taken into account in the model or compensated

3D Measurement Model
Relation between 3D World and 2D Image Coordinates



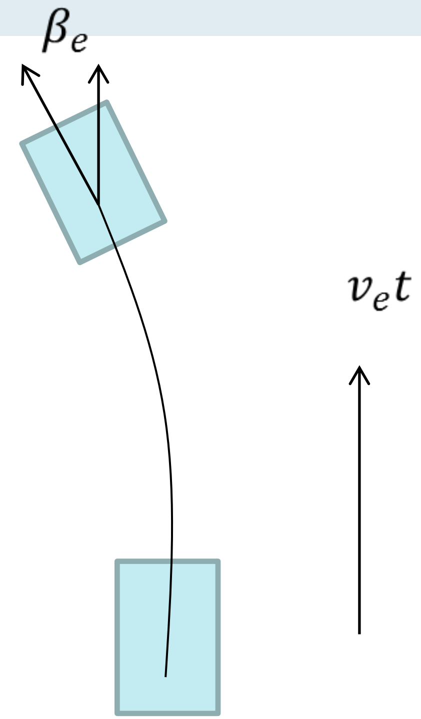
$$x_i = \frac{K_{11}w_x + K_{12}w_y + K_{13}w_z + K_{14}}{K_{31}w_x + K_{32}w_y + K_{33}w_z + K_{34}}$$
$$y_i = \frac{K_{21}w_x + K_{22}w_y + K_{23}w_z + K_{24}}{K_{31}w_x + K_{32}w_y + K_{33}w_z + K_{34}}$$

The coefficients of the camera calibration matrix completely capture the intrinsic and extrinsic parameters of the camera

Monocular Model-Based 3D Tracking of Rigid Objects: A Survey
Vincent Lepetit and Pascal Fua

Ego Motion Compensation

- Simple ego motion model
  - Uses velocity and yaw rate / steering angle
  - Does not incldue the sideslip angle
  - No consideration of dynamic effects (e.g. understeering or oversteering)



$$x_e(t) = \frac{v_e}{\varphi_e}\sin(\varphi_e t) \approx v_e t$$

$$y_e(t) = \frac{v_e}{\varphi_e}(1 - \cos(\varphi_e t)) \approx \frac{1}{2} v_e \varphi_e t^2$$

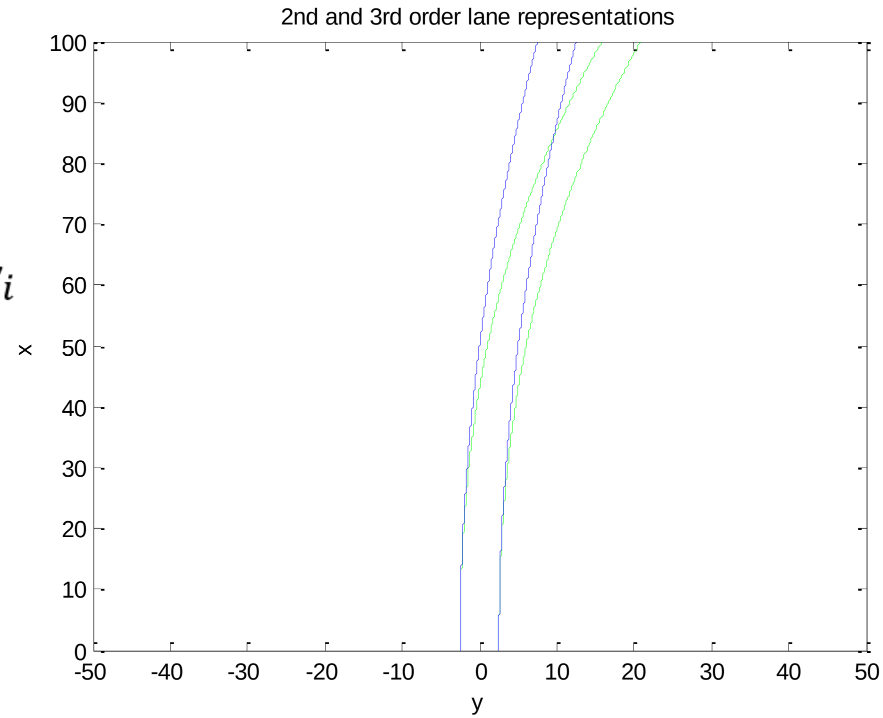
$$\beta_e(t) = \varphi_e t$$

Examples for Motion Models: Lane Tracking

- Ground plane lane representation
  - Second or third order polynomial, e.g.

$$f(x,l) = (\frac{1}{6}c_1 l^3) + \frac{1}{2}c_0 x^2 + \beta x + y_i$$

$$x = [c_1 \quad c_0 \quad \beta \quad y_1 \quad \cdots \quad y_n]^T$$

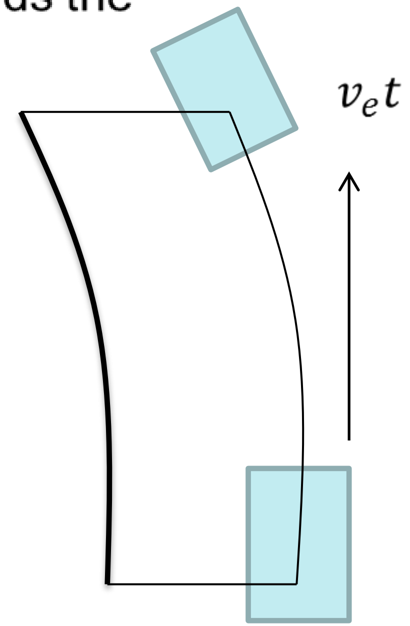


  - Derived from the clothoid model
  - Well known, simple model
  - Does not cover all types of road geometry transitions

Examples for Motion Models: Lane Marking Tracking

- Driving along the parabola with $v_e t$ with a 3rd order model yields the following motion model

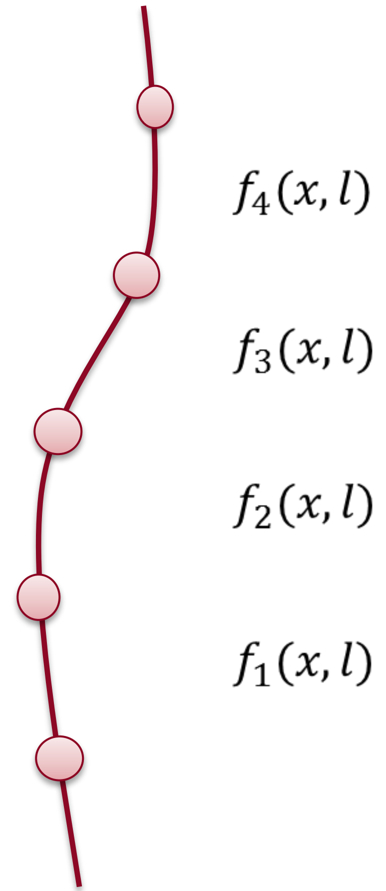
$$x_{k|k-1} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \\ v_e t & 1 & 0 & 0 & 0 \\ \frac{1}{2}(v_e t)^2 & v_e t & 1 & 0 & 0 \\ \frac{1}{6}(v_e t)^2 & \frac{1}{2}(v_e t)^2 & v_e t & 1 & 0 \\ \frac{1}{6}(v_e t)^2 & \frac{1}{2}(v_e t)^2 & v_e t & 0 & 1 \end{bmatrix} x_{k-1|k-1} + \begin{bmatrix} 0 \\ 0 \\ -t\varphi_e \\ -\frac{1}{2} v_e t^2 \\ -\frac{1}{2} v_e t^2 \end{bmatrix} + w_k$$



Examples for Motion Models: New Alternatives for Lane Tracking

- Spline description

- set of control points
- More flexible geometry description
    - Adjustable control point density
    - Needs careful modellig



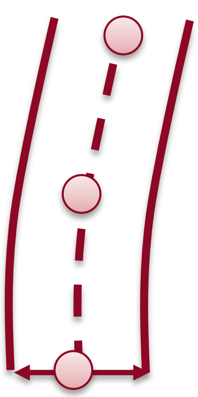
Examples for Motion Models:
New Alternatives for Lane Tracking

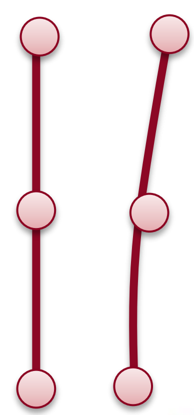
- Spline tracker
  - The set of control points is included in the state vector of a Kalman filter
  - The control points are shifted according to the known ego-motion
  - New points are added on an extrapolated curve in front of the vehicle
  - Passed points are removed behind the vehicle

Lane Tracking: Design Selections

- Parallel lane markings in a single filter
  - More robust
  - Allows extraction of the pitch angle
  - Does not always match with reality

- lane marking tracking using a bank of filters
  - Less robust
  - More flexible
  - Can model splitting and merging



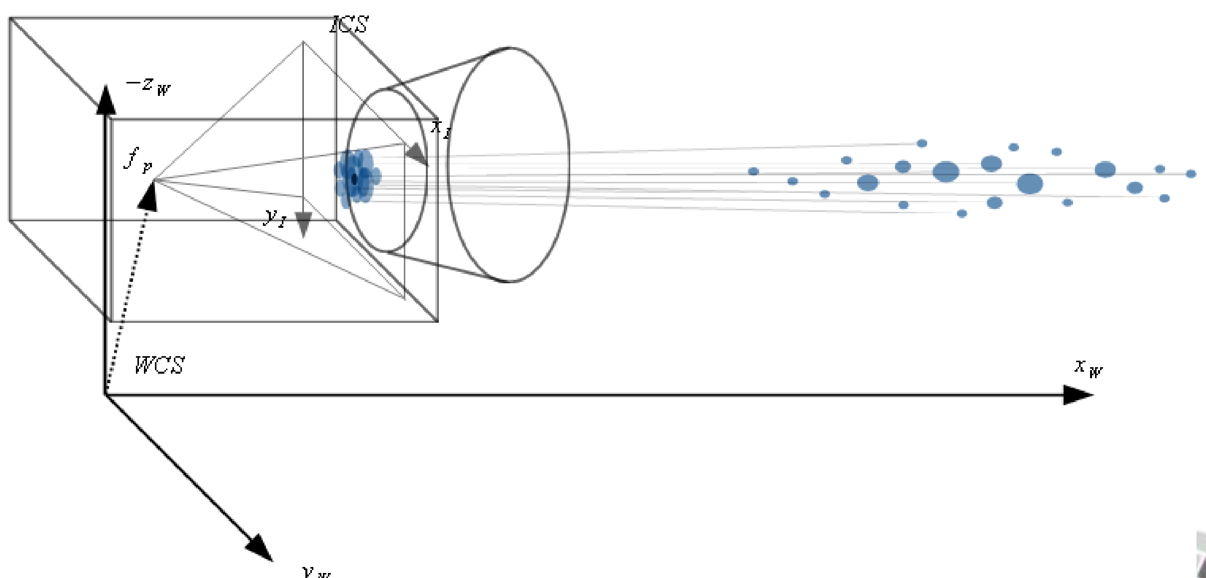


Examples for Motion Models: Traffic Sign Tracking

- State is the position in 3D space

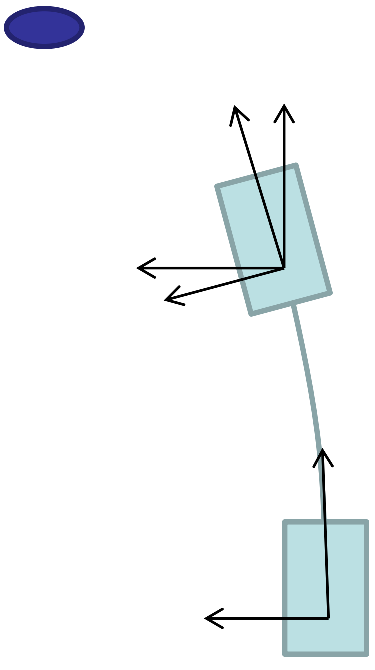
$$\boldsymbol{x} = [x \quad y \quad z]^T$$

  - No target motion components
  - Ego motion compensation motion model
  - Size constraints can be used to refine the distance estimate



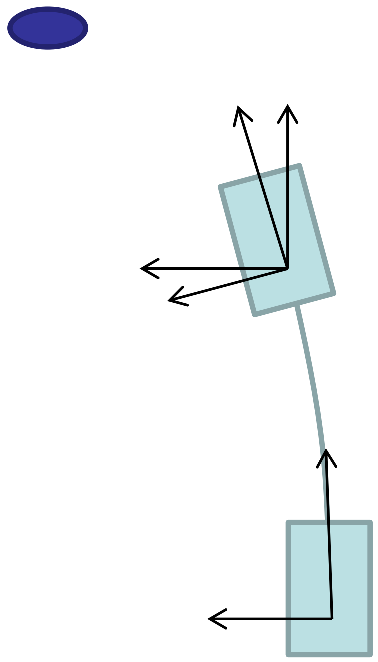
Examples for Motion Models: Pedestrian Tracking

- Ground plane motion
- Constant velocity target model
  - Relative x-velocity given as $v - v_e$
  - Yaw rate given as $-\varphi_e$



Examples for Motion Models: Pedestrian Tracking

- Ground-plane motion model
- CT model with Cartesian velocity and known turn rate (ego-motion)
- Size and ground-plane constraints can be used to give rough distance estimates



$$x = [x \quad \dot{x} \quad y \quad \dot{y}]^T$$

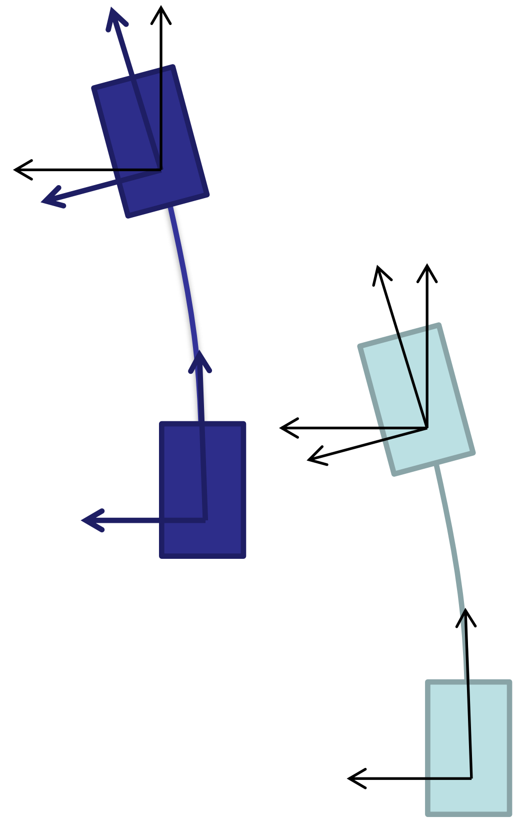
No target rotation component, model can be found in

Survey of Maneuvering Target Tracking.
Part I: Dynamic Models
X. Rong Li and Vesselin P. Jilkov

Examples for Motion Models: Vehicle Tracking

- CT Model with cartesian velocity
  - Ground plane motion model using rotating cartesian velocity vectors
  - Target turn rate is a part of the state vector
  - Relative CT Model with constant cartesian velocity
    - Rotation of the velocity components
  - Sometimes an extension with constant acceleration is used

- Propose to be used within an IMM estimator (with and without turn-rate) to improve filtering performance



$$x = [x \quad y \quad \dot{x} \quad \dot{y} \quad \dot{\varphi}]^T$$

Rotation component

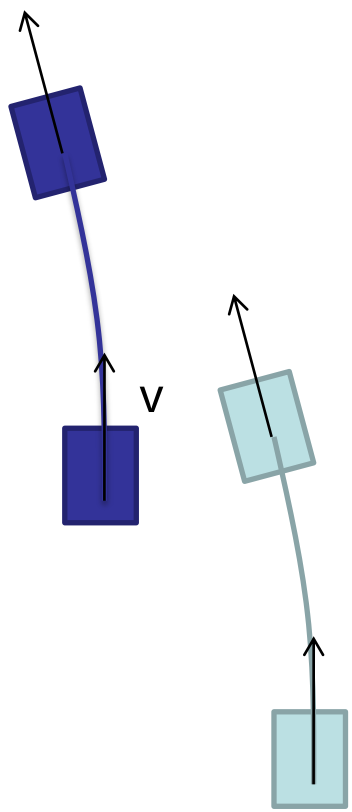
Examples for Motion Models: Vehicle Tracking

- CT Model with polar velocity
  - Ground plane motion model
  - Taylor-expanded at phi=0 to avoid a singularity
  - Unobservable at v=0
  - Sometimes an extension with constant acceleration is used

    Observable dynamics and coordinate systems for vehicle tracking
    Richard Altendorfer

  - Better performance

- Used within an IMM estimator to avoid unobservability



$$x = [x \quad y \quad \varphi \quad \dot{\varphi} \quad v]^T$$

Future Trends

- Robustness will remain a topic for image processing
- More exchange, interaction and fusion between several applications
- Real-time capable 3D reconstruction and ego motion extraction on embedded processors
- Vehicles will form a complex hereogenous sensor network
  - High delay communication with an environmental map over the internet
  - Low delay communication over C2C to nearby vehicles
  - Fusion with different sensors on the host vehicle (Camera, Radar, Gps, Map, Lidar, …)
  - Creation and update and upload of an environmental map
- Autonomous driving

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Accident avoidance by active intervention for Intelligent Vehicles

Thank you.

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SEVENTH FRAMEWORK PROGRAMME

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