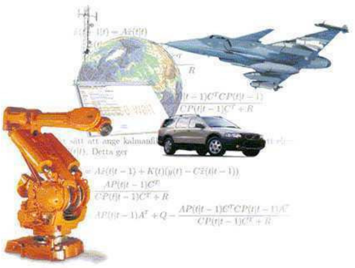
On the Use of Multiple Measurement Models for Extended Target Tracking



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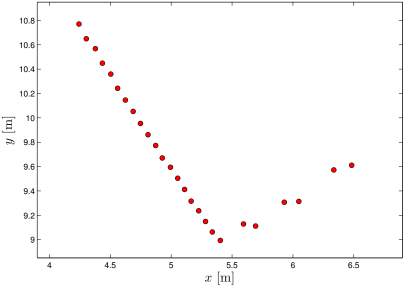
- Includes how extension parameters relate to multiple meas
- The appearance of the measurements is important

- Example:
  Car ≈ rectangular extension
  Laser measurements have line- or L-shaped appearance.



- Both extension and appearance can change over time.

Time changing measurement appearance

- Most extended targets have constant extensions (orientation may change over time).
- We consider constant extension and time changing appearance, especially abrupt changes.
- Observability of state variables may change with appearance.

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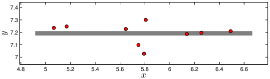
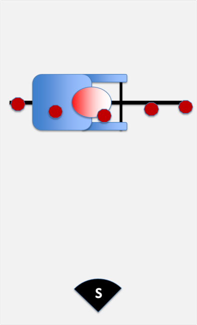
- Example used in paper:
  Bicycles measured by a laser mounted at pedal height

- Measurement appearance varies significantly



Along bike length



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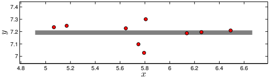

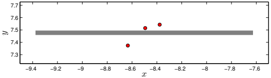

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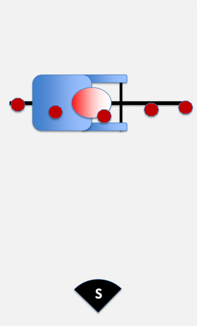
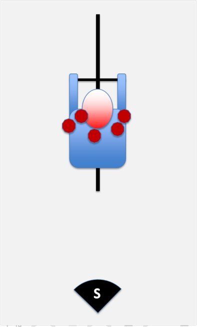


Around pedals



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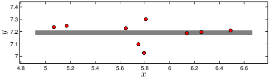

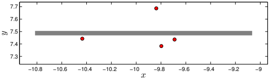

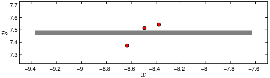

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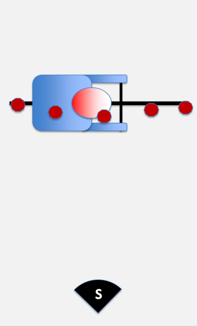
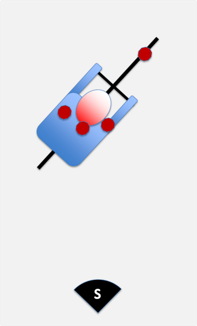
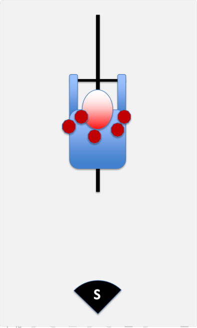


In-between



Around pedals



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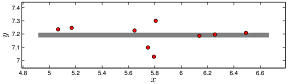

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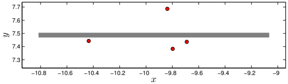

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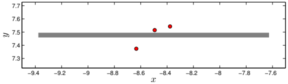

Around pedals

- Two “simple” cases can be identified,
  1. line shaped measurements,
  2. point clusters,

  and ambiguous cases in-between the two.
- The measurement model must handle all possible cases.

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Measurement modeling approaches

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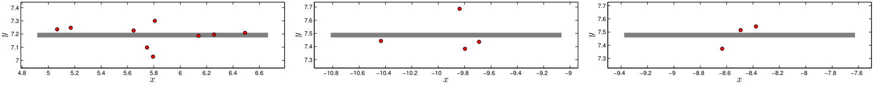

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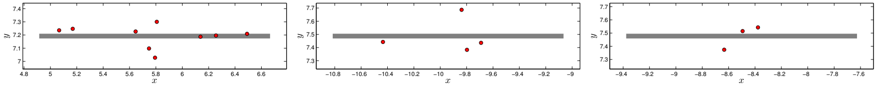
- Heading/orientation and length not observable from point meas
- Observability changes with measurement appearance, and appearance changes with sensor to target geometry.



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    1. Single model with "hard" appearance mode decision.
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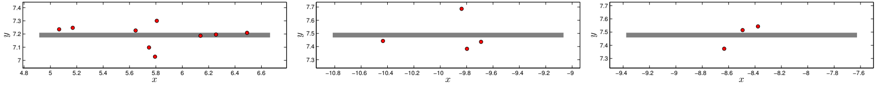
Motivation



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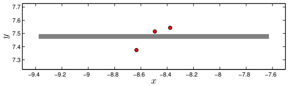
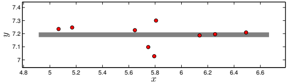
- Gaussian Mixture Multi Model Extended Target PHD filter,

$$D_{k|k}(\xi) = \sum_{j=1}^{J_{k|k}(o)} w_{k|k}^{(j)}(o)\, \mathcal{N}\left(\mathbf{x}\,;\, m_{k|k}^{(j)}(o)\ ,\ P_{k|k}^{(j)}(o)\right)$$

- Extended target state $\xi_k = (\mathbf{x}_k, o_k)$ is combination of kinematic state $\mathbf{x}_k$ and mode o_k.
  - Two motion modes: CT and CV
  - Two measurement modes: P and L





  - Four modes in total: CTP, CVP, CTL, CVL
- Details in the paper.

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- Transition density describes time evolution of target,

$$p\left(\xi_{k+1}\left|\xi_{k}\right.\right)=p\left(\mathbf{x}_{k+1}\left|o_{k+1},\mathbf{x}_{k}\right.\right)p\left(o_{k+1}\left|\mathbf{x}_{k},o_{k}\right.\right)$$

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- Typical assumption: Mode transition independent of $\mathbf{x}_k$,

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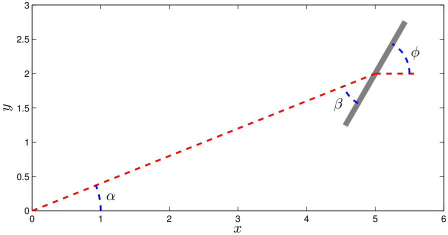
- Assumption valid for motion modes.
- However, measurement modes typically depend on the sensor to target geometry, i.e. on $\mathbf{x}_k$.

- α is angle to center point
- ϕ is heading/orientation
- $\beta = \phi - \alpha$
- If $\cos(\beta) \approx \pm 1$
  point mode is more likely



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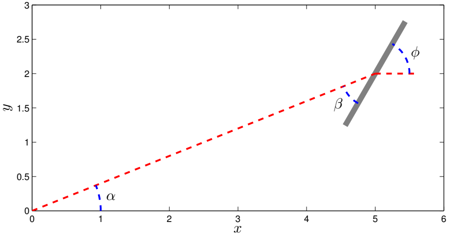
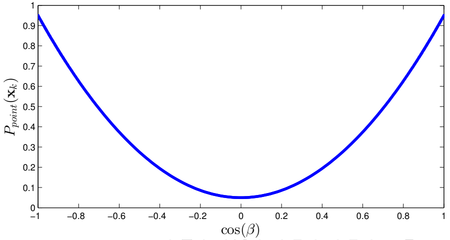


- Probability of transition to, or staying in, point mode, $P_{\text{point}}(\mathbf{x}_k)$, is function of β, i.e. of $\mathbf{x}_k$.



- Transition probability for measurement modes

$$T^{\text{Meas}}_{k+1|k}(\mathbf{x}_k) = \begin{bmatrix} P_{\text{point}}(\mathbf{x}_k) & 1 - P_{\text{point}}(\mathbf{x}_k) \\ P_{\text{point}}(\mathbf{x}_k) & 1 - P_{\text{point}}(\mathbf{x}_k) \end{bmatrix}$$

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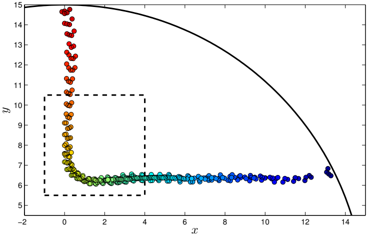
- Full transition probability matrix is Kronecker product

$$T_{k+1|k}(\mathbf{x}_k) = T^{\text{Meas}}_{k+1|k}(\mathbf{x}_k) \otimes T^{\text{Motion}}_{k+1|k}$$

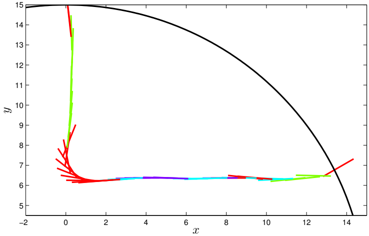
- MM-PHD filter tested on 40 datasets.
  - Single maneuvering bicycle
  - Multiple (2) maneuvering bicycles
- Background was removed by hand before the experiments
- Results in the paper are from a subset of the datasets

Results from experiments

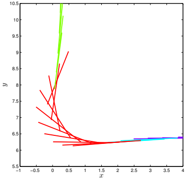
- MM-PHD filter tested on 40 datasets.
  - Single maneuvering bicycle
  - Multiple (2) maneuvering bicycles
- Background was removed by hand before the experiments
- Results in the paper are from a subset of the datasets
- Three MM-PHD filters compared. CT and CV motion model.
  1. P and L measurement models
  2. Only P model
  3. Only L model



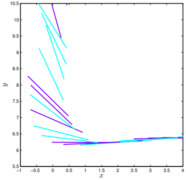
Measurements



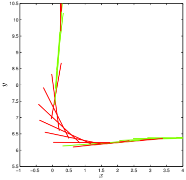
Proposed MM approach



MM approach



Only L model



Only P model

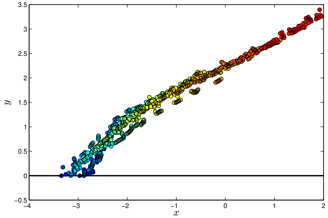
Legend:

CT , P model

CV , P model

CT , L model

CV , L model



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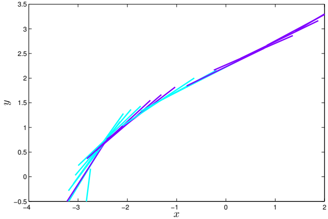

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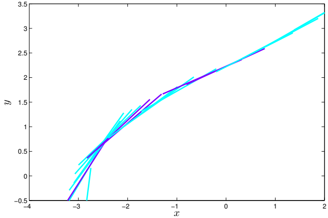

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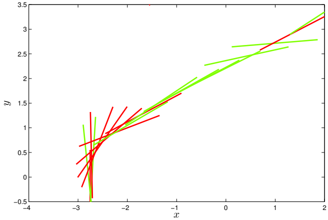

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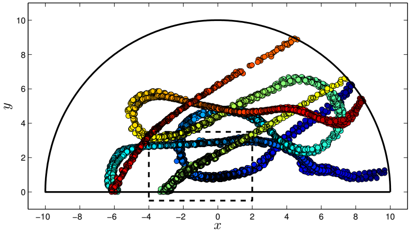

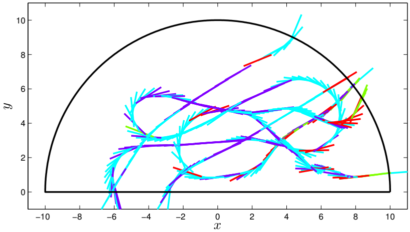

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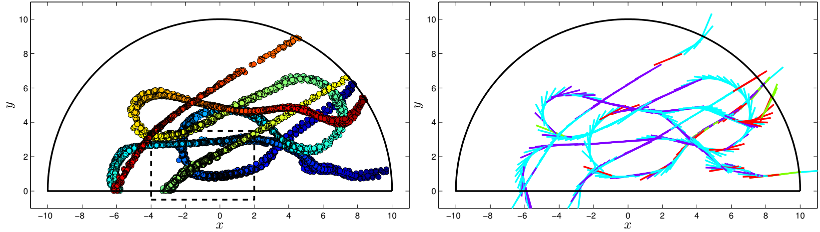
Multiple target results & Summary



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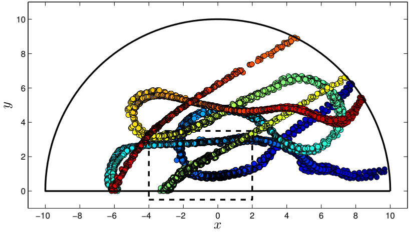

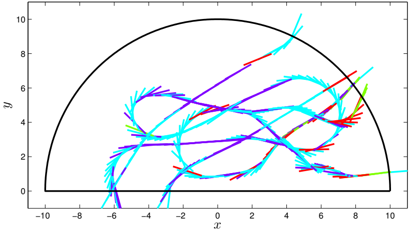

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- Only L model sometimes fails during turns.
- Using both models generally superior.
- In MM case L model can aid in detecting CT maneuvers.

Conclusions:

- The paper presents a MM-ET-PHD filter with kinematic state dependent mode transitions
- Applied to bicycle tracking using laser range measurements
- In addition to multiple motion modeling, the MM approach is suitable when the measurement appearance changes over time

Concluding remarks

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- The paper presents a MM-ET-PHD filter with kinematic state dependent mode transitions
- Applied to bicycle tracking using laser range measurements
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Future work:

- Other types of sensors
- Other types of targets
- Multiple target types, each with multiple appearance modes

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Thank you for listening!

Any questions?