Extended Object Tracking using Hierarchical Truncation Measurement Model with Automotive Radar

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This work is done during his internship at MERL.

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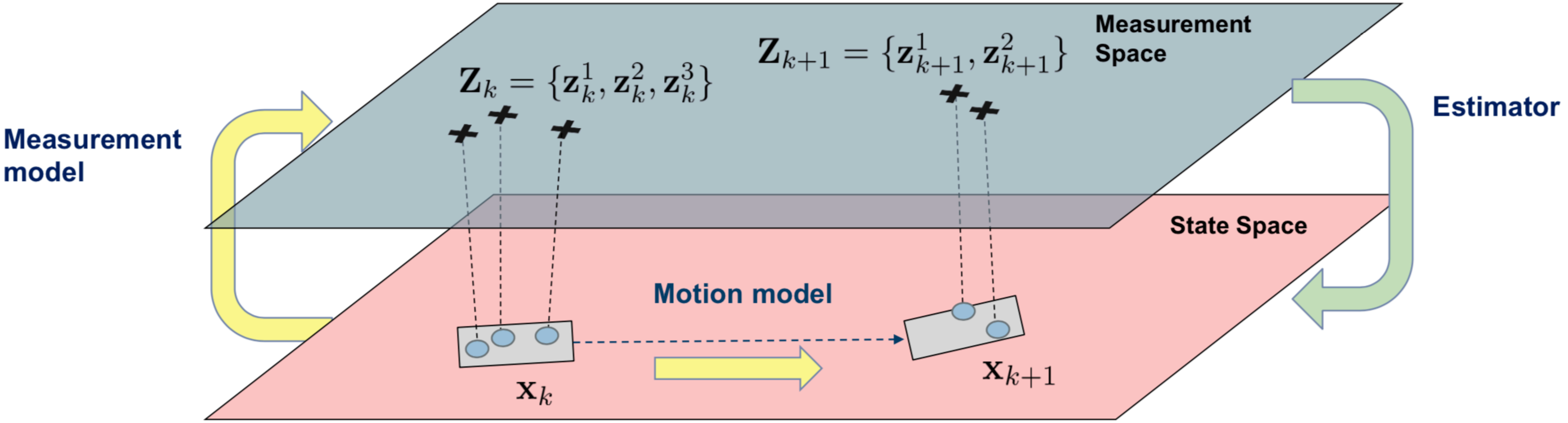
Topic: Extended Object Tracking

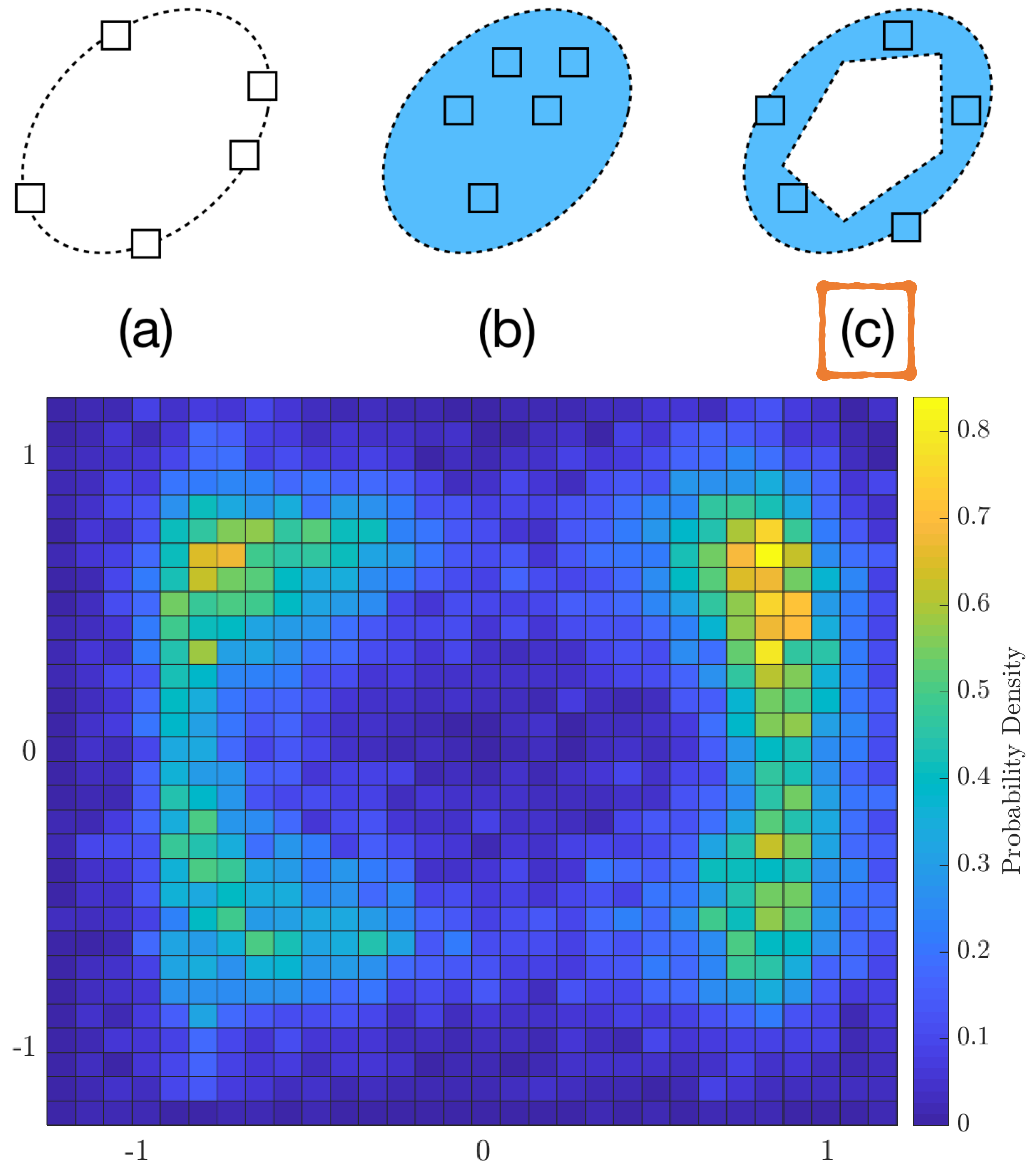
- ***Point object*** generates at most ***one*** measurement per time step.
- ***Extended object*** generates ***multiple measurements*** per time step.
- Object state of interest: position, kinematic state (velocity, heading, etc.) and ***extent state*** (shape and size).
- Recursive Bayesian estimation:



$$\longrightarrow p(\mathbf{x}_k|\mathbf{Z}_{1:k}) \xrightarrow{\text{Prediction}} p(\mathbf{x}_{k+1}|\mathbf{Z}_{1:k}) \xrightarrow{\text{Update}} p(\mathbf{x}_{k+1}|\mathbf{Z}_{1:k+1}) \longrightarrow$$

Motivations

- Real-world automotive radar measurements are typically distributed around edges of rigid objects (e.g., vehicles) with a certain volume.
- Common spatial models: (a) contour model, (b) surface model, are generally not applicable.
- Surface-volume model (c) capture the spatial characteristics of automotive radar measurements.
- Random matrix approach is a prominent example of surface model; it assumes elliptical object shape and is simple to implement.
- Can we leverage on the random matrix approach and the spatial characteristics of automotive radar measurements?



Histogram of accumulated Radar point cloud in unit coordinates, extracted from nuScenes dataset.

Main Contributions

- A new surface-volume model, ***the Hierarchical Truncated Gaussian measurement model***, that resembles the spatial characteristics of real-world automotive radar measurements.

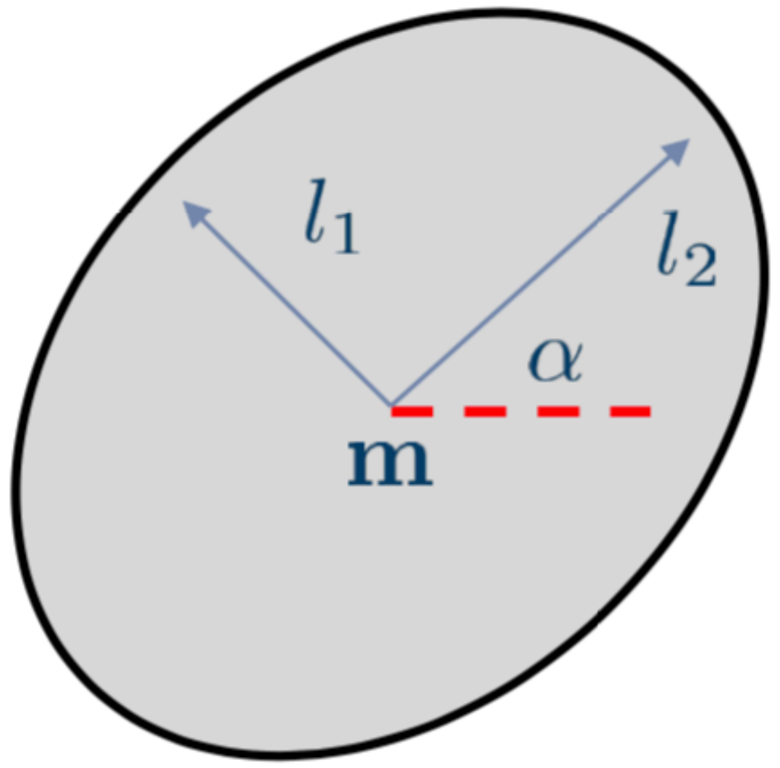
- A new random matrix based extended object tracking algorithm tailored to the new surface-volume model.

★ Integrating the new surface-volume model into random-matrix approach enables light-weight, realistic method implementable on automotive ECU.

Modeling

Dynamic model

- ***Location and kinematic state***: vector x.
  - Constant velocity, Coordinated turn, etc.
  - Gaussian pdf: $N(x; m, P)$.
- ***Extent state***: SPD matrix X.
  - Elliptic shape.
  - Extent typically has constant size, rotating during turns.
  - Inverse-Wishart pdf: $IW(X; v, V)$.



$$= \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} l_1^2 & 0 \\ 0 & l_2^2 \end{bmatrix} \begin{bmatrix} \cos\alpha & -\sin\alpha \\ \sin\alpha & \cos\alpha \end{bmatrix}$$

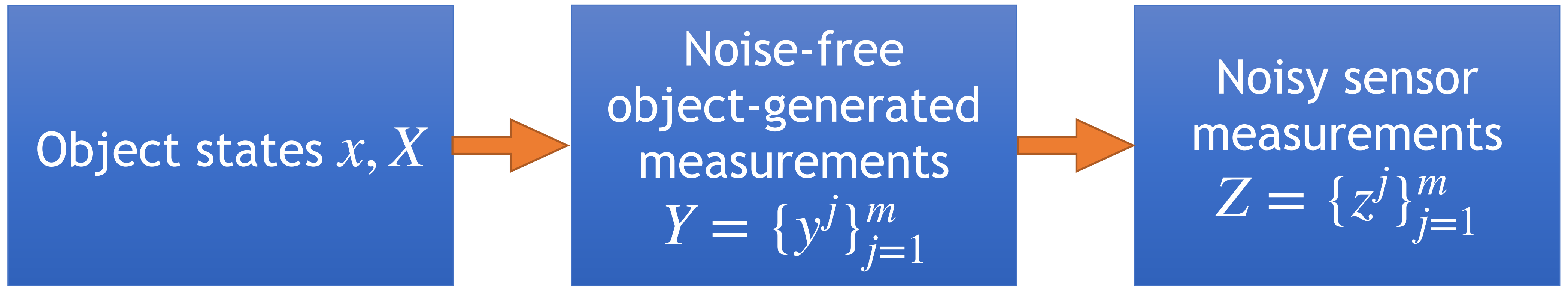
Implicit ellipse equation:

$$(\mathbf{y}-\mathbf{m})^T V^{-1} (\mathbf{y}-\mathbf{m}) = 1$$

Object length and width obtained from eigen-decomposition of X.

Modeling

Measurement model



- Noisy sensor detection z stems from noise-free measurement source y.

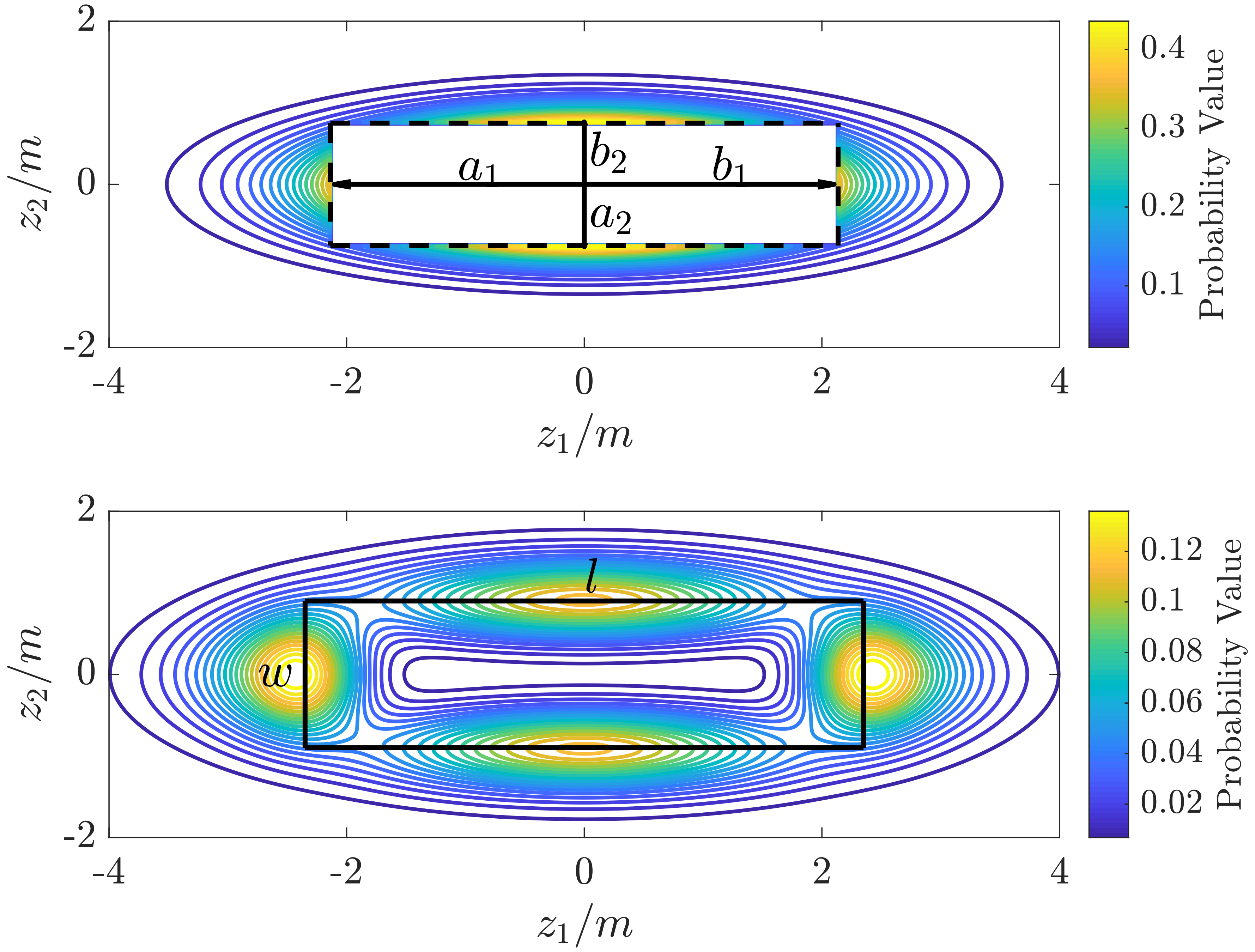
- Measurement source pdf: Truncated Gaussian $p(y\,|\,x, X) = TN(y; h(x), X, D)$.

- Sensor noise pdf: Gaussian $p(z\,|\,y) = N(z; y, R)$.

- Hierarchical Truncated Gaussian measurement likelihood:

$$p(z\,|\,x, X) = \int N(z; y, R) TN(y; h(x), X, D) dy.$$

- Setting truncation bounds to $+\infty$ to model ***self-occlusion*** feature, i.e., partial-view measurements.



Pdfs of Truncated Gaussian and Hierarchical truncated Gaussian.

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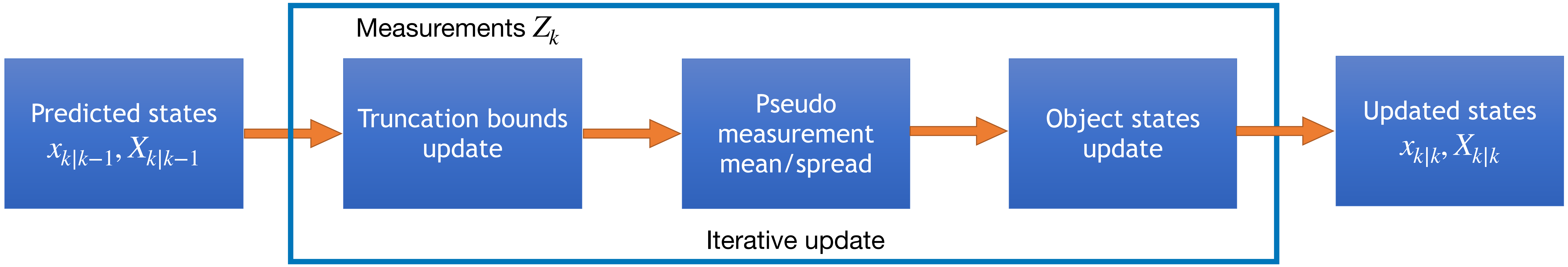
Problem Formulation and Solution

- ***Objective***: Recursively calculate the posterior $p(x_{k|k}, X_{k|k} \,|\, Z^k) \approx N(x_{k|k}; m_{k|k}, P_{k|k}) IW(X_{k|k}; v_{k|k}, V_{k|k})$.
- ***Challenges***:
  - Measurement statistics are biased → Random Matrix approach: object states updated in a *Kalman-filter-like* fashion using *mean/spread of Gaussian distributed measurements*, may not yield good tracking performance.
  - Truncation bounds need to be estimated.
- ***Proposed solution***:
  - Construct Gaussian-distributed pseudo-measurement statistics.
  - Formulate the estimation of the truncation bounds as an optimization problem.
  - Use an EM-type algorithm to ***iteratively update object states and truncation bounds***.



Proposed Update Method

Pseudo-measurement statistics

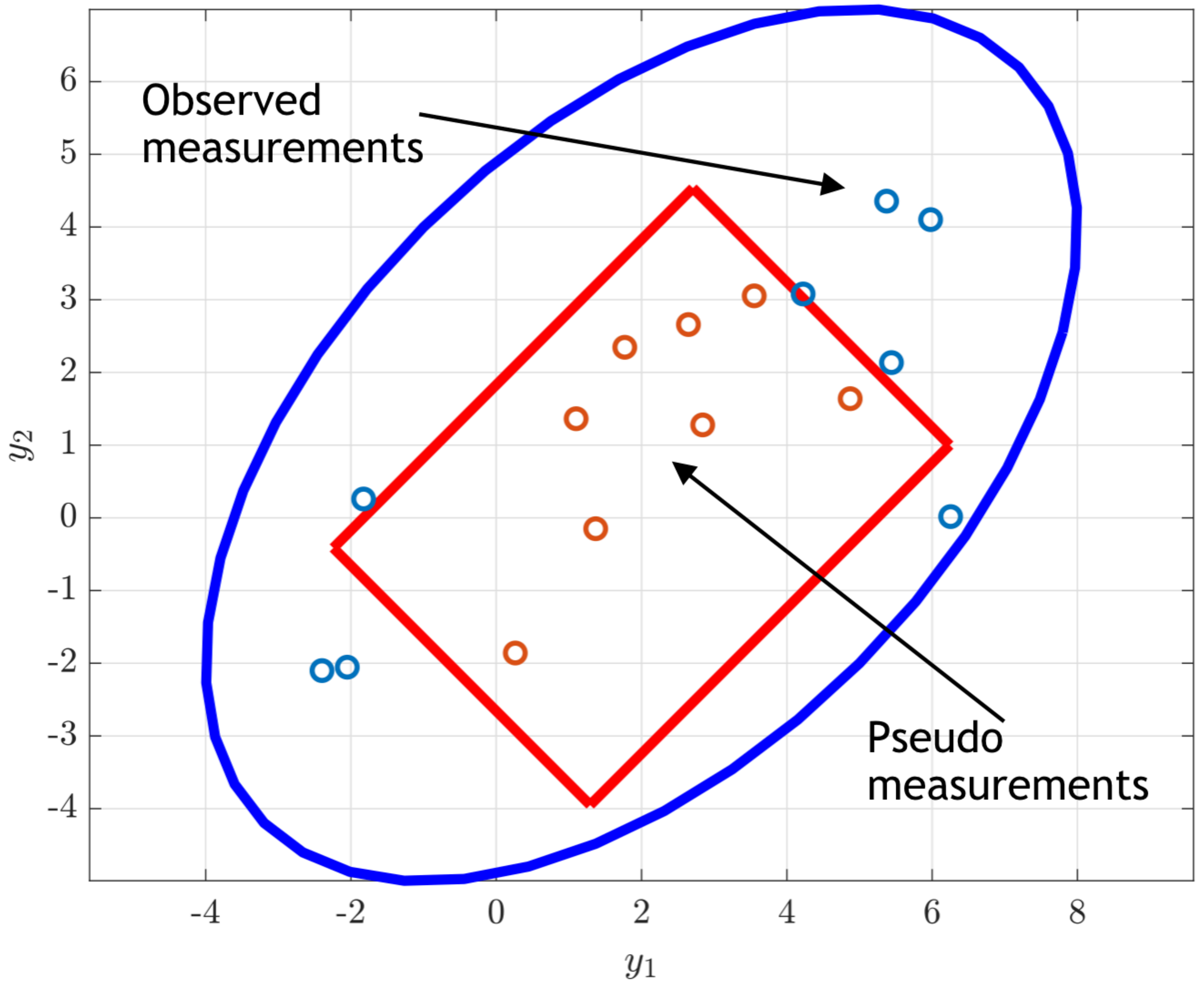
- Compute ***sample*** measurement mean $\bar{z}_k$ and spread $\bar{Z}_k$.
- Compute ***analytical*** mean $\bar{z}_k^c$ and spread $\bar{Z}_k^c$ of Hierarchical Truncated Gaussian distribution

$$p(z_k^c \mid x_k, X_k) = \int N(z_k; y_k, R) TN(y_k; h(x_k), X_k, R^2 \backslash D_k) dy_k$$

- Gaussian-distributed pseudo measurement mean/spread can be constructed as the ***weighted sum*** of the sample and the analytical mean/spread, respectively weighted by

$$c_{D_k} = \int_{D_k} TN(y_k; h(x_k), X_k, D_k) dy_k \text{ and}$$

$$1 - c_{D_k} = \int_{R_2 \backslash D_k} TN(y_k; h(x_k), X_k, R^2 \backslash D_k) dy_k.$$



$$\frac{\#\text{Observed measurements}}{\#\text{Pseudo measurements}} = \frac{c_{D_k}}{1 - c_{D_k}}.$$

Proposed Update Method

Truncation bounds estimation

- ***Objective***: Find the ML estimates of the truncation bounds

$$\arg\min_{a_k, b_k} \sum_{z_k \in Z_k} -\log p(z_k \mid x_k, X_k).$$

- ***Challenges***: Computational demanding for online estimation.

- ***Proposed solution***:

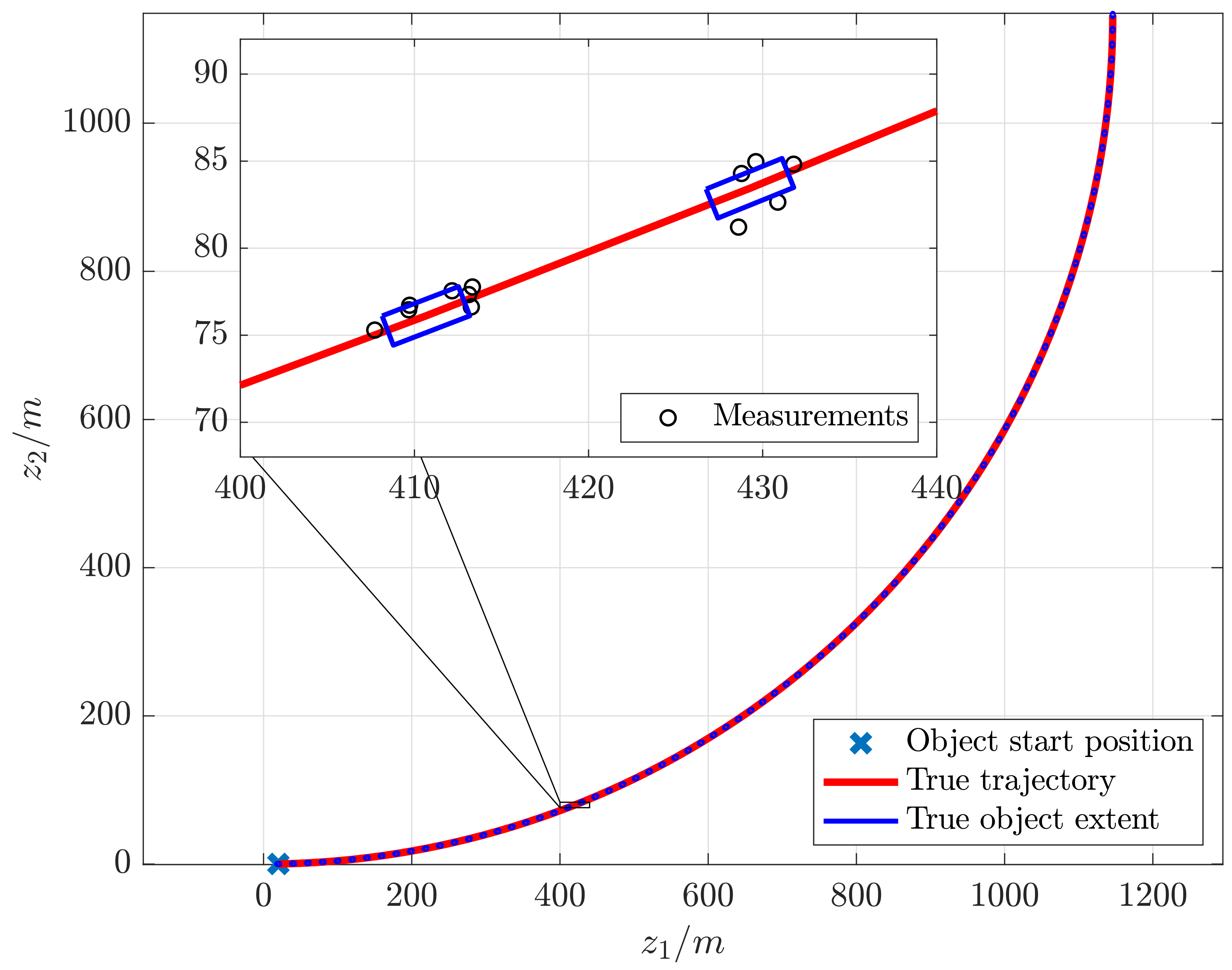
    - Decompose the joint ML estimation problem into up to four ***decoupled*** ML estimation problems using ***expectation-maximization clustering***.

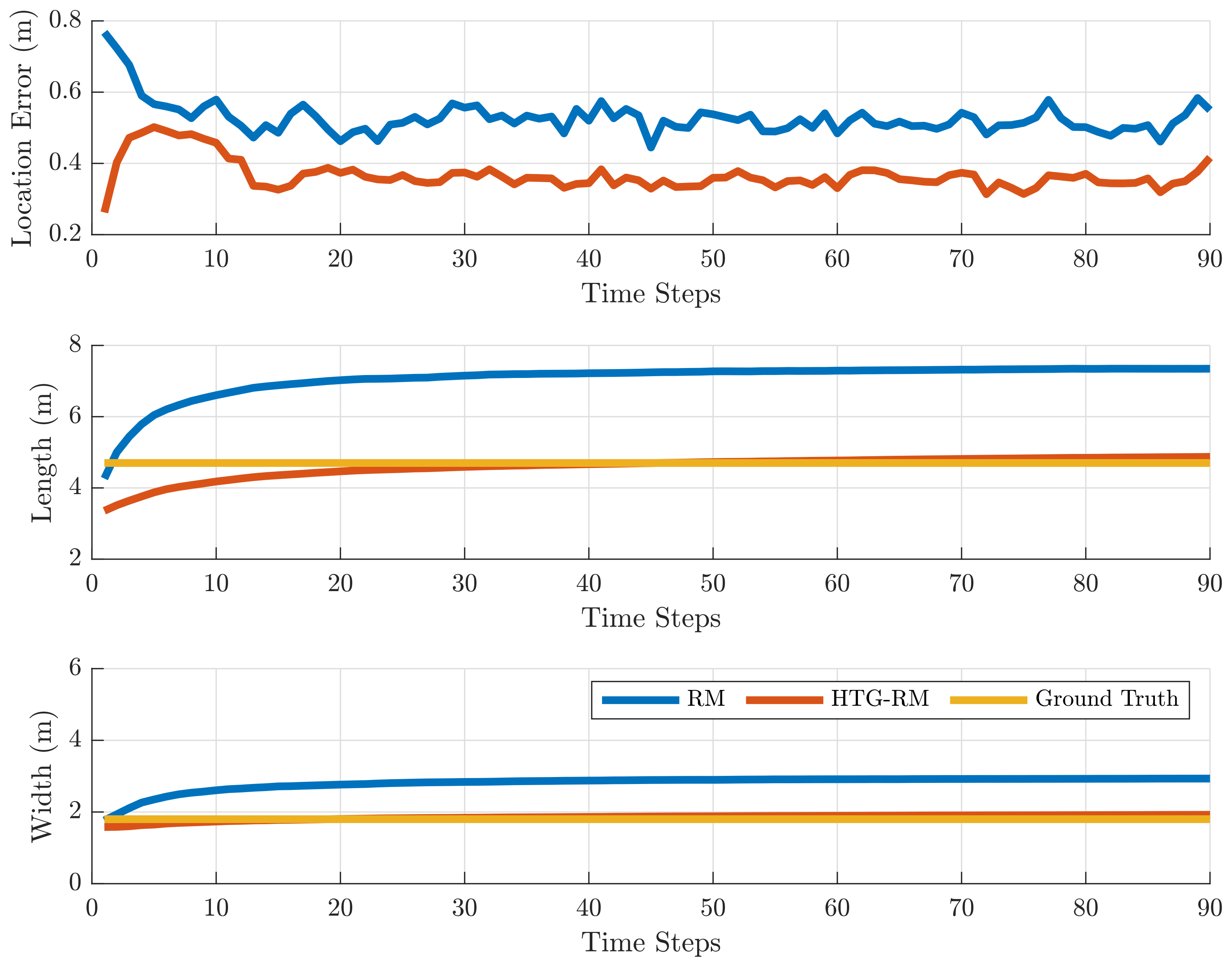
    - For each subproblem (a ***univariate*** constrained optimization problem), find the ML estimate using standard root-finding algorithm.

Simulation Results

Performance evaluation with ideal measurement model

- Rectangular object (4.7-m long and 1.8-m wide) moves following coordinated turn motion model.
- Object detections drawn from truncated uniform distribution and corrupted with Gaussian noise.
- Number of detections is Poisson distributed with mean 8.



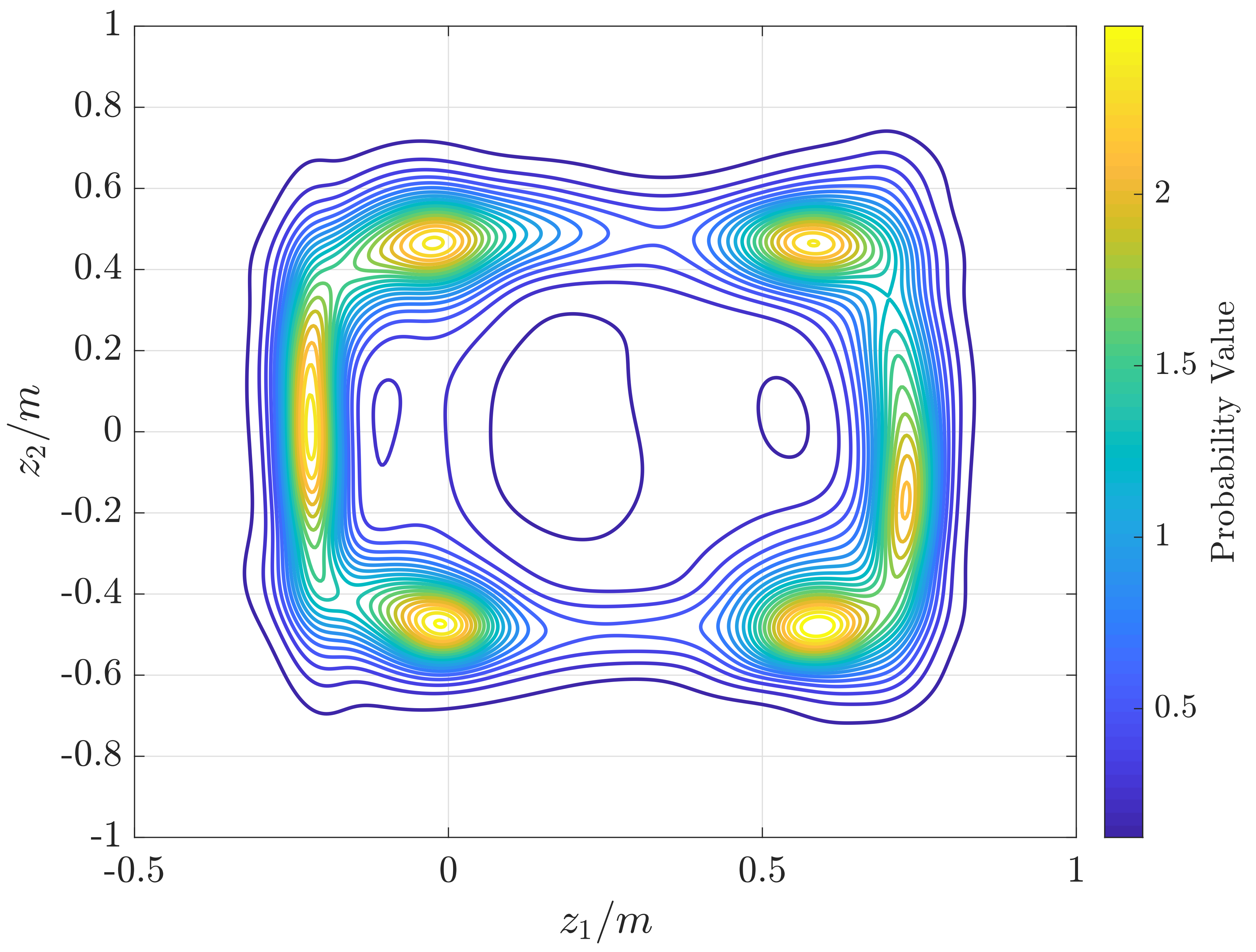


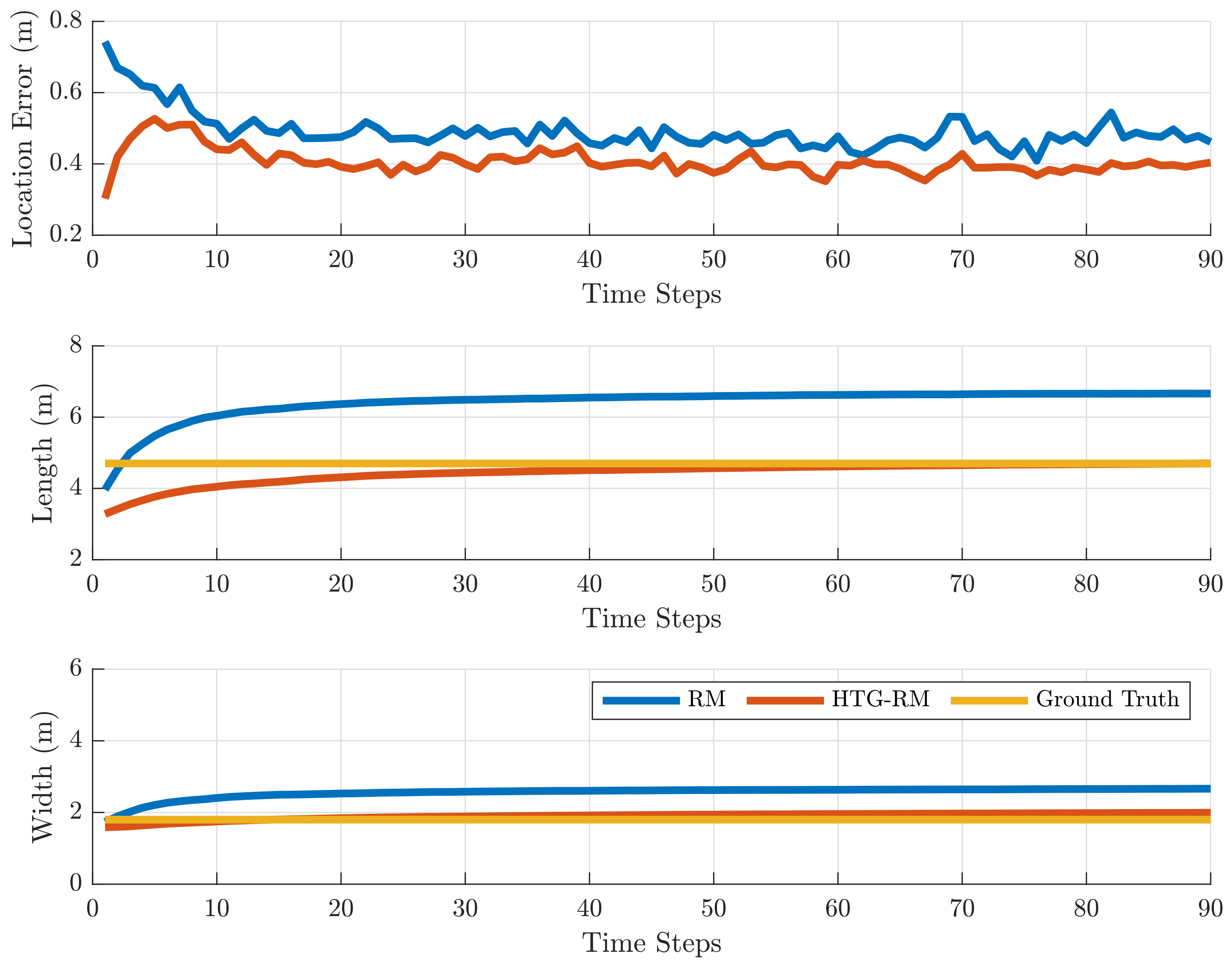
Simulation Results

Performance evaluation with measurement model mismatch

- Object detections drawn from an offline trained variational Radar model (student's t mixture) [Scheel 2018].
- Number of detections is Poisson distributed with mean 8.

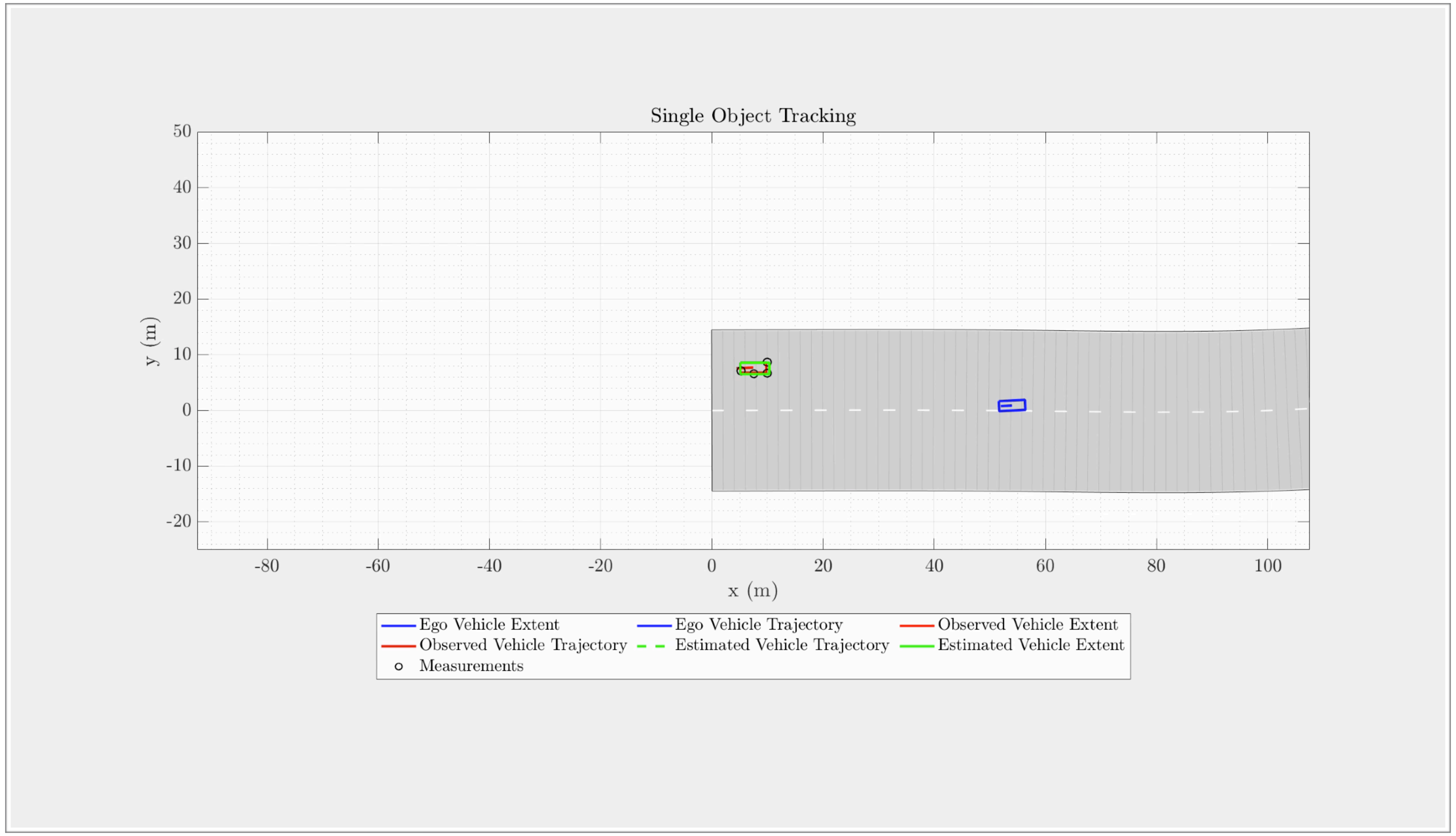
Pdf of offline trained variational radar model





Validation with MathWorks Measurements

- Tracking scenario and synthetic radar measurements generated using MathWorks Automated Driving Toolbox.
- Multiple long-range, medium-range and short-range automotive radars mounted on the ego vehicle.



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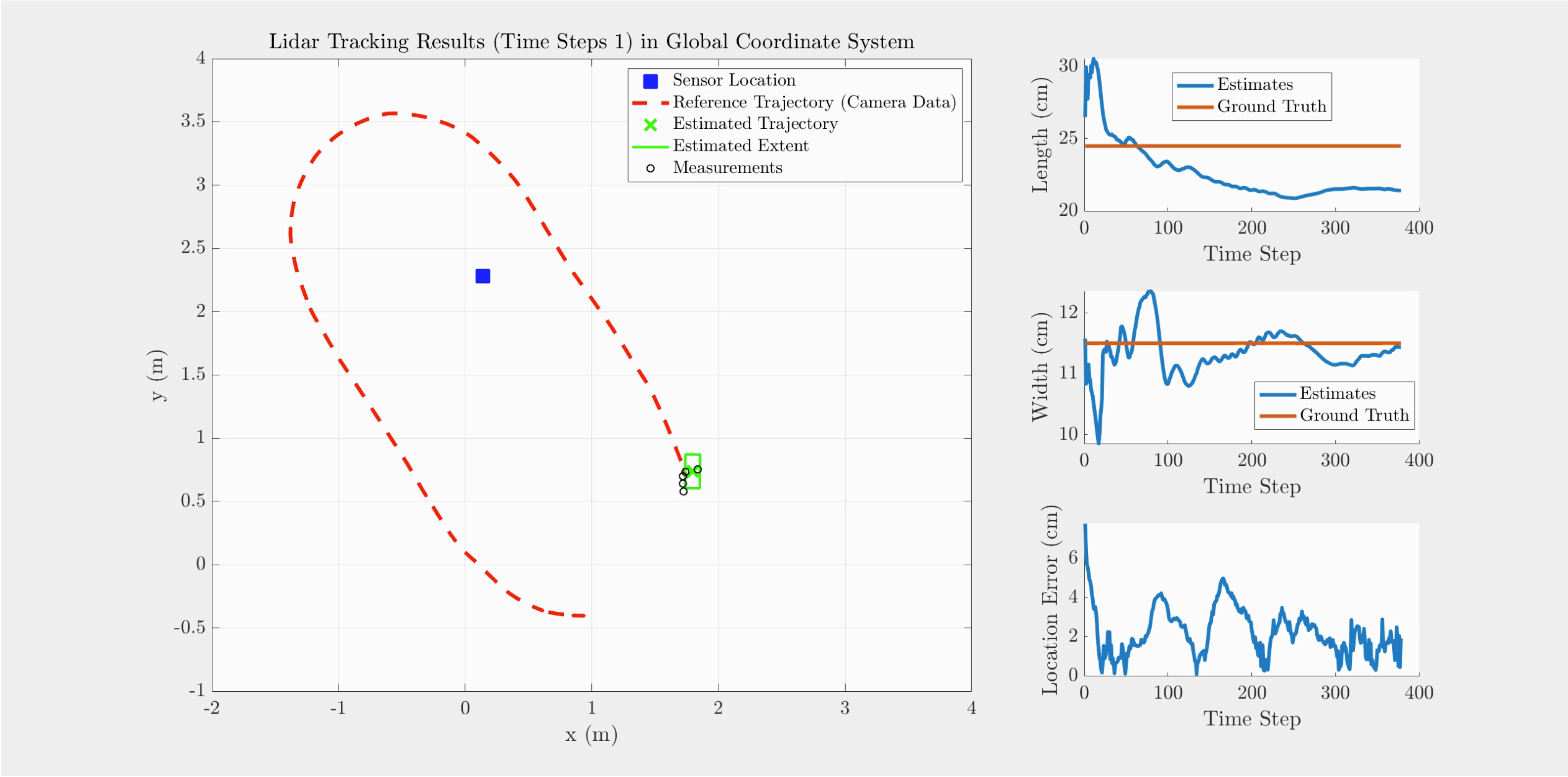
Validation with In-house Hamster Lidar Data

- Hamster: Ackermann steering, velocity control, IMU, ***camera (reference)***, Lidar, wheel encoders, GPS.
- Lidar sensor is fixed and one Hamster car is moving. In general, Lidar measurements lie on the edges of the object.



Summary

- Proposed a new surface-volume model, ***the Hierarchical Truncated Gaussian measurement model***, which resembles the spatial characteristics of real-world automotive radar measurements.
- Developed a new Random Matrix based extended object tracking algorithm tailored to the new measurement model.
- Simulation results validate and demonstrate the effectiveness of the proposed approach.