





Towards Resilient Tracking in Autonomous Vehicles

A Distributionally Robust Input & State Estimation Approach

Kasra Azizi, Kumar Anurag, Wenbin Wan

University of New Mexico

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Phoenix, Arizona, USA



Introduction - Problem & Solution



Image Source: Freepik

The Problem

- Safety
- → State Data
- → Noisy Measurements

The Solution

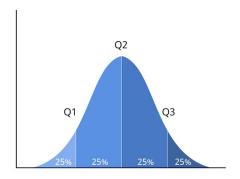
- → Fuse Data
- → Estimate State Using Model
- → Ensure Reliability

Baseline - Input & State Estimation (ISE)

Core Idea

- → Joint Estimation
- → State & Unknown Input
- → Enhance Prediction





Key Limitation

Sensitive to:

- → Non-Linearity
- → Non-Gaussian Noise
- → Outliers



Image Source: Freepik

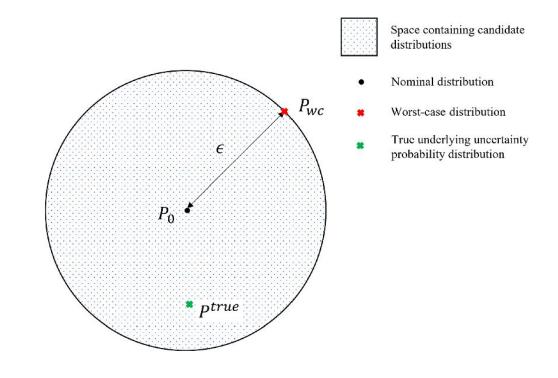
Baseline - Distributionally Robust Estimation (DRE)

Core Idea

- → Robustness
- → Deviating Noise Distributions
- → Ambiguity Sets
- → Worst-Case Optimization

Key Limitation

- → Sensitive to Outliers
- → Ignores Unknown Inputs



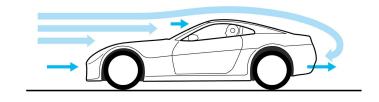
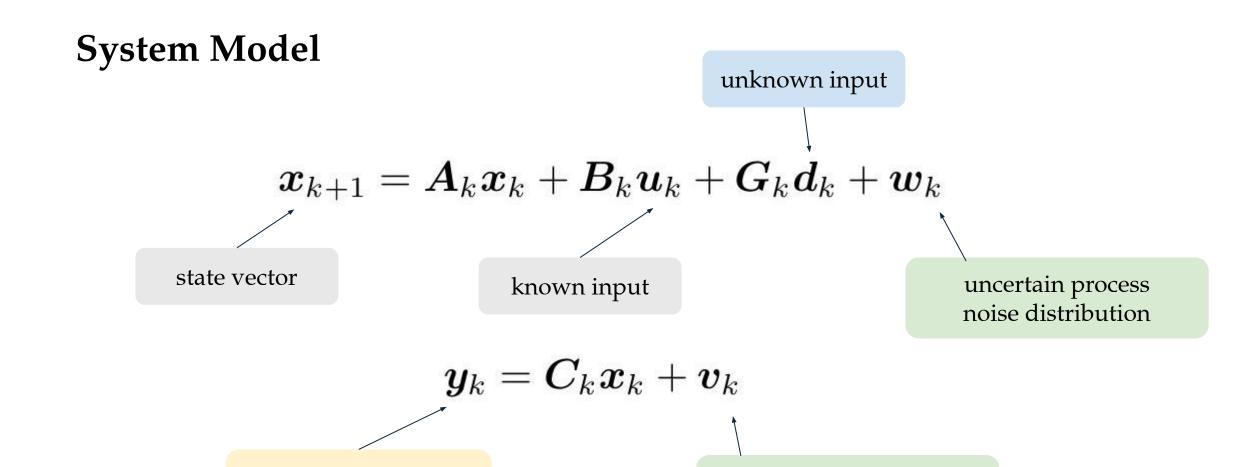


Image Source: Researchgate.net, Gran-Turismo

Problem Formulation



sensor measurements

containing outliers

uncertain measurement

noise distribution

Building Block 1: Unknown Input Estimation

Unknown Forces

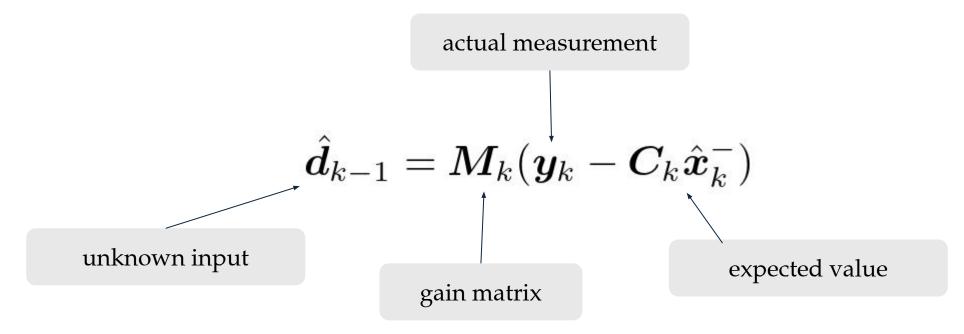
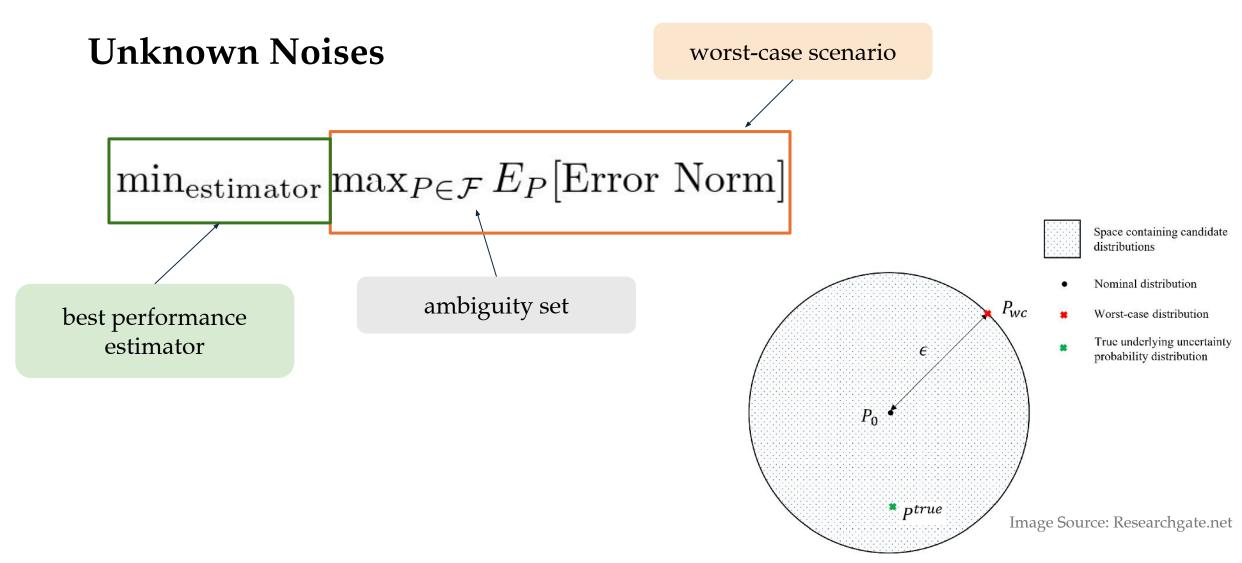




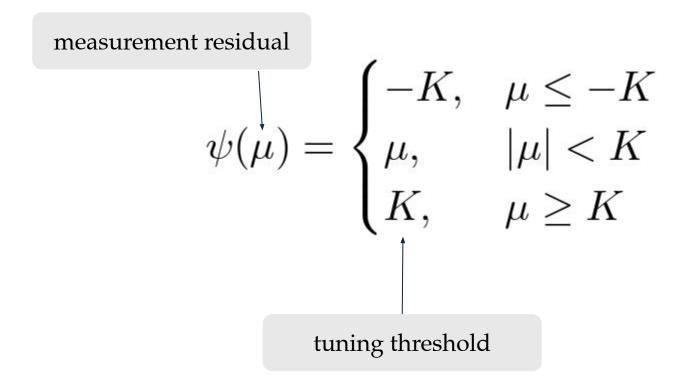
Image Source: Freepik

Building Block 2: Distributionally Robust Estimation

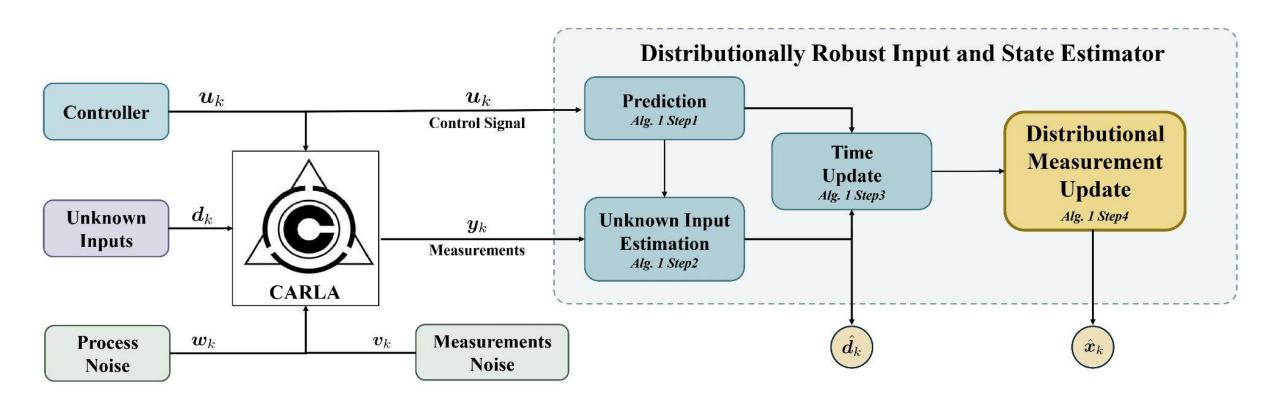


Building Block 3: Robust Update

Outliers



Block Diagram - DRISE Framework



The DRISE Algorithm Cycle

Key Steps

Prediction

$$\hat{\boldsymbol{x}}_{k}^{-} = \boldsymbol{A}_{k-1}\hat{\boldsymbol{x}}_{k-1} + \boldsymbol{B}_{k-1}\boldsymbol{u}_{k-1}$$

Input Estimation

$$\hat{\boldsymbol{d}}_{k-1} = \mathbf{M}_k (\mathbf{y}_k - \mathbf{C}_k \hat{\mathbf{x}}_k^-)$$

I Time Update

$$\hat{oldsymbol{x}}_k = \hat{oldsymbol{x}}_k^- + \mathbf{G}_{k-1}\hat{oldsymbol{d}}_{k-1}$$

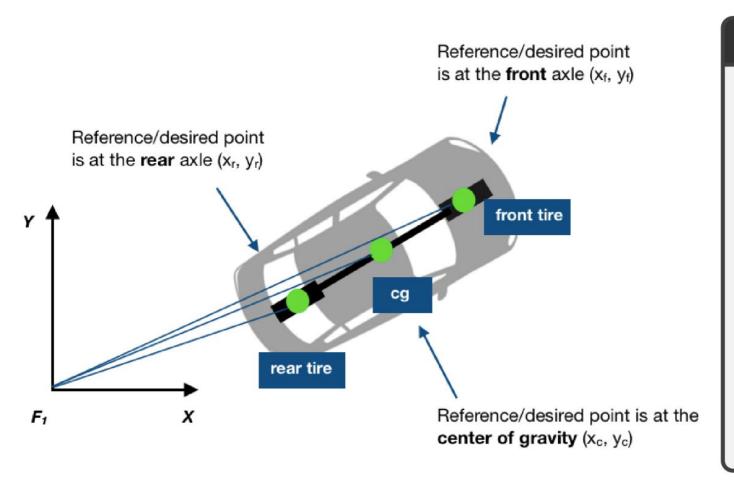
Robust Measurement Update

$$\hat{\boldsymbol{x}}_k \leftarrow \hat{\boldsymbol{x}}_k + \mathbf{L}_k \psi_k (\mathbf{S}_k^{-1/2} \mathbf{s}_k)$$

Notation

- $ightharpoonup \mathbf{M}_k$: Input est. gain.
- ▶ \mathbf{L}_k : Robust gain involving ambiguity sets.
- $\blacktriangleright \psi_k(\cdot)$: Influence function.
- $ightharpoonup \mathbf{s}_k = \mathbf{y}_k \mathbf{C}_k \hat{\mathbf{x}}_k$: Innovation.
- ▶ S_k : Robust innovation covariance.

Simulation Setup



Simulation Settings

- ► Model: Kinematic Bicycle (LTV)
- **States** \boldsymbol{x}_k : Pos, Yaw, Vels
- ▶ Input u_k : Steering, Accel
- ► Unknown Input (d_k) : Time-Varying Signal
- ▶ Noise: Proc (Q_k) , Meas (R_k)
- Outliers/Deviations: Included in Tests
- **▶ Comparison:** KF, ISE, DRE

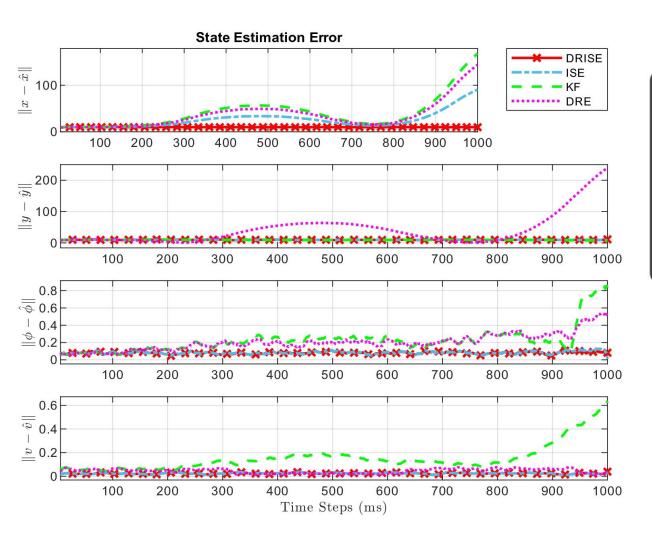
CARLA Simulation Environment



Testing in CARLA Simulator

- ▶ Open-source, high-fidelity simulator for AV research.
- ▶ Provides realistic urban environments, sensors, and physics.
- ► Challenging testbed for evaluating estimator performance under uncertainty.

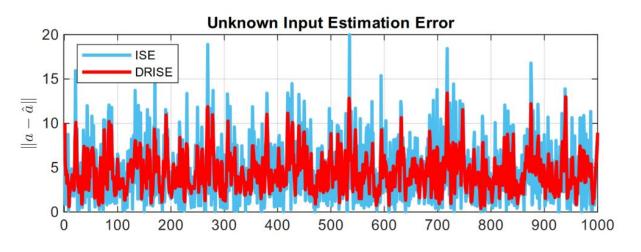
Results: State Estimation Error

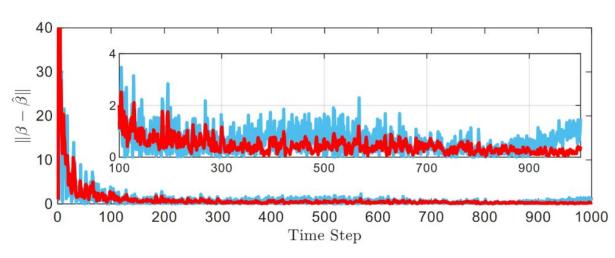


Analysis

- **▶ DRISE:** Lowest Error
- ► **KF:** Highest Error/Divergence
- ► ISE/DRE: Moderate Error

Results: Unknown Input Error





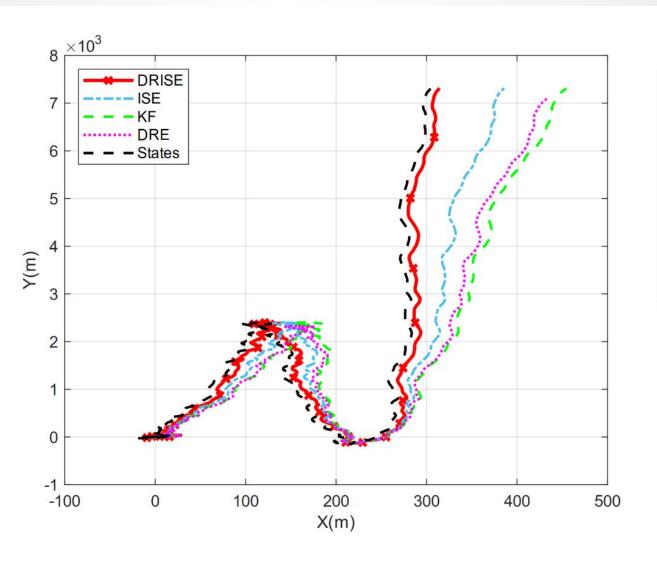
Analysis

▶ DRISE: Lower Error

► **ISE:** Higher Error

▶ **Benefit:** Robustness Aids Input Est.

Results: Trajectory Tracking



Analysis

- **▶ DRISE:** Best Tracking
- ▶ Others: Show Drift
- **Link:** Accurate Est. \rightarrow Better

Tracking

Future Work

Wasserstein distance

Kullback-Leibler divergence

Thank you!

Questions?







OPTIMIZATION AND ESTIMATION LAB